# A Comprehensive Review of Automatic Number Plate Recognition

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*Abstract-* **Automatic Number Plate Recognition (ANPR) has emerged as a notable technology in recent times, owing to its diverse applications in traffic management, law enforcement, and surveillance, which have garnered significant attention. This paper offers a comprehensive overview of techniques and methods used in ANPR systems. It covers various stages involved in ANPR, including the acquisition of images, preprocessing of images, localization of number plates, segmentation of characters, and recognition of characters. Traditional approaches such as template-based matching, feature-based methods, and machine learning-based methods are reviewed, alongside the advancements in deep learning-based approaches. Additionally, this paper discusses different datasets used for ANPR research and provides a comparative study of various ANPR techniques. The article ends by summarizing the significant discoveries made and suggesting potential research areas for future studies in ANPR.**

*Index Terms-* **Automatic Number Plate Recognition, ANPR, image preprocessing, character recognition, dataset, traffic management, law enforcement.**

## I. INTRODUCTION

ANPR, also known as Automatic Number Plate Recognition, is a technological solution that enables the automatic capture, reading, and interpretation of vehicle number plates. It uses optical character recognition (OCR) software and specialized cameras to capture the images of number plates from vehicles as they pass through a monitored area, such as a road, a parking lot, or a toll booth.

ANPR technology was first developed and used in the 1970s. The first recorded instance of an ANPR system can be attributed to the British Police Scientific Development Branch (PSDB) in 1976. An analog computer processed the number plate images captured by a stationary camera to extract the characters. This early ANPR system was primarily used for speed enforcement and was deployed on the A1 Road in the UK.

Over the years, ANPR technology has evolved significantly with advancements in cameras, image processing algorithms, and computing power. Currently, ANPR systems have evolved into advanced and complex technologies that are extensively employed in diverse countries for a wide array of purposes, such as traffic management, law enforcement, parking management, toll collection, and security surveillance. ANPR systems have the potential to revolutionize these areas by automating the process of number plate recognition, thereby reducing manual efforts, and minimizing human error, and transportation and security management.

The typical ANPR process typically involves five main stages, which include the acquisition of the image, pre-processing of the image, localization of the number plate, segmentation of character, and optical character recognition (OCR). Firstly, the number plate image is captured during the image acquisition step. Then, during image pre-processing, the captured image is normalized, and adjustments are made to the brightness, skewness, and contrast to enhance the image quality. Next, the number plate localization step identifies the regions of interest (ROI) within the image where the number plate is located. After that, during character segmentation, the individual symbol images on the number plate are located and identified. In the final step of the ANPR process, OCR, optical character recognition is employed for identifying and extracting the characters from the segmented regions, thus concluding the ANPR procedure.

However, ANPR systems also face several challenges that need to be addressed for reliable and accurate performance. One of the main challenges is the variations in number plate designs, which can vary significantly across different regions, countries, and even within a country. Number plates can have different font styles, sizes, and colours, making it challenging sto design a single ANPR system that can accurately recognize plates from diverse regions.

Another challenge is the variability in lighting conditions, which can impact the quality and clarity of number plate images. Lighting conditions can vary greatly depending on weather conditions, time of day, and location, leading to challenges in capturing high-quality images for accurate number plate recognition. Additionally, factors such as motion blur, occlusion, and reflections can further degrade the quality of number plate images, posing challenges for ANPR systems.

Furthermore, advancements in technology, such as deep learning, have brought new opportunities and challenges to ANPR systems. Although deep learning-based methods, such as CNNs and RNNs, have exhibited impressive performance in number plate recognition, they often rely on extensive training data and computational resources, which may not be readily accessible or practical in real-world situations.

Although ANPR systems face challenges, there have been notable advancements in recent years. Literature has proposed various techniques and methods to enhance the accuracy and reliability of number plate recognition. Traditional methods like template-based matching and feature-based approaches have been commonly used, while approaches that rely on machine learning or deep learning techniques have shown potential in addressing issues related to number plate variations, lighting conditions, and image quality.

The structure of the remaining sections in the following outline is presented in this paper:: Section II provides an extensive examination of existing literature on Automatic Number Plate Recognition (ANPR). In Section III, an in-depth discussion is provided on the different techniques and methods utilized in ANPR. Section IV emphasizes the significance of datasets in ANPR research. Section V provides a comparative study of various ANPR techniques. Finally, Section VI concludes the paper and proposes potential avenues for future research in the field of ANPR.

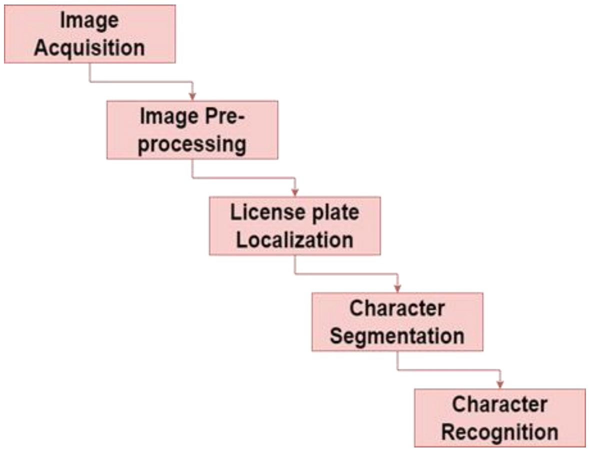


Figure 1 ANPR System Process

## II. RELATED WORK

The field of Automatic Number Plate Recognition (ANPR) has experienced noteworthy advancements and innovation in recent years, with numerous studies exploring various aspects of ANPR techniques, methods, applications, and datasets. In this section, we will conduct a literature review of ANPR to give a summary of the current advancements in this particular field.

Ahmed et al., [1] presented a case study that explores the utilization of Machine Learning (ML) models in managing the towing process of smart cars. The study's proposed mobile system uses a variety of methods to improve the precision of real-time number plate identification. An algorithm was proposed that aims to achieve precise localization of number plates on the car body, extracting the bounding box and converting it into a grayscale image for further processing. The contours of the alphanumeric characters are then extracted from the grayscale image using contour detection filters. After extracting the contours from the grayscale image, the extracted data from the previous step is utilized as input for K-Nearest Neighbours (KNN) model to accurately identify the number plates. The suggested model recognizes number plates from many places throughout the world with an excellent overall classification accuracy of 95%. The system is developed as a mobile application for Android devices, enabling law enforcement personnel to take photographs of towed vehicles. These photos are automatically recorded in real-time by the car towing management system, improving operational efficiency and simplifying the process. The app also provides features for vehicle owners to locate their vehicles, check the status of their cases, and pay fines. The suggested model performs better than certain cutting-edge ANPR techniques in terms of overall processing time, according to a performance evaluation utilizing a variety of measures.

In their publication, Varma P et al., [2] The authors have introduced a unique image processing system for detecting and recognizing Indian number plates, capable of handling challenges like noise, low illumination, cross-angles, and non-standard fonts. The system incorporates several pre-processing methods including morphological modification, Gaussian smoothing, and Gaussian thresholding. Contours are extracted from the pre-processed images for number plate segmentation, and further filtering is applied based on the dimensions of characters and their spatial localization. Character recognition is performed using the K-nearest neighbour technique once the region of interest has been filtered and de-skewered. Experimental findings show the promising outcomes of the proposed methods.

Suvon et al., [3] presented a model that automates the detection and recognition of vehicles through computerized number plate analysis, with potential applications in parking systems and toll collection. The system is specifically designed for detecting Bangla license plates from different towns and a variety of multi-class vehicles. The algorithm employed is YOLOv3 (short for "You Only Look Once v3") and computer vision, for number plate detection, and the Tesseract optical character recognition system for vehicle licensing. Convolutional neural networks are employed for character recognition from the detected number plates. Experimental findings reveal the precision of the number plate detection using YOLOv3 and computer vision is 91% and 95% respectively, while the accuracy of character recognition using convolutional neural networks and Tesseract is 90% and 91.38% respectively, when the number plate is successfully detected and cropped. The system is further tested in a real-world environment using the CNN method, achieving an overall system accuracy of 88.89% in detecting 17 out of 18 cars captured by the Pi Camera input.

Onim et al., [4] propose a model for object detection called YOLOv4 which was used to detect number plates and recognize characters on cars in Bangladesh. The model incorporates a convolutional neural network and Tesseract for number plate detection, obtaining an average mean precision (mAP) score of 90.50%. A Graphical User Interface (GUI) is developed for the system using Tkinter, a Python package, to make it user-friendly. The model for detecting number plates is capable of processing real-time video footage with a typical frame rate of 14 fps on a single TESLA T4 GPU.

Yaseen et al., [5] introduced a novel dataset called North Iraq-Vehicle Images (NI-VI) in their study, which comprises 1500 images captured in three provinces (Duhok, Erbil, and Sulaimani) located in northern Iraq. The dataset was collected in real-time using handheld cameras, providing a realistic representation of vehicle images. This work's key contribution is the creation of a fresh dataset for number plates on cars in northern Iraq that includes Arabic typefaces in a variety of difficult situations, such as scaled, rotated, and translated images. The images in the dataset have resolutions of 4288 x 2848 and 5184 x 3456 and also include images captured under adverse weather conditions including dusty, snowy, and poor lighting, as well as dirty number plates. The introduction of this dataset aims to provide a realistic benchmark for Automatic License Plate Detection and Automatic License Plate Recognition systems, enabling improved performance evaluation and the development of robust algorithms.

Molina-Moreno et al., [6] presented a scale-adaptive deformable part-based model for number plate recognition in their paper. During training, the approach automatically incorporates scale modeling through a widely-used boosting algorithm, which enables it to identify the most significant features at different scales. This approach effectively decreases the time required for test detection by preventing evaluations at multiple scales. Additionally, the technique includes a deformation model with empirical constraints that can adjust to various degrees of deformation in local characteristics on number plates. The experimental findings showcase the robustness, scale, perspective independence, and reliable performance of the proposed detector across a wide range of scenarios. The performance of the proposed approach was compared with the most advanced methods currently available on two datasets, and the results show a significant improvement.

A new approach was proposed by Min et al., [7] for the vehicle number plate location that addresses the limitations of conventional methods in complex road environments. The proposed approach, which utilizes a novel model called YOLO-L and an algorithm for plate pre-identification, aims to enhance the precision and efficiency of number plate detection. The YOLO-L model integrates the k-means++ clustering algorithm so that it determines the optimal size and number of candidate boxes for the number plate and also changes the depth and structure of the YOLOv2 model. The pre-identification algorithm for plates effectively differentiates between number plates and other relevant items, including billboards and traffic signs. Experimental findings reveal that the method achieves an impressive precision and recall of 98.86%, surpassing current methods, and exhibits high real-time efficiency.

In their paper, Li et al., [8] presented a number plate recognition algorithm that is based on a maximum stable extremum region (MSER) in conjunction with a support vector machine (SVM). Unlike traditional algorithms that rely on edge colour, detection, and detection for number plate localization, the proposed approach directly extracts and recognizes characters without explicitly locating the number plate region. The MSER technique is utilized for image pre-processing, providing invariance to affine transformations and adaptability to varying lighting conditions, making it suitable for complex environments. The SVM model is utilized to remove regions that are not characters from the extracted MSER regions. Then, specific geometric characteristics and arrangement regulations of characters on number plates are applied to the screen and identify character regions. Finally, number plate character recognition is performed. Experimental findings demonstrate that the algorithm, which combines MSER and SVM, achieves higher accuracy and efficiency compared to commonly used number plate recognition approaches, indicating its effectiveness for number plate recognition in challenging environments.

Rafique et al., [9] presented a novel approach to address the complex problem of vehicle number plate detection in practical applications. In contrast to previous methods that rely on static cameras, known templates, and colour patterns, this approach treats the number plate as an object. The research primarily addresses three main objectives: (1) detecting number plates (LPs) in a video sequence, (2) detecting partial number plates, and (3) detecting number plates in scenarios where the cameras and vehicles are in motion. Cutting-edge techniques, such as convolutional neural networks with a proposal mechanism (referred to as RCNN), Fast-RCNN, Faster-RCNN, and exemplar support vector machines (SVM), are employed to detect objects and provide effective solutions for these tasks. Comprehensive tests and comparisons reveal that the suggested approach outperforms conventional methods, demonstrating superior results.

Sharma [10] proposed an approach for plate localization and character segmentation that involves morphological operations, edge detection, smoothing, and filtering techniques. The segmented characters are then resized into blocks of size 70x70 and compared with templates in a database using template matching algorithms, such as normalized cross-correlation and phase correlation. The system's performance is then evaluated on 90 patterns under various conditions, and the recognition accuracy of the two methods is compared. Results from the analysis and testing on a database of images reveal that the normalized cross-correlation technique outperforms the phase correlation technique, achieving an accuracy of 67.98% compared to 63.46% for phase correlation.

The paper authored by Xie et al., [11] introduces a novel algorithm for detecting number plates and character recognition. The proposed approach combines a feature extraction model with a Backpropagation Neural Network (BPNN) to effectively manage challenging lighting conditions and complex backgrounds. The algorithm includes a pre-processing step to enhance image contrast, followed by candidate region verification using the integral projection technique is utilized to accurately locate the position of the number plate. Three sets of feature combinations are used in the creation of a novel feature-extraction model, and BPNN is used to train the feature vectors for precise character recognition. The proposed algorithm's effectiveness and efficiency in handling complex backgrounds are demonstrated through experimental results using various number plate samples. When compared to three traditional methods, the processing time was reduced to 46.1ms while achieving a recognition accuracy of 97.7% using the algorithm.

In their paper, Ni et al., [12] suggested a method based on CNN for number plate classification. The authors highlight the increasing use of deep learning in the recognition of number plates and emphasize the importance of data quality for training the network. They note that real-world number plate images often suffer from issues such as illumination variations, size variations, and blurriness, which can adversely affect recognition accuracy. Therefore, number plate classification is crucial to filter out low-quality images and enhancing the overall quality of the dataset. The method suggested employs a seven-layer CNN, and experimental findings demonstrate that the best-achieved classification accuracy is 98.79%.

Selmi et al., [13] presented a deep learning-based ANPR system, comprising three main components: detection, segmentation, and character recognition. Pre-processing steps are applied for number plate recognition and the first CNN model is utilized to classify between plates and non-plates. After applying additional pre-processing procedures to segment the number plate, a second convolutional neural network (CNN) model comprising 37 classes, capital letters (A-Z), and digits (0-9), is utilized for character recognition. The system's performance is assessed on two datasets with diverse conditions that include low image quality, distortion from different perspectives, varying lighting conditions including bright day and night, and complex environmental factors. The results highlight the system's high accuracy in a substantial proportion of cases.

The study conducted by Mondal et al., [14] focuses on the utilization of CNNs, Convolutional Neural Networks for detecting and recognizing images of vehicle license plates. The authors employ self-synthesized features of CNN to attain a high level of accuracy of 90% in state recognition, even when training data is limited. The robustness of the CNN model is demonstrated through its successful recognition of distorted, tilted, and illuminated datasets, indicating its potential for real-world applications.

## III. AUTOMATIC NUMBER PLATE RECOGNITION METHODS & TECHNIQUES

ANPR involves a series of techniques for image processing and pattern recognition that are used to extract number plate information from vehicle images or videos. ANPR methods can be categorized into several key steps, including pre-processing of images, localization of number plates, segmentation of characters, and recognition of characters. In this section, we will provide an in-depth review of various ANPR techniques and methods proposed in the literature.

***Image Pre-processing***

Enhancing the quality of input images through image pre-processing is a critical step in ANPR, as it improves the accuracy of number plate localization and character recognition. Different methods have been proposed for image pre-processing in ANPR, including image normalization, image filtering, and image enhancement.

Image normalization aims to standardize the input images to a common format to account for variations in lighting conditions, image scales, and orientations. Common normalization techniques include histogram equalization, contrast stretching, and gamma correction. Histogram equalization is a technique used to modify the distribution of intensity values of an image to achieve a more uniform histogram, which can improve the visibility of number plates in images with poor lighting conditions. Contrast stretching expands the intensity range of an image to enhance the contrast, which can improve the clarity of number plates against the background. Gamma correction adjusts the gamma value to correct the intensity values of an image, which can improve the visibility of number plates in images with non-uniform illumination.

Image filtering methods are used to reduce noise and improve the edges of number plates in images. The common image-filtering techniques used in ANPR include Gaussian filtering, median filtering, and morphological filtering. Gaussian filtering applies a Gaussian kernel to smooth an image and reduce high-frequency noise while preserving the edges. Median filtering replaces the intensity values of pixels with the median intensity value of their neighbourhood, which can effectively reduce salt-and-pepper noise. Morphological filtering is a technique utilized to enhance the edges of objects in an image through dilation and erosion operations. This process aids in the separation of number plates from the background and other objects to improve their detection and recognition accuracy in ANPR systems.

Image enhancement methods aim to enhance the overall quality of the input images by enhancing the visual characteristics of number plates. Common image enhancement techniques used in ANPR include image sharpening, illumination correction, and colour correction. Image sharpening enhances the edges of objects in an image to improve their visibility, which can help to enhance the edges of number plates. Illumination correction techniques are used to correct the non-uniform illumination in an image, which can improve the visibility of number plates in images with lighting variations. Colour correction techniques are used to normalize the colour properties of number plates, which can help to standardize the number plate formats and enhance the precision of character recognition.

***Licence Plate Localization***

Number plate localization, also known as license plate detection or number plate extraction, is the process of locating the position and size of the number plate region of an image or video frame. Number plate localization is a critical step in ANPR, as accurate and robust localization of number plates is essential for subsequent character segmentation and recognition.

Various techniques have been proposed for number plate localization, including traditional computer vision methods and deep learning-based approaches. Traditional computer vision methods typically involve handcrafted features and machine learning algorithms, while deep learning-based approaches leverage the power of convolutional neural networks (CNNs) for feature extraction and learning.

Traditional computer vision methods for number plate localization often rely on image processing techniques, including morphological operations, edge detection, and texture analysis. Edge detection techniques, such as Sobel, Canny, and Roberts operators, are used to detect the edges of objects in an image, including the edges of number plates. Texture analysis techniques, such as Gabor filters, wavelet transforms, and local binary patterns (LBP), are used to extract texture features from an image, which can be used to differentiate between the region of the image that contains the number plate and the surrounding background. Morphological operations, such as dilation and erosion, are used to manipulate the binary or grayscale images to enhance the number plate region and suppress the noise.

Some traditional computer vision methods also utilize machine learning techniques that include support vector machines (SVM), AdaBoost, or decision trees, for number plate localization. These methods typically require handcrafted features, such as colour, texture, or shape features, which are used as input to the machine learning algorithms for classification or regression. For example, color features, such as colour histograms or colour moments, can be used to differentiate between the area containing the number plate and the rest of the background based on colour properties. Texture features, such as LBP or Gabor features, can capture the texture patterns of the number plate region, which can be used to discriminate it from other regions. Shape features, such as aspect ratio or rectangularity, can be used to characterize the geometric properties of the number plate region, which can help to distinguish it from other objects.

Deep learning-based approaches for number plate localization have gained significant attention in recent years due to their superior performance in different computer vision tasks. Feature extraction and learning from large datasets have been made possible by the remarkable capabilities of Convolutional Neural Networks (CNNs). Many CNN-based methods for number plate localization adopt the region proposal network (RPN) and region-based CNN (R-CNN) framework, which first generates region proposals and then classifies and refines these proposals to obtain the final number plate region.

Other deep learning-based methods for number plate localization include You Only Look Once (YOLO) and Single-Shot Detection (SSD), and efficient and accurate object detection (EfficientDet) methods. These methods use a single neural network to directly forecast the bounding boxes and class labels of the number plate region, without the need for the region proposals. These approaches are known for their efficiency and real-time processing capability, which are well-suited for applications where real-time number plate localization is required, such as traffic surveillance and toll collection systems.

***Character Segmentation***

After the number plate region is successfully localized, the next step in ANPR is character segmentation, which involves extracting individual characters from the number plate region for subsequent character recognition. Character segmentation is a difficult task because of the differences in number plate formats, fonts, and character sizes, as well as the potential presence of noise and artifacts in the number plate region.

Different techniques have been proposed for character segmentation in ANPR, including methods based on image processing, template matching, and deep learning. Image processing techniques often involve extracting individual characters from the number plate region using methods such as image thresholding, connected component analysis, and contour analysis. Image thresholding is used to convert the grayscale or color number plate image into a binary image, where characters appear as foreground objects and the background is set to zero. A connected component analysis is used to identify and extract the connected regions in the binary image, which correspond to the characters on the license plate. Contour analysis is used to analyze the shape and spatial properties of the connected components to refine the character segmentation results.

Template matching-based methods for character segmentation rely on a predefined set of character templates, which are matched against the number plate region to identify and obtain the characters. The template matching process involves computing the similarity measure between the number plate region and the character templates and selecting the character template with the highest similarity score as the matched character. Template matching methods are simple and computationally efficient, but they may suffer from limitations, such as sensitivity to variations in number plate formats, fonts, and character sizes.

Sliding window-based methods involve systematically scanning the number plate image with a window of fixed size and analysing the content of the window to determine if it contains a character. The window is moved across the number plate image in a sliding manner, and the contents of the window are classified as character or non-character based on certain features, such as intensity, gradient, or texture. The sliding window-based methods can be effective in handling overlapping characters but may suffer from high computational complexity due to the exhaustive search over the number plate image.

Deep learning-based methods for character segmentation have shown promising results in recent years, leveraging the power of CNNs for feature extraction and learning. These methods typically involve training CNN to predict the bounding boxes or pixel-level masks of the characters in the number plate region using annotated training data. Once CNN is trained, it can be used to predict the character regions in unseen number plate images. The predicted character regions can then be extracted and refined using post-processing techniques, such as non-maximum suppression or morphological operations, to obtain the final character segmentation results.

***Character Recognition***

Character recognition, which is also referred to as optical character recognition (OCR), is the process of converting segmented characters into text or numerical values. The precision of character recognition plays a crucial role in ANPR because it directly affects the system's overall efficiency and reliability. Character recognition in ANPR is difficult because of the differences in number plate formats, fonts, character sizes, and potential occlusions or distortions in the number plate region.

Traditional methods for character recognition in ANPR often rely on handcrafted features and machine learning algorithms, including k-nearest neighbours (KNN), SVM, artificial neural networks (ANN). These methods typically involve extracting features from the segmented characters, such as shape, texture, or gradient features, and using these features as input to the machine learning algorithms for classification or regression. For

example, shape features, such as aspect ratio, height-width ratio, or the number of holes, can be used to characterize the geometric properties of the characters. Texture features, such as LBP or HOG, can capture the texture patterns of the characters, which can be used to discriminate the different characters. Gradient features, such as edge histograms or gradient orientation histograms, can be used to capture the edge information of the characters, which can help to distinguish between different characters.

Deep learning-based methods for character recognition have shown significant improvements in recent years, achieving state-of-the-art performance in various ANPR applications. CNNs are commonly used for character recognition, as they are capable of learning discriminative features directly from segmented character images without the need for handcrafted features. CNN-based methods typically involve training CNN using annotated training data to learn the mapping between the input character images and the corresponding character labels. Once CNN is trained, it can be used to predict the character labels of unseen characters in number plate images. Predicted character labels can then be combined to form the final text or numerical value of the number plate.

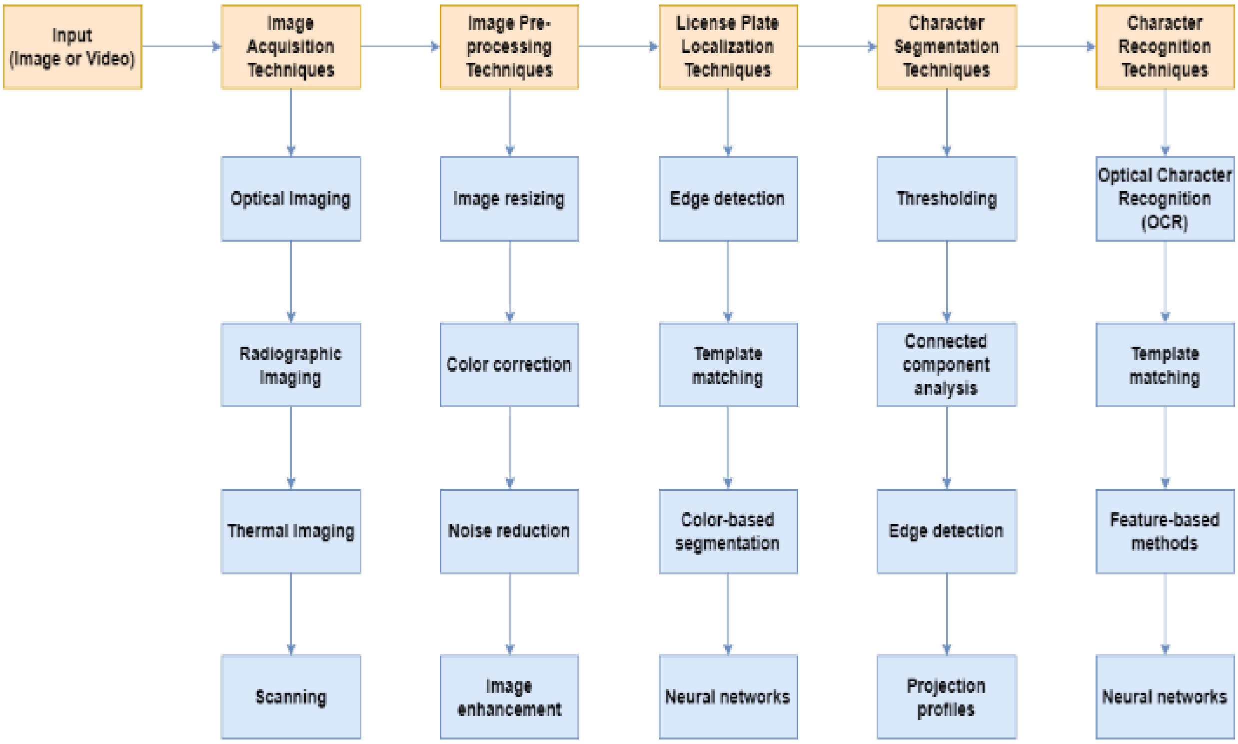


Figure 2 ANPR Techniques and Methods

## IV. DATASET

Dataset plays a crucial role in the development and evaluation of ANPR systems. In this section, we will discuss the importance of dataset selection, the characteristics of ANPR datasets, and some commonly used datasets in the field of ANPR.

Selecting an appropriate dataset for ANPR research is essential as it directly impacts the performance and generalization capability of the developed ANPR system. A well-constructed dataset should be representative of the real-world scenarios in which the ANPR system is intended to be deployed. It should contain diverse and comprehensive samples of number plates with variations in number plate formats, fonts, colours, backgrounds, lighting conditions, and viewing angles. The dataset should also account for different automobile types, such as cars, trucks, motorcycles, and buses, as well as different geographical regions with varying number plate formats and styles.

ANPR datasets typically contain images or video streams of vehicles with annotated number plate regions and corresponding character labels. The number plate regions can be annotated at various levels, including bounding boxes around the number plates, pixel-level segmentation masks, or individual character bounding boxes with character labels. The character labels can include alphanumeric characters, symbols, and special characters that are present on the number plates.

There are several characteristics of ANPR datasets that researchers need to consider when selecting or creating their datasets. These characteristics include dataset size, diversity, the accuracy of annotations, and variability in number plate formats and styles. Larger datasets are generally preferred as they allow for more robust and accurate training of ANPR models. Diverse datasets that capture variations in number plate formats, fonts, colors, backgrounds, lighting conditions, and viewing angles are essential to ensure that the developed ANPR system can handle real-world scenarios. Accurate annotations are crucial for training and evaluating ANPR models as they provide ground truth information for model performance assessment. Finally, datasets that include variability in number plate formats and styles from different geographical regions are important to ensure that the ANPR system can generalize to different number plate formats and styles in different locations.

Several publicly available datasets are commonly used in the field of ANPR for research and evaluation purposes. Some of the widely used ANPR datasets include:

**OpenALPR Dataset:** OpenALPR provides a dataset that includes over 50,000 images of vehicles captured from different locations and under varying lighting and weather conditions. It includes annotations for number plate location and characters, making it suitable for training and evaluating ANPR models.

**Belgian LP Dataset:** The Belgian LP dataset, created by the University of Leuven, contains over 90,000 annotated images of number plates from Belgium. It includes images with different backgrounds, perspectives, and lighting conditions, making it suitable for training ANPR models for European number plates.

**Street View House Numbers (SVHN) Dataset:** The SVHN dataset, created by Google, includes over 600,000 images of house numbers from Google Street View. While not specifically designed for ANPR, it can be used for training ANPR models for digit recognition in number plates.

**LPR-Net Dataset:** The LPR-Net dataset, created by the Chinese University of Hong Kong, contains over 80,000 annotated images of vehicles from urban and highway scenes in China. It includes annotations for number plate location and characters, making it suitable for training ANPR models for Chinese number plates.

**German Traffic Sign Recognition Benchmark (GTSRB) Dataset:** The GTSRB dataset includes over 50,000 images of traffic signs from Germany, which can be used for training and evaluating ANPR models for traffic sign recognition in number plates.

**Vehicle Number Plate Recognition (VLPR) Dataset:** The VLPR dataset, created by the University of Central Florida, includes over 20,000 annotated images of number plates from the United States. It includes images captured from different locations, lighting conditions, and perspectives, making it suitable for training and evaluating ANPR models for U.S. number plates.

**DTK ANPR/LPR Dataset:** The DTK ANPR/LPR dataset, created by DeepTalents, includes over 100,000 annotated images of number plates from various countries, including the United States, Europe, and Asia. The dataset comprises images obtained from various environments, lighting conditions, and plate types, rendering it a diverse training set for ANPR models tailored to different regions.

**COCO-Text Dataset:** The COCO-Text dataset, created by Microsoft Research, includes over 63,000 images with annotations for text regions, making it suitable for training ANPR models used to detect and recognize text, including number plate recognition. It includes images captured from different scenes, including urban, rural, indoor, and outdoor environments.

**KAIST Multispectral Pedestrian Dataset:** The KAIST Multispectral Pedestrian dataset, created by the “Korea Advanced Institute of Science and Technology (KAIST)”, includes over 95,000 images captured from a moving vehicle using multiple sensors, including visible cameras and thermal cameras. It includes annotations for number plate location and characters, making it suitable for training ANPR models for both visible and thermal number plates.

**INRIA ANPR Dataset:** The INRIA ANPR dataset, developed by the French Institute for Research in Computer Science and Automation (INRIA), includes over 6,000 annotated images of number plates from France. It includes images captured from different viewpoints, lighting conditions, and plate types, making it suitable for training and evaluating ANPR models for French number plates.

**VTQ ANPR dataset:** This dataset contains images of vehicles captured from moving vehicles in various locations in the United Kingdom. It includes a large number of images with variations in number plate formats, fonts, colors, backgrounds, and lighting conditions.

**Brazilian ANPR dataset:** This dataset contains images of Brazilian number plates captured from fixed cameras with ground truth annotations of number plate regions and character labels. It includes variations in number plate formats, fonts, colors, backgrounds, and lighting conditions.

**Indian Vehicle Number Plate dataset:** This dataset contains images of Indian number plates captured from fixed cameras with ground truth annotations of number plate regions and character labels. It includes variations in number plate formats, fonts, colors, backgrounds, and lighting conditions.

These datasets, along with others, are widely used in ANPR research for the training, validation, and testing of ANPR models. However, it is important to note that these datasets may have limitations, such as biases in number plate formats, fonts, and styles, limited geographical coverage, and variations in image quality. Therefore, it is crucial for researchers to carefully consider the characteristics of the dataset they choose and validate the performance of their ANPR models on real-world data to ensure their generalization capability.

In addition to publicly available datasets, researchers can also create datasets tailored to their specific ANPR application. Creating a custom dataset allows researchers to have control over the data distribution and characteristics, ensuring that the dataset is representative of the real-world scenarios in which the ANPR system will be deployed. Custom datasets can be created by collecting images or video streams of vehicles with annotated number plate regions and character labels using fixed cameras, mobile cameras, or other data collection methods. The custom datasets can include variations in number plate formats, fonts, colors, backgrounds, lighting conditions, and viewing angles, depending on the specific requirements of the ANPR application.

When creating custom datasets, it is important to ensure accurate annotations of number plate regions and character labels. Annotation errors can introduce noise in the training process and result in inaccurate model performance assessment. Therefore, careful manual annotation or automated annotation methods with high accuracy should be used to ensure reliable ground truth annotations.

## V. COMPARATIVE STUDY

Table 1 A COMPARATIVE ANALYSIS OF PRIOR RESEARCH

| REF | Title | Method/Technique used | Result |
|---|---|---|---|
| Alam et al. [15] | “Intelligent System for Vehicles Number Plate Detection and Recognition Using Convolutional Neural Networks” | Convolutional Neural Network (CNN) | The paper reports that the proposed system attained a precision rate of 96.5% in detecting the number plates and a precision of 92.5% in detecting the characters on the number plates. |
| Onim et al. [4] | “Traffic Surveillance Using Vehicle Number Plate Detection and Recognition in Bangladesh” | Convolutional Neural Network (CNN)<br>YOLOv4<br>Tesseract | The number plate detection model obtained an average mean precision (mAP) score of 90.50%. It was evaluated on real-time video footage and demonstrated an average processing speed of 14 fps on a single TESLA T4 GPU. |

| | | | |
|---|---|---|---|
| Zhu et al. [16] | "Number Plate Recognition in Urban Road Based on Vehicle Tracking and Result Integration" | Convolutional neural network (CNN) | The evaluation results on multiple datasets indicate that the proposed method, which utilizes tracking vehicle and result integration, is effective in recognizing number plates in images of inferior quality obtained from screenshots of surveillance videos recorded on urban roads. |
| Li et al. [8] | "Vehicle Number Plate Recognition Combing MSER and Support Vector Machine in A Complex Environment" | Algorithm was based on Maximum Stable Extremum Region (MSER) and Support Vector Machine (SVM). | The proposed algorithm in the paper achieved higher accuracy. The results of the testing indicate that the proposed algorithm achieves an accuracy of 96.5% |
| Ni et al. [12] | "A Proposed Number Plate Classification Method Based on Convolutional Neural Network" | Convolutional Neural Network (CNN) | The method suggested was based on CNN and achieved a high accuracy of 98.79% in number plate classification. This method can be useful in eliminating low-quality images and improving the quality of the dataset. |
| Selmi et al. [13] | "Deep Learning System for Automatic Number Plate Detection and Recognition" | A second CNN model with 37 to accurately identify and classify all characters in capital letter format (A-Z) as well as digits (0-9). | The system's effectiveness was tested on two sets of data in the evaluation process which contained images captured in diverse conditions, including low image quality, distortion from different perspectives, varying lighting conditions including bright day and night, and complex environmental factors. The results demonstrate that the suggested system achieved a high accuracy rate in detecting and recognizing number plates. |
| Satsangi et al. [17] | "Number Plate Recognition: A Comparative Study on Thresholding, OCR and Machine Learning Approaches" | Viola Jones machine learning algorithm | The authors have used the Viola-Jones machine-learning algorithm for character recognition and have evaluated its performance. The findings show that the proposed system can accurately identify number plates in real-time images. |
| Hossen et al. [18] | "Number Plate Detection and Recognition System Based on Morphological Approach and Feed-Forward Neural Network" | Back-propagation feed-forward neural networks | The study tested the algorithms on a dataset comprising 180 images captured in different conditions. The results showed that the number plate detection, segmentation, and recognition success rates were 93.89%, 98.22%, and 92.77%, respectively. |
| Silva & Jung [19] | "Number Plate Detection and Recognition in Unconstrained Scenarios" | Convolutional Neural Network (CNN) | The results from the research paper show that the proposed Automatic Number Plate Recognition (ANPR) system performs effectively in unconstrained capture scenarios, even when number plates are significantly distorted due to oblique views. |

## VI. CONCLUSION

This paper presents a thorough examination of Automatic Number Plate Recognition (ANPR) techniques and methods. We provided an introduction to ANPR, discussed related work, and reviewed various ANPR techniques, including template-based, feature-based, and deep learning-based approaches. We also discussed the importance of datasets in ANPR research and evaluation and highlighted commonly used datasets for ANPR evaluation. Furthermore, we conducted a comparative study of ANPR techniques based on their performance.

In conclusion, ANPR is an important technology with applications in traffic management, law enforcement, and security. There are various ANPR techniques ranging from template-based approaches to feature-based and deep learning-based approaches. The choice of ANPR technique should be based on the specific requirements of the application and the availability of annotated data for model training. Additional research in ANPR is needed to improve the accuracy, robustness, and efficiency of ANPR systems in real-world scenarios.

**CONFLICT OF INTEREST**

The authors declare no conflict of interest. No external funding was acquired to complete this work.

**AUTHOR CONTRIBUTIONS**
Ahmed Nur Ali has conducted this review under the guidance of Dr. Deepak K. Sinha and the supervision of Dr. Garima Sinha.
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