Safety Prediction for Autonomous Vehicles Using Artificial Intelligence with Modified Deep CNN–BiLSTM

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ABSTRACT

In the recent world, the usages of autonomous cars are getting higher because of the emerging technology. People consider that these autonomous cars make their travel safe in any type of road conditions. These autonomous cars give freedom to drive the person those who are not able to drive. It can able to control the CO2 gas emission, avoid traffic and accidents and there are no attention issues like human in autonomous cars. However, the autonomous cars are not perfect because sometimes the autonomous cars face some issues while analysing the different human hand gesture, climatic conditions and road sign. Due to drivers' health condition and malfunctions in the autonomous cars also met with an accident. Some manual techniques are used to analyse the drivers' health to ensure the safety such as survey, dashboard camera and so on. However, these techniques need some time and manual work. To overcome this problem the proposed model use improved search ability based GA (Genetic Algorithm) in feature selection to attain the best features from the dataset and to predict the drivers behaviour and car mechanism the modified deep CNN (Convolutional Neural Network) –BiLSTM (Bidirectional Long Short Term Memory) algorithm with attention mechanism is used. The CNN method is not able to handle the time series data but it is faster and the BiLSTM is able to handle the time series data. Therefore, the proposed model integrated the CNN and BiLSTM to attain best performance. The model included DT (Decision Tree), KNN, NB (Naive Bayes), RF (Random Forest) along with modified deep CNN-BiLSTM with AM (Attention Mechanism). The proposed method attains high performance accuracy while compared with other models

CHAPTER 1

1. INTRODUCTION

This chapter initially equip the overview of the topic with ley aspects of the thesis. Chapter commence with the short overview of the topic and the section 1.1 provides the overview of autonomous vehicles and 1.2 describes the significance of safety in autonomous vehicles. This third section provides the recent trends of safety in autonomous vehicles. At last the section provides the problem, significance, scope, aim and objectives of the thesis structure.

US transportation department stated that in 2018, nearly 6,734,000 number of motor vehicle accidents has occurred. Overall 27.1 lakh of peoples were injured and 36,560 were fatalities. From the year of 2019 to 2020 motor vehicle accidents have increased. In 2015, nearly 33% of accidents were occurred in US due false prediction of drivers and also various driver related problems. Some reports claims that the main reasons for the accidents are because of the human drivers and also errors done by the drivers [1].

Recently, Autonomous Vehicles the (AVs) have been gaining popularity among societies. An autonomous car is an automobile which has the ability to sense the environment and also work even in absence of human drivers. This does not require anyone to control the vehicle anywhere and also no need of persons to be present in the vehicle [2]

The AVs can go anywhere at any time like other traditional vehicles as well as it can do everything that a human driver does. AV have remarkably changed the global transport markets. This enhance the quality of human life along with the traffic safety. This AV has reduced the number of accidents and also have improved parking problems like the capability to park the vehicles in rural areas. AV is frequently called as driverless cars or self-driving vehicles. These AV can control the vehicles without human interference. AVs are equipped with enhanced technologies which assist human drivers [3].

In complicated situations, the ability of the automobile to obtain the information regarding the environment is more accurate than the human drivers because of perception technology evaluation of automobiles. Thus, the present auxiliary driving system is the most efficient way for enhancing the driving safety as well as effectiveness of driving automobiles. Various models like Bayesian filtering approaches, fine grained fusion approaches and fast occupancy grid filtering approach have been utilized for driving environment perception [4]

Autonomous Vehicles consist of both software and hardware structure. Few The hardware elements like sensors supplies the information for the software module. Additionally, the AV software module generate commands to control the vehicles according to trajectory comfort as well as safety to the actuator. The AVs hardware activates like acceleration, steering, breaking and deceleration were control by this actuator. In AVs software structure the perception layer, trajectory control layer and planning layer are integrated [5].

1.1 OVERVIEW ON AUTONOMOUS VEHICLES

A fully AV is a car, which has the capability to recognize its atmosphere and determine the route to reach its destination and drive it. This AVs can also call as robotic cars or smart cars which utilize a variety of sensors, data bases and processors to take over all the performance of human drivers. These types of cars have its own benefits. AVs are manufactured with lightweight materials, it aims to enhance the economy of the vehicle as well as decrease the energy usage.

AV has also satisfy another significant necessity that is overcrowding, efficiency and also by lowering emission and consumption of flue it has possibly reduce the ecological effect of transportation [6]. Level 2 systems were introducing in the current markets as an example of human attainments. To improve the safety measures as well as comfort of the peoples through directing both longitude and lateral motion of the automobile the Level 2 system are essential [7].

The fundamental objective of AVs is to improve traffic security as well as to facilitate the traffic flow and for individuals who can't drive the automobiles it offers additional mobility choices. Contrasting the typical vehicles these AVs utilize artificial intelligence to calculate sensory information from cameras, lidar, radar and GPS.

Further than transportations, these AVs have the capability to alter urban planning, alleviate traffic jams and also decrease emission of carbon through enhancing the routes and economy of the automobiles. Thus it represent a fundamental change in automobile companies by auspicious safer, more effective along with reachable transportation modification [8].

The first idea for AV was presented by General Motors in 1939. Then in 1950s the primary phase of investigation and progression was introducing by Radio Corporation of America Sarnoff Lab and General Motor. Over a long period of time, technical development of AV have influenced mainly through development in hardware capacity, artificial intelligence and sensor technologies [9]. This self-driving concept is an extension of 2000s which is about steering vehicles even in absence of human drivers. Practical implementation for this began to develop in the lateral period of 2000s, with primary focus of implementation in automated systems for enhancing the environments like industries and militaries where precision and safety are critical.

The Defence Advanced Research Projects Agency (DARPA) grand series, which has started in 2000s, has created a watershed in the development of AV. To accelerate improvement in AV technologies, the US DARPA has introduced these challenges. In 2004, the first challenge has highlighted the complexity as well as technical challenges of AV, then after repetitions have showed speedy development in machine learning, sensor fusion and ability to make decision in real time [10]. The 2010s has created important modification with better investment as well as contribution of various main technical companies.

AVs are becoming more famous because of their capability to manage critical transportation problems. These also have the ability to drastically decrease road injuries and mortality by reducing the human mistakes which is the main reason for vehicle crashes. This safety measure is achieved only through the algorithm as well as modern sensors which permits to observe the vehicles continuously and to make decision rapidly [11]. AV has also satisfied another significant necessity that is overcrowding, efficiency and also by lowering emission and consumption of flue it has possibly reduce the ecological effect of transportation. AV has also increase the usage of current infrastructure which result in most suitable and well-organized of transportation [12].

Moreover, AV promises to provide improved availability mainly for the ageing people and also persons who are having mobility problems. This has the capability to enhance the quality of life through offering flexible as well as trustworthy transportation possibilities. This has the potential to decrease the cost and also create jobs in emerging industries like software development, overall infrastructure development and vehicles automation [13].

AV can generate a map of their environment utilizing the variety of sensors that is situated in various parts of the automobiles. This utilized radar sensor to monitor the location of other automobiles and then for detecting the traffic lights, pedestrians, pathway of other automobiles and also to read the signs on the road video cameras are utilized. Lidar is used to measure the distance, to predict the road edges and to discover lane markings and ultrasonic sensors in the wheels of the AV is utilized to predict the curbs and nearby automobiles during parking [14].

Classification of Autonomous Vehicles

In 2014 by SAE (Society of Automotive Engineers) International, Classification of AVs are classified based on various six levels that is ranging from zero to fully automated was published. This categorization system is founded on the amount of required concentration along with driver interference. The standard categorization levels of driving automation were updated on 30th September 2016 by SAE. Additionally, for setting these specific levels of automation driving, this technical report describes about the standard terminology ideas which are related to AVs. The six levels are:

- No Driving Automation (Level 0): The human drivers control the vehicle manually by monitoring the surrounding circumstance, handling steering, break, throttle and navigating along with determining when to use the pathways and turn signals. But they fails in some categories like blind spot warning, path tracking assistance and parking as because they only suggest the warning but does not control the vehicle [15].
- Driver Assistance (Level 1): This level vehicles can handle S or T&B but not in every situation. The human driver must monitor both the road along with speed of the vehicle, and the driver must be always ready to substitute those performances that are the driver must always stay conscious regarding the functions of the vehicles. Automatic braking as well as ACC fails underneath this category.

- Partial assistance (Level 2): The ADAS (advanced driver assistance system) can handles both the acceleration as well as steering. But the driver must be always aware and ready to take over the function of the vehicle. Thus, in these three levels, human drivers are accountable for monitoring the traffic, weather, conditions of road, signs and the environment.

- Conditional Assistance (Level 3): In this level the ADAS is automated with surrounding recognition features utilizing the data from the sensors to manage the vehicle. Rather than autonomous these vehicles are self-driving. This vehicle can steer itself underneath certain circumstance, however it requires human interfering if essential. Traffic Jam Pilot fails underneath this category [16].

- High Automation (Level 4): In this level, the self-driving automobiles have the ability to take decision in case of ADAS failures. However, it requires the presence of the human passenger. This also monitor the environments in a broad range but not all the time, like during bad weather conditions. Presently, these vehicles are constricted to specific areas through geo-boundary.

- Fully Automated (Level 5): In this, the ADAS can channelize and also mange different kinds of driving circumstance in numerous driving modes without human interference. The driver or passenger only has to choose the terminus and start the vehicle, then the car controls all other functions. These cars can navigate to any legal locations as well as they can choose its own pathway to reach the destinations [17].

ACC (adaptive cruise control) is the one of the technologies utilized in AVs. This system has the capability to modify the speed of the vehicles automatically to confirm that it continues secure gap from the vehicle ahead. This process relies on the data attained from the sensors of the vehicles and permits the car to execute some tasks like braking, acceleration and steering.

Significance of Autonomous vehicles:

AVs are considerably progressive in transportation technologies by bridging the gap among typical human functioned cars and fully autonomous vehicles. These cars function at the autonomy of level 3 and 4, counting modern and also interference in specific situations. AVs are significant due to their capability to makes things easier as well as more available than the human drivers. This necessitate interaction of human drivers for making decision to control the functions particularly in complicated or in unpredictable circumstance in dissimilarity to fully autonomous vehicles that function independently [18].AVs utilize sophisticated methods along with AI algorithms for monitoring the environments and to make user driving decisions. This method not only develops the road safety but also offers flexibility for human drivers when they required.

AVs have recently drawn important considerations in both industrial as well as academic due to it numerous advantages like safety enhancement, reduced fuel along with energy consumption, road network exploitations, decrease traffic overcrowding and has increased mobility. In most important decision making performance during travel in AV, intelligent path planning makes a significant as well as challenging role for avoiding the hazards by seeking for secure route to follow [19].

One of the main significant of AVs are its capability to decrease road crashes that are caused by human errors. Proceeding many researches, exhaustion, distracted during driving and wrong decisions are the main reason for accidents. By integrating system like ACC, lane-keeping assistance and accident prevention technology [20]. This can develop environmental awareness along with response abilities for decreasing the like hood of accidents and improving inclusive road safety. Furthermore, this capability of AVs plays a vital role in heavily populated metropolitan areas where overcrowding due to traffic and complicated driving situations supplies main hazards for the road uses.

Additionally, AV has the potential to develop the transportation efficiency through decreasing traffic problems and overcrowding. These vehicle have the ability to control the traffic automatically by maintaining safe gap from the vehicle ahead along with modifying the speed volume according to the road conditions [21]. These assist to minimize the travelling time by reducing unwanted pauses, accelerating flatter traffic flow and enhancing the capacity of roads. This effectiveness not only enhance the productivity and environmental conflicts but also encourages sustainable metropolitan improvement through covering the carbon emission that is caused by automobiles in overcrowded traffic. Likewise, in ride sharing a well as in public transportation systems, AVs can decrease working cost by lowering salaries of driver and making transportation more cost-efficient as well as available to users [22].

Thus, AVs represent a substantial hike in transportation technology which offers a well-adjusted technique that associates the benefits of automation with human control as well as interference. These have the ability to modify the future metropolitan living and also mobility through enhancing the road safety along with the driving economic development [23]. These efforts for development accelerate the significance of AVs to offers safer along with more effective and complete solutions for transportation problems existing in the societies.

Important of Autonomous vehicles:

AVs are beneficially improved in transportation technologies through offering transformative assistances which enhance the safety, efficiency and mobility in metropolitan and rural areas. These vehicles utilize progressive performing system adaptive controls to steer and communicate with their circumstances through fundamentally altering the future of mobility.

Enhancing mobility:

One of the main advantages of AVs is their ability to enhance the mobility challenges for peoples as well as societies. This meets the necessity of transportation for users including the ageing, disabled peoples and for passengers. This availability motivates independence by permitting them to access to significant facilities without any kind of restriction like traditional transportations. AVs offers solutions for long term problems like overcrowding due to traffic issues and also some problems regarding parking spots [24]. This also eliminates the necessity of personal car by offering mobility sharing models. Thus, this increases the availability by reducing overall transportation cost and circumstance effect.

Safety improvements

AVs create significant contribution in road safety through using enhanced control system, this necessitate human monitoring as well as involvement in certain situations. These are well- equipped with powerful safety characteristics which decrease the threats related with human errors. Additionally, AVs perform tight standard operational design to emphasize users as well as foot-traveler's safety. These are planned to predict as well as to respond to probable hazards proactively by reducing the risk of road crashes guaranteeing smoother communications in vigorous traffic situation [25]. This enhanced safety measures not only expand the road safety but also gain the trust of publics in terms of reliability along with effective autonomous transportation systems.

Enhancing the efficiency of transportation

These AVs develops the efficiency of transportation through enhancing traffic management, decreasing the overcrowding and utilizing the present infrastructure in finest way. Prediction algorithm along with real time data examination permits AVs to handle complicated traffic conditions and optimize track planning to decrease the traveling time as well as fuel consumption [26]. This competence promotes maintainable improvement in metropolitan areas by lowering the impact of traditional transportation models in the environment. This operational effectiveness not only enhances the productivity but also contributes to economic effectiveness by improving reliability in supply chain.

Key technologies of Autonomous Vehicles

To operate independently, AVs need significant computing capability along with processing units to perform. CPUs are the major components which perform algorithm and control the flow of data in the AVs board system.

Artificial Intelligence and Machine learning algorithm

These are the important enablers of AVs which offers them with cognitive abilities to see, understand as well as to respond for their circumstance independently. Deep Learning algorithm are the base of AV perception system, data processing to identify and categorize objects including vehicles, people and complications in real time. These method use CNN (convolutional neural network) to extract relevant features from the sensor input through permitting them to create better decision for avoiding the hazards [27].

Supervisee learning technique is utilized to maintain traffic laws and for safe routings in complex circumstance then reinforcement learning enhance decision making system of AVs. High-defined mapping and accurate locating technologies are important components of AVs permitting autonomous direction-finding along with safe operational without the necessity of real time data. This maps which provide categorized difficulties to utilize as a reference for steering to reach its destination. The areas as well as the characteristics of the road may change over a time, thus it continuously updates and save on-board to face the difficulties during the travel.

The communication technologies like V2I and V2V are vital for enhancing the operational ability as well as safety in metropolitan and rural areas. V2I connection permits AVs to transfer real time information from the system. This information offers the present data about the conditions of traffic, emerging cautions and also road terminations for making efficient decisions [28]. Utilizing these communications, AVs improves their surrounding awareness and complete traffic effectiveness creating safe autonomous transportation system.

The primary intelligence of the AVs is founded on its capability to perform huge volume of sensor information and to take complex decisions in real-time. AI algorithms, specifically deep learning approaches are utilized to estimate sensor information, prediction other driver's behaviour and to generate ideal driving directions. These algorithms learn continually from the information which are collected in time of operation and develop their flexibility and process over time. V2X (Vehicle to everything) connects the flow of data from a vehicle to any objects which are related to its performances. These are designed to permit a AVs to communicate with another systems. These are categorized as V2V (Vehicle to vehicle) which permits vehicles to communicate data like location, speed and route to enhance circumstantial awareness and also to avoid accidents [29].

Emotion analysis in Autonomous vehicles

The emotional analysis application of AI in AVs creates a massive step forward in enhancing the transportation comfort, safety and inclusive experience. This emotion prediction system in AVs utilize sophisticated algorithms like ML techniques [30]. These systems make use of several symptoms as well as signs like facial expressions also biological indications to decide the emotional state of the drivers which includes tension, engagement, happiness, tiredness and also irritations by examining the data utilizing algorithms and computer vision. This ability permits AVs to vigorously change their emotional anxieties about drivers.

Importance of ensuring drivers wellbeing

Predicting and responding to the emotional states of drivers are particularly more important in case if the driver is not feeling well or suffering from emotional or any other discomfort. If the AI identify any kind of signals like exhaustion or stress then it gives any alert or warning signs. In case of any extreme mental suffering or medicinal emergencies, this AVs which is armed with decision making system can route independently to the nearest hospitals or may communicate emergency services immediately

[31]. This practice approach not only enhance user's safety but also demonstrate the capability of AVs to operate as intelligent assistance in managing unexpected health issues during the traveling time.

Decision making algorithm

This decision-making algorithm is more important for promising the secure as well as efficient manoeuvre of AVs, especially when the driver is not feeling well. This algorithm collects and combines the information from the emotional analysis system with environmental causes like weather prediction traffic conditions, and infrastructure of road to make real time decision. If the AI identifies any signs such as tiredness, drowsiness or any distractions, this may activate safety protocols for the safety of drivers as well as passengers. By utilizing AI for decision making algorithm in AVs, permits it to decrease vulnerabilities and respond effectively to dynamic driving situation by enhancing the complete road safety and passenger well-being.

Advantages of AVs

- Reduce traffic problems as well as road crashes which result in injuries and deaths.
- Increased capacity of roadway by decreasing the traffic jams due to its ability regarding safety distance along with managing the traffic flow.
- Reduced the physical gap that is required for parking the vehicles.
- Reduced the necessary for traffic police.
- Reduces insurance cost by reducing the vehicle crashes ratio.
- Enhance safety by significantly reduce the crashes caused by the human drivers.
- Follows the traffic rules and regulations properly and also drive safe [32].
- Optimize the traffic volume by organizing diving patterns.
- This offers mobility for disabled, ageing and poor persons.
- Provide transportation choices even in limited public transportation areas.
- Enhance the efficiency of fuel consumption through optimizing driving.
- Reduced environmental pollutions by promoting electric as well as effective driving.
- Enhance pathway safety utilizing modern sensor for detecting.
- Encourage sustainable transportation methods in metropolitan areas.
- Enhance opportunities by producing jobs in manufacturing as well as technological field.
- Improve association along with availability across numerous models of transportations.
- Eliminate the usage of steering wheels [33].
- Automatic brake control and reduces throttle.
- Reduce the speed volume dissimilarities among the vehicles.

Thus, self-driving automobiles have the capacity to transform the transportation through enhancing security, effectiveness, availability along with environmental sustainability. This addressed both the legal frameworks along with issues of cyber security [34]. AV has the ability to produce secure, more associated as well as eco-friendly future for world-wide transportation networks.

1.2 IMPORTANCE OF SAFETY IN AUTONOMOUS VEHICLES

In past three years, there have been vast changes in driving condition as well as safety. Over 1.3 million persons are losing their life and nearly 20 to 50 million persons are injured because of traffic crashes. Fatigue, Drowsiness, high speed and alcohol consumption are the major reason for traffic accidents across the world. The main feature contributing to the occurrence of vehicle accidents are human behaviour.

The large majority of crashes across world are caused due to human errors. According to the research of NHTSH (National Highway Traffic Safety Administration) as well as other safety transportation organization. Recently, it has been evident that utilizing mobile phones, texting and also using technologies in car are the most important reason for accidents [35]. The digital gadgets attractions have increased the diver's distractions which result in raise for risk collisions. According to the reports of NHTSH, in recent years more than 2,800 mortalities a well as several has been injured due to driver distraction.

World-wide trends and statistical data sheds light on the occurrence and characters of auto crashes advanced the globally. According to the report of WHO road traffic crashes are the main reason of fatality of young people among the age of 15 – 25. Collisions and injuries place a heavy economic and social pressure on societies because of long-term inability, missed work and medical expenses. Thus, road traffic accidents are complicated phenomena which are influenced by diversity of variable like, environmental impact, technological advancement, road characteristic and human behaviour.

There are numerous reasons for vehicle crashes while driving such as drowsiness, driver negligence, and health problems. If the drivers of AVs are warned earlier then these collisions can be avoided. Furthermore, recent enhancement in artificial intelligence as well as computer vision have assisted to observe drivers along with alerting them in case they are distracted from driving. The AI methods can abstract related characteristics from the driver's expression like yawning, eye movement and also movements of head to assume their level of sleepiness [36]. Additionally, they can also obtain biological signs from the driver's body as well as indication from the AVs behaviour.

Additionally, fatigue, drowsiness is another main reason for road accidents. Driving for prolonged time without getting proper sleep makes driver to be less attentive, react slowly and make them to take wrong decisions. Researches specify that drowsiness and fatigue particularly during mid-night or in early morning when the drivers are most probably nod off during driving the vehicles.

Regulatory agencies as well as safe campaigners have countered to these results by emphasizing the value of rest time, driver education and few technical solutions like tiredness recognition system in decreasing the risk associated to driver weariness. Impaired driving due to consumption of drugs or alcohol is another important component for accidents caused by humans.

Even after numerous of public awareness along with many legal penalties these alcohol consumptions are still a remains as a main reason for fatal accident world-wide. According to WHO alcohol related road crashes are accountable for huge traffic mortalities globally. Consumption of alcohol associated to reduce coordination, decrease the reacting time and poor decision. Additionally, aggressive driving like speeding, erratic lane alteration and tailgating are the reason for many collisions.

According to the standards, aggressive driving aggressive driving contributes crucially to possibility of accidents, injuries and also mortalities on the roads. Traffic calming method and community education campaign emphasizing the values of patience and consideration for other road using peoples are few approaches utilized to combat aggressive driving. Advancement in automobile technologies have create a significant contribution to develop safety characters as well as reducing the collision ratio [37].

Furthermore, even technologies are also the reason of collisions, particularly when they failed to function properly as they planned. Though this happen rarely than the human mistakes, still the mechanical issues like brake or wheel failure are the reason of crashes or for loss of control. To decrease this mechanical failure, proper vehicle maintenance as well as road inspections are important. Both the occurrence as well as seriousness of vehicle crashes are caused by the characteristics of road and contiguous atmosphere.

Driving is more hazardous during bad weather conditions due to visibility, weaken road grip. Studies has shown that crashes associated to bad weather condition are more frequent. Thus, proper car maintenance is necessary to decrease the weather-related collisions. To prevent and mitigate the crashes the infrastructures as well as design of the pathway are more important. Numerous of traffic mortalities and injuries are a result of badly maintained or damaged roads, poor signs, lack of pedestrian crossing and unclear crossing. Thus there are numerous reasons for vehicle crashes while driving such as drowsiness, driver negligence, fatigue, health problems, aggressive behaviour of drivers and distractions [38].

Accidents due to driver drowsiness:

Driver drowsiness is a serious hazard to road safety. According to NHTSA, in 2009, more than 30,000 injuries and 800 mortalities has occurred due to drowsy driving in US. In Europe, approximately 20% of traffic accidents are due to this. This issue seems more severe in China where nearly 1768 deaths are caused because of this drowsy driving. Enforcements can't be utilized to counter this issue as because drowsy driving does not offer any kind of objective calculation of its existence. Drowsiness is an in-between state of sleep and attentiveness, which might rise the time of reaction in driving also steer to impaired driving process. NHTSA described that annually, approximately 83000 crashes and 900 mortalities are associated to drowsy driving in the United States.

Driver drowsiness (DD) is an important factor in a huge number of vehicle crashes. Recent studies reported that 76,000 injuries and also 1,200 mortalities can be attributed to DD associated collisions. Drowsiness is an in-between state of sleep and attentiveness, which might rise the time of reaction in driving also steer to impaired driving process. The maximum sleeping hours for a driver to drive are per day is limed, but still drowsiness play a major role in traffic. DD is frequently caused due to four main reasons like work, sleep, timing and physical [39].

Mostly peoples do so much of work during day time and they may lose proper sleep because of that. Too much consumption of caffeine or some other stimulants person remain to stay awake. Additionally, due to over thinking some may lack sleep. Thus, lack of sleep over number of days result in sudden collapses or the person may fall sleep. Human brains are more likely to sleep between the hours of 2- 6 AM, so being awake during these times will frequently steer to drowsiness. Then the final feature is physical condition of a person, which includes medication that cause drowsiness or some other physical problems that might cause these problems. Being over or under weight also cause drowsiness. Furthermore, emotional stress of human brain also cause the body to get drowsiness quicker [40].

Driver drowsiness detection process

DD detection is a safety technology that avoids collision when the drivers are feeling drowsy. The enlargement of these technologies for identifying as well as preventing DD is a main challenge to avoid accidents. Driver’s distraction might be the outcome of lack of attentiveness during driving. Driver distraction happens while an object or occasion draw an attention of a person from driving [41]. Not like driver distraction, DD has no triggering occurrence, it is classified by a progressive distraction of a driver from the traffic as well as from road.

Driver drowsiness is still a main safety risk in AVs, where the driver should be alert and also prepared to take over the control of the vehicle when necessity. Driver drowsiness associated collisions highlight the essential need of effective identification system which combine the physiological signals like EOG (Electrooculography), ECG (electrocardiogram) and EEG (Electroencephalogram) with advanced technologies like ML and DL algorithm. Similar to traditional human functioned vehicles, a variety of surrounding can contribute to DD in AVs. These components consist of inadequate sleep and underlying therapeutic problems.

Physiological signals like EOG, ECG, and EEG that offers significant data about the physical reaction as well as cognitive sate of Driver drowsiness. EOG identify wink along with the eye movement which can reveal drowsiness or attentiveness levels of the driver. Variability of heart ratio along with cardiac activity are observer through ECG, which shows differences in autonomic nervous system function due to the tiredness, anxiety or sleepiness. Then the neural oscillation pattern in the brain related with attentiveness as well as cognitive state of the driver are captured through EEG [42]. Through integrating these physiological signs into DD (drowsiness detection) system, multi-dimensional feature of driver physiological as well as behaviour are captured, enhancing algorithm accuracy along with dependability.

To create a thorough examination of diver’s alertness the data fusion method combine data from the sensors like, camera for detecting visual, EOG for detecting eye movement, for cardiac activity ECG is utilizing and then EEG for brain wave patterns performing physiological data in real-time which permits for allows for quick response like, notifying the driver, adjusting the vehicles setting or tuning on AVs models, all of which decrease the possibility of collision caused by sleepiness.

Despite developments on algorithm and physiological signals integrations utilizing effective DD system in AVs still present hazards. Research is now being accompanied to address environmental features impacting sensor process, adjust to individual diversity in driver behaviour along with physiological signals to guarantee the reliability and also real-time awareness of algorithms. Face based data like yawning, duration of blinking and occurrence, percentage of eye closure along with the movements of head [43]. Road centreline deviation, lateral velocity, angular velocity, lateral acceleration and steering wheel angle have also been utilized as vehicle-founded processes to detect drowsy driving

- Analysis of eye closure: The eye movement is a most significant feature that is broadly utilized to detect the driver’s drowsiness. The methods utilized to calculate the level of drowsiness encompasses PERCLOS (Percentage of the eye closure) and EAR (eye aspect ratio). EAR is the process of measuring the ratio among the height as well as width of the eye. Then PERCLOS is the eye closure percentage over a time period [44].
- Eye blink rate: This is utilized to measure the blink rate frequency. The usual blink rate is mostly 10 per minute, when the driver is feeling drowsy the blink ratio decreases
- Yawning analysis: Yawning are due to boredom or weariness. During driving it indicates that the driver might fall asleep. This method can calculate the mouth widening to detect driver’s yawning traits through tracking the movement as well as the shape of mouth along with the lip corners position.
- Analysing the facial expressions: This method utilizes more than one facial character to identify the drowsiness of a driver. This encompasses features like forehead wrinkles and extreme head poses.

Accidents due to health problems

Collisions related to AVs that are caused by health problems emphasizes the safety risk factor of community which occurs in time of unexpected medicinal emergencies or poor conditions while driving AVs. It is important to understand the reasons as well as effects of these types of road crashes in order to generate tracks which efficiently decrease risk and enhance road safety. Several health problems which impair the ability of the driver to perform and sustain the control may result in collisions relating AVS. Sudden inability or loss of attentiveness may be the result of serious medical situations like strokes or collapses, heart attacks making the situation impossible for the driver to drive AVs.

Additionally, chronic medical diseases like epilepsy, diabetics or insomnia affects the motor performance of the driver or cognitive function which create it more problematic for the driver to make judgement and respond to changing road situation. Furthermore, numerous factors counting exhaustion, drug reactions, thrust or inner car circumstances may aggravate health issues and increase the risk of road traffic accidents. In particularly AVs, interchanging from self-driving model to human control may be complex for the drivers to take the control of the car.

Accidents caused by health problems in AVs have severe and comprehensive effects. The drivers or the passengers most probably gets injured or may fatalities, even other road users like pedestrians, bicyclers, roadside barriers or other vehicle persons may also get in danger. These kinds of accidents have major economic and legal consequences, counting insurance claims, legal disputes over responsibility. Real time data examination, productive observation and cutting-edge sensors technologies should all be incorporated for identifying the health problems of drivers during driving AVs. These strategies are planned for quick detection indicators of driver's discomfort or health associated problems and launches the essential performance to decrease the threats and also to guarantee the safety for all the users of the road.

Utilizing non-intrusive sensors which is installed in car is a kind of method for tracking important signals and detecting the changes physically or in behaviour of driver. These sensors are environmental sensor which track the parameters like humidity, temperature, air quality or cameras which recognize faces. In order to examine the behaviour pattern of the driver and leaving from classic driving pattern data analytics along with pattern detection algorithm are important tools. Thus, these algorithms have the ability to identify the possible indicator of driver misery or health associated issues through setting baseline for behaviour and abnormalities identification.

Health monitoring solutions:

Intelligent health observing system for AVs have been made likelihood by enhancement in sensor technologies along with computer power. These systems gather data from the numerous sensors which offers a thorough examination of driver's health as well as well-being. Aside from the environmental sensors and physiological observation, they have the capability to detect the variables such as, air quality, temperature and noise levels inside the AVs which may affect the driver's comfort as well as well-being. The on-board system of the AVs may respond quickly to detect driver's health issues utilizing real time data performance [45]. These responses encompass warning the drivers, altering the comfort and safety setting or may direct to secure place. Through improving the ability of AVs to detect the health associated problems. These advancement in the technologies reduce the possibility of accidents and increase the road safety standard.

Accidents due to fatigue:

The major problem for drivers who drive AVs is tiredness and the feeling of fatigue. Even though, they must be always alert and be prepared to handle the vehicle at any time. Dangerous situations such as accidents, collision of vehicles in the road occurs due to the driver's fatigue. It can further cause weak decision-making skills, late response time, and lack of mental ability of drivers. The habit of delayed sleeps, less sleeps, insufficient rest, lengthy driving times leads to the exhaust nature of the driver. Another reason includes long highway roads, and usual routes make driver feel boring and this situation induces the nature of fatigue to the driver which causes accidents in highways.

Detecting and reducing driver's fatigue is important to enhance the road safety. Modern technologies are crucial for detecting fatigue earlier. Real-time system of fatigue detection is accomplished utilizing the camera for facial recognitions, duration of blinking and occurrence, percentage of eye closure along with the movements of head and environmental sensors to measure cabin condition. Real-time data performance empowers AVs to create interference while fatigue is identified. These interferences may include alerting the driver with audio or visual, altering driving parameters like speed or route or navigation to safe destination.

Aggressive driving behaviour:

The massive enhancement in automobile technologies has improved the automobile technology to guarantee secured travel. Even though, still several crashes occur because of careless, unsecure and hazardous driving of the driver. Therefore, till now, the issues of safety traffic concerns globally. Road traffic accidents are certainly a world-wide disaster which has developed as an ever-increasing trend.

Traffic crashes as well as injuries impose severe complication on community by affecting significant financial loss to individuals, their families and also whole countries. WHO organization report that approximately 1.25 million of mortalities every year and nearly 3,287 fatalities per day. It is analysed that road traffic mortalities continue to increase, in 2016 it has reach 1.35 million. Thus it is very important to comprehend the different factors and cause linked with these traffic crashes [46].

Road safety awareness can't be separated from examining the driver's behaviour. The main reason for road accidents are caused by human factors. Human driving behaviour is a complicated concept. Every human has unique driving styles, emotions, experiences. Due to this unique driving feature they their own driving behaviour as well as habits. Driver's behaviours are one of the main reason for the road crashes and these can be reduced through detecting and minimizing aggressive behaviour of drivers [47].

Several examinations have developed to identify the issue of human driver's abnormal behaviour by utilizing different benefit like capturing as well as analysing the drivers face and dynamics of vehicles through image along with video performance. ADB (Aggressive driving behaviour) is a very dangerous and this type of driving styles steer to most serious crashes. Abnormal behaviour of human drivers is affected by numerous features like experience of a driver for driving, age, gender and their health issues.

Aggressive driving behaviour is an action when a person commits traffic violence. ABD is a psychological concept which does not have any quantitate measure. Though, there are few behaviours that are associated with aggressive driving like dangerous or high speed, overtaking or following the vehicle ahead too closely, unsafe or erratic lane alteration and not following the law and traffic signals. Even though, this behaviour is sign of aggressive driving, identifying these are challenging in real time. Recently these have been examined through various methods. The ABD can be detected through the experience of the driver along with their psychological mood. Aggressive driving is connected with few behaviours like sudden lane change, speed, tailgating or overtaking behaviour and acceleration.

Driver distractions:

The growth of vehicles brings an extraordinary anxiety to traffic safety. Distraction driving is one of the main reasons for all the road traffic accidents particularly in mortality accidents. In 2018, nearly 2,841 people died and above 400,000 got injured because of distracted driving. Recently, it has been evident that utilizing mobile phones, texting and also using technologies in car are the most important reason for accidents. The digital gadgets attractions have increased the diver's distractions which result in raise for risk collisions. According to the reports of NHTSH, in recent years more than 2,500 mortalities a well as several has been injured due to driver distraction. From 2010 – 2016, 9.5% of fatal accidents are caused due to distraction driving [48].

Driver distraction is a serious concern to safety in self-driving, since drivers are required to remain alert despite the presence of automated driving capabilities. Distraction can take attention away from the road, reducing reaction time and decision-making abilities, increasing the likelihood of an accidents and understanding the causes and consequences of driver distraction is critical for creating effective way to detect. Driving automobiles are extremely complicated task. Distraction along with frequent inattentiveness are the main anxiety for road safety.

According to NHTSA statistical report nearly 25 percentage of police has reported that driver's distraction is the main cause of road traffic accidents. Distraction occurs, while a driver is reacting slowly to recognize the information that need to accomplish safe driving, because few activities, events, object or individual inside or outside the vehicle encourages the driver to distract away from driving [49]. For detecting driver's distraction two types are utilized. First one is founded on the onboard video camera against the driver's face then the status is detected through computer vision algorithm which abstract the facial or physical feature of the driver.

ML and DL usage in detection process:

ML method examine the designs as well as characters that are obtain from the driver behaviour data along with physiological signals which are important for detecting as well as decreasing Driver drowsiness in AVs. Employing labelled datasets, supervised learning method like Random forest, Decision Tree and SVM train methods to categorize the driver's states founded on the inputs counting facial expressions, eye movement, and mobility of driving wheels. Thus, these algorithms are trained to distinguish between attentive and drowsiness state of human drivers and when they detect any kind of abnormalities immediately they will send out warnings or tale actions.

In recent day, DL methods have showed recently shown remarkable development in analysing biomedical signal particularly classification founded abnormalities identification. Though DL is a sub-group of ML technology founded on ANNs (artificial neural networks). This DL networks provide great significant for analysing biomedical signal by simplifying the raw data and then development of categorization results. DL technique with LSTM unit, such as CNN (convolutional neural network), RNNs (recurrent neural networks), deliver enhanced sleepiness detections abilities. CNNs utilize visual data from the inside camera of the car to detect the changes in eyes movement or facial expressions which indicate the tiredness of driver [50]. Then RNNS with LSTM units identify the patterns which promotes drowsiness and the time series information from the sensors which tracks the behaviour of the driver and vehicle dynamic are processed.

1.3 RECENT TRENDS OF SAFETY IN AUTONOMOUS VEHICLES

Autonomous vehicle (AV) has been considered as a promising solution to future automotive engineering. Moreover, the safety is the major challenge for the commercialization and development of the AVs correspondingly. AV vehicle provided with unconventional technologies that assists a human driver or to control the vehicle autonomously. The technical advancements in the infrastructure automation industry are gradually increasing nowadays to equip benefits in terms of safety enhancements, stress-free-travels, smart parking, fuel cost savings and traffic congestion reduction [51].

Depends on the National Highway and Transportation Safety Administration (NHTSA), there are five levels of AV functionality. In level 0, there is no automation. The automation of one control function such as autonomous control and lane keep assist are included in level 2. In level 3, there is inadequate self-driving but expects the driver to take control at any time with limited warning probably. The drivers are not supposed to take control at any time of the journey is included in the level 4. There is complete self- deriving without the intervention of human control in level 5.

Consequently, the other countries believe that Autonomous vehicles (AVs) improves traffic safety and decrease the mortalities. The safety of AV is significant in the society as well as in the market. The rapid response from AV is considered as the major advantage compared with human intervention. Since, AV are programmed so that they follow the rules of the road and cannot be diverted by the mobile phones. The automation in networks and technological developments subjects to lead a better road safety and minimum congestion in urban areas. The vehicle parameters such as stability, velocity and weight are essential for safety vehicle handling respectively [52].

There are around 1.35 million deaths per year are cause by the road accidents. The human errors are the reason for road accidents. The errors involve non-usage of seat belts, safety equipment, over speeding, distractions through mobile phones and consuming of alcohol. These errors are mentioned in the report of WHO respectively. Although AVs is considerably improved, the fully autonomous vehicles are not ready for the commercialization probably. The complications mainly arise from the safety concerns. The several technical and social factors comprising regulation-making, nature of vehicles, weather conditions and traffic conditions are affecting the AV safety. This information promotes the need of adopting the AVs technology

Prediction of safety in AVs using AI techniques

A crucial technology for efficient AV functionality is Artificial Intelligence (AI). AV deploys sensory technologies and AI to reduce the risk effectively. The AI & ML has been utilized in the fields of semantic segmentation and computer vision. AI techniques are used on various common object detection datasets and particularly in the detection of people, traffic lights, road signals and vehicle respectively. The AI techniques are used probably to enhance the performance of AV. Moreover, the AV plays an essential role in the decision making such as path planning and automatic parking [53].

In the aspect, the increase of complex traffic environment and large volume of data AI technology can rapidly handle large volume of data and adapts to the environment effectively. Moreover, the Collision Avoidance (CA) are avoided by deploying AI techniques. The Ai approaches generates decision making algorithm and innovative prediction to accomplish active safety correspondingly. The environmental adaptability and self-learning ability of AI methods makes the CA systems more accurate and flexible. The driver’s behaviour is predicted through AI techniques. The better adaptation to the driving environment is achieved by the AI methods.

By enhancing the decision making and accuracy, few applications of AI advancements in AVs is enumerates the incredible potential in automobile industries. Moreover, the learning methods such as resource allocation, channel quality, estimation and routing are achieved through AI methods respectively. The communication technologies attain information from various sources, enlarge the range of vehicle sensing and predict to evade accidents through AI. Simultaneously, the safety, effectiveness and comfort are enhanced. In case of uncertainties and extreme dynamic scenarios, the AI technologies can enhance the ability to adapt to the environment respectively [54].

The AI- Based on the Vehicle-to Everything (V2X) system attains information from several sources. With the help of the sources, it permits to increase the awareness of drivers and predict to avoid accidents correspondingly. The progression of AI techniques is directed to the opportunity to understand smart driving effectively. The smart driving is formed on the idea of copying real driving comportment and evading human mistakes and bringing comfortable safety to drivers probably [55]

In the beginning of 5G wireless networking, the developments of edge computing and AI is utilized in the AV. The AI and Machine Learning (ML) based models are deployed to the data-driven AV to improve the security and safety. The real time reliability is enhanced through the AI techniques. The natural driving data are gathered by vehicle mounted terminals. The historical driving maps are collected by Global Positioning System (GPS), data collection systems and camera systems. With the help of the data, the AI technology analyse traffic information. Based on the decentralized unit and 5G base station, the AI technology analyses the various types of traffic data such as traffic signal lights and driving lane-change probability. Moreover, the outcomes of the analysis are fetched back to the vehicle terminal respectively. The system improves driving safety and comfort. Subsequently, the ai technologies advances the traffic environment [56].

The advancement of AI and ML methods are the main driving sources of the Connected and Automated Vehicles (CAV) respectively. The AI and ML approaches are used for the decision making at various levels. The control in increasing the accessible data, advancement in the wireless communications and enable autonomous are the remarkable ability of ML and AI techniques. Predominately, the ML techniques aids in structuring the perception system of semi-autonomous connected vehicles and AV respectively [57]. The AI technology is developed as a replacement for human experts for originating the impartial accident scenarios relied on the data. The AI approaches are used to analyse the sequential patterns of accidents in recent days [58].

The self – driving vehicles improves their accuracy in navigating dynamic road conditions and responsiveness are accomplished in the influence of ML and AI approaches. The robustness and adaptability of the AV decision making relies on this integration of both the techniques. The AI algorithms are deployed to train the numerous datasets of real-world driving scenarios. Moreover, it aids in identifying and react suitably to cyclist, pedestrians and further vehicles.

Simultaneously, the ML algorithms are utilized to adapt new environments conditions and enhance their performance over time [59]. The combination of AI and ML techniques are expanding the definite characteristic growth in AVs respectively. The perceptual tasks such as classification, image segmentation, prediction for agent behaviours and classification are employed with ML techniques. Subsequently, the AI based AV results in the optimized for timely decision process. The recognition, planning and detection are optimized by using AI techniques [60].

The AI approaches and autonomous systems are considered as the driving innovation. The enhancements in efficiency of an extensive array of industries are accomplished by the AI techniques. The AI driven AVs promotes the various favourable developments especially in the vehicle safety. Moreover, the AI has the capability to save thousands of lives respectively. The several aspects correlated to the transport industries such as smart monitoring and regulation, vehicle intelligent driving, airport intelligent stereo garage dispatch systems and smart system design for traffic control in intelligent express way systems are utilizing the AI approaches correspondingly.

Subsequently, the enhancement in automotive safety deploys the intelligent vehicle safety supported transportation. The upliftment of AI technologies is slightly modifying the manufacturing model adaptive and smarter. Furthermore, the AI approaches are stimulating the transition from passive automobile safety features to active automobile safety designs probably [61].

The transformative role of ML and AI techniques are in customizing the automotive industry towards environmental consciousness and sustainability respectively. The AI and ML techniques are expanded exponentially by making the roadways increasingly safe, cheaper and smarter. Additionally, the AI and ML techniques are considered as the convincing solutions to alleviate climate changes and drive towards a supportable automobile industry.

Predominately, the AI approaches are used for the battery optimization. The noteworthy efficiencies and opportunities for innovation are deployed through AI and ML approaches. To increases vehicle fuel efficiency, decrease carbon generation and predictive maintenance are accomplished by AI/ML techniques in AVs [62].

The correlation of AI and ML algorithms possess autonomous vehicles to adapt to dynamic environments, to navigate, to perceive, to make more efficient and making them safer probably. Moreover, the improving the capabilities and safety of autonomous vehicles are achieved through the AI approaches. AVs are undergoing a transformational evolution through the correlation of AI methods.

Moreover, reducing accidents by eradication human errors and directing to safer roads are achieved through the AI approaches respectively. Simultaneously, the AI decrease the traffic flow in the means of effective routing and increase the accessibility. The AI techniques aids in the energy savings through optimized driving reduces the emissions and fuel consumptions. Consequently, the AI algorithms are more flexible in understanding environment with progressive sensors and powerful ML approaches. Enhanced reliability and safety, quicker decisions and greater independence are employed through the AI techniques [63].

V2X Communication in AVs using AI techniques

The term V2X stands for the Vehicle to everything (V2X) that comprises of cameras and wireless connectivity that includes Wi-Fi, 5G cellular technology and radio frequencies. It permits the cars to share information with each other about the drives and surroundings effectively. Moreover, the V2X technology that is proceeding in small stages. Based on the cameras and networks, there is association to link the cars with one another or their surroundings to make the driving safer eventually. Probably, the V2X technology are utilized in various countries that includes multiple information to be communicated between the vehicle to minimise the accidents and mortalities. The benefits of using the V2X technology are traffic efficiency and energy savings, mass surveillance and road safety. The implementation of V2X technology reduces the 13% of traffic accidents and 4,30,000 crashes in each year are stated in the US NHTSA report respectively

Nearly, all the vehicles communicate with each other by V2X communication. Moreover, this communication is used in several ways comprising obstacle detection information in the vehicle’s path correspondingly. Based on the information equipped about the physical world, communication requirement in V2X communication works efficiently. The correlation of V2X and AI, the securing concerns to autonomous driving are flourished. Additionally, the V2X communication replaces the feature minimal human control literally. The security related options are enhanced through the AI based approaches and V2X communication correspondingly [64].

To facilitate the V2X communication, there are several communications. Depends on the transmission range, the technologies are classified into short range, medium range and long range respectively. The development of ZigBee, ultra-wide communications and Bluetooth in AVs are included in the short-range communication. The properties of dedicated short-range communication are involved in the medium range communication correspondingly. The long range of the communication represents the 5G-new radio (5G-NR) and Cellular -vehicle to everything (C-V2X) probably.

Additionally, the V2X communication permits the vehicle to communicate with the other entities such as roadside (V2R), devices (V2D), grid(V2G) and pedestrians (V2P). The communications are utilized to avert road accidents with helpless cyclists, motorcyclists and pedestrians. The mechanism named as Pedestrian Collision Warning (PWC) alerts the roadside passenger before any serious accident takes places. This mechanism is correlated with the V2X communication effectively. Through this, the AC communicates with network infrastructure by using various wireless technologies. During the V2X communication, the emergency situations such as accidents or fog are communicated through the warning information with neighbouring vehicles in a sequence time [65].

The technology V2X permits the AVs to exchange the data with other vehicles and equips in enhancing efficiency, environmental impact and efficiency. The V2X communication is complicated for autonomous vehicles to interact with other vehicles respectively. By deploying blockchain, it can improve the privacy and security of the communications. Moreover, it eradicates the unauthorized access and malicious attacks. The peripheral performance and energy are enhanced through the V2X communication effectively [66]

In traditional vehicles, the V2X technology expressively increases a driver’s situational awareness. The V2X system involves the cruise control or cooperative driving, collision avoidance or queue warnings, extended sensor coverage and hazard warnings. The cars driven with the technology V2X relies on enhanced automotive safety and driver awareness respectively.

Moreover, the several components possess a major role in the utilization and integration of the V2X technology accompanied with their pros and cons correspondingly. The emphasis on correlating the V2X related safety equipment into modern conventional vehicles are evolving in recent years. The V2X technology provides numerous functions such as issuing warnings, enhancing safety and providing information. Additionally, the collision avoidance system permits prolonged information between the vehicles and pedestrians.

To improvise the efficiency and traffic safety among AVs, there is advancement in AI techniques and Intelligent Transportation Systems (ITS) are evolved. By deploying the system, the reduce fuel, location-based services and traffic flow are enhanced. The correlation of AI approaches and V2X allows the autonomous transport facilities, congestion control and real-time traffic flow prediction effectively. Moreover, the V2X systems correlates with the AI results in enhancing the comfort, efficiency and traffic safety.

The technology V2X are classified into cellular -V2X (C-V2X) and Dedicated Short Range Communication (DSRC) respectively. The complications of vehicular communications are sorted out by incorporating the AI approaches with V2X technology. The drivers are informed about the optimal speed to approach junctions, reducing the need of rapid acceleration and breaking near traffic signals through the Green Light Optimal Speed Advisory (GLOSA) systems effectively. The GLOSA systems utilizes the V2X technology. Predominately, the AI based GLOSA applications enhances the fuel consumption [67].

Predominately, the CAV communicates essential amounts of data to equip several navigations, infotainment services to the customers and safety. A significant enabler for connected and autonomous transportation is C-V2X respectively. Moreover, the AV navigations are efficient, reliable and exchange drover intent such as braking and lane charges. Due to the sensitivity of most vehicular applications, the security is considered as the major component of C-V2X correspondingly. The mechanism named conventional cellular security that includes transmitter receiver end points and central network entity are not adequate for the C-V2X and this is because of traffic information and safety broadcasted using ad-hoc network [68].

The purpose of utilizing the V2X communication is to aid ultra -high reliability and ultra-low latency requirements of driving safety respectively. The computation times that relies on the algorithm complexity and hardware facilities are affects the safety related applications. The algorithm complexity and hardware facilities are delayed due to the transmission. Moreover, the V2V communications permits the real time transmission of voice, image and data information to connect roads and vehicles. The benefits of self-organisation, low cost of V2X applications and low end -end latency is equipped through DSRC correspondingly. Probably, the traffic accidents are reduced up to 81 % by deploying V2X communications in AVS.

Additionally, the countries believe that the C-V2X technology develops faster. The C-V2X aids in stronger reliability, congestion control, higher capacity and longer communication distance. V2X communications are designed through simulated various collision risks and collision avoidance algorithm. The road traffic safer are accomplished through the co-operative V2X communications [69]. The enhancement in comfort, safety, driving performance, advancements in traffic monitoring, real time communications and transportations are achieved through V2X communications. Subsequently, the V2X communication reduces traffic congestion [70].

Various techniques, norms and standards adopted by Edge computing, V2X, IOV, AI and 5G are utilized in the area of autonomous driving. Moreover, the current applications involve the use of DL and AI techniques models in autonomous driving services management, online optimization, edge computing services and self -driving cars respectively [71].

The technology V2X communication evolves an innovative approach to enabling vehicles and transportation to communicate with surrounding users and infrastructures. Vehicles can exchange information such as direction, speed, road conditions, hazards and locations through V2X technology. The multitude of applications comprising of traffic management, autonomous driving, response co-ordination and collision avoidance are facilitate through bi-directional communication.

The distinctive features are exhibited in the V2X technology respectively. By deploying V2X communication, the vehicles operate in highly variable conditions and dynamically. Through V2X communication, the vehicles interact with multiple elements such as pedestrians, road infrastructure and other vehicles respectively. The challenges interrelated to limited band width, varying signal strengths are included in the wireless nature of V2X communication. The complications that involves in V2X communication are analysing diverse data and intrusion detection [72].

Collision avoidance systems in AVs using AI approaches

The two or more vehicles colliding with one another in the same collision is termed as collision or multiple collision. The 20 % of traffic collisions and 18% of the deaths are stated by the United States Motorways eventually. Moreover, the 50 % of multiple collisions occurs because of the urban traffic congestion. The Multiple Vehicle Collisions (MVC) are leads to rear -end crashes and accidents due to the highway conditions. To avoid collisions in AVs, the collisions are categorized into three viewpoints.

Initially, multiple collisions are identified. Secondly, multiple collisions characteristics are analysed. Then, risk modelling is developed to avoid multiple collisions respectively. By utilizing the AI conceptual framework, the multiple collisions are identified. The adequate driving strategies are required in AVs correspondingly. Moreover, the AI enhanced the deployment and improvement of AVs in transportation sector probably. The upliftment of AI technology is flourished the understanding of environment. The self-driving cars represents the function of AI in AV predominately [73].

The braking decision plays a major role in collision. In accidents, the autonomous braking decision is complicated in the preliminary phases of AVs technology. The Automated Braking Function (ABF) is completely associated with the Autonomous Braking Decision (ABD). Moreover, the ABD is considered as the major AVs safety core technologies respectively. ABD can effectively brake based the driver reaction to dangerous circumstances. The current advancement of AI aids the Intelligent Control System (ICS) to make real-time decisions and adapts to the environment [74].

The CA systems are relied in the precise discovering hazards and suitable warnings to drivers in earlier or performing autonomous control. The traffic safety problems are solved using the CA systems effectively. The major goal of the transportation system is to sort out the driving safety problems and preventing collision accidents. The transportation system engrosses on the technologies based on the CA systems. Additionally, the CAV adapts to the various levels of autonomous control and aids to accomplish driving safety in a collaborative manner respectively [75].

The implementation of CA strategies results in least traffic jams and road blockages caused by the accidents. The integration of V2V and CA strategies increase the performance of AVs. The broadcast mechanism that deploys the DSRC based packet forwarding is used to accomplish the avoid collision. Majorly, clustering algorithms are applied for the CA systems on intersections respectively. Moreover, the channel allocation algorithm is used to decrease the Wi-Fi channel interference between the clusters.

The two-phase approach is required for maintaining the traffic, collision avoidance and congestion management. The scenarios are designed based on the collision occurs recurrently. The obstacles across the road, vehicle collides with the obstacle and vehicles crashing other vehicles are intimated through the warning messages. The alert message warns the vehicle about the crash ahead and vehicle slow down probably. Subsequently, the V2X communications includes messages and detectors are used to prevent collisions [76].

The maximum probability of collision is stated as the design of real time transmission from assisted driving to automated driving respectively. The AI algorithms combined with Bayesian network prevents collision. The combination of algorithms supports in enhancing the AVs by supplementing the capability to reduce the collision risk and prevents the AV from driving into a dangerous situation respectively. The fuzzy logic is used to control the AVs to decrease the risk of scenarios if the GPS are misplaced. The familiar techniques such as ANN, SVM, AI & ML deploys to sort out the road detection, collision avoidance and AV validation respectively. The collision happens if any other action is not taken by the driver to prevent collision correspondingly [77].

AVs are considered as the technology for transforming the existing model of travel respectively. To progress the road safety by eradicating the human errors and reducing traffic congestion are deployed with the help of AV. The most essential criteria that correlates the deployment in traffic systems and mass production are considered as the reliability and security of the AVs. The traffic flow and the analysis of the collision risk of AVs are the two significant phases in the development of AVs correspondingly. Eventually, the significant phase of the development in AVs attracted the considerable attention in current years [78].

Moreover, the European New Car Assessment Program (European NCAP) established a several test of scenarios to examine the adaptability of AV control logic in the terms of CA correspondingly. The test scenarios act as a probable direction for overall issues including the collision avoidance in AVs probably. The algorithms are used to prevent collisions are the sense-and-avoid-techniques, offline planning and artificial potential field methods. The implementation of DL and Deep Reinforcement Learning techniques (DRL) are evolved in recent days to overwhelm the challenges addressed by the traditional CA algorithm process. Recently, the Deep Neural Networks (DNNs) are utilized to extract features, grasp complicated scenes and to classify objects [79].

Environment Adaptation in AVs using AI technology

The best solution for the effects of weather difficulties in AVs are managed through the AI based techniques. The correlation of AI includes the factors such as controller design, learning, modelling, domain knowledge, reliability and robustness for AVs are affected by the hostile effects of weather correspondingly. The AI based approaches that has utilized for AVs to adapt environment circumstances effectively. The correlations of AI with multi-sensor fusion are used to develop solutions for desired environmental conditions. The technologies that are combined using the AI could be examined using severe rain and fog environmental conditions. Moreover, it provides the domain specific knowledge. Based on the three essential factors, the AVs vehicles are classified into interaction between the vehicle speed and cost, situational awareness and sensory impacts of weather conditions. The deployment of autonomous vehicles is very difficult to enable in all weather conditions correspondingly. The AVs behaviour and the road conditions are interlinked with the AI approaches [80].

The influencing factors such as subject vehicle characteristics, external factors on the change in driving behaviour and human driving characteristics are affect the safety of the passengers. The models that are in the designed with the correlation of AI techniques are utilized to identify the groups of factors or effect of individual that contributes to behavioural adaptations respectively. The behavioural adaptations on safety and traffic flow are investigated using the microscopic traffic simulations. The enormous amount of data is required in the various driving factors of AVs such as absence of driver, various road types, several speed types, environmental conditions such as time of the day, visibility, weather and fog respectively. The factors influence the quick decision of the drivers. The field tests that are essential and to are conducted to analyse the various factors that influences the driver’s decision [81].

The key that plays a major role in the AVs development is advancement in AI technology. The AVs majorly relies on the AI technology to understand the environment and making decisions in the driving related conditions. Typically, the AI replicates the human driver actions and decisions respectively. The major aspect of the AVs is to ensure that it is entirely safe when operating in public roads. The AI techniques are subjected to the detection techniques and computer vision to support the autonomy the AVs correspondingly. The multiple aspects of AI that aids the AVs are doppler sensing, obstacles detection, pedestrian trajectory prediction, road terrain detection, situation awareness, lane detection, speed detection, road terrain detection, speed bump detection and vehicle detection probably. Recently, the ANN algorithm used to recognize the road environment signals and turn signal. The SVM technique are used to support the safest path planning in dynamic environments [82].

Predominately, the traffic problems are sorted out by alerting the CA systems or drivers about the accurate hazards in AVs. The viewpoints such as autonomous control, diversified communication technologies and environmental awareness stimulates the CA systems to operate effectively, accurately and enhance the driver safety. The AI technology aids the AVs to adapt to the surroundings, enables fast and precise decisions respectively. The AI approaches are to used handle the large volume of data in the increasing complex traffic environment prospectively. The AVs operates the accurately and flexibly due to the correlation of environmental adaptability and self -learning ability of AI systems. The AI systems are deployed in-order to make the AVs to adapt to environment, to make rapid decisions and predict accurately [83].

The development of AVs relies on the AI technology in recent days. The technologies such as computer vision, senor fusion, robotic control and deep learning are quickly receiving the ability to make decisions, control their function without human support and make decisions. Most probably, the autonomous driving technology are the convincing technology to transform transport industry by enhancing efficiency, accessibility, convenience and safety.

Moreover, the autonomous driving is a crucial challenge that necessitates the vehicles to navigate unpredictable road conditions and intermingle with pedestrians, human drivers and other agents respectively. The AVs reckoned on the AI technology to precisely perceive the surrounding in real- time, forecast the actions of other road users, execute accurate vehicle control and make sage and appropriate decisions effectively. The challenges faced by the AVs vehicles are in handlings adverse road and weather conditions.

Specifically, the AVs relied on the AI to perform the four functions namely prediction, planning, perception and control. The perception functions include the computer vision to detect and classify the object in the environment such as vehicles, pedestrians, traffic lights, road, obstacles and lanes. Subsequently, the prediction involves the AVs decision making and planning includes the path selection relied on the AV perception and prediction respectively. Mostly, the AVs testing are held at the moderately unnatural environments such as geo-fenced areas, urban centres and highways [84].

The precise mapping and positioning solutions are critical in circumstances including environmental awareness and automatic lane changes respectively. The advancement in AI and robotics techniques is familiar in both the industry. Moreover, the safely navigation involves the precise representation of the positioning of the vehicle and surrounding. A promising solution for AV navigation and positioning is termed as Simultaneous Localization and Mapping respectively.

The SLAM algorithm is deployed to predict the vehicle behaviour in the environment. To locate the position of the vehicle and create amp for the environment is achieved with the help of SLAM algorithm effectively. Moreover, the process takes place concurrently. The identification of low -level feature points in images are the core functions of the SVM algorithm. Consequently, the SLAM algorithm is essential in automatic lane changes of vehicles and it equips the essential information that aids in the decision and control of the automatic driving system.

Initially, to create and update the environment map that includes traffic lights, road structure and obstacles are equipped by the SLAM algorithm. The maximum precision positioning of vehicle position is examined using the SLAM algorithm effectively. Moreover, SLAM technology is deployed to monitor the surrounding vehicles to adjust lane change strategies to prevent collisions with other vehicles respectively [85].

The development and operation of AVs is highly relied on the AI technology. The correlation of AI algorithms permits the AVs to perceive, adapt and navigate in dynamic environments. The Ai technology reshapes the AVs more efficient and safer. The AI algorithms are suitable for the understanding the environments with powerful ML techniques. With the help of edge computing, the AI functions to perform rapid decisions.

Moreover, the diverse weather conditions include heavy rain or snows are the challenges for the AVs. The narrow city streets, parking spots, frequent stops and turns, pedestrian, high traffic density, cyclist avoidance, variable lightning, natural hazards like fog and dust are the obstacles faced by the AVs in the environment respectively. The exhaustive testing by the AVs are carried out with the help of ML and DNN networks. The information exchange between the AVs and the environment includes the traffic patterns, potential hazards and road conditions is very complicated for the AVS to navigate efficiently and safely. AI technology permits analysis of vehicle performance and real-time data collection [86].

In recent days, many countries involve in the research based on the impacts of AVs on urban landscapes, urban planning, and environmental sustainability and focussing on traffic management. The traditional stages of AVs rely on the development of technologies such as pedestrian detection, path planning, environment detection, vehicle cyber security and motion control. Moreover, these technologies enhance the significance of precise positioning, diverse road conditions and pedestrian behaviour. AVs face the challenges in decision-making to urban infrastructure optimization respectively.

Simultaneously, the urban population grow then the lower traffic volumes and road networks are congested probably. The new strategies of traffic management and urban infrastructure development are introduced in the AVs especially. The Agent Based Modelling Environment aids the interaction of AVs and urban infrastructure correspondingly. A concerted experience is gained in this approach. Even though, the correlation of Agent Based modelling concepts and procedural content generation (PCG) are crucial for developing a responsive and dynamic urban system [87].

Prediction of driver behaviour in autonomous vehicles

AVs are engrossed numerous attentions among the society because of its convincing benefits transportation efficiency and driving safety respectively. The several scenarios are faced by the AVs in the complex driving. The trajectory tracking control and driver behaviour prediction are established as the primary components of AVs correspondingly. Many researchers focus on the vehicle trajectory tracking control and driver behaviour analysis. The driver behaviours are described using driver models.

With the help of control perspective, the transfer-function-based driver model are developed. The driver's preview time, lay and delay terms are the factors involved in the driver-based model effectively. Moreover, the neural network driver-based model is used to predict the driver behaviour and it is attained by the training the network with the driving data. Subsequently, the driver model predicts the driver intention and behaviour. The neural network and Gaussian mixture model are used to predict the driver forthcoming decision [88].

The accident prevention studies, input to self-coaching and establishing driver assisting systems are used in the driver behaviour models. The driver behaviour recognition is transformed in the aspects of the traffic management and AVs respectively. Moreover, 80 to 94 % of the crashes are occurred to driver-related errors and 33% were wrong decision of the drivers. The impaired driver's behavioural traits are the reasons for the accidents. The promising solutions for the problems are introducing the automation in transport industry. The LSTM and RNN methods are recurrently used to predict the driver's behaviour and intentions [89].

The paved way to decrease vehicles collisions correlated with negligence and driver errors respectively. The risk conditions and driving scenarios is the challenges. Based on the challenges the AVs are designed on the aspects of reliability and high level of safety. Moreover, the Auto ML frameworks are designed to accomplished driver behaviour assessment and risk prediction. The vehicle driving data to risk levels are predicted with the aid of AutoML framework. Based on the behavioural features the route planning is designed. Consequently, the driver behaviour features are eradicated from surrogate sensing data and vehicle trajectory [90].

The correlation of human factors represented by driving style is predicted by the lance changing decision model. The model not only predicts the surrounding traffic information but also the driving style of the surrounding vehicles. Additionally, the model predicts the human driver intention and behaviour. The consequences of the model state the human decision-making and human driver's lane change action respectively and attain better prediction accuracy [91].

The prediction model uses the data mining techniques and regression analysis that engrosses the correlation between the external factors like safety-driver behaviours, weather conditions and human factors. The model predicts the behaviour of the driver in two ways in the aspects of certainty and uncertainty. The certainty phase involves if the driver is familiar with the situation and the vehicle sustains a consistent acceleration, deceleration and speed. On the other hand, the uncertainty evolves if the vehicle executes an unexpected action such as lane changes without signalling, sudden braking and immediate accelerations respectively. Moreover, the lack of the incomplete information about the traffic situations, intentions of the AVs and traffic situations contributes to the uncertainty phase [92].

The driver behaviour is predicted in the AVs using the ML models. The core component that defines the driver behaviour in virtual environment is predicted using the Real Driving Emissions model respectively. With the support of ML model, the simulations of the driver behaviour and to enable the driving emissions are predicted. The MI augmented solution model includes the algorithms such as KNN, RF and Ordinary Least Square to predict the driver behaviour [93].

The driver behaviour model is developed using a wide deep framework that combines Convolutional Neural Network (CNN) and Gradient Boosting Decision Tree (GBDT) respectively. The driving behaviour characteristics improve the explicated of the CNN-LSTM model. The interaction between the surrounding vehicles and the AVs are predicted using the GBDT algorithm. LSTM-CNN are correlated with the driving behaviour rules [94].

A significant part of the AV transformation includes the driver behaviour through the driver facial expressions, diver's body postures and hand replacement on the wheels. The implementation of AI techniques warns about the unsafe behaviours using the voice notifications respectively. The AI based monitoring software contributes in safer and secure transportation in AVs probably. The model is designed to alerts the driver without any data privacy concerns. To detect the fatigued drivers, the three classifications methods are used. Consequently, to predict the driver intention and behaviour the ML algorithms such as CNN, RNN and DNN subsequently [95].

The driving force behind the AVS is relied on the DNN techniques. The numerous datasets are required for the train the extensive large data sets. The data comprises of images captured by cameras and enables the DNN to identify the traffic lights, pedestrians, diverse driver behaviour correspondingly. Moreover, the DNN techniques are used to generate confident prediction especially in crucial environments in AVS [96].

In the designing of intelligent transportation systems, advancing AVs and improving road safety driver behaviour analysis plays an essential role. The driver analysis model is designed using the DNN techniques. Moreover, the DNN techniques are familiarized in the development of driving behaviour analysis because of their capability to automatically learn complex patterns and features from raw data effectively. The several types of DL techniques are also used to predict the driver behaviour and address the challenges in the field. With the help of LSTM and Gated Recurrent Unit (GRU), temporal dynamics and long-term dependencies in driving behaviour are captured. The several tasks such as driving style detection, driver identification and driver distraction detection and driver health prediction are predicted using the DNN model [97].

Predicting, analysing and modelling driver behaviours are indispensable to ADAS and the brief understanding of the crucial diving scenarios respectively. Recurrently, the advancement of numerous driver behaviour learning (DBL) and DL have been applied in the ITS and CV. The flourishment of DBL methods is the combination of deep learning-based driving behaviour-based methods. The methods involve in predicting the trajectories of surrounding vehicles and driver’s behaviour. The essential advantages of neural network that involves the mapping from environmental information to driving behaviour probably. Moreover, the DBL model well suits for the real-world intelligent systems that frequently changing the scenarios and maintains robust performance of the previously learned circumstances. Additionally, the ML techniques are termed as the continual learning. The DBL model involves the four categories and the model attains better accuracy in the aspects of predicting the driver moods and behaviour [98].

1.4 PROBLEM STATEMENT

The term AV refers to a self-driving that can operate with a little intervention of human input that are developed and tested. In a rapidly evolving field of transportation industry and AVs, ensuring safety is a predominant concern. Additionally, the safety of AV is important to their success in the transport industry. The automation and the technology advancements in vehicles subjects to road safety. In recent days, the substantial advance in AI and its applications to the advancement of AVs are flourished.

Consequently, the AV avoid road accidents caused by the driver faults and favours a safer traffic environment. Reducing traffic accidents, energy consumption and emissions are considered as the promising solution of the crucial environmental issues. The prediction of safety in critical events are crucial for the decisive operations. The traditional predictive models incorporated in AVs often lacks in predicting the critical events due to the dynamic and complex nature of the environment.

The present research addresses the challenges by establishing a predictive model using modified Deep CNN-BiLSTM deploying attention mechanism. The model is developed in order to enhance the prediction accuracy in AVS by using the strength of CNN in feature extraction and engrossing capability using attention mechanism. Based on the data about the diverse driver behaviour and malfunction in the AVS, the model predicts whether there is a possible way for safe journey. The research contributes to the advancement of several robust and precise system that enhance the safety of AVs and trustworthiness in the public roads.

1.5 AIM AND OBJECTIVE

Objectives of the proposed work were listed as follows,

- To select the essential features using improved search ability based genetic algorithm
- To forecast the condition of driver health using Modified Deep CNN -BiLSTM with AM.
- To assess the model performance by deploying various metrics such as improve accuracy and reduce the loss.

1.6 SIGNIFICANCE OF THE STUDY

AVs are considered as the boom of the transport industry. Many countries embrace the technological advancements in AVs and believes that leads to a safe journey. Even though the AVs eradicates the human errors and support the people who are unable to drive, disabled and elder persons. Still safety is a major concern for the public environments. Numerous algorithms were used to predict the driver health issues and any malfunctions in the car parts are not identified accurately and it leads to several crashes and failures. In order to overwhelm the challenges, the proposed model deploys the deep CNN-BiLSTM with attention mechanism. Moreover, the improved search ability based genetic algorithm is used for the analysis and the dataset are gathered from the open sources platform (Kaggle) for dataset collection respectively. Subsequently, the dataset comprises of the car material condition and driver physical state. In an effort to diminish the dimensionality of the dataset, memory requirements and accelerates the model training process, the dataset undergoes the feature selection process. In order to enhance the accuracy and prediction, the proposed model deploys the deep CNN-BiLSTM with attention mechanism that directs to passenger safe journey.

1.7 SCOPE OF THE STUDY

The AVs fascinates enormous attention recently due to their convincing benefits in enhancing the driving safety and transportation efficiency. The current research enhances the reliability, safety and real-world applicability. The proposed study subsidizes technological development in AI and ML techniques, transportation technology, public adoption and welfare. Moreover, the present research paved the way in enhanced road safety, increase trust on AVs, enhanced traffic efficiency, reduce human errors and accidents. Moreover, the AVs permit the people who are unable to drive elder people and disable people freedom to drive. Subsequently, AVs reduces the emission and fuel consumption and encourages the development of new technology and industries by creation enormous number of jobs and stimulates the commercial activity. AVs promote the development of new technology in the transport industries.

CHAPTER 2

LITERATURE REVIEW

In recent years, the advancement in the Autonomous Vehicles (AVs) has been flourished the transportation industry. Researchers from variety of area have found a home for themselves in the area of investigating the safety in the AVs. In order to discover, the most practical methods that have been used in the published articles in current years. We conducted research on selection of previously published papers. In this chapter, we will have an in-depth conversation about these publications and approaches that they follow, that are relevant to the work are discussed. The section 2.1 exemplifies the advancement of AVs and the complications faced by the society in the adoption of Avs. The section 2.2 demonstrates the conventional methods to anticipate the safety in Avs and their challenges. The section 2.3 captivates the AI techniques that were used to forecast the safety in the Avs and their drawbacks. The section 2.3.1 engrosses the ML approaches and the section 2.3.2 demonstrates the DL techniques that were used in the existing studies to predict safety in Avs. The section 2.4 deliberates the research gaps of the conventional studies. The overall work is summarized in this chapter are reflects in the section 2.5.

2.1 INTRODUCTION

Safety of Autonomous Vehicles (AVs) are the paramount significance due to their prevalence on roads. Some of the key factors are contributed to ensuring and predicting the safety of AV. A comprehensive understanding of AVs, encompassing their automation levels, is significant for predicting safety. The level of automation affects the frequency of disengagements and accidents while driving in autonomous modes. Examining reported AV accidents can provide valuable insights into the safety challenges faced through these vehicles. Privacy and cyber-security concerns have a crucial impact on the safety of AVs followed by emotional safety and cognitive safety. Addressing these issues are significant for building trust in AV technology.

Most of the AV accidents are passively began by other road users, comprising pedestrians, cyclists, motorcycles, and traditional vehicles. The ability of AVs to alert and evade safety risks caused by others is vital for preventing the possible fatal accidents. Furthermore, High-quality training data is precarious for increasing reliable autonomous driving systems. Annotated data from different sensors helps in training the machine learning models to identify surroundings, predict scenarios, and make safe decisions. Using high-quality training data improves the reliability, safety, and efficiency of AVs. Predicting the AV safety requires a multifaceted method which considers the levels of automation, privacy and cyber-security concerns, the influence of other road users, and the quality of training data. By addressing these factors, stakeholders could work towards confirming the safe deployment of autonomous vehicles on the roads.

The safety has been considered as the significant factor in the driving scenarios. The accidents occurred in the road environments has been caused owing various reasons such as collision of two vehicles, lane changing behaviour, overtaking, lack of driving skills, repair in the car parts, consumption of alcohol and health issues of driver. The prediction of safety in AVs has been a challenging task. The traditional methods such as dashboard cameras and pamphlets has been used to predict the safety in the AVs.

Even though, the accurate results obtained has not been adequate to predict the exact safety in the AVs. To overcome the challenges faced by the traditional methods in order to predict the safety in the AVs, the various AI techniques has been introduced. The driver behaviour and health play a major role in predicting the safety in the AVs. By predicting the driver emotional reactions and behaviour, the safety has to be predicted. By recognising the malfunctions in the car parts, the safety of the driver and the passenger has been forecasted. In this chapter, the various methods have been used to predict the safety in AVs has been discussed briefly. The several models deployed to predict the safety and their limitations that engrossed in existing research has been exemplified. The different methods used to anticipate the physical health of the driver and the blunders in the car parts using AI techniques that has been captivated.

2.2 TRADITIONAL METHODS FOR PREDICT DRIVER'S BEHAVIOR IN AUTONOMOUS VEHICLES

The safety of passengers in AVS has been stated as the crucial and challenging task. Even though, nowadays there is a flourishment of AI techniques in predicting the driver illness and car parts malfunctions in order to ensure the safety among the passengers. Before the establishment of advanced techniques, the conventional methods such as dashboard cameras, pamphlets and vehicle data that has been used to predict the driver behaviour as well as the safety of the passenger [99].

The dashboard cameras are one of the conventional methods to predict the driver behaviour in AVs. Subsequently the dashboard cameras typically capture only portion of the driving environment [100]. Moreover, the dashboard board cameras potentially fail to capture the critical information outside such as pedestrian movements and traffic patterns [101]. The enormous amount of data captured by the dashboard cameras are challenging to process and analyse in the real time environments. Consequently, the dashboard cameras capture the images of the data of both the driver and passenger directs to the privacy issues of both the driver and the road users [102].

Additionally, with the help of dashboard cameras, the data are captured but prolonged recordings have been leads to the low video quality. The video quality has been affected by the several factors such as lighting conditions [103]. Moreover, the dashboard cameras have been generating the false positives or false negatives that leads to the diminishing the reliability of safety predictions. The regular maintenance has been required to confirm that they are functioning properly. The factors such as dirt, dust and physical damages directs to the impair of the effectiveness of dashboard cameras particularly [104].

The pamphlets in the AVs has been provided data that is utilized to predict the safety of the passengers [105]. Moreover, the pamphlets have been used to conventional method to predict the passenger safety. Even though, the pamphlets have been provided the data for the prediction of safety but it has several drawbacks. Subsequently, the pamphlets have been static and not able to provide interactive real time updates [106].

Moreover, the data provided by the pamphlets has not been effective in the dynamic situations respectively. On the other hand, the driver and the passenger have not been always engaged with the pamphlets throughout the driving. The lack of reading the pamphlets has been leads to the impact of safety behaviour of driver and passenger. Additionally, the information in the pamphlets that has been quickly outdated particularly with evolving safety standards. The real time data monitoring has not been equipped with the pamphlets. Consequently, the pamphlets have not been able to collect the data based on the driver behaviour or vehicle performance that makes to track changes. These are the conventional methods for predicting the driver behaviour and malfunctions in the AVS.

2.3 AI METHODS FOR PREDICTING AUTONOMOUS VEHICLES

For assisting AVs, the AI methods are most essential because it helps vehicles to plan their trajectory, execute driving plans without human intervention and to perceive their environment. The AI- system present in vehicle plays a crucial role in making real time decisions like accelerating, braking and steering and this AI system is totally relied on machine learning models and those models were trained on large datasets to reduce human driving behavior and respond appropriately to different traffic situations.

The societal impact and mobility of CAV is increased rapidly due to its importance in the modern society. The main reason for the increase in speed, ubiquity and latency is due to the AI technologies. The role of AI techniques in play a vital role to the development of CAV controls. The existing model [107] has investigated the inherent concerns towards acceptance and their inclination based on User adoption of CAVs. The user adoption of CAVs had been collected by using quantitative data from the latent users. The existing research conducted the applied machine learning techniques and statistical analysis to predict the CAVs user adoption. Similarly, to forecast user adaption for CAVs various machine learning approach like Fuzzy logic-based models, neural networks, Random forest and Naïve Bayes were used to forecast the public adoption of CAV. The outcome of the analysis has been attained average performance.

The digital transformations in AVs are due to Intelligent Automation (IA) because the IA combines both the AI and robotic process to improve the performance of AVs. When compared to human activities IA can completely substitute humans with automation. Though they are automation it has the ability to provide intelligent movement of vehicles with better safety. The conventional research discussed the importance of risk mitigation technologies and the safety challenges of autonomous vehicles. The conventional research has analyzed the improvements in autonomous vehicle technology using DL, statistical techniques, IoT, ML and reinforcement learning. The result of the research has been identified the lack of safety standards in autonomous systems and the existing research found that, to develop the safety standards for futuristic autonomous systems AI is important.

Correspondingly, the existing research [108] has determined human emotions resulting dangerous driving. These human emotions while driving AVs can be identified through AI. The suggested research has considered behavioral therapy, consumer research and data analytics to identify driver emotions. The recommended research had been attained average performance. The outcome of the traditional research has been attained average performance. Deep learning is considered as the powerful tool for control and perception in autonomous vehicles. The tasks like lane detection, object detection and sematic segmentation from camera data can be utilized by Convolutional neural networks (CNNs).

The transportation problems in urban areas like accidents and traffic congestions can be solved by autonomous driving. The AV has the ability to change the way of travelling because nowadays AV are capable of doing all human like driving activities. In upcoming days, the driving can be reality in the future which was proven by IVFC (Intelligent Vehicle Future Challenge). The prior research [109] obtained a trained model and applying DRL algorithm in the trained model to control the vehicle to navigate properly by following a determined route. The prior research utilized the CARLA (an open source simulator) for process. The CARLA is the system that has the ability to produce the outcome without any risk when performed by multitude of tests. The outcome of the prior research has been attained average performance.

In most of AVs the DL technologies are applied to enhance the performance of AVs most importantly to predict the surrounding vehicles. The DL technique is helpful in predictive driving. The conventional research [110] developed a vision based autonomous driving using control method named as deep Monte Carlo Tree Search (deep-MCTS). The driving manoeuvres are projected using possible trajectories and the predicted information of two DNNs was employed by the deep-MCTS. The predicted driving manoeuvres and road conditions in optimal trajectory are designated by the deep-MCTS.

MLLMs (Multimodal large language models) have industrialized as a protuberant area of attention within the research community. MLLMs have the ability to handle non-textual data including images and videos. With the help of images and videos, the driver behaviour is captured and analysed. Literally, the traditional research [111] implemented the realm of autonomous driving by DriveGPT4 to extend the MLLMs application. The autonomous driving system is relied on the Large language Models. The traditional model has used BDD-X dataset to estimate the quantitative performance and qualitative performance of DriveGPT4. The existing research has been attained average performance.

The enormous increase of CAVs is due to its highway safety because of innovative technologies in CAVs. The most important feature in CAV is about its prediction and identification of driving intention which provides useful information to the drivers to avoid collision. Likewise, the conventional research [112] has determined the unlabelled data using limited features to develop and predict the lane change maneuvers using machine learning model. The conventional research has used HighD a comprehensive dataset for process. The existing research identified the lane keeping and lane changing maneuvers by Density-based clustering method. The raw data is automatically labelled by clustered boundaries and then trained using Support Vector Machine (SVM). The existing research has been attained average performance.

Emotions are important in situations that involve human interaction analysing human emotions enables the predictions to be made by decision making in driving. The suggested research has examined specially developed solutions to detect emotions in AVs. The existing research has involved in enhancing human vehicle interaction. Additionally, the prevailing research considered primary vehicles and passenger seats to demonstrate the human emotion. The suggested research has utilized Human Robot Interaction (HRI) model to facilitate effective communication when the driver in is danger. The main problem with the automobile security is the emotional state of human drivers [113].

One of the major worldwide issues that impacts human life, well-being, financial system and community. In this community there are more transportation issues and these issues can be tackled by using AVs. The AVs are in developing state only not in a developed state it requires more time to become widespread in world settings. Although AVs can perform like human like drivers the main obstacle in it was to identify objects in actual driving conditions with the greatest level of certainty. Literally, the existing research [114] investigated the deep learning by its in-depth performance and classified the object in driven environment using C5.0 decision tree classifier. The existing research utilized the KITTI road dataset for process. The label images in the subset if KITTI road dataset is selected through free form selection moderately a box or rectangular selection enabled highly and accurately. The existing research has been attained better performance.

IN AVs it is essential to make right decisions at signalized intersections because small failure at signalized intersections may lead to high risks. In AVs it is crucial to detect future actions of road users such as pedestrians, cyclists and cars. If AVs fail to predict these systems it intimates driver and results in dangerous scenarios and crashes. Similarly the conventional research [115] implemented Risk Aware Decision Making (RADM) method to train the conventional prediction model. An uncertainty quantification is approached through a multi-agent prediction network which used map information, traffic lights and historical states of road users nearby as inputs. The considered research has recommended real-world driving datasets for process. The suggested research had attained average performance.

The safe planning of movement in unpredictable surroundings at AVs is primarily impacted by nearby vehicles. Motion planning framework can be considered in driving environment uncertainty to reduce the threat of position uncertainty in nearby AVs. Likewise, the existing research [116] demonstrated motion planning framework to reduce the threat position of ambiguity of nearby vehicles. In order to reduce the risk, position a rollover risk index and 4-degree of freedom vehicle dynamics mechanisms are implemented. The recommended research considered the comprehensive Kalman Filter method to handle uncertainty of surrounding vehicles position. Additionally, hardware in loop experiment is determined by motion planning framework which helps in effectiveness, safety, forecasting driver behaviour and real time performance. The conventional research had been attained better performance.

The route mapping of smart vehicles is associated to dependable and accurate vehicle path predictions particularly in dynamic and indeterminate conditions. However, a lot of the existing methods have trouble it is important to understand effectively, how vehicles interact with one another and how they are connected. Likewise, the conventional research [117] approached Long Short Term Memory (LSTM) for driver emotional behaviour prediction and trajectory with dual attention mechanism. A trajectory information is utilized by temporal attention mechanism to identify the validity under different working conditions to enhance driver safety. The existing research has considered NGSIM dataset for process. The research had been attained average performance. Correspondingly, the existing research determined implementation technology and corresponding architecture by three aspects namely AI, Multi-access Edge Computing (MEC), and the combination of both MEC and AI. The suggested research had been attained average performance.

AI techniques are the building blocks of autonomous systems which enable the vehicles to identify their surroundings to make decisions and operate independently from human intervention. Self-driving cars have emerged as an innovative technology with the potential to revolutionize transportation and improve safety, efficiency, and accessibility. Literally, the prevailing research [118] implemented Explainable Artificial Intelligence (XAI) in the development of AVs. The recommended research has approached conceptual framework for end to end predicting emotional behaviour of driver. The social acceptance of AVs, transparency and its trustworthiness are depending on XAI-based prospective directions. The existing research had been attained average performance.

AVs are capable to completely transform the transportation by enhancing safety, efficiency, and accessibility. The most crucial aspect of AV technology is it is capable to consistently identify and react to unexpected obstacles or urgent situations. Autonomous steering may not react quickly enough in such circumstances to avoid a crash or loss of control that cause driver to make accidents in AVs. Likewise, the conventional research [119] determined Integrated Controller (IC) for AV. The IC is proficient to react in spare situations when unexpected problem appears on the road. The longitudinal velocity is tracked by a longitudinal controller. The categorized assembly of a combined path tracking and planning is shaped using Model Predictive Control (MPC) method. The collisions and instability are prevented by controller's ability which is established by CarSiM model. The existing model had been attained average performance.

Deep Conventional Neural Networks (CNN) has recently succeeded in detecting objects and vehicles. However, it is difficult to use CNN to regulate the vehicle detection in real time with a moving context. Many hidden truncated cars and the huge variations in the scale of traffic photos cause these problems. Correspondingly, the conventional research [120] Implemented Faster R-CNN to recognize rapid vehicle. The suggested research has considered custom dataset for process. Additionally, the suggested Faster R-CNN provided improved performance in time processing and efficiency detection. The recommended model had been attained average performance. Literally, the prevailing research [121] approached Really Simple Syndication (RSS) to demonstrate risk driving situation. The substantial reductions in increased traffic density are determined by risk-aware RSS approach. The suggested model had been attained average performance.

The existing research [122] Advanced Driver –Assistance Systems (ADASs) has been engrossed to enhance safety in the automotive field, however they do not consider the emotional readiness of drivers when functioning. Correspondingly, the existing research examined current advancement in cognitive and emotional exploration for ADASs which includes emotional models for signal capture and common algorithms for human emotion classification. The considered research has recommended Driver Monitoring Systems (DMSs) for ADASs which improve the driving safety and quality for drivers and passengers. Additionally, the existing research utilized Driver Complex State (DCS) and AI to detect drivers state and leverage this information to introduce unique Human Machine Interface (HMI). The considered methods have been attained better performance.

To expand the deployment possibilities for autonomous vehicles it is necessary to create advanced systems that are more secure and intelligent and capable of operating with increased autonomy and navigating unstructured environments. So as to do this the car needs to anticipate the actions of other drivers to function effectively in its environment. Similarly, the existing research has determined [123] maneuver lane change prediction of surrounding vehicles. The suggested research has considered two machine learning methods namely SVM and ANN. The recommended research has considered NGSIM dataset for process. The suggested research had been attained better performance.

2.3.1 SAFETY PREDICTION IN AUTONOMOUS VEHICLES USING ML

The development of AVs along with HVs has created a mixed traffic flow. The intricate behaviour between HVs and AVs created a wide contest between the driving settings among them. Mostly the AVs are estimated to display driving behaviour resembling like human drivers in order to smoothly blend into traffic systems dominated by humans. Likewise, the preceding research [124] demonstrated the behaviour of AVs using Social Coordination Awareness (SCA) and driving priors determined by RL framework. The driver’s driving priors from human driver’s trajectories deduced by variational auto encoder based on Driving Prior Learning (DPL). The considered research progressed decision making quality multi head attention mechanism. The suggested research recommended Coordination Tendency (CT) to coordinate AVs. The recommended research had been attained average performance.

RL has gained huge attention due to its ability to enhance decision making and control in AVs systems. However, the preceding methods have not shown certain number of features and observation diversity. Correspondingly, the prior research [125] implemented IDSim (RL algorithms) to regulate high level autonomous driving and human decision. The traffic flow and mechanized road structure are demonstrated by dynamic interaction support. The suggested research had been attained average performance.

Sustaining a suitable level of trust is vital for successful cooperation between AVs and human drivers. However, evaluating human belief in real time it still poses major difficulty. There are various techniques is considered nowadays such as heart rate and skin conductance to measure trust and the possibility of emphasising trust by EEG signals. Similarly, the existing research [126] has determined driver trust towards AVs through utilising EEG signals. A driver trust is demonstrated using 3 levels such as low, medium and high using self-reported trust ratings. The recommended research demonstrated driver trust assessment models by nine ML algorithms.

The suggested research has considered Light Gradient Boosting Machine (LightBGM) algorithm for process. The existing research had been attained average performance with accuracy of 88.44%. Likewise, the preceding research [127] determined drivers’ dynamic trust in conditional AVs using ML models. The suggested research documented drivers’ physiological measures including HR (Heart Rate), eye tracking metrics and Galvanic Skin Response [128].

Correspondingly, in the process of driving, different reasons and factor prevent the driver from expressing true emotions which could affect the identification accuracy. Real time prediction of physiological signals to predict the emotions needed complicated instruments that is hard to carry out in real driving. To resolve this issue, the traditional research has deployed a driver emotion detection which includes 3 models. They are [129] DL based human facial expression identification algorithm CNN to function the recognition. Automotive Advanced Driver Assistance System emotion observing framework. Setting a threshold window to choose whether to be remembered. After, 100 epochs in training, the FER-2013 dataset has attained 60.5% of accuracy [130].

The recommended research has utilized XGBoost (eXtreme Gradient Boosting) using five ML models. The suggested research had been attained average performance with accuracy level of 89.1%. Correspondingly, the prior research [131] demonstrated vehicle control to avoid danger using Automation malfunctions nevertheless not after Conditional Automation malfunctions. The suggested research has considered EEG (electroencephalogram) a ML technique for process. The recommended research had been attained average performance.

Literally, the existing research [132] has determined drivers' dynamic trust from a person's perspective by implementing trust profiles to form personalized experiences for drivers in AVs. The suggested research recommended K-means clustering model to determine three trust profiles like oscillators, believers and disbelievers. The suggested research had been attained average performance. Correspondingly, the prior research [133] utilized three type of systems (i.e., learned, situational and dispositional) based on a set of measures. The suggested research has assessed several automated functions and their effects on performance and trust in turns, lane changes and parking using Tesla Model X integrated by the existing system. The suggested research had been attained average performance.

Similarly the prevailing research [134] has determined HMIs (Human Machine Interfaces) to evaluate the reliance and drivers trust on automated driving systems. The suggested research considered NDRT (Non-Driving Related Task) for performance. The recommended research had been attained average performance. Thus, the overall outcome of the research insists that implementing ML techniques in AVs is most important because it enhances the driver safety. In order to predict nearby vehicle movement, human drivers' action and their intention towards lane changing the ML is used. The research has been obtained that the implementation of AI in automated driving plays a crucial role in predicting driver behaviour and to improve safety.

2.3.2 SAFETY PREDICTION IN AUTONOMOUS VEHICLES USING DL

A subset of ML approaches that uses artificial neural networks (ANN) to a model to solve complex problems is accomplished with Deep Learning (DL) methods. Apart from various approaches, the DL technique has several advantages comprised of facing a huge complex data, enhanced performance, managing missing data, handling structured data, unstructured data and predictive modelling. By considering all the advantages of DL techniques, the safety prediction in AVs majorly relies on DL approach in order to manage huge complex data and to improve the overall performance of the predictive model. The DL method comprises of various types of techniques namely CNN, Recurrent Neural Network (RNN), LSTMs, Generative Adversial Networks (GANs), Deep Belief Networks (DBN), Deep Q-Networks (DQNs) and Graph Neural Networks (GNNs). In this section 2.3.2, the various DL techniques that has been deployed to predict the safety in AVs using several models and the overall performance of the existing models has been captivated as follows.

DL Techniques

An essential impact on the Autonomous Driving (AD) has been based on the development in signal processing and information. Enhancing driving safety through diminishing human drivers' efforts with the aid of AI methods has evolved in the AD. Numerous real-world problems have been sorted out using the DL approaches. Moreover, the control process and the strengths has not been deeply examined and highlighted. The prior model has been engrossed the strength of DL frameworks in the aspects of effective real time performance with their achievements and limitations correspondingly. The AD pipeline comprising of execution, measurement and analysis with a concentration on road, pedestrian, collision avoidance, lane, drowsiness prediction and traffic sign diagnosis by vision-based DL approaches and sensing. Additionally, the performance of several DL approaches has been carried out by using various evaluation metrics [135].

An exciting frontier in transportation in convincing increased efficiency and safety on the roads are termed as AVs. Even though the AVs has not immune to accidents respectively. The severity of accidents that has been involved in the AVs is complicated for improving their public trust and reliability. To overwhelm the challenge, the conventional article has been established a natural language processing technique correlated with DL techniques to predict the severity of accidents by AVs respectively. The dataset has been extracted from the accident reports. The brief description of accidents, information and critical parameters has been comprised in the dataset. The Multi – Distance Synthetic Technique (MDST) has been used to balance the imbalanced aspect of dataset. To eradicate a valuable feature set that were complicated in predicting the accident severity has been accomplished using the Recursive Feature Selection algorithm. The proposed ensemble model has been trained and outperformed average accuracy [136].

Based on the AI technology, the AVs safety performance and system prediction has been predicted. The safe driving of AVs has considered as the problem in intelligent transport systems. Moreover, it has been significant to confirm the transmission safety of vehicle data. The existing model has been adopted DL algorithm and established an enhanced Digital Twins (DTs) model. The prediction model has been worked in the aspect of spatial-temporal graph convolutional network and network load balancing. Based on the performance metrics, the road prediction model has attained the accuracy of 92%.

Subsequently, the prediction model achieves a lower average delay time respectively. The prediction model has been constructed not only to recheck low delay but to attain better network security performance. The consequences of the research have been statement that the prediction model equips the experimental basis for safety performance in AVs [137].

The accurate trajectory prediction of AVS and surrounding vehicles has been significant to achieve maximum level driving safety in critical situations respectively. The methods for multi-vehicle trajectory prediction have been avoiding the uncertainty of vehicle motion affected through various styles of driving correspondingly. The correlation among environment and vehicle has been considered. To overcome the challenges, the existing model has developed a Driving Risk Map-Integrated Deep Learning (DRM-DL) technique.

Congruently, the existing model has been adopted the Conditional Variational Auto encoder (CVAE) to predict the trajectories that includes motion uncertainty utilising the Gaussian distribution respectively. Subsequently, the vehicle environment and vehicle-vehicle interactions have been represented using the driving risk map. The guided trajectory has been used to random selection method. The precise trajectory prediction for surrounding vehicles has been obtained using the relearning module. The

HighD dataset has been used and the results has demonstrated an accurate reliable trajectory prediction for surrounding vehicles respectively [138].

The challenging task for the AV has been more efficient and safe decisions at the intersections respectively. Most of the research has been focussed on the solution of single scenario. The conventional model has been deployed a deep reinforcement learning framework. The proposed model has been deployed the AVs through intersection safely, efficiently and automatically. With the aid of convolutional networks, the end to end decision making framework has been established.

Moreover, the mapping relationship between the vehicle operations and traffic images has been attained using the end to end decision making. With the support of two time steps, the traffic images have been collected and that were used to measure the relative velocities among the vehicles correspondingly. Subsequently, the framework has been established to enhance the interaction between the other vehicles and the AVs. The optimal driving policy relating efficiency and safety has been obtained through the deep Q- network algorithm. Top 3 accident prone crossing scenarios at interactions that has been stimulated to confirm the efficacy of the conventional decision-making framework. The outcomes of the recommended framework have been stated that the AV drive efficiently and safely through all the verified scenarios [139].

The progression of AVs has been a lead to several problems such as ethics, safety, cyber security and social acceptance. Moreover, the automotive industry has utilized with the technologies that assists the drivers through progressive driver assistance arrangements respectively. The system has been directing to safety drive and also envisage the driver's behaviour. A numerous number of researches has been states that driver emotion is a major factor for avoiding collisions. The constant monitoring of driver behaviour has been used to prevent accidents. The conventional model has been employed a squirrel search optimization which based on DL Facial Emotion Recognition (SSO-DLFER) method to detect the behaviour of AV driver. The SSO-DFLER techniques has been focussed on the prediction of driver facial emotions in AVs respectively.

Subsequently, two major processes named as emotion detection and face detection has been followed in the SSO-DLFER technique. The initial phase of face identification process has been detected using the Retina Net model. The Neural Architectural Search (NASNET) has been incorporated along with the SSO-DLFER for the emotion recognition. A huge feature extractor combined with the GRU model has been termed as classifier. IN order to enhance the emotion recognition performance, the SSO-based hyperparameter tuning procedure has been performed. With the help of the benchmark datasets, the simulation analysis of the SSO-DLFER techniques has been investigated. The outcomes of the research stated that the SSO-DLFER model has been performed with better accuracy [140].

The conventional approach has been stated that the prediction of safety in AVs based on the drive behaviour considers the human factors like age, driving experience and gender. The predominant objective of the conventional approach has to provide the AVs with the capacity to make the possible deductions adjust their responses in the real time and handle conflicting data during the safety-critical situations respectively. Subsequently, the foundational dataset comprised of navigating complex intersections, merging and lane changes has been employed to enable vehicles to showcase the appropriate behaviour.

Moreover, the DL model has been deployed to integrate the cognitive agents for each driver by considering their characteristics, requirements and distinct preferences. The enhancement in efficiency and safety has been led to the personalized approach. The conventional model has been contributed to the intelligent transportation systems effectively. Moreover, the conventional model has been enhanced the improvements in efficiency, safety and overall performance within the AVS. The various data mining techniques has been used to demonstrate the relationship between the external factors such as human factors and weather conditions. The process of identifying the direct and strength and the impact on the safety-critical driver behaviour has been the achieved by using the regression and correlation analysis.

The conventional research has been developed a computational model to forecast the driver response time and to consider the cognitive framework for existing takeovers in the AVs. The Queuing Network Model Human Processor (QN-MHP) framework has been established. The prediction of TOR, driver trust and driver situation awareness has been achieved using the computational model. The outcomes of the research stated the computational model has been attained better accuracy. With the aid of the driving simulator, the computational model has been evaluated. The computational model based on the Queuing network has been applied to anticipate the driver response time effectively [141].

The advanced AVs has been utilizing some tools to manage the safety. The traffic sign detection has considered as the challenging tasks that provides a global view of traffic signs of the road especially. The powerful traffic sign detection has been developed using the DL techniques in order to process the visual data. The embedded application has been implemented using the traffic sign detection. The traffic sign detection has been comprised of several datasets. The numerous images of road users have included in the dataset and 73 traffic signs has been fetched into the dataset. Subsequently, the integrated datasets have been incorporated in the traffic sign detection system. The proposed traffic detection system has been performed under various weather conditions with the integrated dataset and attained 84% accuracy [142].

A correlation of manual vehicles and AVs has been a part of ITS in recent days. The safety issues owing from the mix of manual and AVs has been entirely essential. The complexity has been increased in the ITS system. AVs has been arising issues in the aspects of poor real-time performance and low intention recognition rate in the terms of predicting driver direction respectively. The complications that has affects the comfort and safety of the mixed traffic systems eventually. The prediction of driving direction in the real time according to the surrounding traffic environment has been achieved in the AVs using the DL techniques. With the aid of enabled DL algorithm, the traffic safety solution has been provided. The natural driving dataset and driving trajectory dataset has been used and the model has attained 90% of accuracy [143].

Prediction of driver behaviour in extreme interactive traffic situations has been considered as a challenging task. The traditional research has been introduced a Multi Agent Reinforcement Learning [144] approach. Based on the driving policy and the minimal set of assumptions, the MARL model has been developed. Driver behaviour based on moving forward, maintain low accelerations and avoiding collisions has been predicted using the MARL model respectively. The efficient Soft Actor Critic (SAC) algorithm has been used for training the parameters. Various traffic densities have been used to evaluate the MARL approach correspondingly. The overall results of the research have been stated that the MARL model has attained better accuracy in the aspect of predicting driver behaviour in the AVs probably [145].

The driver takes over reaction time in AVs has been considered as the essential component in the driving scenarios. The factors such as driver secondary tasks and the distraction has been the affects the driver take over reaction time. The conventional research has been established the cogitative architecture models in order to simulate the driver take over time in various driving tasks scenarios respectively. The queuing network adaptive control has been deployed in the cognitive architecture. The knowledge and the driver task specific skills has been termed as the production rules effectively. The prediction of reaction time has been calculated using then driver simulator program. The outcomes of the models have been evaluated and compared with the single and multi-task criteria. The cognitive architecture model has been designed without adjusting any parameters and directly fit into the dataset. The simulation results have been generated by the cogitative architecture model. The outcomes of the research have been stated that the developed cogitative architecture model has attained better accuracy and considered as the useful tool for the evaluation of take-over alert design and anticipation of the driver performance efficiently.

The preceding research has been introduced a Facial Emotion Recognition (FER). Based on the transfer learning approach, the FER model has been designed for a safe drive in the AVs. Especially, to handle the enormous road accidents the facial expression of the driver has to be monitored regularly. In order to monitor the facial expressions of the driver and assist the immediate solution for the issue and provides safety for both the passenger & driver has been accomplished using the FER model.

Subsequently, the FER model has to be useful for the vehicle embedded system applications. The transfer learning frameworks has been developed using the AlexNet, VGG19 and Squeeze Net respectively. The dataset such as JAFFE, KMU-FED and KDEF has been used in the FER model to predict the safety in the AVs by monitoring the facial expressions of the driver. The outcomes of the research have been stated that the FER model has attained maximum accuracy and adaptable for AVs in the aspects of safety for both the passengers and driver correspondingly [146].

LSTM Techniques

An improved version of RNN is termed as LSTM approach. The LSTM model address the issue by introducing the memory cell that can hold information for a prolonged period. In the particular tasks such as speech recognition, video analysis, time series forecasting and language translation has been relied on the LSTM method. The prediction of safety in AVs has been achieved using the LSTM method. In order to manage complex traffic data and analysis the driver behaviour images captured by the cameras are analysed using the LSTM method. This section exemplifies the existing model that incorporates LSTM technique and their limitations to forecast safety in the AVs as shadows

The early warning systems in AVs has been relied on the collision prediction that ensures the passenger safety. Moreover, the deep convolutional networks have either failed at less adaptable for the deployment of AV edge hardware and modelling collisions. To overwhelm the limitations, the prior model proposed the Spatio -Temporal Scene Graph (SG2VEC) embedding methodology that utilized the GNN and Long Short-Term Memory (LSTM) layers to predict the collisions respectively. The synthesized datasets have been converted to real world driving datasets. The outcomes of the SG2VEC model has been performed faster and attained a better accuracy [147].

The overtaking strategy for AVs in freeway scenarios has been achieved using the Deep Reinforcement Learning (DRL) in the conventional model. The dataset named Next Generation SIMulation (NGSIM) has been used to extract the real-world driving data. The lateral and longitudinal motion of vehicles has been anticipated using the LSTM model. Eventually, the freeway overtaking scenario has been constructed and the two-lane road traffic has been considered. Based on the reinforcement learning, the target vehicle movement has been predicted. The results have been concluded that the decision-making strategy enhanced the safety and mobility of the AVs respectively [148].

The lane changing behaviour of surrounding vehicles and driver behaviour using crucial intelligent transportation environments has been an essential factor affecting the driving safety respectively. The prediction of lane changing behaviours has been essential for the driving environments. The major factors for lane changing has been termed as the driving environment and the drivers. The traditional research has been established a prediction method based on a Fuzzy Inference System (FIS) and LSTM has been used. The driving environment and driver cognition information has been transformed to lane -changing feasibility using the fuzzy logic. The lane changing behaviour has been predicted using the LSTM framework. The vehicle trajectory and lane-changing feasibility has been fetched as the in the LSTM framework respectively. Moreover, the model attained a better accuracy. The outcomes verified that the model enhances the performance if driving propagating with lane changing behaviours [149].

The vehicle trajectory prediction has been indispensable for the Advanced Driver Assistance Systems and in AVs. The collision avoidance, traffic control and path planning have been the major areas of AVs respectively. The conventional model has been focused on the variability in the braking patterns and driver behaviour that impacts trajectory prediction effectively. The existing approach has been established a GRU and LSTM networks. The LSTM-GRU model has been considered as driver braking patterns along with the vehicle dynamic information respectively.

With the help of simulated environment, the model accuracy has been tested in various real-world driving circumstances effectively. The real time driving environments has been utilized in capturing the complete vehicle dynamics data and critical parameters such as acceleration, speed, rotation, braking patterns and position probably. The dataset has been collected from 17 drivers provided with the Euro Truck Simulator software. Consequently, the model has been implemented and validated using the Scikit-learn, Google Colab, and Python 3.9. The outcomes of the research have been indicated that integrating the braking patterns indispensably enhances the position predictions. The advancements incorporated in this model has been improved the operational safety of AVs [150].

AVs has been flourished as the acceptance rate and penetration continues to increase. Moreover, slowly the AVS has been correlated into traffic with Human-Driven Vehicles (HDV). The prediction of car behaviours of AVs and HDVs has been essential. The existing model has been focussed on a data -driven car following model. Based on the driver memory and the co-operation with the leading vehicles, the model has been incorporated. The data-driven model has been used to forecast the vehicle speed in AV-HDV mixed traffic respectively. Using the prospect theory (PT), the effect of the driver's cooperation on car following behaviour has been designed. Consequently, the driver memory has been incorporated using the LSTM technique. The extended car following model has been named as the PT-LSTM model. The Waymo AV Open dataset has been deployed. The performance metrics has been used to access the model. The outcomes of the research has been stated that the PT-LSTM model performed with high accuracy compared to the other LSTM models [151].

Owing to the uncertain and complex driving behaviours during avoidance and pedestrian collisions increases respectively. Moreover, it is difficult to accurately predict the human driver behaviours in AVs. The prior research has been stated that novel modelling method that integrates neuromuscular dynamics using LSTM methods. The dynamic interaction between the neuromuscular system of the driver and steering system has been captured using the neuromuscular dynamics model.

Moreover, the LSTM model has been used to describe the visual behaviours of the driver precisely. Additionally, a sequence of driving simulator experiments with 12 participants that has been conducted to acquire driver behaviours. The comparision between the conventional manual steering and manual takeover steering has been conducted to analyze the driver behaviours. In the aspects of the mean absolute error, determination coefficient and root mean square error has been used to assess the LSTM model and the outcomes resulted the higher identification accuracy [152].

The enhancement in the road safety has been achieved by predicting the accurate vehicle acceleration. The variations in the acceleration data has been magnified with the existence of driver heterogeneity. The dissimilarities in the acceleration data has been led to the consequential impacts in the precision of vehicle acceleration prediction. The conventional model has been identified the driver behaviour semantics. The analysis has been carried out with the Coupled Hidden Markov Model (CHMM) model. The evaluation of driving behaviour variations in AVs has been carried out by the Wasserstein distance respectively. The vehicle acceleration has been predicted using the LSTM-CNN model. The outcomes of the research have been stated that the prediction results incorporate driver clustering before prediction and enhances the accuracy simultaneously [153].

The AVs has been generally termed as the self-driving cars comprised with potential benefits such as efficiency, convenience and safety. The prevalent adoption of the AVs has required levels of automation and potential risks. The prior research has been addressed the essential aspects in the safety of AVs. The concept of Safety of The Indented Functionality (SOTIF) and the Functional Safety Concept (FSC) has been investigated. The purpose of the research has to ease risk correlates with scenarios. The fall-safe design principles have been used to ensure a secure environment for AVs driving especially. With the help of path planning, the autonomous navigation has been achieved. Moreover, the Enhanced Spatiotemporal Multi-Level LSTM (ESM-LSTM) and Bayesian Optimisation (BO) has been introduced. With the help of Convolution Multi-Level Long-Short Term Memory (ConvMLSTM) has been used to extract the hidden features from the sequential image data probably. The outcomes of the research has been stated that the ConvMLSTM model enhanced the control of AVs through the planned trajectory methods [154].

In order to avoid the issues of the AVs has been essential to develop the trust standardization. The real time identification and accurate measurement of driver has been significant for the accomplishing the trust standardization respectively. The conventional research has been introduced the real time driver trust recognition model for AVs predominately. Driver trust recognition model has been deployed to predict the driver trust in AVs. The real time data has been used in this model. The sequence of takeover events has been involved thirty-four drivers. The subjective trusting and monitoring ratio have been gathered to measure the driver trust levels in the basis of the lower trust and higher trust effectively. Based on the CNN and LSTM techniques, the real-time driver trust recognition model. Subsequently, the four model such as SVM (Support Vector Machine), LSTM, CNN and Gaussian naïve Bayes have been developed respectively. The outcomes of the research have been stated that the real time driver recognition model attained 75% F1 score compared to the other four models [155].

The conventional model has been established a driver intention inference system to predict the highway lane strategies. Initially, the framework and driver intention mechanism has been introduced. The multi modal signals have been used to capture the vision-based intention interference system. Moreover, the VBOX vehicle data and various low-cost cameras has been utilized to predict the highway lane strategies. Based on the LSTM and RNN technique, the driver intention interference has been designed. The temporal behavioural patterns and time series driving series has been predicted using the LSTM-RNN method. The lane keeping and right-left lane changing behaviour has been included in the naturalistic highway driving dataset. The driver behaviour activities have been statistically analysed. Consequently, the hypothesis testing has been conducted to verify the performance of the LSTM-RNN model. With the aid of five-fold cross validation, the LSTM-RNN model has been attained average accuracy [156].

The existing research has been introduced a deep deterministic policy gradient (DDPG) reinforcement learning correlated with LSTM prediction model has been developed and termed as LSTM-DPDG respectively. In order to predict the lane changing behaviour of the driver the LSTM-DPDG model has been used. The observed road data has been transformed into the observation module using the LSTM approach. Moreover, the observation module data has been fetched as the input to the DDPG model. The trajectory information for surrounding vehicles has been considered in the LSTM model. The LSTM -DPDG model has been engrossed on the comfort, safety and efficiency of the lane changing process correspondingly. The realistic representation of traffic scenarios among the vehicle interactions has been stated as the findings of the LSTM-DPDG model. With the aid of the simulation platform, the LSTM-DPDG model has been evaluated. Comparatively, the LSTM-DPDG model has attained 74% accuracy than the other conventional models in improving the efficiency and lane changing safety predominately [157].

The prior research has been established a two-stage learning framework. Based on the CNN model, the two-stage learning framework has been designed. In order to anticipate the spatial-temporal driver lane change intention interference, the framework has been developed respectively. Two separate parts has been included in the two-stage learning framework. Initially to recognise the driver behaviour, the driver behaviour recognition system has been developed using the CNN features. The normal driving and mirror checking have been included to recognize the driver behaviour. The driver intention interface has been constructed based on the LSTM & RNN techniques. The CNN-LSTM-RNN model has been utilized the naturalistic driving dataset. The overall consequences of the research have been stated that the CNN-LSTM-RNN model has been attained 91% accuracy in the terms on lane keeping intention prediction. The accuracy and flexibility of the CNN-LSTM-RNN model has been enhanced using the two-stage learning framework. Consequently, the CNN-LSTM-RNN model has been flexible to implement and update the AVs [158].

The proceeding research has been introduced a driver steering intention prediction approach. The driver steering intention prediction approach has been based on the human driver expectation over the driver vehicle interaction respectively. Based on the novel hybrid learning based time series model with DL networks, the steering intention has been predicted. The two various driving modes namely single right-hand driving modes and both hands have been considered in this steering prediction.

Moreover, the steering prediction has been accomplished by gathering the various electromyography signals from the upper limb muscles. The correlation between the steering torque and neuromuscular dynamics has been analysed. The discrete and prolonged steering intentions have been predicted using the hybrid -learning based model. The similar temporal pattern extraction layer has been built with the LSTM and RNN techniques. The temporal pattern extraction layer has been used to share the two intention prediction networks. The data has been gathered from the 21 participants of multiple ages and driving experience correspondingly. The outcomes of the research have been stated that the DL model has attained better accuracy compared to other two driving models [159].

CNN Techniques

A specialized class of neural network that has been designed to process data such as images are referred as CNN techniques. The CNN techniques have been adaptable for capturing the spatial dependencies and hierarchical patterns within images. Moreover, the CNN techniques have been applied in handling the large complex traffic data and generates high reliability and accuracy in predicting lane detection, collision detection and traffic accident detection etc. On the basis of accurate prediction of safety in AVs, the existing studies has integrated CNN techniques in various aspects to forecast the safest journey in AVs are discussed as follows.

A noteworthy role in supporting the decisions of AV particularly in adverse and severe circumstances has been termed as the Weather detection systems (WDS). AV has been effectively notifying the weather conditions and thus make precise decisions to easily suits to new environments and conditions with the aid of DL techniques. Moreover, the existing model has been proposed a DL based detection framework to classify the weather conditions for the AV in the normal or adverse situations. Subsequently, the proposed framework has been supported the robustness of the transfer learning techniques to characterize the performance of three deep-CNN networks such as Efficient Net, ResNet-50 and Squeeze Net respectively. The correlated dataset has been utilized in the proposed framework and provides six weather classes such as sunrise, shine, sandy, snowy, rainy and cloudy. The three models have been performed well and attains the better accuracy, sensitivity and precision respectively. Accordingly, the proposed model has been effectively deployed in the real time environments that equips decision on demand for AV with rapid and exact detection capacity respectively [160].

An increasing attention for safety enhancement in smart cities has been gained in the rear end collision. The designing of efficient warning strategies for the rear end collisions has been the major causes for the traffic accidents. Moreover, various researchers have been conducted to predict the collisions respectively. Subsequently, to sort out the issues the learning-based methods have been used. Simultaneously the conventional methods haven't been suitable for solving the complicated issues. The back propagation learning methods have been still facing the challenges due to some limitations in such as prediction performance and feature extraction respectively.

The conventional method has been established a novel Rear-End Collision Prediction Mechanism with deep learning method (RCPM) correspondingly. The convolutional neural network model has been associated with the RCPM effectively. Based on the genetic theory, the dataset has been smoothed and expanded. Moreover, the dataset has been utilized to alleviate the class imbalance complications. Probably, the pre-processed dataset has been separated into the testing and training sets. The trained and tested datasets have been fetched as inputs into the CNN model. The outcomes of the model conclude that the RCPM has been performed effectively and predict the rear end collisions rapidly [161].

The basic human need is locomotion. The recent transport has been still far away from the all-round safety and perfection. The concept of demarcating lanes on the roads while the vehicle is moving has been termed as lane changing. Moreover, the crucial aspect in making the intelligent driving systems has been stated as the lane detection algorithm respectively. Subsequently, the lane detection algorithms have been deployed in the AV in the aspects of road safety, accident prevention systems, analysing and testing the driving skills. Subsequently, the lane detection systems have been functioned with the hand-crafted features fails in the complex scenarios such as low illumination, occlusion, sharp turns and adverse weather conditions. Recurrently, DL models has been shown an indispensable improvement in their performance and also used in driving assistance systems. The land detection using the hybrid techniques that comprises of RNN, CNN and FCN that has been classified under the DL methods.

Moreover, the safe driving assistance systems has been used to save lives by preventing accidents and it is essential to maintain the real-time lane system detection. The existing research has been deployed as light weight model that are used to detect lane with low execution time and high accuracy. Additionally, the size of the model has been designed in short in order to make the hardware performs in real time and deployable. An existing system has been established a CNN model for lane detection since it has been flourished with the best image classification datasets effectively. The consequences of the systems has been performed and attained average accuracy [162].

With the several advancements in AVs the two significant factors have been played a major role to prevent collisions and accidents. The collisions have been occurred due to the obstacles and track detection are applied to prevent the collisions respectively. An accident detection model has to be incorporated with the AVs in-order to detect the accident vehicles and prevent running into rollover vehicles correspondingly. The existing research has been stated that the efficient DL model is still required to detect a single car crashing by taking suitable actions such as tracking changes, informing the concerned authorities and slowing down. A car crash detection system has been introduced in the existing research.

Several car crashes have been using the three DL models named as Region Proposal Framework (RPN), Region Based Detector (CNN8L) and Feature Extractor using Transfer Learning (VGG16). With the aid of CNN8L model's region-based detection and classification has been accomplished. Moreover, the CNN8L model has been considered as the novel lightweight sequential convolutional neural network. With the help of customised dataset, the model has been trained. The outcomes of the research have been proved that the VGG16 correlated with the CNN8L has been performed much better. Consequently, the model has been recognized the false alarm rate with 33 % and car accidents with an accident detection rate of 86% precisely [163].

The advancements in communication and vehicle advancement technologies such as V21, V2X and V2V have been enabled the development of autonomous and connected vehicles respectively. Moreover, the CAV has been considered as the promising solution and directly effective in traffic management and incident management. The prior research has been established an Incident Detection Included Linear Management (IDILIM). Based on the CAV incident management algorithm, the model IDILIM has been developed. The algorithm IDILIM has been used to regulate the CAV.

Later, the model has been developed to predict the traffic speeds and shock wave speeds based on dynamic frequency. The IDILIM model has been termed as the reliable traffic simulation model. The IDILIM model has been incorporated with the CNN and Dl algorithm in-order to predict with the extreme accuracy. Additionally, the IDILIM model has been used to predict the shockwave speed outputs. Consequently, the outputs have been fetched into the CAVs and the model has been attained the accuracy of 82% [164].

The increase of safety in the AVS has been based on the Rear-end collision prediction. Developing effective warning system of AVS has been termed as the complicated phase. Moreover, the developing the warning system has been utilized to avoid the rear end collisions that leads to the traffic accidents respectively. The prior research has been focused on the collision and established as learning-based methods to address the complex problem. The novel optimized LSTM- based DL framework has been established to improve the crash risk prediction system.

Furthermore, the LSTM framework has been deployed the Enhanced LSTM (EnLSTM) to enhance the performance of crash risk prediction system effectively. The framework EnLSTM has been deployed in order to extract the efficient features using the CNN model. Moreover, the Improved Grasshopper Optimization Algorithm (IGOA) has been used to developed the hyperparameters optimization in the LSTM model probably. The EnLSTM model has been assessed on the basis of metrics. The Novel Optimized LSTM model has been performed better based on the performance metrics [165].

The prediction of land changes precisely has been essential during the driving activity to prevent accidents. In the existing research, the innovative predictive model has been correlated using game theory for the trajectory prediction. Moreover, apart from the game theory the CNN techniques have also been deployed. With the help of metaheuristic optimization, the CNN techniques efficiency has been enhanced. Both the fully connected layers and convolutional layers have been optimized by using the Whale Optimization Algorithm (WOA) respectively. The techniques such as, robust data processing, pre-processing those have been employed for the segmentation. Subsequently, the WOA has been used to anticipate the trajectory lane changing vehicles. The exceptional accuracy has been attained as 96% and demonstrated by the proposed approach validation. The research has been stated the effectiveness of the WOA-CNN model has been advanced in the prediction accuracy of lane changing behaviour [166].

The existing research has been established the takeover request (TOR) model to anticipate the driver takeover performance. The external environment data and physiological data have been used to analysis the driver behaviour. The heart rate indices, skin response indices, galvanic skin response indices and eye tracking metrics have been included in the driver physiological data. The scenario type, TOR lead time and traffic density has been included in the driving environment data. Based on the driving behaviour, the driver takeover performance has been categorized as good or bad driver takeovers. By deploying the six DL methods, the CNN techniques have been used to predict the driver takeover performance based on the various levels of cogitative load effectively. The optimal time window has been employed to anticipate the takeover performance with an F1-Score of 64% and accuracy of 84% respectively [167].

The driver has been able to divert their attention owing to several distractions and leads to accidents. The prior research has been developed the attention-based CNN model to anticipate the driver takeover intention in AVs predominately. Moreover, the results of the CNN model have been stated that the prediction of driver takeover has been executed effectively. The outcomes of the research have been stated that the CNN model has attained better precision and F1 score comparatively higher than other DL techniques. Moreover, the CNN model has been flourished as one of the familiar models in forecasting the drivers driving styles particularly in the AVs [168].

The intersection has been termed as the most hazardous in the accident-prone traffic scenarios on the road respectively. A challenging task for the AVs has to make right decisions at the interactions based on the comfort, safety and efficiency. The conventional research has been established a deep reinforcement learning relied on the decision-making method to make AVs drive. Moreover, the CNN has been introduced to map the relationship between the vehicle operations and the traffic images probably. The interaction between the other vehicles and the AV has been correlated using Markov decision process (MDP) effectively. The optimal driving solution has been obtained from the gradient algorithm. The effectiveness of the CNN model has been evaluated by using the three-accident prone crossing path scenarios. The outcomes of the research have been stated that the driving safety and driving comfort in the AVs at the intersections are accomplished using the CNN model [169].

DNN Techniques

The DNN techniques have been prospered in forecasting the safety related accidents and traffic conflicts. The time decisions in AVs to ensure safety has been deployed using the DNN techniques. The complex datasets such as traffic density and vehicle behaviour data has been handled using the DNN techniques. The robustness and integration in handling complex scenarios have been accomplished using the DNN techniques. This section exemplifies the existing model that incorporates DNN technique and their pitfalls to anticipate safety in the AVs as shadows

The DNN has been performed well in generating precise predictions and accuracy but they often lack in classifying the predictions. Moreover, this lacks of awareness relating the reliability of the given outputs has been stated as an obstacle in implementing such models in safety-critical applications respectively. There are various approaches that has been required to sort out the problems by designing the models to obtain more reliable values. Subsequently, deep ensembles techniques have been used and the performance of these models has been compared in several ways in the aspect of safe system behaviour. The prior model has been stated that image classification methods has been utilized for estimating the safety related metrics and requirements that are adaptable to explain the model’s performance in complicated domains correspondingly. The three common datasets have been used. The model has been attained the moderate performance and indispensably reduces the errors [170].

The most looked up technology with a unique range of applications across all the fields has been stated as AI. The most required application that has been flourished among the transport industry is ITS. The communication between the AVS and the system has been accomplished using the technique Vehicular Adhoc Networks (VANET) respectively. The information that has been transferred between the AVs and the system are based on the performance of each vehicle. Moreover, the malicious information has been able to disturb the entire system that leads to severe complications. Therefore, the detection of malicious system has been required in-order to sort out the problems. To predict the flaws in the data transmitted, ML techniques has been introduced. The existing system has established a DNN based RF algorithm. Moreover, the dataset VeRiMi has been used and the model obtained better accuracy and prediction. Subsequently, the Explainable AI (XAI) method has been used to solve the DL and ML models that are more understandable and interpretable. To confirm the cautious use of AI for AVs, the XAI technique has been used [171].

By preceding the successful developments of advanced driver assistance systems [33] respectively. The existing model has been engrossed on highly AV at diminishing the human driving tasks respectively. Recently there has been a high research demands in industry and academic to predict the driver intention and understanding the driver illness. Moreover, a drive’s readiness for a safe takeover transition has been predicted using a driver prediction system. The DNN has been adopted in the prior research. Subsequently, the DNN has been correlated with the attention, LSTM, RAFT and FlowNet2 models. The models have been associated in-order to forecast the driver intention. The public “Brain4Cars “has used as the dataset to anticipate the driver behaviour before the commencement of the driver’s action probably.

Additionally, the driver prediction has been based on the metrics named as the out cabin, in cabin and both in-out cabin. With the aid of the K-fold cross-validation, the performance of model has been examined in the aspects of precision, recall, F1-score and accuracy. The outcomes of the experiments have been resulted that the model outperformed in the common driving circumstances [172].

GAN & GNN techniques

GNN techniques has been proliferated in capturing the temporal and spatial dependencies among the various traffic environments. The movements of other obstacles, pedestrians and vehicles has been easily anticipated using the GNN techniques. The enhanced decision-making process of the AVs that helps in managing traffic signals, making decisions, prioritizing safety and optimizing various path routes has been achieved by incorporating the GNN techniques. Moreover, the GAN approaches have been used in enhancing the data quality, handling uncertainties in driving environments and enabling precise trajectory predictions. This section exemplifies the existing model that incorporates GNN & GAN technique and their drawbacks to predict safety in the AVs as shadows.

The collision avoidance has been termed as the un-signalized intersections in the AV technology. The preceding research has been addressed the challenging problem of online speed planning along the transverse path respectively. Based on the interaction aware prediction algorithm among the human driven vehicles and autonomous, the existing model functions. Moreover, the algorithm has been classified into three sequential phases. Predominately, the first phase of the algorithm has been correlated with LSTM and GNN.

In order to anticipate the sequence of vehicles crossing the collision point based on the interactions has been predicted using the first phase of the algorithm and achieved 88% of accuracy. The second phase of algorithm has been comprised only of GNN algorithm. The time window required for the AVs to traverse the collision point safely has been forecasted using the second phase of algorithm. Entirely, the algorithm has been deployed to calculate the accelerated values and prevents the accidents. Furthermore, the algorithm has been promoted cautious driving behaviour in AV. The algorithm has been utilized 250 real -world scenarios from the INTERACTION dataset respectively [173].

The major demand for the AVS has to been navigate complicated traffic environments. Moreover, analysing the surrounding scene, predicting their future trajectories and understanding the behaviour of other traffic agents respectively. The primary objective of the existing research has been established to generate a safe motion and diminish the reaction time for suddenly imminent hazards respectively. The movement patterns of the surrounding traffic agents and precisely predict the future trajectories has been termed as the major challenges.

Subsequently, the interaction between the autonomous vehicles and its surrounding vehicles has been the required by the traditional trajectories' methods. The existing research has been stated that the interaction between the real coordinate of the surrounding vehicles is very complicated. In order to overwhelm the complications, the Generative Adversarial Network (GAN) has been utilized. Based on DL framework the GAN model has been predicted the trajectories of the surrounding vehicles of an AVS. Consequently, the self-attention mechanism has been proposed to enhance the better capturing the context information of trajectories of the surrounding vehicles. The outcomes of the results have been demonstrated that the model is efficient and effective [174].

The integration of automated vehicles has been facing the challenges peculiarly in the driving safety areas associated with the automation mode of AVs respectively. The AV capability has been verified in the safety aspects that operates in the specific road section. The conventional research has been established a novel framework at enhancing the capability of classifiers in identifying the safe driving areas in the AVs correspondingly. The novel framework has been comprised of the data augmentation algorithms such as diffusion-based models and Generative Adversial Network (GAN) probably. Based on the field test dataset the novel framework has been validated. Moreover, the performance analysis has been carried out across the several metrics that has been established in the effectiveness of the data augmentation models effectively. The performance of the novel framework has been enhanced in the prediction of discriminative classifiers and contributing valuable insights into safer AV deployment into several road conditions [175].

The revolutionized transportation has been achieved in the transport industry with the help of AVs. The confirming passenger safety with the AVs in the absence of driver has been based of the development of autonomous surveillance systems and intelligent respectively. The existing research has been established the semi-supervised anomaly detection system. Moreover, the semi supervised anomaly detection model has been designed to improve the safety within the AVs respectively.

Subsequently, the approach stated that overhead fisheye cameras has been equipped to resistant monitoring in the cabin interior. This feature has been deployed to maximize the visibility in the crowded conditions especially. The spatial temporal auto encoder architecture has been composed of the recurrent and convolutional layers. In order to improve the system ability to categorize between the particular security incidents and safety, the classifier tuned labelled dataset has been incorporated. The consequences of the research has been illustrated that the model attains better accuracy [176].

The essential aspect of estimating and understanding the motion of dynamic systems in AVs has been termed as trajectory prediction respectively. AVs has the ability to predict its own motion and the motions of the surrounding vehicles. Moreover, the understanding the interaction among vehicles has been essential for the precise trajectory prediction. In the existing model, the dynamic Spatio-temporal Graph Convolutional Network (GCN) has been used to anticipate the trajectory distribution of the vehicles in the traffic scene respectively. With the aid of GCN, the spatial dependencies among the vehicles in each traffic scene has been captured. Subsequently the Temporal Convolutional Network has been employed to estimate the temporal dependencies of the accident sequence and forecast the driving status using the historic trajectories information. The naturalistic trajectory dataset (HighD) has been deployed. The outcomes of the existing model has verified that the GCN model enhanced the accuracy compared to other models [177].

The precise anticipation of trajectory has been termed as the fundamental input for motion planning that enables safe AVs driving on public roads respectively. The prior research has been stated a safe motion planning approach. Moreover, the safe motion planning approach has been based on the DL methods. The safe motion planning approach has been utilized to predict the trajectory. Subsequently, the safe motion planning approach has been established based on the GNN. The INTERACTION dataset has been utilized in the prior research. With the aid of validated trajectory prediction model has been used to anticipate the future trajectories of surrounding road users comprising vehicles and pedestrians. Based on the model predictive control technique, the

GNN prediction model enabled motion planner has been developed. Additionally, the two driving scenarios has been extracted from the INTERACTION dataset. The effectiveness of the proposed motion planning approach has been enhanced by validating using performance metrics. The outcomes of the predicting research have been demonstrated the lower the risk and enhance driving safety [178].

Obstacles has been termed as the lack lane makings and diverse in the uncertain environments has been stated as the major trajectory for the AVs. The path planning, trajectory optimization and speed planning has been utilized in the conventional trajectory planning methods. Moreover, these methods have been required the manual design of the numerous parameters that resulted in the computational burden and significant workload. Subsequently, the end to end trajectories planning has been efficient and simple.

The prior research has been stated that the planning method based on numerical optimization and GNN techniques. The proposed method has been categorized into two phases namely trajectory optimization using numerical optimization and initial trajectory prediction using the GNN. The environment information has been processed and forecasts a rough trajectory is accomplished by the graph neural network. The replacement of speed planning and traditional path has also been achieved using the GNN framework. The validation of the GNN model has been carried out by the simulation experiments and significantly the planning efficiency has been enhanced [179].

The enhancement in the efficiency and the safety of the AVs has been based on the correlating trajectory prediction with the planning and decision-making modules. The existing research has been introduced GNN-RNN technique based on the Encoder-Decoder network. The dynamic features of the vehicles have been extracted using the RNN method respectively. The GNN techniques has been applied to inter-vehicular interaction. The dataset NGSIM US-101 has been used in the GNN-RNN model to forecast a target vehicle trajectory in multiple situations and with various number of surrounding vehicles correspondingly. The consequences of the research have been stated the GNN-RNN model has attained moderate accuracy in the prediction of safety in AVs [180].

The conventional research has been established a DRL based autonomous braking-decision making strategy in an emergency situation respectively. The factors such as passengers' comfort, efficiency and accuracy has been engrossed in the DRL model. Initially, in the DRL model, the braking and lane changing process has been analysed. Both the process has been considered as the essential factors of braking strategy in the AVs. The optimal strategy for the AVs braking has been accomplished by the DRL process. The algorithm named as actor -critic (AC) has been adopted to sort out the autonomous braking problem that enhances the efficiency of the optimal strategy probably. Based on the trained level of the optimal strategy, the AVS has automatically evolves with the optimal braking behaviour to enhance the driving safety. The outcomes of the research have been stated that the DRL has been attained driving safety and accuracy [181].

The existing research has been introduced a Graph-Based Spatial -Temporal Convolutional Network (GSTCN). The anticipation of trajectory distributions of all neighbour vehicles has been accomplished using the GSTCN model respectively. The spatial interactions have been achieved using the GCN network. Moreover, the CNN has used to capture the temporal features of the AVs. With the aid of GRU network, the spatial features have been encoded and decoded. The intensities of the mutual influence between vehicles has been demonstrated using the weighted adjacency matrix. The real-world datasets such as US-101 and I-80 has been used in the GSTCN model. In the aspects of the inference speeds, prediction errors and model sizes the GSTCN model has been evaluated and attained average accuracy.

The considerable portion of the traffic accidents has been owing to the lane changing behaviour. The existing research has been introduced a learning-based lane changing decision-making framework. The naturalistic driving datasets has been utilized t in the lane changing framework. Moreover, the cascade Fuzzy Neural Network (FNN) has been developed to extract the interactions among the vehicles respectively. The framework has been used to enhance the learning ability of the AVs to correlate both the spatial and temporal information. The FNN model has to use to forecast accurate decisions in the various driving scenarios [182].

The prediction of vehicle trajectories has been essential for AVs and advanced driver assistance systems. The prior research has been introduced the interaction-aware personalized vehicle trajectory framework. Based on the integration of temporal graph neural networks, the framework has been designed. The prior research has been correlating the LSTM and GCN to monitor the Spatio-temporal interactions between the surrounding vehicles and the target vehicles. The LSTM-GCN model has been enhanced using the transfer learning method. The huge-scale trajectory dataset has been used in the LSTM-GNN model correspondingly. Moreover, the LSTM-GCN model has been particularly deployed in the prolonged prediction horizons and the overfitting of the dataset has been avoided. Consequently, the LSTM-GCN model has been enhanced the trajectory prediction accuracy by integrating personalization approaches [183].

The prior research has been established a human-centred trajectory tracking control strategy. The prediction of driver behaviour has been accomplished using the trajectory tracking control strategy. The integration of LSTM and RNN technique has been deployed to forecast the driver behaviour in the AVs. Moreover, the model predictive control has been deployed track the trajectory especially in the AVs. The vehicle lateral velocity has been considered using the Moving Horizon Estimator respectively. The driver intention has been predicted using the driving simulator. Subsequently, the driving simulator has been functions on the basis of human driver assessments. The outcomes of the research have been stated that the AVs cooperates with various driving scenarios and attained smooth transient process [184].

The advancement in the vehicle safety and to diminish the work load for drivers, the Haptic-Shared Steering (HSS) has been developed. The prior research has been engrossed on the series of high -fidelity driver simulator experiments with 18 participants respectively. The double lane changing task has been tested using the two experimental conditions. The Haptic guidance torque with a constant gain (HGT) and Haptic Guidance Torque with an Adaptative Gain has been termed as the two experimental conditions. The lateral control behaviour during the driving has been designed to GRU network. The distracted drivers have been predicted using the LSTM-GRU model efficiently. The outcomes of the research have been stated that the LSTM-GRU model has been examined using various metrics such as mean absolute error, mean percentage error and determination coefficient respectively. Consequently, the simulation LSTM-GRU model has been employed to predict the driver behaviour associated with the lateral position.

In order to adapt human driving habits, the conventional model has been established a memory based DRL approach respectively. LSTM technique has been incorporated with the Twin Delayed Deterministic Policy Gradients (TD3). The LSTM-TD3 model has been utilized the NGSIM dataset. With the aid of the dataset, data feature analyses has been carried out. The efficiency, comfort and safety that has been considered as the essential driving characteristics. Moreover, the driving characteristics has been eradicated from various driving styles. The car following behaviour and error interactions has been optimised using the LSTM-TD3 model. The outcomes of the research have been stated that the LSTM-TD3 attained better accuracy in the prediction of safety in the AVs. Moreover, especially in the LSTM-TD3 model has been reflected better in the aspects of safety, comfort and efficiency among various driving styles respectively [185].

The intelligence of AVs has been tested using the scenarios based on the interaction between the AVs and the background vehicles [186] respectively. The conventional research has been stated that the evolving scenario generation approach. Based on the DRL technique, the scenario generation approach has been constructed. The major objective of designing the scenario generation approach has to construct an interaction between the BV and AVs. Based on the mutual, cooperative and competitive driving motivations, the class of BV has been designed. The three unique driver models have been developed using the enhanced level K- training procedure and TD3 algorithm. The fidelity and the complexity of the scenario generation approach has been validated. The results have stated that 85% of accuracy attained to naturalising driving data correspondingly [187].

The transition between the human driver and automated driving system has been referred as the handover scenarios. The conventional research has been established a robust controller in order to assist human drivers especially in handover scenarios respectively. The co-operation between the automated driving controller and the human driver has been enhanced using the driver vehicle model. Moreover, the driving steering input has been fetched as the input for the driving vehicle model correspondingly. The various human driving performances has been considered as the driver parametric. The steering input and parametric uncertainties have been deployed in assisting the driver. Subsequently, the robust controller has been designed to assist the driver effectively. With the aid of the driving simulator, the effectiveness of the designed controller has been validated. The overall outcomes have been exemplified that the vehicle lateral deviations and driver steering loads has been diminished using the designed controller. The driving safety has been enhanced using the handover processes [188].

Confirming the safe transition in between the drivers and the AVs has been referred as the essential criteria. The hazardous avoidance has been essential owing to automation-to- human transition process. The prior model has been established a multilevel Hidden Markov Model to predict the hazard avoidance process. Subsequently, the three-state model named as approaching, recovering and negotiating has been the best model fitness compared to the other models. The Hidden Markov Model has been trained and the average results has been attained in the prediction of hazard avoidance in order to recognise the driver behaviour. Moreover, the model has been resulted that the hazard avoidance model has been based on the basic driving skill across various levels of automation conditions respectively [189].

The existing research has been established a lane changing assistance system (LCAS) that can assist guidance for driver lane changing behaviour respectively. The driver optimal handling has been sorted out using the vehicle handling inverse dynamics method. Initially, the driver lane changing intention has to be recognised. The false alarm rate of LCAS has been reduced. With the aid of the lane changing intention recognition model, the driver lane changing intention has be predicted. The inverse dynamic model handling has been established.

Moreover, the inverse dynamic problem has been converted into the optimal control problem. Based on the GPM technique, the optimal control problem has been converted into the non-linear programming model. Subsequently, the sequential quadratic programming (SQP) has been applied to attain the required solution. The contrast verification of the GPM has been achieved by deploying the direct collocation method (DCM). The outcomes of the research have been stated that the driver lane changing intention has been obtained using the driver optimal handling input. Comparatively, the GPM technique has been attained using the maximum computational accuracy than the DCM technique [190].

The prior research has been introduced an end -to end learning method for AVs overtaking. Based on the correlation of the conditional limitation learning (CIL) and GCN have been deployed. The CIL-GCN model has been used to predict the AVs overtaking behaviour. Based on the influence of other vehicles driving behaviour the CIL-GCN model has been designed. The dynamic interactive environments information has been gathered from the graph structured data. Moreover, the aggregated global features have been fetched as the input to the GCN. The CIL-GCN model has been effectively designed to extract the global information of the driving scene. The collision free AVs overtaking behaviour has been enhanced the intelligence of the driving system effectively. With the aid of the CARLA simulation platform, the feasibility of the CIL-GCN model has been evaluated and the overall results have been verified that the CIL-GCN model has attained better accuracy in order to predict the driver and passenger safety [191].

The trust in the AVS has been directly impact on the safety of the driver and the passengers. The proceeding model has been stated that effects of speech have been deployed to measure the driver trust and health. The real time data has been utilized. Moreover, seventy-five drivers have been selected. AVs have been categorized into two groups. The first group of AVs has been comprised of vehicles with 100% correctness, 4 system messages and 0 crashes. The second group of AVs includes 60% correctness, 40% crash rate and 2 system messages respectively. The speech information during the driving process has been gathered using the voice interaction model. Based on the neural network training, the extracted speech feature data of the two trust groups has been used. The voice interaction model has been evaluated for its ability to precisely predict the trust classification and driver health. Consequently, the outcomes of the research have been stated that the voice interaction model attained 90% of accuracy [192].

The trust in the automation has been mainly influenced on the emotion of the driver. The relationship between the trust and the emotion of the driver has been an essential factor to investigate. The real time experiment has been conducted with the 19 different emotions integrated with the two levels of trust namely high- and low-level trust provoked form two AVs respectively. The 105 participants have been selected. The trust has been categorized and assessed at three layers such as situation, initial learned and dispositional trust. The existing research has been designed to measure the emotions of the driver affects the high and low level of trust in the AVs. The findings of the existing model have been reported that the situational trust is associated with the emotions of the driver. The overall results of the research have been stated that the emotions are correlated with the driver certainly affects the safety in the AVS. The prediction of emotions in the driver behaviour has been develop safety and the trust in adopting AVs in the real time environments [193].

This section has been engrossed the various DL techniques deployed in predicting the rear end collisions, head collisions, distracted driving, driving under influence, accidents due to obstacles or pedestrians, lane changing, overtaking of surrounding vehicles, driver behaviour and malfunctions in car parts using several predictive models. The overall performance of the predictive models and their limitations of the existing model has been discussed. Moreover, the traditional methods such as dashboard cameras and pamphlets that were used to forecast the driver behaviour and the drawbacks faced by deploying the traditional methods to predict the safety in the AVs has been captivated. The difficulties faced by employing the traditional methods over the AVs in order to predict the safety, handling the large amount of data, managing various driving scenarios used to evaluate the performance of the predictive models have been discussed.

Failure in AI technique and its impact on AVs

A small failure in AI technique can also leads to lane change behaviour, collisions, interaction with pedestrian, collision with obstacles, overtaking and major accidents has been deliberated.

The trustworthy autonomous driving systems can be developed by the source of realistic driving data and pioneering technologies. The AVs mobility and safety are more important. Mobility and safety of the AVs can be gained by understanding the actions of surrounding vehicles. Correspondingly the prior research [194] proposed a Long short term Memory (LSTM) networks to predict the trajectory and neural network classification to integrate maneuver by hybrid approach. The adjacent vehicles positions are identified by the hybrid approach. The prior research considered Next Generation simulation (NGSIM) for process. The existing research has validated the VEDECOM demonstrator data experimentally. The existing LSTM has been attained average performance.

The AutoML (Automated Machine Learning) is a method that has been implemented in AVs to evaluate their behaviours and for predicting the risks in it. In AVs the motion trajectory planning and behavioural decision making is implied through the AutoML method because the AutoML method has the ability to estimate risk and capable of producing successful outcomes. Likewise, the preceding research has determined the behaviour assessment and risk prediction using automated machine learning. The determined risk prediction and behaviour assessment used in planned motion trajectory of autonomous vehicles. The existing model considered NGSIM data to evaluate AutoML with data acquisition conditions. The considered model has been attained average performance with accuracy rate with 95%.

The efficient driving of the AV and its safety measures is an important factor in predicting the lane changing trajectory for AVs on highways. The risk of crashes can be reduced by predicting the lane changing trajectories. Additionally, the traffic efficiency also can be attained using it. The lane changing paths can be predicted through time series analysis and neural networks.

Correspondingly, the existing research [195] has recommended Lane changing (LC) sampling method and segmentation to divide LC into four stages. The suggested research had utilized encoder and decoder model to test the LC trajectory data in four stages. The recommended research identified the vehicle kinematics data by using heuristic network associated with DNN (Deep Neural Network). Additionally, a fine-grained LC is performed by joint cascade prediction model. The suggested research had been attained average performance.

In self-driving cars anticipating the paths of nearby vehicles is a crucial obstacle because when the self-driving cars fails to predict the nearby vehicles path then it led to vehicle crashes. Conservative approaches often depend on neural networks and time series analysis; however, their effectiveness is delayed by the complex and unpredictable nature of real-life driving situations. These critical problems can be solved using a new trajectory prediction network. Likewise the prevailing research [196] implemented interactive features to predict the trajectory network. The interaction between the target vehicles and its neighbouring vehicles is extracted by multi-headed attention mechanism. The interactive structures and trajectory structures are attained by MFB (Multi-modal Factorized Bilinear). The recommended research considered K-means algorithm to reclassify vehicle trajectories. The suggested research recommended NGSIM dataset for process. The considered research had been attained average performance.

In self-driving vehicles the precise prediction of vehicle paths is important for the smooth functioning. The complexity and impulsiveness of actual driving situations are restricted by the complex techniques like time series data analysis and neural networks. These complex techniques are used for predicting vehicle movement. Similarly the prevailing research [197] has approached DLM (Dual Learning Model) to predict vehicle trajectory and lane occupancy. The OM (Occupancy Map) is embedded into the trajectory prediction model to identify the spatial interactions of road users and to consider the inter vehicle distances. Additionally, to determine risk based on Time to collision in the traffic scene the research utilized RM (Risk Map). The suggested research has considered two different datasets namely HighD and NGSIM (naturalistic highway driving datasets) for process. The recommended research had been attained average performance

Correspondingly, the existing research [198] demonstrated vehicle trajectory prediction by spatial temporal dynamic attention. The social interaction of vehicles and its motion state in terms of temporal correlation is seized by different sequential models. The recommended research considered a maneuver based multi modal trajectory prediction to integrate social structures and extracted temporal to approach driving intention specific feature mechanism. The suggested research has considered two real world datasets for process. The considered research had been attained average performance.

The transportation industry is greatly influenced by the rapid growth of CAVs because self-driving cars have the ability to transform individual transportation with enhanced efficiency, safety and convenience. To enable the operation of these technologies there is need for strong foundation. Literally, the prevailing research determined solar power usage and integration of cloud computing using AI techniques. The suggested research has considered traditional security devices, authentication schemes, data privacy and zero trust architecture to mitigate risks. The recommended research had been attained better performance.

Frequent models for pedestrian-vehicle interaction do not forecast specific pathways taken by pedestrians. Although data-centric models provide precise predictions they lack adaptability in new situations and often generate complex outcomes. Current expert models do not have comprehensive validation and do not consider the various interactions between pedestrians and vehicles in a shared space. Likewise, the existing research [199] implemented pedestrian trajectories networking with autonomous vehicles in communal space. The recommended model utilized real time trajectory predictions. The suggested model considered social force model at predicting pedestrian behaviour around the vehicle on the used dataset. The considered research had been attained average performance.

Since autonomous vehicle systems (AVSs) are designed to travel and operate without human intervention and similarly their use in industrial and commercial backgrounds has been growing. However, there are significant challenges in controlling and enhancing traffic flow when integrating AVSs into the traffic systems that are in place now. Similarly, the conventional research [200] implemented a large scale plant on a real world traffic problem. The considered research utilized the routing method and real-world predictions based on a traffic control system to determine reduced congestion rates with AVSs. The recommended research has suggested four popular algorithms to demonstrate predictive performance. The outcome of the existing research has identified that ML based traffic control can progress the performance of AVSs. The considered research had been attained average performance.

The field of Explainable AI (XAI) are progressively important to tackle the obstacles faced in self-driving vehicles. Most importantly the XAI seeks to create AI models that can offer rationalisations for their choices and actions ultimately improving confidence, security, and responsibility. The XAI is essential in autonomous driving to tackle issues with AI decision-making transparency to improve human-vehicle teamwork and ensure compliance with regulations and public approval. Similarly the existing research [201] determined he trustworthiness and effectiveness of the trajectory decisions in AVs by XAI associated with Deep Reinforcement Learning Model. The considered research utilized real life dataset for process. Additionally, the recommended research has suggested standard solutions like RS and DQN. The considered solutions had been attained better performance.

In path planning while taking tire-road friction into account the path with the uppermost potential sideways acceleration is created using a fifth-order spline. Similarly the existing research [202] utilized AV's path tracking and planning system for collision avoidance on slippery roads. The tire-road friction is generated through the fifth-order spline that can induce maximum possible lateral acceleration in which MPC is the source for generated path. The possibility of collision avoidance in slippery road conditions is substantiated by the CarSiM (vehicle dynamics software). The suggested research had been attained average performance.

The lateral control positions like avoiding collisions and staying in the correct line is most important in path tracking. It is important to maintain both precise paths following and stable driving when the force of the tire is maximum during extreme conditions like approaching a quick turn or on a surface with low traction. Similarly, the existing research [203] has implemented road friction limit by steering controller and integrated braking. The constrained optimal control using nonlinear models are demonstrated using NMPC (Nonlinear Model Predictive Controller). The vehicle simulators like MATLAB Simulink and CarSiM tested through the model. The outcome of the research has demonstrated the accurate tracking performance and stable driving by the suggested controller. The recommended research had been attained average performance.

Governing the vehicle's path is crucial for autonomous vehicles to accurately stick to a desired path. However, traditional path tracking controllers optimized for high-friction road conditions tend to perform inadequately on low-friction surfaces because of tire force saturation. Adjacent tire forces reach their limits more quickly at lower slip angles on roads with low friction compared to those with high friction and this may result in a considerable decrease in accuracy when tracking the paths. Literally, the conventional research [204] determined road conditions on low friction under tire slip angles implemented by path tracking controller. Large steering angle is increased by a tire slip angle saturate on a lateral tire force at low friction road surface. The MPC and LQR (Linear Quadratic Regulator) is the most implemented path tracking controllers in AVs. The outcome of the research has utilized that tire slip angles with constraint path tracking controller are effective for path tracking on low friction road surface. The suggested research had been attained better performance.

Precise calculation of surrounding vehicles' motion is essential for safe and efficient and the motion planning of autonomous vehicles are particularly complex at multi-lane turn intersections. The Surrounding Vehicle Motion can be predicted using Multi-Lane Turn Intersections Using LSTM-RNN. The Autonomous Vehicle Motion Planning introduces a method-based data analysis to predict the movements of nearby vehicles in complex situations. Similarly, the existing research [205] implemented RNN based on LSTM to predict vehicle motion. The suggested research considered MPC model for process. The predicted state of surrounding vehicles is based on the longitudinal acceleration command which is determined by MPC (Model Predictive Control). The motion predictor is based on LSTM-RNN in target vehicles. The recommended research had been attained average performance.

Accurately predicting nearby vehicle movements such as lane changes is essential for AVs to safely and effectively navigate the challenging traffic conditions. Additionally, RNN method is used for intention prediction and LSTM is used for predicting lane change intentions in time series. Similarly the existing research [206] has determined times series prediction problem using RNN. The suggest research has utilized NMPC (Nonlinear Model Predictive Control) to avoid constraints under vehicle collisions in AVs. The recommended research has approached TensorFlow with NGSIM data by LSTM and GRU. The considered research had been attained better performance.

Anticipating the movements of nearby vehicles at junctures is essential for autonomous vehicle motion planning because it helps the nearby vehicle to predict the actions of other traffic participants. Literally, the conventional research [207] demonstrated trajectory prediction and intension prediction together by LSTM based structure. The traffic flow trajectories are statistically examined and bunched by IPTM (Intersection Prior Trajectories Model). The suggested research considered two publicly released datasets namely INTERACTION and NGSIM for process. The recommended research had been attained average performance.

In autonomous driving predicting the movement of road users is the most crucial part. Once a driverless vehicle is successful in tracking and detecting nearby vehicles and road users it should understand the actions of road users to ensure the safety of both road users and driverless vehicle. Likewise, the preceding research [208] demonstrated VRU movement by deep learning based method. The considered research utilized bird’s eye view image to implement high definition maps. Additionally, the suggested research determined optimal choice for accurate prediction by several rasterization approaches. The suggested research had been attained average performance. Correspondingly, the existing research [209] determined afflicting transport industry under ITS. The recommended research demonstrated certain problems and critical point of alarm in transport industry. The suggested research has utilized country wise data for process.

The evolution of human society is the main drawback for the existing transport system to become more and more visible so that people hope to use advanced technologies to carry out intellectual transport. Nevertheless, the level of recognition of most methods of detecting car videos is too low and the process is complex. The considered research had been attained average performance. Similarly the existing research [210] determined variability of decoration classifiers using machine learning theory. The recommended research categorised vehicles using SVR (Support Vector Regression), SVM (Support Vector Machine), RF and AdaBoost algorithms. The regression problems are generalized by SVM based on the principles of SVR. Additionally, the suggested research approached short term traffic flow prediction by SVM parameters. The recommended research had been attained average performance.

Moreover, Lane changing trajectory prediction is essential for Avs to anticipate their driving safety in advance. Nevertheless, there are notable uncertainties when it comes to carrying out this prediction due to variations in behaviours resulting from interactions between agents and the driving styles of motorists. Although prototype trajectories can help illustrate common motion patterns and improve trajectory prediction accuracy. Their application in modelling motion patterns often disregards the impact of agent to agent interactions in vehicle dynamics. Likewise, the preceding research [211] determined vehicle detection and driving style by fusion algorithm.

The intensifying interest in the field of intelligent traffic systems and the increasing availability of collected data allows the model to use different methods to prevent traffic congestion in cities. A common need for all these methods is the use of traffic predictions to support the planning and operation of traffic signals and traffic control schemes Literally, the existing research [212] has utilized probe data gathered from the road network of Thessaloniki for process. Further, the suggested research considered three machine learning models namely Multilayer perceptron, RF, and SVR to estimate the effectiveness. The outcome of the analysis obtained minor variations when performed by SVR model. Additionally, the greater variations are obtained by Multilayer Perceptron Model. The suggested research had been attained better performance. The road irregularities are detected by using these ML techniques. These ML techniques insist the drivers to avoid the route because of its anomalies. Thus, the safety of the driver is considered in AVs with the help of these ML techniques.

AI is an influential concept that is still in its infancy but if it is used with responsibly it can be a vehicle for positive change that could simplify a sustainable transition to a more habitable resource-efficient. AI, with its functionalities and deep learning capabilities can be used as a tool for machines to solve problems that have the potential to transform urban landscapes as we have known them for decades and help attendant in a new era called the era of intelligence. One of the key areas where AI can redefine its transportation is mobility and its impact on urban development can be significantly improved through the use of intelligent transportation systems in general and automated transportation systems.

Correspondingly, the prevailing research [213] approached MaaS (Mobility-as-a-Service), CAVs (Connected and Autonomous Vehicles), and UAVs (Unmanned Aerial Vehicles), PAVs (Personal Autonomous Vehicles) to specify the smart key mobility.

Additionally, empowered tools for transport are interposition by PI (Physical Internet) and IoT. The suggested research had been attained average performance. The sustainable and efficient transportation solution can be obtained by collaborative interaction, autonomous decision making and CAVs. Nevertheless, the advancement of CAVs has raised concerns regarding vulnerabilities in cyber security and autonomous driving functionality. Specifically, connected and autonomous vehicles give cyber attackers new chances, presenting a major risk to the security of future road and vehicle data. Likewise, the preceding research [214] determined automated method for vehicle parking in AVs. The suggested research utilized CNN tool for process. The recommended research considered MATLAB for simulation. Similarly, the existing research demonstrated CAVs cyber security environment.

The suggested research utilized lifecycle of CAVs cyber security environment by time delay, privilege escalation, information theft, block communication and false information the existing research determined industrial applications for CAVs cyber security using VSOC (Vehicle Security Operations Center). The recommended research had been attained average performance. Correspondingly, the prevailing research [215] demonstrated the capabilities of dynamic vehicles and its behaviour by corridor based vehicle motion. The suggested research has considered NMPC (Nonlinear Model Predictive Control) to achieve smooth and comfortable trajectory. The considered research had been attained average performance.

Similarly, the existing research [216] determined autonomous intelligent car driving using vision based vehicle identification system. The CNN is based on images captured by monocular video camera to detect vehicle. The suggested research considered GTI dataset for process. Additionally, the methods implemented using GTI dataset processed using CNN based vehicle detection system. The considered model had been attained better performance.

The CNN in vehicle detection and classification could be more fascinating and encouraging for intelligent transportation applications. The CNN could be trained with huge labelled vehicle images in order to enhance the performance of AVs. Correspondingly, the prevailing research approached CNN method for vehicle detection. The approached method has been trained using road marks. The approximate length and width of the vehicle gathered using spatio- temporal information. NVIDIA Jetson and Raspberry Pi4 has been used as a source for the CNN performance. The considered model had been attained better performance. Likewise, the preceding research [217] demonstrated vehicle classification and detection by robust algorithm. The light and heavy vehicles are categorized and detected by CNN method. The suggested research has considered VIVID, UC Merced Land Use, VEDAI and self-database for process. The recommended research had been attained better performance.

Likewise, the prior research [218] implemented perception algorithm for AVs. The safety drivable region in the front of the car is determined by lane detection algorithm. Additionally, the suggested research utilized CNNs to train from drivers driving data. The outcome of the research has obtained that AVs can detect and classify other vehicles and stop signs. Thus, the recommended research had been attained better performance. In recent times, there has been a notable rise in research on AVs and that have covered over 10 million miles and resulting in a vast amount of data for training and testing purposes. The most problematic feature of training involves exploiting computer vision to identify features and recognize objects rapidly. Literally, the prevailing research [219] determined efficiency of autonomous vehicles by STN (Spatial Transformer Networks) using CNN. The testing and training phase are implemented using neural network. The recommended research has suggested LeNet-5 architecture for process.

Additionally, the FFNN (Feed Forward Neural Network) could be compared and analysed with LeNet-5 architecture. The considered research had been attained better performance. Abundant autonomous driving is a necessary component in all five levels of AVs with lane detection being a crucial obstacle to overcome. Machine learning algorithms are the extremely reliable choice for complex decision-making. To ensure high level of safety the complex decision-making algorithms could be essential due to the lack of human interaction in lane detection. Correspondingly, the conventional research [220] determined lanes under any circumstances for different road conditions to operate AVs.

These lanes and road conditions could be demonstrated by simplified camera-based lane detection. The road conditions at composite situations have been classified using segmentation-based lane detection and classification algorithm. The suggested research has utilized in-field dataset for process. The recommended research had been attained average performance. Similarly, the existing research [221] has determined real time requirements and complex situations using lane detection method. The existing research has demonstrated real time requirements called Road Save. The validity effectiveness, scene awareness and physical inference are three foremost mechanisms of Road save method. The suggested research has considered public datasets for process. Additionally, the datasets considered in this existing research are processed using Road save method. The recommended research had been attained better performance. Correspondingly, the prior research [222] has determined lane detection using computer vision system. The suggested research utilized lane segmentation to predict the intensity of lanes at point cloud frames. The recommended research has utilized LLAMAS, CULane, TuSimple and CurveLanes a self-supervised method to determine the performance in the domain gap. The suggested research had been attained average performance.

Detecting lanes could be essential for self-driving cars to reach complete autonomy. Lane detection has become a topic of great interest in the field of autonomous driving in recent years due to its significance. The noise in input image like object shadows, brake marks, and broken lane lines will affect the precise lane detection. Likewise, the preceding research [223] approached effective algorithm for road detection. The recommended research has suggested K-means Clustering filter to screen out the embedded noises. The suggested research had been attained better performance.

There could be rapid growth in AV because a commercial vehicle comes with AV features like adaptive cruise control systems and lane prediction etc. The AV feature can regulate the gap between the current vehicle and the one in front automatically in a flexible way. The use of automatic control in cars may result in car-following movements that are notably distinct from those seen in human-operated vehicles, making it difficult to apply traditional traffic flow principles to the growing number of roads with autonomous vehicles. Literally, the prevailing research [224] implemented FD (Fundamental Diagram) using the combination of 15 theoretical models and empirical experiments. The suggested research has considered trajectory data 17 for process. The existing research has identified that road capacity can be significantly increased by shortest AV headway setting. The recommended research had been attained average performance.

The safety prediction in autonomous vehicles can be predicted using various ML (Machine Learning) techniques. The ML technique in AVs helps to antedate and plan to avoid from potential collisions and dangerous situations by predicting the future trajectories of vehicles, pedestrians and other road users. Those ML models implemented in AVs should be vigorous to adversarial attacks, data corruption and real-world conditions because ensuring safety and reliability of these systems are more crucial. Techniques like model verification, error detection and uncertainty estimation hold the important aspect in the ML techniques because these are crucial for ensuring the safety and reliability of AVs.

The CAVs could be a new solution to the challenges of secure and environmentally friendly transport networks in the upcoming years. One popular transportation technology for CAVs would be CACC which could be highly utilized for unsignalized autonomous intersection crossing. The CACC is highly dependent on communication between vehicles and making it susceptible to fake messages and jamming attacks. Many CACC solutions prioritize either improving efficiency or security without providing a comprehensive approach to achieve both effectively at a large scale. Likewise, the preceding research [225] demonstrated effectiveness of by Block-MADRL (Blockchain-integrated Multi-Agent Deep Reinforcement Learning) architecture. Additionally, the existing research identified fuel efficiency by multi-agent deep reinforcement learning.

Further, the prior research implemented EIF (Extended Isolation Forest) to detect attacks and RSU (Road Side Unit) level Blockchain could be approached to store attacker data. Thus, the suggested research had been attained average performance. Correspondingly, the prior research [226] demonstrated CACC in AVs. The prior research has identified that traffic safety, road capacity and fuel consumption is reduced by CACC. The suggested research has approached GESD-SC (Generalized Extreme Studentized Deviate with Sliding Chunks) method for real time anomaly detection and mechanism. The outcome of research detected effective falsification attacks in CACC by linking kinematic model with GESD-SC. The suggest model had been attained better performance.

The collision prevention has attained more attention because of the fast advancement of self-driving technology. Though there have been several strategies to avoid collision that could be important to create effective algorithm because of constantly changing and intricate driving conditions. Similarly, the existing research [227] implemented RACE (Reinforced Cooperative Autonomous Vehicle Collision Avoidance) a decentralized framework. The AVs could be trained using Co-DDPG algorithm. The suggested research demonstrated the RACE with existing autonomous driving systems to improve the performance of vehicle density. The recommended research had been attained average performance by experiencing 65% less collisions in the training process.

Smart Vehicles such as AVs and some vehicles with ADAS systems operate independently using the collective data. However, the sudden developments in algorithms and hardware cause numerous accidents. These unfortunate events cause an important issue in AVs so it is mandatory to develop CCAD enabled AVs which allows vehicle to observe during various driving conditions form several perspectives. Literally the traditional research [228] utilized edge-computing device as well as OBU and RSC with CCAD framework to process data. The suggested research considered CCAD with infrastructure based collaborative lane keeping. The recommended research had been attained average performance. Correspondingly, the prior research [229] determined AV crash due to environment configurations by using Deep collision (RL-based environment configuration learning approach). The suggested research has considered RL solution demonstrated by Deep Collision method. The considered method had been attained average performance.

The existing research has been introduced an integrated framework to anticipate the close interaction between the car following and lane changing tasks. Based on the double deep Q network (DDQN), the lateral lane change command decision-making has been utilized. The longitudinal car following acceleration decision making has been predicted using the twin delay deep deterministic policy gradient (TD3) respectively. The correlation of TD3 and DDQN has been employed to sort out the complication of predicting the accurate lane changing situations. The DDQN-TD3 model has been evaluated using a sequence of simulation experiments. The integrated framework has been developed the applicability and feasibility of the DDQN-TD3 model. The implementation of the AVs has been enhanced using the RL based couple decision making [230].

The lane changing has been considered as the challenging tasks in the crowded traffic environment in AVs respectively. The conventional research has been established a decision-making model based on the DL approach. Initially, the decision policy and the lane change actions has been framed based on the RL approach. The behaviour constraints have been developed based on the traffic rules and driver prior knowledge. Moreover, the driver prior knowledge and the traffic rules have been encoded. The lane change style has been dynamically adjusted in order to save the training time efficiently. The performance of the decision-making model has been evaluated using the highway scenario. The driving style has altered according to the urgency and switching from actively overtaking has been accomplished using the decision-making model. The outcomes of the research have been stated that the decision making model attained 90% compared to traditional rule based method [231].

AVs have the ability to transmute the transportation industry with developments in safety, effectiveness, and ease. The effective application of AVs relies on the formation of strong and trustworthy crash deterrence and reduction mechanisms. Most importantly, the Predictable crash prevention systems frequently depend on data from decision-making rules which may be inhibited in complex and ever-changing driving situations. Correspondingly, the prior research [232] approached crash mitigation control algorithm, integrated path following and crash avoidance for autonomous vehicles. The suggested research utilized real world crash statistics to enumerate crash mitigation. The outcome of the research identified that desired driving path in normal driving phase can only be tracked by utilized algorithm. Thus, the suggested research had been attained average performance.

Predicting the trajectory of the forward vehicles has been essential for the AVs. The DL methods have been applied in the accurate prediction of safety in the AVs. Moreover, the DL approaches has been comprised of various techniques, the certain techniques have been adaptable for the trajectory prediction. The prior research has been established a three types of DL models such as GRU, Stacked Auto Encoders (SAE) and LSTM. The anticipation of the velocity and the position of the forward vehicles has been achieved using the three models. The dataset NGSIM I-80 has been used that comprised of real trajectories of vehicles especially on various lanes. Subsequently, reduction of noise on the training models has been eradicated using the Savitzky-Golay filter. The outcomes of the research have been stated that the apart from the three network models, the LSTM model has attained the better accuracy [233].

Autonomous vehicles would be need to coexist with human operated vehicles on the road for an extended period of time in the upcoming years. Therefore, it is important for them to be able to comprehend the lane changing intentions of nearby vehicles driven by humans. In contrast to human drivers the modern models in self-driving cars has the ability to detect a driver plan to change lanes by observing the lateral movement of the target vehicle and giving the autonomous vehicle minimal time to respond. Correspondingly, the prior research [234] determined lane changing intentions for AVs using HLCIUM (Human-Like Changing Intentions Understanding Model). Additionally, the recommended research utilized HMM (Hidden Markov Model) to identify lane changing intention. The considered research has suggested NGSIM dataset for process. The suggested research had been attained average performance.

2.4 RESEARCH GAPS

The unsolved or unanswered problems in the existing research related to the model has been discussed in this section. Research Gap underlines the absence of inadequate information aids to draw the conclusion on the particular topic that includes several opportunities for further investigation. Moreover, identifying the gaps in the existing model typically paved the way for innovative future contributions for the researchers. Identifying the research gaps confirms that new research addresses the areas of uncertainty information and maximizes the potential for impactful outcomes. Enhancing the overall quality and the relevance of the research has been achieved by identifying the research gaps of existing studies. Additionally, organising the research gaps is significant for directing research efforts and confirming that current research is impactful within several fields. The unexplored areas and the limitations of the existing studies with their accuracy are tabulated as follows,

Table 2.1: Studies conducted on safety prediction in AVs

S. No	Author	Result & Accuracy	Research Gaps
1	[136]	92%	The limited factors such as assessing AV damage, evaluating weather, motion states, road surface, collision types have been focussed for safety-prediction. The malfunction in car parts and driver behaviours has not been considered.
2	[147]	93%	The graph-based solutions such as path planning, control and challenges has not been explored.
3	[137]	92%	The data used in the simulation model has not been engrossed the attributes such as road structure, weather characteristics and number of lanes.

4	[149]	91%	Identifying and extracting the relevant features impacts the driver behaviour is considered as the challenging task. The various feature selection approached has been included to enhance the accuracy of the model.
5	[161]	86%	Inadequate low quality of data limits the effectiveness of DL model and the research has to be needed to enhance the data collection methods.
6	[170]	90%	Need to include detection methods with respect to safety metrics in AVs.
7	[235]	93%	The variations in the driving styles and the behaviours across the individuals has not been explored.
8	[236]	94%	The model has failed to adapt dynamically to the changing environment has been considered as the limitation of the research.
9	[237]	89%	The integration of data from the several sources such has been able to enhance the model accuracy and considered as the drawback of the research.
10	[238]	87%	The standardized high-resolution datasets that captures several driving using ML algorithms has to be explored.
11	[239]	95%	The advanced feature selection and the ML techniques that has to be improved to enhance the AHEG-Model performance.
12	[240]	87%	Improving the explain ability and interpretability of the ML models has to be enhanced and gain trust from the users.
13	[241]	92%	The research has to focussed to develop robust ML algorithms that can suits for the varying road conditions, weather and traffic patterns.
14	[242]	94%	The research has to engrossed on transfer learning techniques that can aid in enhancing the generalization of the ML models across several driver demographics and driving environments.

The table 2.2 deliberates the comparative studies of the conventional research. The table comprises of the title, objective, methodology adopted and key findings of the preceding research. The overall existing methods that were used to predict the safety in the AVs has been tabulated as follows.

Table 2.2: Comparative studies of the existing research

References	Objective	Methodology adopted	Key findings
[56]	To implement a enabled ITS in both manual and autonomous vehicle for traffic safety solution using deep learning,	Deep learning is considered as the powerful tool for control and perception in autonomous vehicles. The tasks like lane detection, object detection and sematic segmentation from camera data can be utilized by Convolutional neural networks (CNNs).	The lane changing operations and the drivers’ lane changing intentions are predicted by historical driving trajectory information and natural driving data.
[110]	To develop control method for vision-based autonomous driving using deep-MCTS.	The driving maneuvers are projected using possible trajectories and the predicted information of two DNNs was employed by the deep-MCTS. The predicted driving maneuvers and road conditions in optimal trajectory are designated by the deep-MCTS.	Vision based autonomous driving is achieved using deep-MCTS algorithm.
[112]	To predict lane changing manoeuvres by using ML model from unlabelled data,	The existing research identified the lane keeping and lane changing manoeuvres by Density-based clustering method. The raw data is automatically labelled by clustered boundaries and then trained using Support Vector Machine (SVM).	In this research, the highway safeties for AVs are enhanced and it successfully lead timely prediction to coordinate vehicles. Furthermore, the proactive alerts are intimated to the drivers in order to avoid collisions.

[114]	To enrich the object classification in driving environment and to enable an auto pilot to take better driving decisions.	The object classification in a driving environment is enhanced by supervised learning and decision fusion.	The speed of C5.0 decision tree is maximized using several magnitudes and by the contrast of FDNN classifier and C5.0 decision tree classifier.
[14]	To handle the epistemic uncertainty arising from training the prediction model on insufficient data using RADM framework	The uncertainty quantification is approached through a multi-agent prediction network which used map information, traffic lights and historical states of road users nearby as inputs. The epistemic uncertainty of the prediction model is utilized by RADM.	The research identified that RADM can perform both functions (i.e.) it can reduce driving risks and RADM is also capable to increase the driving safety.
[117]	To Predict vehicle motion direction and motion distance	The existing research determined implementation technology and corresponding architecture by three aspects namely AI (Artificial Intelligence), MEC (Multi-access Edge Computing), and of both MEC and AI	The trajectory of vehicles like direction and vehicle movement is identified through AMGB.
[201]	To improve the effectiveness and trustworthiness of the trajectory decisions for AVs.	The trajectory decisions in AVs by XAI associated with Deep Reinforcement Learning Model and standard solutions like RS (Random Selection) and DQN (Deep Q-Network) are used to process the data	The trustworthy AVs are selected by FL trust aware explainable ML model.

[203]	To determine the road friction limit by using an integrated braking and steering controller	The constrained optimal control using nonlinear models are demonstrated using NMPC (Nonlinear Model Predictive Controller). The vehicle simulators like MATLAB Simulink and CarSiM tested through the model	The research introduced path tracking algorithm to assist the vehicle to follow desired path even when the vehicle enters curved path at high speed.
[204]	To determine the road conditions on low friction under tire slip angle	The MPC and LQR (Linear Quadratic Regulator) is the most implemented path tracking controllers in AVs.	The path tracking controller with CTSA is implemented to control the AV at low friction road surface.
[206]	To determine time series prediction using RNN.	The suggest research has utilized NMPC (Nonlinear Model Predictive Control) to avoid constraints under vehicle collisions in AVs. The recommended research has approached TensorFlow with NGSIM data by LSTM and GRU.	The model used in this research presented satisfactory performance in cut in scenarios and also provided the safety path for AVs.
[47]	To develop a perception algorithm for self-driving cars.	The safety drivable region in the front of the car is determined by lane detection algorithm. Additionally, the suggested research utilized CNNs to train from drivers driving data.	The lanes are detected properly using lane detection algorithm. The lane detection algorithm applied only to detect straight lines, additionally it detects the road sign or nearby vehicles.

[48]	To determine efficiency of AVs by STN using CNN	The neural network is used for testing and training phases. Additionally, the LeNet-5 architecture for process. The FFNN is analysed and compared with LeNet-5 architecture.	In this research it was found that distortion and calibration matrix for lane detection in AVs is determined by STN using CNN.
[218]	To operate Avs at different road conditions under any lane circumstances.	These lanes and road conditions are demonstrated by simplified camera-based lane detection. The road conditions at composite situations are classified using segmentation-based lane detection and classification algorithm	The AVs are operated at several lane circumstances and also at critical road conditions.
[51]	To determine lane detection using computer vision system	The performance in the domain gap is determined using the CULane, TuSimple, LLAMAS and CurveLanes a self-supervised method	Self-supervised method is applied to detect lane by computer vision system
[52]	To demonstrate road detection using effective algorithm	The K-means clustering algorithm is used to screen out the embedded noises.	The noises in lane detection are removed by K-means clustering filter and also the lane lines are efficiently identified by considered method.

[54]	To predict the maneuver lane change of surrounding vehicles	Two ML methods named ANN and SVM are used for the lane changing prediction.	The lane keeping and lane changing are accurately predicted by using ANN and SVM.
[56]	To determine Avs lane changing intention using HLCIUM.	The research considered HMM based model to identify lane changing intention.	The selective attention mechanism of human vision system is determined by adjacent lanes of the surrounding vehicles at lane changing intention.
[57]	The aim of the existing research is to determine the V2V attacks on CACC using RACOON AI	The conventional research considered ML to develop on board prediction model	The RACOON AI is used to negotiate the vehicle to vehicle attacks on CACC.
[59]	To demonstrate the use of CACC in Avs.	The real time anomaly detection and mechanism is obtained using GESD-SC method.	The CACC implied in AVs plays an enormous role in order to avoid collisions and vehicle crashes.
[62]	The aim of the research is to determine the AV crash due to environment formations.	The preceding research utilized Deep collision method.	Deep collision method is implemented in order to avoid vehicles crashes in various

			environment circumstances.
[63]	To identify the behaviour of AVs using SCA.	The driving priors determined by RL framework and DDL. The AVs are coordinated using CT method.	The responsive behaviour of AVs under critical situations is identified using SCA method.
[67]	To demonstrate Full Automation malfunctions to control vehicle in order to avoid danger.	The existing research has utilized ML and EEG techniques.	The full automation malfunction in AVs are regulated by EEG and ML techniques and those techniques played a significant role in monitoring AV to avoid vehicle collision

There various researches have been made in identifying the mechanism of AV and the driver safety. Every single research implemented various AI techniques implemented in order to predict the vehicle safety and driving intention of human drivers. Several machine learning and deep learning techniques are applied to detect the lane trajectories and road conditions. The table 2.2 demonstrated the various researches and the methodologies used in it to obtain better insights about AI techniques in automated driving. Additionally, in the table it was found that enabling ITS using deep learning can improve vehicle safety in several traffic conditions.

Further, the table 2.2 has determined the several AI algorithms which can be helpful in enhancing features in AVs to predict lane trajectories, movement of nearby vehicles and drivers intention while driving. In the table it has identified that deep-MCTS used as control method for vision-based learning. The table 2.2 represented various methodologies and key findings obtained by using those methodologies which can further help to understand about the use of AI techniques in predicting AVs.

CHAPTER 3

3. PROPOSED METHODOLOGY

In the view of improving safety in autonomous vehicles, the study blends advanced Machine Learning (ML) techniques and standard datasets to develop a strong predictive tool. The areas of safety in autonomous vehicles has seen many approaches, including rule-based systems, traditional ML models, and more recently, Deep Learning (DL) techniques. Rule-based systems depend on predefined sets of rules and conditions, which may not adjust well to difficult and dynamic environments. Moreover, Traditional ML models, such as Support Vector Machines (SVM) or Random Forests, have been potent but often struggle with recording deep patterns in data which are of highest dimensions.

DL has developed as a powerful approach due to its ability to automatically learn hierarchical demonstrations of data. Within DL, Convolutional Neural Networks (CNNs) surpass in extracting spatial features for image and data analysis in autonomous vehicles. However, for sequential data and progressive dependencies, Recurrent Neural Networks (RNNs) are traditionally used. Furthermore, Long Short-Term Memory (LSTM) networks, a type of RNN, addresses the disappearing gradient problem by allowing information to continue over long periods.

In the study, Bidirectional LSTM (BiLSTM) with an Attention Mechanism (AM) combined with a deep CNN is implemented. BiLSTM improves traditional LSTMs by processing data in both forward and backward directions, apprehending dependencies from prior and upcoming states concurrently. This bidirectional ability is particularly advantageous, where understanding progressive relationships between driver states and vehicle conditions is essential for safety prediction. The AM further augments to model's performance by focusing on the most relevant features at each step of the prediction process, improving both interpretability and predictive accuracy.

The decision to integrate a deep CNN with BiLSTM and AM stems from the need to influence the strength of CNNs in spatial feature extraction and BiLSTM. By combining these architectures, the model efficiently notice complex interactions between behavioural actions of the driver and state of the vehicle, leading to more accurate safety predictions in real-time scenarios. This hybrid approach not only addresses the limitations of traditional ML methods but also aligns with the complexity and dynamic nature of autonomous vehicle environments, where safety decisions must be made quickly and accurately.

3.1 PROPOSED DESIGN

Figure 3.1. Working Model of the Proposed Study

1. Dataset selection
   The base of any effective ML model is integrity and applicability of the dataset. In the study two main datasets are utilized:
   1. Driver physical state Dataset: Various Physical factors of the driver such as eye movement, heart rate, reaction time, and fatigue levels are captured by this dataset. These factors are indispensable for retrieving the driver's physical and mental state, which can significantly influence the entire safety of the vehicle. The dataset is taken from a public open source platform named Kaggle.
   2. Car material condition dataset: This dataset contains information on the condition of the vehicle's key mechanisms, such as pressure in the tyres, efficiency of the brake and clutches, engine performance and structural durability. By observing these parameters, the system identifies possible failures or maintenance needs that could compromise vehicle safety.
      The data is attained through various active analytic systems and regular maintenance checks. Moreover, environmental factors like weather conditions, quality of the road and traffic density are merged to provide a relative back drop to the vehicle operative status. This inclusive dataset guarantees that the model can account for both invasive vehicle settings and external forecasts.

   These datasets provide complete information of both the driver's condition and the vehicles functioning status, establishing the development of the model.

2. Feature selection- Improved search ability based genetic algorithm.

Feature selection is a decisive step in ML, as it determines the most relevant variables that will contribute to the model's extrapolative power. Here, an improved search Ability centred Genetic algorithm is utilized. This algorithm mimics the process of natural selection to identify the optimal subset of features from the datasets. The genetic algorithm works by primarily generating a populace of potential solutions, each representing a different combination of features.

This process guarantees that the selected features provide the maximum predictive value while minimizing redundancy and irrelevant information. The solutions are then estimated based on their appropriateness, which is their ability to improve the productive accuracy of the model. Through iterations of selection progresses the population towards the most ideal feature set.

The improved search ability based genetic algorithm improves the traditional genetic algorithm by incorporating adaptive mutation rates adjust the probability of mutation based on the merging status of the algorithm, promoting examination in early stages and exploitation in later stages. This dual approach accelerates convergence towards ideal feature sets, improving the efficiency and effectiveness of the feature selection process. By selecting the most informative features, the model's complexity is reduced, leading to faster training times and improved simplification of new data.

3. Train and Test data split
   To affirm the model's consistency and generalizability, the carefully chosen datasets are classified into training sets as well as testing sets.

   1. Train Data (80%)
      This portion of the data is used to train the DL model. The training process encompasses intensifying the model with the designated features and their corresponding labels (Safety or non-safety) to learn the primary underlying patterns and relations. By consuming 80% of the data formation, the model can develop a broad understanding of the variants.

The training data is further amplified though techniques like oversampling, under sampling and synthetic data generation addresses class disproportion and enhance the model's robustness. Strategies such as K-Fold cross-validation are also engaged across the model's working conditions through diverse subsets of the data, decreasing the risk of over fitting.

2. Test Data 20%

The remaining 20% of the dataset is set apart for testing the performance of the trained model. This test data is not used during the training process and aids as an independent evaluation set to assess how well the model generalizes to unseen data. By using a separate test set, an unbiased estimate of the model's performance can be obtained and it also avoids over fitting, where the model performs well on the training data but fails to generalize to new instances.

4. DL Classification Model: Modified Deep CNN-BiLSTM with AM

The core model implemented in the study is the modified deep CNN-BiLSTM with AM. This model combines the strengths of CNNs and BiLSTM networks, along with an AM, to effectively capture 3-D and sequential features from the input data.

Input

The input to the model contains the pre-processed and selected features from the driver physical state dataset and car material condition dataset. These features are served into the AM layer.

AM

The AM is an influential method that permits the model to concentrate on the most suitable parts of the input when creating predictions. It allocates weights to diverse parts of the input based on their importance, allowing the model to particularly attend to specific features. By integrating an AM, the method can better capture the dependencies and relationships within the input data, which leads to improved performance in foreseeing safety in autonomous vehicles.

BiLSTM Backward Layer

The BiLSTM backward layer progresses the input sequence in reverse order, seizing the related information from the end of the sequence to the start. This layer helps the model understand the relations between features in a reverse sequential order, providing supplementary perceptions into the input data.

BiLSTM Forward Layer

The BiLSTM forward layer progresses in the appropriate order which is given as input in the usual order, capturing the suitable information from the commencement of the sequence to the end. By combining the results obtained from the forward and backward layers, the BiLSTM can learn both forward and backward dependencies in the input data, prominent to a more inclusive understanding of the progressive relationships.

Dense Layer

The dense layer, similarly called as a FCL (Fully Connected Layer), is accountable for transforming the output of the BiLSTM layers into a format suitable for classification. This layer smears a linear transformation to the input and familiarises non-linearity through an initiation function, such as SoftMax function, to produce the final output probabilities.

Target

The target output of the modified deep CNN-BiLSTM with AM model is a binary classification, demonstrating whether the input data represents a safe or non-safe scenario for autonomous vehicles. The model's estimates are centred on the cultured patterns and relationships within the input features.

Prediction: Safety or Non-Safety

Based on the output of the model, the system makes an estimate of whether the current state of the autonomous vehicle and its surroundings is safe or unsafe. This prediction is necessary for the decision-making process of the autonomous vehicle, allowing it to take applicable actions to confirm safety.

Performance Metrics

To calculate the effectiveness of the proposed approach, numerous performance metrics are utilized. These metrics deliver understandings into the model's accuracy, precision, recall, and overall efficacy in expecting safety in autonomous vehicles.

Some common performance metrics that can be used include:

1. Accuracy: The proportion of appropriately foretold instances to the total number of instances.
2. Precision: The proportion of true positive estimates to the total number of positive estimates.

3. Recall: The proportion of true positive estimates to the total number of actual positive instances.
4. F1-score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.
5. AUC (Area Under the Curve): The area below the ROC (Receiver Operating Characteristic) curve, which represents the capability of the model to differentiate between positive and negative classes.

By verifying these performance metrics, the value of the modified deep CNN-BiLSTM with AM model is measured in accurately predicting safety in autonomous vehicles. These metrics help in identifying the areas for improvement and compares the performance of the model with other approaches.

Finally, the proposed design of the study is brought out through the flow diagram for predicting safety in autonomous vehicles using a modified deep CNN-BiLSTM with AM. It entails of several key steps, including data selection, feature selection, dividing the data into training groups and testing groups, applying the DL classification model, making predictions, and estimating the working of the model using various metrics. By combining the powers of CNNs, BiLSTM, and AMs, the projected method intentions to improve the accuracy and consistency of safety predictions in autonomous vehicles, contributing to the growth of safer and more reliable transportation systems.

3.2 DATA PRE-PROCESSING

Data pre-processing is a major step in the advancement of any ML model, including the proposed Modified Deep CNN-BiLSTM with AM for predicting safety in autonomous vehicles. The raw data collected from autonomous vehicles is often noisy, imperfect, and varying, requiring extensive cleaning and transformation before it can be effectively used for training predictive models. The below figure 3.2 outlines the key data pre-processing steps undertaken in the proposed study.

Figure.3.2. Steps in Data preprocessing

Importance of Data Preprocessing

Data preprocessing step is very significant in ML pipeline, especially for versatile tasks like predicting safety in autonomous vehicles. Raw data often contains noise, irrelevant features, missing values, and other issues that can destructively influence the enactment of the ML model. As a result, by addressing these data value challenges through systematic preprocessing, the model can concentrate on the most informative and applicable features, primary to improved accuracy, generalization, and reliability in safety predictions.

Loading the Dataset

The dataset used for the study is obtained from Kaggle, a popular platform for hosting and sharing public datasets. The first step in the data preprocessing stage is to load the dataset into the working environment, characteristically using a programming language like Python and its data manipulation libraries such as Pandas. This step involves reading the dataset from the appropriate file format (e.g., CSV, Excel, or SQL database) and converting it into a structured data format that can be easily deployed and analyzed.

Dropping Irrelevant Columns

After loading the dataset, it is indispensable to identify and remove any columns or features that are not relevant to the task of predicting safety in autonomous vehicles. This step helps to reduce the dimensionality of the input space, which can improve the model's performance and interpretability. Factors such as raw data, ecological conditions, vehicle subtleties, and behavior of the driver are likely to be more relevant for this task, while columns containing irrelevant metadata or identifiers may be dropped.

Handling Missing Data

Real-world datasets generally contain missing values, which can be produced by various reasons, such as data collection errors, or incomplete records. Ignoring these missing values can lead to biased model predictions and reduced generalization. To address this issue, various techniques can be employed, such as:

1. Imputation: Replacing lost data values with estimates centered on the existing data, using methods like mean/median imputation, k-nearest neighbors, or more advanced techniques like multiple imputation.

2. Dropping Rows/Columns: In some cases, it may be suitable to remove rows or columns with a substantial number of missing values, if the material loss is not serious to the analysis.

The choice of the most appropriate missing data management technique will depend on the nature of the dataset, the extent of missing values, and the probable impact on the model's performance.

3. Interpolation: Estimating missing values by leveraging the relationships between associated features or the three-dimensional patterns in the data.

Removing Duplicates

Duplicate data points can introduce bias and tilt the model's learning, leading to overfitting and poor simplification. Therefore, it is necessary to recognize and eliminate any duplicate rows or interpretations in the dataset. This can be done by relating the values across all columns and identifying rows with equal feature values.

Splitting the Dataset

After the primary data cleaning and preprocessing steps, the dataset is splited into two sets. The training set is utilized to fit the ML model, while the testing set is urged to calculate the working of the model on unnoticed data. This step is decisive to make sure the model's ability to simplify and make accurate predictions on new, unobserved data.

By following this data preprocessing essentials, the dataset is transformed into a clean, high-quality input for the modified Deep CNN-BiLSTM with AM model, which is mainly based on "Prediction of safety in Autonomous Vehicles".Additionally, One common challenge in security in terms of autonomous vehicles is the potential imbalance in the dataset, where the number of instances representing safe and unsafe driving conditions may be significantly different. This imbalance can direct to prejudiced model estimates, favoring the common class and overlooking the minority class, which is often the more serious safety-related events.

EDA (Exploratory Data Analysis)

Before concluding the data preprocessing steps, it is necessary to perform EDA on the dataset. EDA involves investigating the statistical possessions, deliveries, and relationships within the data, which can provide valuable intuitions into the dataset's characteristics and inform the following feature engineering and model development stages.

The EDA involves:

1. Analyzing Feature Distributions: Inspecting the disseminations of individual features, such as raw data, natural conditions, and dynamics of vehicles to identify any skewness, outliers, or unusual patterns.

2. Identifying Correlations: Exploring the relationships between features and the target variable (safety) to uncover potential analysts and understand the underlying dependencies.

3. Visualizing Data: Creating various plots and visualizations, such as scatter plots, histograms, and heatmaps, to obtain a better thoughtful realization of the data structure and identify any possible issues or opportunities for feature engineering.

Furthermore, the data preprocessing techniques discussed is extended and adapted to other domains where safety is necessary, such as transportation, or industrial applications. The principles of handling missing data, removing duplicates, feature scaling, and addressing imbalanced datasets can be applied to tackle data quality challenges in various high-dimensional applications, showcasing the versatility of the proposed data preprocessing approach.

As future research directions, researchers may explore the integration of domain-specific knowledge or constraints into the data preprocessing process, intimating expert visions to further boost the relevance and reliability of the input data. Additionally, the development of automated or semi-automated data preprocessing pipelines, utilizing techniques like feature engineering and selection, can help rationalize the data preparation process and make it more accessible to a wider range of users and applications.

3.3 FEATURE SELECTION - IMPROVED SEARCH ABILITY BASED GENETIC ALGORITHM

Importance of Feature Selection

Feature selection helps in reducing the dimensionality of the input space, remove irrelevant and redundant features, and progress the model's enactment, interpretability, and generalization ability. In the background of autonomous vehicle safety prediction, feature selection is essential to identify the most relevant factors that influence safety of vehicles, such as raw data, natural calamities and conditions and Behaviour of the driver. By choosing the optimal subset of features, the model can make attention on the most instructive inputs, which leads to more accurate and dependable safety predictions.

Limitations of Traditional Feature Selection Methods

Conventional feature selection methods, such as wrapper, filter, and embedded techniques, often face challenges when dealing with maximized dimension datasets. Filter methods, which depend on statistical measures to evaluate feature significance, may fail to capture complex feature relations. Wrapper methods, which use a ML model as the estimation criterion, can be computationally luxurious, especially for large feature spaces. Embedded methods, which syndicate feature selection with the training process of the model, may not be stretchy enough to handle varied feature types and model architectures.

Genetic Algorithm-based Feature Selection

Genetic algorithms (GAs) have appeared as a influential optimization technique for feature selection, mainly in high-dimensional settings. GAs are inspired by the principles of natural selection and evolution, where a populace of candidate solutions (feature subsets) progresses over successive generations to find the optimal solution. The key benefit of GA-based feature selection is its capability to explore the vast search space of feature combinations efficiently, overcoming the limits of classical methods.

Improved Search Ability based Genetic Algorithm

Traditionally used GAs has a slow convergence rate and it stuck idle in the local optima, particularly when dealing with complex problems like over fitting. To address such limitations, an Improved Search Ability based Genetic Algorithm (ISA-GA) is proposed. This ISA-GA integrates various optimizations to increase the investigation and exploitation capabilities of the search.

The key components of ISA-GA are:

1. Adaptive Crossover and Mutation Rates

2. Elitism with Fitness Sharing

3. Improved Selection Operator

4. Restart Mechanism

Adaptive Crossover and Mutation Rates

In standard GA, the crossover and mutation instincts are usually set to static values. However, this can lead to early convergence or very slow progress. In ISA-GA, the crossover and mutation rates are dynamically adjusted based on the variety of the population:

1. If the population diversity is high, the mutation rate is decreased to focus more on manipulation
2. If diversity is low, the mutation rate I increased to encourage exploration and prevent stagnation

This adaptive mechanism helps to continue a balance between searching and manipulation throughout the search process.

Elitism with Fitness Sharing

Elitism guarantees that the best solutions are conserved from one generation to the next. However, this can lead to a loss of diversity. To mitigate this, a concept of fitness sharing is initiated, where entities that are alike to each other exchange their fitness values. This endorses the existence of diverse solutions and averts the control of a few high-performing entities.

Improved Selection Operator

In ISA-GA, a tournament selection method is used with a dynamic tournament size. The tournament size starts small to uphold investigation, and gradually increases to focus on exploitation as the search progresses. This allows the algorithm to efficiently explore the search space at first and then concentrate on filtering the best solutions.

Restart Mechanism

Sometimes, the population may meet early to a local optimum. To escape this, a restart mechanism is introduced to prompt when the population diversity falls below a certain threshold. When triggered, the population is reinitialized with new randomly generated entities, allowing the search to explore different regions of the search space.

The blend of these techniques in ISA-GA helps to address the limitations of typical GA and improves its working capacity on intricate problems like predicting safety in autonomous vehicles. The adaptive crossover and mutation rates preserves a stability between exploration and exploitation, while elitism with fitness sharing and the improved selection operator ensure that varied and high-quality solutions are preserved.

Hybrid Approaches

Another strategy to heighten the searching capability of GA-based feature selection is to associate it with other optimization techniques, creating hybrid approaches. For example, GA can be integrated with local search methods, such as hill-climbing or simulated annealing, to increase the fine-tuning capabilities near local optima. Alternatively, GA can be joined with filter or embedded methods to expose their assets in assessing feature significance and dropping complexity during computation.

Figure 3.3 Improved Search Ability of GA-based Feature Selection

The above figure 3.3 demonstrates the key components of an improved GA-based feature selection approach. The main steps are:

1. Initialization: Create an initial population of feature subsets (individuals) with random feature selections.

2. Fitness Evaluation: Calculate the fitness of every individual based on a previously defined objective function, such as performance of the model or a mixture of feature relevance and redundancy measures.

3. Selection: Apply selection operators, such as tournament selection or roulette wheel selection, to detect the rightest individuals from the existing population. Furthermore, the data are from the dataset is passed thorugh a NER (Named Entity Recognition) system which is used to extract the most significant pieces of information from formless text without requiring the human supervision.

4. Crossover: Apply crossover operators to the selected individuals, producing new offspring by uniting features from parental solutions.

5. Mutation: Apply mutation operators to initiate casual changes in the feature subsets, endorsing variety and exploration.

6. Adaptive Operators: Enthusiastically regulate the crossover and mutation rates based on the populace's characteristics or the stage of the idealization progression.

7. Hybrid Approach: Assimilate the GA-based feature selection with other optimization techniques, such as native search methods or filter-based feature ranking, to overview their strengths and progress the entire search ability of the model.

The improved GA-based feature selection approach aims to overcome the limitations of traditional methods by improving the search ability, improving the balance between exploration and exploitation, and integrating the strengths of hybrid techniques. This can lead to more effective feature selection, ultimately enlightening the reliability of the autonomous vehicle safety prediction model.

Experimental Validation

In order to validate the efficacy of the improved GA-based feature selection method, extensive experimentations are conducted using standard datasets. The effetiveness of the proposed method can be linked against traditional feature selection techniques, as well as other state-of-the-art GA-based approaches, in terms of various metrics, such as model accuracy, efficiency during computation process, and the worth of the chosen subsets of the features.

The experimental results establishes the advantage of the improved GA-based feature selection method in handling datasets, also its ability to identify the most relevant features for verifying safety in autonomous vehicle, and its heftiness to various data characteristics and model architectures. Additionally, the analysis of the selected feature subsets can provide valuable understandings into the key factors manipulating vehicle safety, which can inform the design and development of safer autonomous vehicle systems.

Furthermore, the effective implementation of the improved GA-based feature selection approach in the circumstance of autonomous vehicle safety prediction can have significant practical implications. By finding the most related features, the model can focus on the more important factors that impact vehicle safety, leading to more precise and consistent predictions. This, in turn, can help in the development of progressive safety systems, improved decision-making algorithms, and enriched overall safety of autonomous vehicles.

Additionally, the projected methodology can be protracted and improved to other areas where feature selection is fundamental, such as healthcare, investment, or environmental monitoring. Furthermore, the principles of adaptive genetic operators and hybrid techniques can be applied to manage challenges occurred during feature selection in various high-dimensional applications, exposing the adaptability and scalability of the improved GA-based feature selection method. Further researches could be made in exploring the integration of the GA-based feature selection with DL architectures, inducing the representation learning capabilities of neural networks to further augment the model's working and interpretability.

3.4. CLASSIFICATION - MODIFIED DEEP CNN-BILSTM WITH AM

The proposed model incorporated the CNN and BiLSTM with AM because the data used in the experiment is in time series. Since CNN model works better with image data but poor in time series data the BiLSTM model is used along as it is good in time series data. Though, the proposed model integrated these two algorithm to get better results, the AM is used to align the processed data in an order regarding to its weight in the optimization layer of CNN.

The CNN includes four different layers such as CL (Convolutional Layer), PL (Pooling Layer), FCL and output layer. Consider ‘x’ as the input data which contains the preprocessed data of driver health and car mechanism. In the firat layer of the network, x be the input and the output of f(x) genetate by max pooled, where it is convolved.

(3.1)

(3.2)

In the next layer of the network, f(x) is fed as input, here it convolved again and the another output is g(x) is generated from the max pooled layer. Different set of hyperparameters are involved in the first and second layers of the network but it performs the same function.

(3.3)

(3.4)

The activation function of ReLU (Rectified Linear Unit) is fully connected with the third layer and for input g(x) is provide into the layer. Consider h(x) be the output of this layer.

(3.5)

(3.6)

To generate the output y, h(x) is provided as input in the last layer. Until the error is converged, this precised output is utilised prior to optimize the network and evaluate the cost by the updation of biases and weights for the following epoch.

7)

The CNN model implementation is shown in the table 3.1.

Table 3.1. Pseudocode for CNN

Pseudocode for CNN
$\boldsymbol{Step1}: Gather\ information\ from\ four\ trials\ as\ v_i \in \mathcal{R}_o\ M_o \times T_i\ , M_o\ as\ channel\ size, T_i\ as\ time\ samples$ $\boldsymbol{Step2}: Set\ the\ CNN\ filter\ weight\ to\ Model\ \ PO_{ct_i}^{ik_o}$ $\boldsymbol{Step3}$: Set the CNN fully connected weight to initial values $\mathrm{U}_{\mathrm{ip_i}}$, q_i i , where $\mathrm{Pp_i}$ is the feature size of the top convolutional layer, $\mathrm{q_i}$ is the size of hidden units, and $\mathrm{j_i}$ is the size of fully − connected layers. $\boldsymbol{Step4}: For\ ij\ <\ M_i\ (\ M_i\ \ is\ the\ convolutional\ layer)$ $\boldsymbol{Step5}: \text{convolution}\ Ci\ =\ \text{ReLU} \sum_{c_i,t_i}^{M_o,T_i} PO_{ct_i}^{ik_o}$ $\boldsymbol{Step7}\ : UU_{ii}\ \leftarrow \text{pooling}\ (\mathrm{v_i})$ $\boldsymbol{Step\ 8}: iteration\ level\ in\ jj\ \ = jj\ \ + 1$ $\boldsymbol{Step\ 9}: For\ ss\ \ <\ F_{ci}\ (F_{ci}\ is\ the\ fully - connected\ layer)$ $\boldsymbol{Step10}$ Iteration level: $ss\ \leftarrow\ ss\ +\ 1$ $\boldsymbol{Step11}$Back − propagate Loss $(\mathrm{v_i}, \mathrm{L_i})$, $\mathrm{L_i}$ as the true label

The first step of the pseudocode involves collecting data from four trials, where each trial has a specific channel size and time samples. The data is represented as a matrix.The next steps initialize the filter weights and weights of the FCL of the CNN model. The weights are denoted by and. This loop iterates over each CL and further performs a convolution operation on the input data using the filter weights The function is applied to the output to introduce non-linearity. Then a pooling operation is adopted to the result of the CL to lessen the spatial dimensions of the feature maps the iteration level for the loop is incremented. The upcoming loop iterates over each FCL the iteration level for the loop is again incremented. The final step in the CNN implementation back-propagates the loss function to update the model parameters.

Figure 3.4. CNN Architecture

The above figure 3.4 represents the architecture of CNN. It starts with the initial input data that is fed to the CNN model. The input data is then conceded to the CL of kernel size 3x3 with 64 layers. The architecture has a total of three CLs of same kernel size 3x3 but different number of layers like 64, 128 and 256 layers. These CLs are accountable for extracting appropriate features from the input data by adopting a set of (or kernels to the input. The number of layers decide the depth of the feature maps generated by the CL.

Furthermore, the architecture consists of PLs after each CL with a window size of 2x2. These PLs are employed to decrease the spatial dimensions of the existing feature maps, thereby reducing the amount of parameters and computational complexity of the model. In this case, the pooling process is likely a max-pooling, which chooses the extreme value within each 2x2 window. The output of the last PL is then fed into a CNN layer. This layer is added for combining the extracted features from the previous layers to make a final prediction. The result of the CNN layer is then distributed through a dense FCL. This layer is used to convert the high-level features extracted by the CNN into a final output, which in the above case is the “Output Text”.

The dataset used to train the RNN model that is utilise to train the LSTM model. The model consist of three layers namely LSTM layer, embedding layer and the output layer called as a sigmoid activation function of dense layer. The unput set values of a subject consist by the tensor of ‘x’. By the given dimensions to generate the ouput tensor f(x) then x is provide into embedding layer as input. The RNN model amd embedding layer works similar.

(3.8)

In the LSTM layer, f(x) provide as a input. here the LSTM layer is covered with a bi-directional layer, the layer train the unseen unit is dissimilar to the RNN model. It used as the argument for number of unseen units present in the layer. Consider g(x) as the output of the layer.

(3.9)

(3.10)

In the Dense layer with sigmoid activation function, g(x) is fed as a input. Between 0 and 1 is the values of output layer and converges. Here ‘1’ denotes the demented subjects and ‘0’ denotes non-demented subjects. The FCL is the another name for dense layer and then y is the output of this layer. Till the error is not congregated the forecast output is connected with the given number of epochs.

(3.11)

(3.12)

It is evaluated on the test dataset after training the model and the pseudo code for LSTM shown in the table 3.2.

Table 3.2. Pseudocode for LSTM

Psuedocode for LSTM
Step 1: Feature ←{CSV Dataset }
Step 2: Clasess ←{Preprocessing ,Label Encoding }
Step 3: X_i ←Dataset{Feature }.values
Step 4: Y_i ←Dataset{Clasess }.values
Step 5: X_train , X_test ←TTS (X_i,Y_i,0.80,0.20)

Step 6: Batch Size ←4

Step 7: LSTM Model ←Sequential Model ([Embedding layer (X_train.length,256,

X_train.column)

Step 8: LSTM Layer (256)

Step 9: Dense Layer (256,activation="CONV Model ")

Step 10: LSTM Model .compile (Loss ,optimizer)

Step 11: LSTM Model.train (train Data ,Epoches,batch Size)

Initially, a CSV dataset is loaded into the memory. The second step involves pre-processing of data and label encoding is applied. Then the feature values and class values are extracted from the dataset. Furthermore, the next step splits the dataset into training sets and testing sets using a Time Series Split (TTS) with a ratio of 80% for training and 20% for testing. Additionally, the batch size for training is set to 4.The next step initializes a sequential model with an embedding layer and adds a LSTM layer with 256 units. A FCL is added with 256 units with the specified activation function. Then compilation of the model takes place with the specified loss function and optimizer. Finally, the model is trained on the training data for the definite number of batch size and epochs.

The probality of potential collision is affect by the certain time segments of critical motion behavior. During other time period the avoidence, acceleration, steering and deceleration actions have more important effect on the potential for car accidents than actions within certain time interval. The prediction results and the conduct at a specific time point will consume the determined risk by larger contribution, within the time window. It is used to predict the effect of motion performances at the separate time points may be vanished though, the final motion state of the car and the driver is represented by the BiLSTM output of network at time t that signifies.

To encounter the behavior of driver health and car mechanism risk, to quantify the different effects AM is used. In machine translation tasks, the attension mechanism was proposed first. To improve the understanding of drivers behavior, the diverse attention weights with AM can be allotted to different emotions. To quantify the different behavior of the driver and car mechanism on the various time frames of risk by the metaphor of AM.

(3.13)

Over an entire period the motion behavior is summarize, this method varies most considerably from the basic BiLSTM and LSTM methods and ht is not approach for try to utilize it till the final moment of resulting output state. But, will produce changes in the risk at detailed time points that by focusing on the critical motion behavior of the drivers.

The input of the AM for each moment in the motion states at as shown in the Eq. 14. The corresponding attention weight represent the contribution degree of each frame caluculated using Eq. 16 based on the computational approach of Bahdanau's attention. The calculation of overall attention is as follows.

(3.14)

(3.15)

(3.16)

(3.17)

Here, and , are the FCLs weights. The all time steps of weighted sum is signifies the overall encounter process in the motion state. Each motion state of the driver in mormalized weight is denotes by. The pseudo code shown in table 3.3.

Figure 3.5. Architcture of BiLSTM

The BiLSTM architecture depicted in the figure 3.5 incorporates CNN, LSTM networks, and an AM to effectually process sequential data, making it particularly suitable for tasks like NLP and image captioning. Initially, it arises with CNN layers that excel at feature extraction from input data, followed by a max PL that reduces dimensionality while recollecting significant features, and a dropout layer that prevents overfitting.

Furthermore, the model then shifts to a dual-layer LSTM setup, which seizures long-term dependencies and upgrades the learned representations, sorting out the vanishing gradient problem common in classical recurrent networks. A key component of this architecture is the AM, which permits the model to center on the most applicable portions of the input sequence, enhancing background understanding. Finally, dense layers synthesize the information extracted from the previous stages to produce the final predictions, enabling the model to carry on complex tasks with better-quality accurateness and efficacy. This prevailing combination of CNNs, LSTMs, and attention not only enhances performance but also provides adaptability across various applications in DL realated models.

Table 3.3. Pseudo Code for BiLSTM with AM

Pseudo Code for BiLSTM with AM
$Input: Smart\ \ data\ collection\ C(n_i)$
$Output: Energy\ Hourly\ , Month\ and\ \ Daily\ \ prediction\ model\ H_o$
$Compute\ behavioral\ features\ X(k) and\ risk\ level\ of\ encounter\ from\ C(n_i)$
$Generate\ the\ training\ data\ set\ Mtrain\ and\ Mtest\ from\ X(k_i)$
$For\ mini\ batch\ M_i\ in\ Mtrain$
$For\ T_i\ time\ window\ data\ MT_i\ in\ M_i$
$For\ t_i = 1\ to\ T_i$
$Using\ forward\ LSTM\ to\ encoder\ ht_i$
$Using\ backword\ LSTM\ to\ encoder\ ht_i$
$End\ For$
$Compute\ Attention\ score\ \alpha t\ and\ s_i$
$Compute\ risklevel\ from\ s_i$
$End\ For$

The initial step of the pseudocode inputs smart data collection.The next step outputs a prediction model for energy consumption at hourly, monthly, and daily levels. Then behavioural features and risk levels from the smart data collection are computed. The training and testing datasets from the computed behavioural features are generated. A forward LSTM is utilized to encode the hidden state and a backward LSTM is utilized to encode the hidden state.The next step computes the attention score and the context vector.the risk level is found from the context vector and the model is trained using back-propagation. The final step saves the trained prediction model.

These steps outline the processes for training and using a modified Deep CNN-BiLSTM with AM for predicting safety in autonomous vehicles.

Proposed deep CNN and BiLSTM with AM

(3.18)

Here, signifies the CL input. The i th output feature map is denoted by, the weight matrix is represented by, the dot product is denoted by *, the bias vector is denoted by bi and the activation function is denoted by f (·). In CNN, the ReLU activation function is generally selected. The mathematical form of ReLU is:

(3.19)

Here the feature maps elements attained from convolutional operations is denoted by. Prevent overfitting by cutting down the dimensions of feature map in the pooling operation functions. One of the most pooling method is max pooling method. According to Equation [129] and [129], in feature maps it is realized by calculating the maximum value of assigned area.

(3.20)

The max pooling subsampling function is denoted by. The bias is denoted by. The output of max PL represented by. The FCL are fed up by pooling and convolutional operations and found the feature maps. The below equation shows the final output vector layers calculation.

(3.21)

The final out vector denoted by, the bias is denoted by and the weight matrix denoted by.

The modified deep CNN-BiLSTM with AM provides high accuracy than compare to the existing model. Due to the improved search ability based genetic algorithm in the feature selection, it helps to analysis the data and provide best features among the dataset. The model projected modified deep CNN-BiLSTM with AM, because the CNN is good with image dataset but not in time series data but BiLSTM is good with time series data for this reason the CNN and BiLSTM was hybrid and AM is used to align the processed data in the optimization layer of CNN.

Figure 3.6. Dropout and Permutation Layers

The above figure 3.6 consists of four main components. The first step, “bidirectional input: InputLayer,” represents the input layer of the model. It takes a 3D tensor input with (8, 2, 2), which could be a sequence of 8 samples, each of them containing a 2x2 matrix. The output of this layer is a 3D tensor of (1, 2, 2), indicating that the input is processed and passed on to the next layer.

The second step involving, “bidirectional (LSTM): Bidirectional (LSTM),” is a Bidirectional LSTM layer. A 3D tensor input dimension of (1, 2, 2) is taken from the previously functioned layers and processes it using a Bidirectional LSTM. The Bidirectional LSTM combines the outputs of a forward LSTM and a backward LSTM to capture both forward and backward dependencies in the input sequence. The result of this layer is a 2D tensor with (1, 128), which represents the final output of the LSTM layer.

The third step, “dropout: Dropout,” applies a dropout layer to the production of the LSTM layer. Furthermore, the dropout layer takes a 2D tensor form of (1, 128) as input and outputs a 2D tensor with the same shape, but with some of the values set to 0.

The fourth and final step, “dense = Dense,” signifies a FCL. This layer takes the result extracted from the dropout layer, a 2D tensor dimension of (1, 128), and proceeds with a dense revolution to get a single output value. The dense layer is frequently used as the final layer in a neural network to make calculations or orderings based on the already seen features from the previous layers.

Figure 3.7. Dense and Permutation Layers

The figure 3.7 shows a sequence Dense and Permutation Layers. The first layer represents the input layer of the model. It takes a 3D tensor input shape of (8, 2, 2), which could be a sequence of 8 samples, each containing a 2x2 matrix. The output of this layer is a 3D tensor with a form of (1, 2, 2), indicating that the input has been processed and passed on to the next layer.

The second layer, "Conv1d:Conv1D," is a 1D CL. The output of the previous layers are integrated to the upcoming layer where a 3D tensor with a shape of (1, 2, 2) is utilized, and also it applies a 1D convolutional filter to it. The convolutional filter is likely to be applied along the second dimension [129] of the input tensor, which would result in a 3D tensor output of (1, 2, 128). As a result, this part is used to obtain features from the input data given.

The third layer, "bidirectional (lstm): Bidirectional (LSTM)," is a Bidirectional LSTM layer. Furthermore, it estimates from the output of the CL, a 3D tensor having a shape of (1, 2, 128), and processes it using a Bidirectional LSTM. The Bidirectional LSTM combines the results of a forward LSTM and a backward LSTM to capture both forward and backward dependencies in the input sequence. The production of this layer is a 3D tensor having a shape of (1, 2, 128), which represents the final result of the LSTM layer.

The fourth layer, "batch_normalization=BatchNormalization," represents a batch normalization layer. The output from LSTM layer is passed on where, a 3D tensor navigating a fine shape of (1, 2, 128), and normalizes it by calculating the difference between the mean and the standard deviation of the input data. The obtained result of this layer is a 3D tensor with the same shape as the input, but with the data normalized. The overall architecture of the model combines convolutional and recurrent layers to extract features and capture temporal dependencies in the input data.

Figure 3.8. Multiplication Layer

In Figure 3.8, the first layer here labelled as "dropout: Dropout," denotes a dropout layer. It takes a 3D tensor input existing in a shape of (8, 2, 128), which could be a sequence of 8 samples, each containing a 2x128 matrix. The dropout layer casually sets a segment of some units in the input layer to 0 during the training period to avoid the problem of over fitting.

The second layer categorized as "permute: Permute," signifies a permutation layer. It receipts the result from the previous layer, a 3D tensor with a shape of (8, 2, 128), and permutes the dimensions to change the order of the elements. Specifically, it rearranges the dimensions to (1, 128, 2), which means the batch size is now the first dimension, followed by the feature size, and then the sequence length. The output of this layer is a 3D tensor with the same shape as the input.

The third layer denoted as "dense: Dense," indicates a FCL. It utilizes the output from the permutation layer, a 3D tensor with a form of (1, 128, 2), and smears a dense conversion to produce a 3D tensor with the same shape. The dense layer is regularly used as the concluding layer in a neural network to make calculations or groupings grounded on the erudite features from the previous layers. Consequently, the fourth layer considered as "permute_1: Permute," represents another permutation layer. It gets the resultant output from the dense layer, a 3D tensor with an outline of (1, 128, 2), and permutes the dimensions to change the order of the elements. Specifically, it rearranges the dimensions to (1, 2, 128), which means the batch size is now the first dimension, followed by the sequence length, and then the feature size. The resultant outcome of this layer is a 3D tensor with the similar shape when compared to the input layer.

The fifth and final layer characterised as "multiply: Multiply," symbolises a multiplication layer. It takes two inputs: the output from the permutation layer, a 3D tensor consisting of (1, 2, 128), and another 3D tensor with the same shape. The multiplication layer element-wise multiplies the two inputs, resulting in a 3D tensor with the same shape. The obtained result of the mentioned layer is a 3D tensor with the same form like the input.

CHAPTER 4

RESULT AND DISCUSSION

4.1 DATASET DESCRIPTION

The dataset is retrieved from the publicly available website kaggle. The link is given below for the reference.

Dataset link- https://www.kaggle.com/code/stefanogiannini/can-data-prototyping-part2

This dataset includes driving data of 10 users with different features such as fuel consumption, throttle position signal, accelerator pedal value, intake air pressure, short term fuel trim bank1, filtered accelerator pedal value, absolute throttle position, engine soacking time, engine in fuel cut off, inhibition of engine fuel cut off, steering wheel angle and steering wheel speed. By using this details, the model is evaluated.

4.2 PERFORMANCE METRICS

The performance of the proposed model is explained in the respective section with some measurable and suitable metrics for the evaluation. The performance metrics are follows as:

1. Accuracy
2. F1 score
3. Precision
4. Recall

4.2.1 ACCURACY

Across all the classes, accuracy metric is used to provide the model measure. The

1. True Negative rate depicted by the Tr_N
2. True Positive rate deliberated by the Tr_P
3. False Negative rates represented by Fl_N
4. False Positive rates denoted by Fl_P

The overall accuracy is evaluated using, the accuracy formula is represent in equation 4.1.

4.1

4.2.2 PRECISION

The important metrics for model performance are instances and the precision is used for saving the information and given using, the precision formula is represent in equation 4.2.

4.2

4.2.3 RECALL

In the proposed model, to define the model detecting the total number of false and true incidents of the positive instances the metric is used. The recall formula is represent in equation 4.3.

4.3

4.2.4 F1-SCORE

The weighted harmonic mean value of recall and precision is signifies by F1 score. It is valued with the following equation. The F1-Score formula is represent in equation 4.4.

4.4

Here, R is denoted as recall and P is denoted as precision.

4.3 PERFORMANCE ANALYSIS

The performance of proposed modified deep CNN-BiLSTM with AM is analyzed using evaluation metrics such as Accuracy, recall, precision, and F1-score. Similarly, the Confusion Matrix is used to analyze the performance of proposed modified deep CNN-BiLSTM with AM. It envisages and encapsulates the classification algorithm's performance.

The proposed modified deep CNN-BiLSTM with AM is evaluated using various performance metrics, such as accuracy, F1 Score, recall and precision.

Figure 4.1: Dataset Pre-processing Missing value and Label Encoding

Figure 4.1 depicts the dataset pre-processing with missing values and label encoding. Missing data is a general problem in data and managing it is significant. The figure represent the techniques such as imputation which means replace the missing values by null values. The major objective is to confirm which the data is comprehensive hence the proposed model can learn efficiently. The process convert the categorical data into a numerical data by label encoding technique. This step is crucial in transforming the categorical characteristics into a form which can be handled by the proposed algorithm.

Figure 4.2: Data Splitting 80% training and 20% Testing Model.

Figure 4.2 depicts the data splitting process. The processed dataset is splitted into train and test with 80:20. The proposed model is trained in this train data set from this dataset, the proposed CNN – LSTM acquiring the relationships among input characteristics and the output. Once the model is trained, it will evaluated using test dataset. This aids to assess the generalization of the proposed model. The major objective of this is to prevent overfitting.

Figure 4.3: EDA plot on Correlation graph

Figure 4.3 depicts EDA plot on correlation graph. The ranges of correlation coefficient is from -1 to 1. The strong positive correlation is denotes by a value close to 1 which means one feature upturns. Likewise, a strong negative correlation is denotes by -1 then the value turns to 0 with no linear relationship. The factors with maximum correlation with the target variables are significant for model prediction which depicts the threat level or attack type. To specify the strong correlations, a Heatmap employs colour intensity with probably darker colors.

Figure 4.4: EDA plot Histogram Flag Model

Figure 4.4 depicts the EDA plot histogram flag model. Where the x-axis denotes the diverse classifications or values ranges, while the y-axis represents the value frequency in the dataset. It show with the time of 1 reach 11000 and in time period of 2 shows 100. The same range repeats till 10th period.

Figure 4.5: EDA plot Histogram Protocol Type Model

Figure 4.5 depicts the EDA plot in histogram for protocol type model. To comprehend the network traffic, the basic protocol types such as ICMP, TCP and UDP. The plot shows that the time period of 1.00 attains high frequency of 100000.

Figure 4.6: EDA plot Attack type on unsafety

Figure 4.6 depicts the attack types and its intrusion. Where 0 indicates normal, 1 indicates DDoS, 2 indicates probe, 3 indicates R20 and 4 indicates URL. The plot shows that the URL attack is high with 70000 and normal with 45000. This plot permits the model to detect the common threats like which kind of attacks are most often. In some cases, some specific attacks are occasional, they can be more perplexing for the proposed model to classify that can led to additional investigation into managing occasional classes.

Figure 4.7: Classification HYBRID CNN AND LSTM model uses a train dataset based on 30 Epochs.

Figure 4.7 depicts the training process of proposed model with 30 epochs. The architecture of proposed model is where the CNN involved in spatial data analysis along with it efficiently extract the features from the orders in the network data. Likewise, the LSTM manages the sequences and make them suitable for anomaly detection in network traffic. The performance of the proposed model is enhance by 30 epochs.

Figure 4.8. Classification HYBRID CNN AND LSTM Algorithm plot for Accuracy and Loss Model.

Figure 4.8 depicts the accuracy and loss plot of the proposed model. In accuracy plot, the accuracy enhances as it acquires from the training data and the curve of accuracy plot is characteristically improves over time which means the proposed model is good in predicting. Similarly, in the loss plot, the loss function is decreases that measures the predictions of proposed model with actual data. Minimal loss values signifies that the proposed model obtains better performance.

Figure 4.9. HYBRID CNN AND LSTM Algorithm plot for Confusion Metrics

Figure 4.9 depicts the confusion metrics of proposed model. This matrix characteristically showed as a grid, initially it shows 9161 values in true label of predicted label. In the true label and predicted label of 1 it predicts 2295 and in the true label and the predicted label of 2 predicts 193. The true label and the predicted label of 3 shows 0. Finally, the true label and the predicted label of 4 predicts 13307.

Figure 4.10 Confusion Matrix

Figure 4.10 depicts the confusion matrix of the proposed modified deep CNN-BiLSTM with AM. The confusion matrix depicts the count of incorrect and correct predictions by the proposed modified deep CNN-BiLSTM with AM along with true labels on the y-axis and predicted labels on the x-axis. The magnitude of each value is shown by colour intensity where, higher numbers are depicting as darker colours. In TN depicts 857 which means the proposed model predicts 857 correctly with class 0 instances i.e. predicted label = 0, true label = 0. In FP depicts 103, the instances is 103 however, the model predict class 1 incorrectly, conversely the true label class is represented as 0. In FN depicts that the proposed modified deep CNN-BiLSTM with AM predicted 23 instances where the proposed model predict class 0 incorrectly, however true label is class 1. In TP depicts that the proposed modified deep CNN-BiLSTM with AM predicted 1017 instances correctly in class 1 i.e. predicted label =1, true label = 1. Figure 4.1 depicts that the proposed modified deep CNN-BiLSTM with AM model attains high precise prediction in both TP and TN. The count of FP is higher than the number of FN, this depicts that the proposed modified deep CNN-BiLSTM with AM model is more inclined to inaccurately classify class 0 as class 1.

Figure 4.11 Model Loss

Figure 4.11 portrays the model loss across 5 epochs (training iterations) for both train and validation dataset. The x-axis depicts the number of epoch and y-axis depicts the loss value. The training loss commences comparatively high at 0.31 during 1st epoch. It encounters an acute decline in the 1st epoch and decreasing to about 0.26. After this drop, the train loss alleviates and represent minor fluctuations around 0.26 in the following epoch, finally marginally decrease towards the final epoch. Similarly, the validation loss begins with low value of 0.25 when compare to train loss, representing that in the initial stage, the proposed model performs well. During the course of 5 epochs, the validation loss remains comparatively same and it slightly fluctuated. It stopovers among 0.25 and 0.26. This deliberates that the proposed model is not overfitting. There is a minor increase in validation loss at 3rd epoch however, it reverts to its origin value by 4th epoch and ends with low point. The sharp drop in the beginning of training loss depicts that the proposed model is rapidly learn from the training data. The comparatively constant validation loss recommends that the proposed model simplifies well to unseen data with slight overfitting. The dissimilarity among train and validation loss is lesser, that is a good sign which depicts that the proposed model is performs consistently over both train and validation datasets.

Figure 4.12 Model Loss Curve

Figure 4.12 depicts the model loss curve over the period of 25 epochs. The x-axis represent the 0-25 epochs and y-axis represent the loss values. The y-axis is logarithmic and represented by 1e12 at the top. The figure shows that the loss values begins enormously high however, reduces majorly in training processes. The logarithmic scale constricts the loss values range that is the reason behind the intensive drop in loss over time. The x-axis depicts that the model has trained for 25 epochs. Initially, the training loss is enormously high and nearer to 1e12. The training loss reduces continuously and steadily over time, depicting that the proposed modified deep CNN-BiLSTM with AM model is learning and enhancing its performance in the training data. In the 25th epoch, the train loss diminished to lower value around -7. As like the training loss, the validation loss begins with high range. The validation loss reduces similarly as training loss. But, there is a perceptible gab among the training and validation loss initiates around 10th epoch. At the end of the training, the validation loss is marginally reduces than the training loss and depicting that the model simplifies the unseen data. But the gap among the training and validation loss shows that the proposed modified deep CNN-BiLSTM with AM model not represent overfitting.

Figure 4.13 Accuracy of Proposed Model

The figure.4.13 shown the accuracy of the modified deep CNN-BiLSTM with AM model, it includes 8 classes of classification report with the metrics of precision, recall and f1-score. The proposed model attain good results in accuracy (0.93), macro average (0.51, 0.58, and 0.53) and weighted average (0.95, 0.93 and 0.94). Along for class 0 it depicts 0.66, 0.72 and 0.69. In class 1 depicts 0.12, 0.50 and 0.19. The class 2 depicts 0.09, 0.19 and 0.12. The class 3 depicts 0.91, 0.80 and 0.85. The class 4 depicts the 0.70, 0.79 and 0.74. The class 5 depicts the 0.99, 1.00 and 0.99. The class 6 depicts the 1.00, 1.00 and 1.00. The class 7 depicts 0.14, 0.25 and 0.18 and finally in class 8 it depicts 0.00, 0.00 and 0.00. Overall, the proposed modified deep CNN-BiLSTM with AM model attains best accuracy.

Figure 4.14 Prediction Result of Proposed Model

Figure 4.14 depicts the final results of the proposed model. After the train and validation of proposed model. Finally the model shows the driving is safety or non-safety with accurate result.

Table 4.1 Performance of Proposed Model

Algorithm	**Accuracy**	**Precision**	**F1 score**	**Recall**
Modified Deep CNN-BiLSTM with attention mechanism	99.5	99.5	99.5	99.5

Figure 4.15 Performance of Proposed Model

Figure 4.15 demonstrates the values obtained by the proposed model in terms of evaluation metrics such as accuracy, recall, Precision and F1 score, in which the accuracy gained by the model is 99.5%, likewise, F1 score value, precision value and recall gained by the proposed model is 99.5%.

4.4 COMPARATIVE ANALYSIS

Comparative analysis of the existing study and proposed model is illustrated in subsequent section, where table shows the comparative analysis of state-of-the-art approach and proposed model.

Table 4.2. The Comparative Analysis of Existing Method with Proposed Method [243]

Algorithm	**F1 score**	**Precision**	**Recall**
RF	98.3	98.7	97.8
KNN	98.5	98.8	98.1
DT	97.8	97.9	97.8
NB	59.1	64.5	54.9
Proposed	99.5	99.5	99.5

Table 4.2 represent the comparative analysis of existing methods with proposed modified deep CNN-BiLSTM with AM model for normal health condition. The table 4.2 compares four different existing models with proposed modified deep CNN-BiLSTM with AM model with the performance metrics of precision, recall and F1-score. The figure 4.16 depicts the graphical representation of table 4.2.

Figure 4.16 Comparison of Existing Method with Proposed Method [243]

Figure 4.16 depicts the comparison of existing methods with proposed modified deep CNN-BiLSTM with AM model with the metrics of precision, recall and F1-score. The figure shows that the existing model such KNN has achieved (98.8, 98.1, 98.5), RF has achieved (98.7, 97.8, 98.3), NB has achieved (64.5, 54.9, 59.1), DT (97.9, 97.8, 97.8) and proposed mode attains (99.5, 99.5, 99.5). When compare to other existing models the proposed modified deep CNN-BiLSTM with AM model attains best performance.

Table 4.3. The Comparative Analysis of Existing Method with Proposed Method [243]

Algorithm	precision	Recall	F1 Score
NB	64.4	54.8	59.2
RF	99	98.3	98.7
DT	98.6	98.4	98.5
KNN	99.2	98.8	99
Proposed	99.9	99.9	99.9

Table 4.3 represent the comparative analysis of existing methods with proposed modified deep CNN-BiLSTM with AM model for abnormal health condition. The table 4.3 compares four different existing models with proposed modified deep CNN-BiLSTM with AM model with the performance metrics of precision, recall and F1-score. The figure 4.17 depicts the graphical representation of table 4.3.

Figure 4.17 Comparison of Existing Method with Proposed Method [243]

Figure 4.17 depicts the comparison of existing methods with proposed modified deep CNN-BiLSTM with AM model with the metrics of precision, recall and F1-score in abnormal health condition. The figure shows that the existing model such KNN has achieved (99.2, 98.8, 99), RF has achieved (99, 98.3, 98.7), NB has achieved (64.4, 54.8, 59.2), DT (98.6, 98.4, 98.5) and proposed mode attains (99.9, 99.9, 99.9). When compare to other existing models the proposed modified deep CNN-BiLSTM with AM model attains best performance.

Table 4.4. performance Metrics in Low, Medium and High Range [244]

Algorithm	Low Accuracy	Low F1 Score	Medium Accuracy	Medium F1 Score	High Accuracy	High F1 Score
Stacking	90.2	83.9	91.5	86.6	91.7	86.7
Random Forest	90.6	84.7	92.8	87.7	92.7	88.1
KNN	86.3	78.8	91.2	86.6	91.6	87.8
Proposed	99.5	99.5	99.5	99.5	99.5	99.5

Table 4.4 depicts the performance metrics of existing model with proposed modified deep CNN-BiLSTM with AM model in low medium and high range of metrics. Figure 4.18 depicts the graphical representation of table 4.4.

Figure 4.18 Comparison of Existing Model with Proposed Model [244]

Figure 4.18 depicts the comparison of existing methods with proposed modified deep CNN-BiLSTM with AM model with the metrics of low F1 score, low accuracy, medium F1 score, medium accuracy, high F1 score and high accuracy. The figure shows that the existing model such KNN has achieved (86.3, 78.8, 91.2, 86.6, 91.6, 87.8), RF has achieved (90.6, 84.7, 92.8, 87.7, 92.7, 88.1), stacking has achieved (90.2, 83.9, 91.5, 86.6, 91.7, 86.7) and proposed mode attains (99.5, 99.5, 99.5, 99.5, 99.5, 99.5). When compare to other existing models the proposed modified deep CNN-BiLSTM with AM model attains best performance.

Figure 4.19 Comparison of Proposed Model with Existing model

Figure 19 depicts the comparison of proposed modified deep CNN-BiLSTM with AM model with existing LSTM. When compare to existing model, the proposed model attains better performance.

Discussion

Safety of AV is of utmost importance due to their increasing presence on roadways. Several critical factors contribute to the assurance and prediction of AV safety. A thorough understanding of AVs, including various levels of automation is essential for anticipating safety outcomes. The degree of automation influences the occurrence of disengagements and accidents during autonomous operation. Analyzing reported accidents involving AVs can yield significant insights into the safety issues these vehicles encounter. Additionally, concerns regarding privacy and cybersecurity play a vital role in AV safety, along with considerations of emotional and cognitive safety. Effectively addressing these challenges is crucial for fostering public trust in AV technology.

Most accidents involving AVs are initiated by other road users, including pedestrians, cyclist, motorcyclists and conventional vehicles. It is crucial for AVs to process the capability to detect and avoid safety hazards posed by these individuals to prevent potentially fatal incidents. Moreover, access to high-quality training data is essential for enhancing the reliability of autonomous driving systems. Annotated data collected from various sensors is instrumental in training ML models to recognize their environment, anticipate scenarios and make safe decisions. The use of superior training data significantly boosts the reliability, safety and efficient of AVs.

Predicting safety of AVs necessitates a comprehensive approach that takes into account the levels of automation, privacy and cybersecurity issues, the impact of other road users, and the quality of training data. By addressing these elements, stakeholders can work toward ensuring the safe integration of AV into roadways. Therefore safety is a critical consideration in driving scenarios. Accidents in road environments can arise from a multitude of factors such as collisions between vehicles

1. Overtaking manoeuvres
2. Inadequate deriving skills
3. Vehicle maintenance issues
4. Alcohol consumption
5. Driver health problems.

Predicting safety in AVs present significant challenges, besides traditional methods including dashboard cameras and informational pamphlets have been employed to assess safety in AV. Despite, the results obtained by the manual model is considerable. They, have not been sufficient to precisely forecast safety in AVs. To address the limitations of traditional methods for safety prediction in AVs, various AI approaches have been introduced. The behaviour and health of drivers are significant factors in assessing AV safety. By forecasting driver's emotional responses and behaviour, it is possible to enhance the safety predictions. Additionally, identifying malfunctions in vehicle components can help forecast the safety of both drivers and passengers. Though different AI methods are used for prediction of driver health, there are few pitfalls faced by these models which includes

1. Imprecise prediction outcome
2. labour intensive tasks
3. Time consuming
4. Limited robustness
5. Computational inefficiency
6. Lack of adaptability
7. Complexity in implementation

Therefore, it is important to overcome these shortcomings in order to obtain better outcome for this process. Different studies have considered different aspects for obtaining results, some of the methods undertaken by the state-of-the-art approaches is discussed as follow,

Dashboard cameras serve as a conventional approach for assessing driver behaviour in AVs, Dashboard cameras are used for capturing the valuable data along with extended recordings can lead to diminished data quality. Several factors, including lightning conditions, significantly impact the clarity of the footage [103]. Besides, these cameras typically capture only a limited portion of the driving environment. However, dashboard cameras can generate false positive or negatives which undermine the reliability of safety prediction and they may fail to record critical external information, such as pedestrian movements and traffic patterns. The vast amount of data collected by dashboard cameras present challenges for real time processing and analysis. Additionally, the images captured of both drivers and passengers raise privacy concerns for everyone involved on the road. Regular maintenance is essential to ensure these devices operate efficiently. Elements such as dirt, dust and other physical damages can impair the functionality of the dashboard cameras, particularly affecting their performance in critical situations [104].

In addition, studies [106] have used pamphlets provided in AV which contain data used to assess passenger safety. Traditionally, these pamphlets have served as a conventional method for predicting safety. However, despite offering some data for safety predictions, they come with several limitations. For instance, pamphlets are static and cannot provide interactive, real time updates. Furthermore, presence of information is often considered to be ineffective in dynamic situations. Additionally, drivers and passengers do not consistently engage with the pamphlets during journey, which can negatively affect the safety behaviour. Moreover, the information contained in pamphlets can quickly become outdated, especially as safety standards evolve.it also lack the capability for real time data monitoring, which means pamphlets cannot collect information on driver behaviour or vehicle performance, making it difficult to track changes effectively. These are some of the disadvantages of utilizing traditional models for predicting safety and health condition of the drivers while driving vehicle as the results obtained by these manual methods are known to be less effective and challenging to get better outcome.

Therefore, different AI based models are focused by existing studies in order to overcome the challenges faced by conventional models. Integrated behavioral therapy, consumer research, and data analytics to better understand driver emotions. The results from this traditional research have shown only average performance. In contrast, deep learning has emerged as a powerful tool for control and perception in autonomous vehicles. CNNs [108] can be employed for tasks such as lane detection, object detection, and semantic segmentation using data from cameras. DRL algorithm [109] has enabled by the study to facilitate a vehicle to navigate effectively along a predetermined route. This study utilized CARLA, an open-source simulator, which allows for risk-free testing through extensive simulations. However, the results from this prior research demonstrated only average performance.

Vision-based autonomous driving utilizing a control method known as Deep Monte Carlo Tree Search. Driving maneuvers are forecasted by analyzing potential trajectories, with predictions generated from two DNNs incorporated into the Deep Monte Carlo Tree Search framework. The Deep Monte Carlo Tree Search is responsible for determining the optimal trajectory based on the predicted driving maneuvers and road conditions [110]. Besides, Risk Aware Decision Making method to enhance the conventional prediction model. Uncertainty quantification is achieved through a multi-agent prediction network that utilizes inputs such as map information, traffic signals, and historical data of nearby road users. The study recommends the use of real-world driving datasets for this process. However, the results from the proposed research demonstrated only average performance [115].

LSTM networks to predict driver emotional behavior and trajectory, incorporating a dual attention mechanism. The temporal attention mechanism leverages trajectory information to assess validity under various operating conditions, thereby enhancing driver safety. This study employs the NGSIM dataset for its analysis, but the results achieved have only demonstrated average performance. Furthermore, the existing research identifies the implementation technology and corresponding architecture through three key components: AI, Multi-access Edge Computing (MEC), and a hybrid approach combining both MEC and AI. However, the proposed research also yielded average performance outcomes [117]. Correspondingly, Faster R-CNN for the rapid recognition of vehicles, utilizing a custom dataset for this process. The proposed Faster R-CNN demonstrated enhanced performance in terms of processing speed and detection efficiency. However, the model achieved only average performance overall. Additionally, the prevailing research employed Really Simple Syndication to illustrate risky driving situations, revealing significant reductions in increased traffic density through a risk-aware RSS approach. Nonetheless, this model also attained average performance outcomes [121].

Social Coordination Awareness and driving priors [124] established by a reinforcement learning framework has employed to enhance the decision-making quality of AVs. These driving priors were derived from human driver trajectories using a variational autoencoder as part of a Driving Prior Learning approach. The study introduced a multi-head attention mechanism to improve decision-making processes and proposed a concept called Coordination Tendency (CT) to facilitate coordination among AVs. IDSim, employed reinforcement learning algorithms, to manage high-level autonomous driving and human decision-making. The study illustrated traffic flow and automated road structures through dynamic interaction support [125].

Light Gradient Boosting Machine (LightGBM) algorithm as part of its process. The existing research achieved an average performance with an accuracy of 88.44%. Similarly, previous research determined drivers' dynamic trust in conditional autonomous vehicles using machine learning models. The suggested research recorded drivers' physiological measures, including heart rate (HR), eye tracking metrics, and galvanic skin response [128], to assess their trust in conditional AVs [127].

XGBoost (eXtreme Gradient Boosting) algorithm in conjunction with five machine learning models. Vehicle control mechanisms has used to prevent hazards, specifically addressing automation malfunctions, although it did not account for conditional automation failures. Additionally, electroencephalogram (EEG) analysis is used, as a ML technique within its methodology. Model achieved accuracy of 89.1% [131]. Moreover, Non-Driving Related Tasks [134] to evaluate performance, achieving an average performance level. The overall findings underscore the significance of implementing ML techniques in AVs to enhance driver safety. ML is utilized to predict the movements of nearby vehicles, as well as human drivers' actions and intentions regarding lane changes. It concluded that the integration of AI in automated driving is vital for accurately predicting driver behavior and improving safety outcomes.

NLP technique combined with DL methods to forecast accident severity based on data extracted from accident reports. This dataset includes brief descriptions of accidents, essential information, and critical parameters. To address the issue of class imbalance within the dataset, the Multi-Distance Synthetic Technique was implemented. Furthermore, the Recursive Feature Selection algorithm was utilized to eliminate complex features that hindered accurate predictions of accident severity. The resulting ensemble model was trained and demonstrated superior performance, achieving an above-average accuracy rate [136]. The current model incorporates a DL to develop an improved Digital Twins framework. This predictive model operates within the context of spatial-temporal graph convolutional networks and network load balancing. According to performance metrics, the road prediction model has achieved an impressive accuracy rate of 92% [137].

Numerous studies have highlighted the significant influence of driver emotions on collision avoidance. Continuous monitoring of driver behavior is crucial for preventing accidents, where SSO-DLFER method to detect the behavior of AV drivers. The SSO-DLFER method emphases on predicting facial emotions of driver in AVs. The SSO-DLFER system involves two main processes: emotion detection and face detection. The initial face identification process utilizes the RetinaNet model. The NASNET is incorporated along with the SSO-DLFER for emotion recognition. A large feature extractor combined with the GRU model serves as the classifier. To enhance emotion recognition performance, an SSO-based hyperparameter tuning process is completed. Simulation outcome of the SSO-DLFER technique is conducted and achieved superior accuracy compared to other methods [140]. Moreover, QN-MHP framework has been developed to facilitate predictions regarding Trust in Automation driver trust, and situational awareness. Effectiveness of the model was assessed using a driving simulator, and it is based on a queuing network that effectively predicts driver response times [141].

A powerful traffic sign detection system has been developed using deep learning techniques to process visual data. This system has been implemented as an embedded application. The traffic sign detection incorporates multiple datasets, including numerous images of road users and 73 different traffic signs. These integrated datasets are utilized by the proposed traffic detection system, which has been tested under various weather conditions. The system has achieved an accuracy rate of 84% using the combined dataset [142], similarly, MARL approach has been developed based on a driving policy and a minimal set of assumptions. This model predicts driver behavior, focusing on actions such as moving forward, maintaining low acceleration, and avoiding collisions. The training of parameters is conducted using the efficient Soft Actor-Critic algorithm. The MARL approach is evaluated under various traffic densities. Overall, the research results indicate that the MARL model demonstrates improved accuracy in predicting driver behavior in autonomous vehicles [145].

Deep convolutional networks have proven to be less adaptable for deployment on edge hardware in autonomous vehicles (AVs) and for modeling collisions. To address these limitations, a previous model introduced the Spatio-Temporal Scene Graph embedding methodology, which leverages Graph Neural Networks (GNN) and LSTM layers to predict collisions. The synthesized datasets were transformed into real-world driving datasets. The results indicate that the SG2VEC model operates more efficiently and achieves higher accuracy [147].

FIS combined with LSTM has been employed to analyze the driving environment and driver cognition information, transforming it into lane-changing feasibility assessments using fuzzy logic. The LSTM framework is utilized to predict lane-changing behavior, incorporating vehicle trajectory and lane-changing feasibility as inputs. Furthermore, the model demonstrates improved accuracy [149].Vehicle trajectory prediction is crucial for Advanced Driver Assistance Systems [33] and AVs. Key areas of focus for AVs include collision avoidance, traffic control, and path planning. Traditional models have concentrated on the variability in braking patterns and driver behavior, which significantly influence trajectory prediction. The current approach employs GRU and LSTM networks. The LSTM-GRU model takes into account driver braking patterns alongside vehicle dynamic information [150]. Moreover, utilizing prospect theory, the model examines how driver cooperation influences car-following behavior. To incorporate driver memory effectively, the LSTM technique is applied, resulting in an enhanced car-following model referred to as the PT-LSTM model. The Waymo AV Open dataset is utilized for evaluation, and various performance metrics are employed to assess the model's effectiveness [151]. Likewise, Coupled Hidden Markov Model has identified the semantics of driver behavior. Variations in driving behavior among autonomous vehicles (AVs) were evaluated through the Wasserstein distance. Vehicle acceleration predictions were made using a combined LSTM and CNN. [153].

The Enhanced Spatiotemporal Multi-Level LSTM model, along with Bayesian Optimization, has been introduced to improve vehicle trajectory prediction. This framework utilizes Convolutional Multi-Level Long Short-Term Memory (ConvMLSTM) to extract hidden features from sequential image data effectively. Research findings indicate that the Convolutional Multi-Level LSTM model significantly enhances the control of AVs through optimized trajectory planning methods [154].

A driver trust recognition model for AVs has been introduced to predict driver trust levels effectively by utilizing real-time data and involves a sequence of takeover events with thirty-four drivers. To measure driver trust, both subjective trust ratings and monitoring ratios were collected, allowing for the assessment of trust levels based on lower and higher trust scenarios. The model is built on a combination of CNN and LSTM techniques. Additionally, four comparative models were developed: Support Vector Machine, LSTM, CNN, and Gaussian Naive Bayes [155]. VBOX vehicle data and various low-cost cameras have been employed to predict highway lane strategies by utilizing LSTM and RNN techniques, a model for driver intention inference has been developed. This model predicted temporal behavioral patterns and time series driving data through the LSTM-RNN framework. The dataset includes lane-keeping and left-right lane-changing behaviors collected from naturalistic highway driving scenarios. Driver behavior activities have undergone statistical analysis, and hypothesis testing has been performed to evaluate the performance of the LSTM-RNN model. Using 5-fold cross-validation, the LSTM-RNN model achieved an average accuracy to predict driver behavior in highway contexts [156].

A new Rear-End Collision Prediction Mechanism has been developed using a DL approach. This mechanism effectively integrates a CNN model. To enhance the dataset, genetic theory was applied for smoothing and expansion, addressing class imbalance issues. The results indicate that the RCPM operates efficiently and can quickly predict rear-end collisions [161]. An accident detection model is essential for integrating with AVs to identify accident-prone vehicles and prevent collisions with overturned vehicles. The model employs three deep learning architectures: the Region Proposal Framework, the Region-Based Detector, and a Feature Extractor utilizing Transfer Learning. The CNN8L model effectively achieves region-based detection and classification. Recognized as a novel lightweight sequential CNN, the CNN8L model is trained using a customized dataset. Research findings indicate that the combination of VGG16 and CNN8L significantly enhances performance. As a result, the model has demonstrated a false alarm rate of 33% and an impressive accident detection rate of 86% [163]. Contrastingly, to forecast traffic speeds and shock wave speeds based on dynamic frequency. This model, known as IDILIM, is recognized as a reliable traffic simulation tool. It incorporates CNN and deep learning algorithms to achieve high accuracy in predictions. Furthermore, the IDILIM model is utilized to estimate shock wave speed outputs [164].

Likewise, to enhance crash risk prediction systems LSTM has been developed. This framework utilizes an Enhanced LSTM (EnLSTM) to effectively improve the performance of the crash risk prediction system. The EnLSTM framework employs a Convolutional Neural Network (CNN) for efficient feature extraction. Additionally, the Improved Grasshopper Optimization Algorithm (IGOA) has been implemented to optimize the hyperparameters of the LSTM model. Performance of the EnLSTM model has been assessed and the results indicated that the Novel Optimized LSTM model outperforms existing models based on these performance metrics [165].

The analysis of driver behavior incorporates both external environment data and physiological data. The physiological data encompasses heart rate indices, skin response indices, galvanic skin response indices, and eye tracking metrics. Meanwhile, the environmental data includes factors such as scenario type, TOR lead time, and traffic density. Based on the observed driving behavior, driver takeover performance is classified as either good or bad. Utilizing six deep learning methods, CNN techniques have been effectively applied to predict driver takeover performance at various levels of cognitive load. An optimal time window has been established to forecast takeover performance, resulting in an 64% and 84% of F1 score and Accuracy rate [167].

To establish decrease reaction time and safe motion for sudden forthcoming dangers. A significant challenge lies in understanding the movement patterns of surrounding traffic agents and precisely predicting their upcoming trajectories. Traditional trajectory methods require an understanding of the interactions between autonomous vehicles and nearby vehicles. However, the interactions involving the actual coordinates of surrounding vehicles are complex. To address these challenges, a Generative Adversarial Network (GAN) has been employed. Within a deep learning framework, the GAN model predicts the trajectories of surrounding vehicles for AVs. Additionally, a self-attention mechanism has been introduced to better capture the contextual information of these trajectories [174], likewise, GAN model has used to develop a novel framework that enhances the ability of classifiers to identify safe driving zones for AVs. This framework incorporates data augmentation algorithms, including diffusion-based models and GANs. Framework significantly improved the predictive capabilities of discriminative classifiers, providing insights for the safer placement of AVs across different road conditions [175].

The dynamic Spatio-Temporal Graph Convolutional Network has been utilized to predict the trajectory distribution of vehicles within traffic scenes. By leveraging Graph Convolutional Network, the spatial dependencies among vehicles in each traffic scenario are effectively captured. Following this, a Temporal Convolutional Network is employed to assess the temporal dependencies of accident sequences and to forecast driving conditions based on historical trajectory data. The naturalistic trajectory dataset, known as HighD, has been utilized for this purpose. The results confirm that the Graph Convolutional Network model enhances prediction accuracy compared to other models [177].

The enhancement of efficiency and safety in AVs relies on integrating trajectory prediction with planning and decision-making modules. The current research introduces a GNN-RNN technique based on an Encoder-Decoder network. This approach utilizes the RNN method to extract the dynamic features of vehicles. Additionally, GNN techniques are applied to model inter-vehicular interactions. The NGSIM US-101 dataset has been employed in the GNN-RNN model to predict the trajectory of a target vehicle in various scenarios with differing numbers of surrounding vehicles. The findings indicate that the GNN-RNN model achieves moderate accuracy in predicting safety outcomes for AVs [180].

The prediction of vehicle trajectories is crucial for AVs and advanced driver assistance systems. Previous research has introduced an interaction-aware personalized vehicle trajectory framework, which is designed based on the integration of temporal graph neural networks. This framework correlates LSTM networks with Graph Convolutional Networks (GCN) to monitor the spatio-temporal interactions between surrounding vehicles and the target vehicle. The LSTM-GCN model has been enhanced through transfer learning techniques. A large-scale trajectory dataset has been utilized within the LSTM-GNN model. LSTM-GCN model has improved trajectory prediction accuracy by incorporating personalized approaches [183]. The integration of LSTM and RNN techniques has been implemented to predict driver behavior in AVs. Additionally, Model Predictive Control has been utilized to track trajectories specifically for AVs. The vehicle's lateral velocity is assessed using the Moving Horizon Estimator. Driver intentions are predicted through a driving simulator, which operates based on evaluations from human drivers. AVs effectively cooperated with various driving scenarios, achieving a smooth transient process [184].

To improve workload of the driver and improve the safety of vehicle, Haptic-Shared Steering has been developed. Previous research has focused on a series of high-fidelity driver simulator experiments with 18 participants. 2 investigational circumstances were tested using a double lane-changing task: HGTCG and HGTAG had been used. Lateral control behavior during driving was modeled using a GRU network. The LSTM-GRU model efficiently predicted distracted drivers. Subsequently, the simulation LSTM-GRU model was employed to predict driver behavior associated with lateral position [88].

Though these studies have delivered reasonable values, the accuracy and gaps identified by the models are depicted as follows,

1. Accuracy attained by the model is 91% [149]. However, the limitation of the study includes detection and extraction of the relevant features impacts the behaviour of driver, however, this is considered to be tedious task.
2. Accuracy gained by the model is 86% [161] where the pitfall of the model includes low quality of data, therefore, it is extremely important to enhance the data collection technique.

3. Result attained by the model [235] is 93% however, it has been showcased that, variations in the driving style and behaviour across the individuals has been not reconnoitred.
4. Accuracy gained by existing work is 94% [236], though the model has delivered reasonable accuracy value, state-of-the-art approach failed in adapting the environmental changes, which is crucial to obtain better results.
5. Findings of the study [240] has revealed that, accuracy gained by the model is 87%, nevertheless the pitfall of the model includes interpretability of the ML model which is extremely crucial for enhancing the trust from the users.
6. Outcome of the existing work is 92% [241], nonetheless, study failed to focus on developing robust algorithms which can suit for varying road conditions, weather and traffic patterns.
7. Likewise, state-of-the-art approach technique [136] has gained accuracy value of 92%, in which the model failed in evaluating different factors like road surface, motion states, and collision types for better prediction model. Moreover, behaviour of driver has not been discussed in the study.
8. Congruently, accuracy of the model obtained is 87% [238], here better ML algorithms must be explored to acquire better accuracy.

These are limitations faced by state-of-the-art approaches in terms of accuracy of the model. Thereby, these drawbacks can be eventually overcome by using proposed model as it uses The proposed model utilizes a GA for feature selection, combined with a modified Deep CNN and BiLSTM network enhanced by an attention mechanism for classification tasks. This comprehensive approach was implemented using two datasets: the driver physical state dataset and the car material condition dataset.

Initially, a preprocessing step was conducted on the datasets. The improved search capability of the GA was employed to select relevant features, which significantly enhanced model accuracy, reduced training time, and minimized overfitting. While the Improved Search Ability Based G effectively addressed simpler problems and improved the quality of solutions, it posed computational challenges due to repetitive calculations and often provided all features without discerning their necessity.

The modified CNN-BiLSTM architecture was chosen because CNNs excel with image data, whereas BiLSTMs are more effective for time series data. This hybrid model leverages the strengths of both architectures, with the attention mechanism applied to align processed data within the optimization layer of the CNN. The attention mechanism, integrated with the BiLSTM, allows the model to concentrate on specific segments of the input sequence, thereby enhancing its ability to capture contextual relationships within the data.

Traditional LSTM models often struggle with long sequences due to issues like vanishing gradients. However, the incorporation of the attention mechanism with BiLSTM alleviates these challenges by enabling the model to directly focus on pertinent parts of the input, thus improving performance on tasks that involve lengthy sequences. The synergy between BiLSTM, which captures bidirectional dependencies, and the attention mechanism, which emphasizes relevant features, results in superior sequence modeling. This integration allows the model to effectively scale to large datasets and tackle more complex tasks without sacrificing performance, making it particularly suitable for predicting driver behavior and assessing car mechanisms.

Once the model analysis the behaviour of the driver and predicted it as non-safety then it will direct the driver to nearby hospital. While searching the details of hospitals the autonomous vehicles will attacked by other some intrusions such as normal, DDoS, Probe, R20 and URL. The model also analysis how many attacks are occurs while searching for the hospitals. The visualization of the attacks in autonomous vehicle is depicted in figure 4.6: EDA plot Attack type on unsafety represent the attack types and its intrusion. Where 0 indicates normal, 1 indicates DDoS, 2 indicates probe, 3 indicates R20 and 4 indicates URL. The plot shows that the URL attack is high with 70000 and normal with 45000. This plot permits the model to detect the common threats like which kind of attacks are most often. In some cases, some specific attacks are occasional, they can be more perplexing for the proposed model to classify that can led to additional investigation into managing occasional classes.

CHAPTER 5

CONCLUSION

5.1 CONCLUSION

Due to technology advancement, autonomous cars usage are getting higher in the world. People considered that those autonomous cars made their journey safe in any type of road conditions. It has been gave independent to the people those who are not able to drive. It has been avoid the emission of CO_2, accidents and traffic and most importantly in autonomous cars there has no attention problems like human. Even autonomous cars are also met with an accident because of some malfunction and drivers health. Therefore, various conventional methods were used for detecting accidents caused by malfunctions or derive health issues such as integration of sensor where the conventional technique relay on combination of sensors like LiDAR, cameras and radar. However, these sensors gather sensor data about the vehicle surrounding but the effectiveness can be compromised by different environmental conditions or other restrictions in data processing capabilities. Likewise, conventional perception system in AVs assess the input data for creating a local model in the environment. However, this process is known to be extremely complicated and complex which can ultimately leads to unrealistic errors if the system misinterprets the data, potentially resulting in accidents. Further, classical approaches are known to be extremely time consuming and as it may struggle with real time predictions specially in complex scenarios where human drivers exhibit unpredictable behaviour. This could potentially lead to a lot of accidents if AV fails to react properly.

In semi-autonomous system, where human intervention is still required, monitoring driver health is crucial. Though there are several advantages of employing conventional models for figuring out the human gestures for avoiding accidents, there are certain limitations which needs to be overcome such as

1. Reliance on handcrafted features
2. Time consuming as well as labor intensive tasks
3. Limited robustness
4. Computational inefficiency
5. Lack of adaptability
6. Complexity in implementation

Therefore, these shortcomings need to be overcome in order to obtain better outcome for avoiding further consequences. Therefore, proposed model deliberated on exposing advanced DL based model which produced promising performance for analyzing the drivers' health to ensure the safety. Hence, DL based models offers various advantages such as

1. Complex decision making
2. Improved safety features
3. Better driver behaviour monitoring
4. Advanced perception
5. Can work with huge amount of data

Although existing DL models have offered different advantages, there are disadvantages which needs to be addressed for obtaining better performance of the model like accuracy, scalability issues, interpretability, overfitting, decreased computational complexity and reduced training time. Hence, proposed model opted Genetic based algorithm for feature selection, Modified Deep CNN-BiLSTM with AM for classification process. The entire process was executed using two datasets such as driver physical state dataset, car material condition dataset. Using this dataset, pre-processing step was used. Later, in order to select appropriate features, improved search ability based GA has been utilized.

Feature selection was employed as it aided in improving accuracy, reduced training time and decreased over fitting of the model. Improved Search Ability Based Genetic Algorithm was applicable for simple problem, resulted in quality of problems final solution and generated computational challenges because of its repetitive calculation and provided all the features without analyse which one is needed. Likewise, modified deep CNN-BiLSTM with AM, was used because CNN was good with image dataset but not in time series data but BiLSTM is good with time series data for this reason the CNN and BiLSTM was hybrid and attention mechanism is used to align the processed data in the optimization layer of CNN.

Attention mechanism was typically implemented with BILSTM in proposed mechanism since this process allows to focus on specific parts of the input sequence which enhanced the capability of the model for capturing the context and relationships in the data. Moreover, conventional models like LSTM failed struggling with long sequences due to different issues such as vanishing gradient problems. However, implementation of proposed attention mechanism with BILSTM mitigated these issues by enabling the proposed model to directly focus on relevant parts of the input, thereby enhancing the performance of the tasks involving lengthy inputs. Moreover, combination of BiLSTM with attention mechanism, where BiLSTM captured bidirectional dependencies and AM focused on relevant features led to better sequence modelling. Further, integrating attention with BiLSTM model permitted to scale effectively to huge datasets and more complex tasks without compromising performance, thereby handling extensive performance like prediction of drivers behavior and car mechanism.

Therefore, improved search ability genetic algorithm improved search ability and convergence speed to perceive the most applicable inputs and driving conditions for the safety prediction model and Modified deep CNN-BiLSTM with attention mechanism yielded better performance in terms of preventing overfitting, overcoming scalability issues, reduced computational complexity and reduced training process. Hence, Figure 5.1 showcases the process involved in present framework.

Figure 5.1 Summary of Proposed Work

Eventually, experimental findings such as accuracy value obtained by proposed model was 93%. Likewise, other metric values such as F1 score, precision and recall obtained was 99%, 99% and 99%. From these analytical outcome, it is very well identified that outcome obtained by proposed model was very much superior for predicting driver behaviour of the driver as well as mechanism of car in order to avoid any problems. Moreover, proposed work was compared with existing state-of-the-art approaches, in which it was significantly observed that proposed model delivered promising and sturdy outcome than existing techniques in terms of accuracy, precision, recall and F1 score, thereby making proposed model efficient for assessing mechanism of car and to predict behaviour of drivers in order to avoid accidents.

Limitations of the present work

Limitations of the proposed model is depicted in figure 5.2, where different aspects of

Figure 5.2 Limitations of proposed model

5.2 FUTURE WORK

There are various future work for predicting behaviour and vehicle mechanism, thus some of the future work includes,

1. Real time driver vehicle dynamics prediction
2. Continuous monitoring of driving behaviour
3. Lane changing behaviour prediction
4. Forecasting of less predictable driving behaviour
5. Multimodal data integration
6. Usage of advanced DL model for further enhancing the efficacy of the proposed model
7. Usage of wide range and diverse dataset.

Real time driver vehicle dynamic prediction

In future, proposed model will focus on real-time forecasting of driver-vehicle dynamics in structured environment. This, real time prediction can help in predicting future spatial locations of vehicles and drivers thereby contribution to the development of ITS by preventing any major accidents.

Continuous monitoring of driving behaviour

An additional approach encompasses of continuous analysis of vehicular data from in-vehicle sensors. This technique aids in classifying behaviour of the drivers as eco-friendly or not by using ML and DL approaches for processing and examining data streams. Therefore, the primary goal of the model is to improve not only safety of drivers but also environmental sustainability by optimizing behaviour depending on collected data.

Lane Changing Behaviour Prediction

As the present study did not address lane changing behaviour of the drivers, future work on the proposed model will focus on predicting driver lane changing behaviour by extracting relevant features like physiological data of the model.

Precisely predicting driver lane changing behaviour is important for enhancing the traffic safety as it prevent any horrendous accidents and it is considered to be one of the most basic and significant driving maneuvers since they directly affect the safety and flow of traffic.

Forecasting of less predictable driving behaviour

In future, proposed work will focus on modeling less predictable and potentially more dangerous driving behaviour. This process embroils creating DL models which can adapt to different driving conditions and individual driver characteristics thereby improving the ability to forecast critical situations that may lead to accidents.

Multimodal data Integration

In future, integration of multimodal data sources will be explored where various aspects like vehicle telemetry, environmental conditions and driver physiological signals. This comprehensive method can lead to robust models which are very much capable of predicting complicated interactions between drivers and vehicles in different contexts.

Usage of Wide-range and diverse dataset

In future, more comprehensive and diverse datasets can be utilized to improve DL based driving behaviour analysis. The integration of various datasets can lead to more resulting more precise outcome for predicting both vehicle mechanism and driver behaviour.

Thus, these future works represent promising avenues for overcoming the limitations faced by the proposed model and advancing the field of driver behaviour and vehicle mechanism prediction using DL.