Smart System for Protection of Chest Infectious Diseases: Enhancing Detection and Prevention Using Advanced Technologies: DPDCDS

Mansour Al-Hlalat

Lecturer
Department of Computer Science
University of Jordan, Amman, Jordan

***Abstract*- This research aims to assist a country in dealing with chest diseases and mitigating their negative effects through the design of an integrated computer program known as the Detecting and Preventing Chest Diseases System (DPDCDS). The DPDCDS is a low-cost and user-friendly system developed to aid in disease detection and prevention. The proposed DPDCDS utilizes digital image processing techniques on captured images of a person's face, hand, and arm to determine the likelihood of infectious chest diseases such as COVID-19. This fast and cost-effective system can be deployed across various healthcare facilities, airports, health centers, universities, schools, and government institutions to facilitate the swift identification of individuals at high risk of chest diseases. By implementing this system in public places, the government can protect its citizens from disease transmission and curb the rapid spread of infectious diseases. Consequently, the government can consider reopening public areas and workplaces, as the automated system efficiently detects individuals with a high probability of infection. The DPDCDS includes a sub-system known as the Detecting Infectious Chest Diseases System (DICDS), which focuses on identifying individuals at risk of infectious chest diseases. Additionally, another sub-system, the Defense Laws System (DLS), is developed to monitor compliance with defense laws, such as maintaining a physical distance of two meters and wearing face masks in public places. The DLS helps the government detect violators of these laws, categorize regions based on their adherence to regulations, and deploy monitoring and inspection measures in non-compliant areas. The DICDS achieves an accuracy rate of 98.3%, while the DLS achieves an impressive accuracy rate of 98.3%, indicating its effectiveness in accurately detecting infectious chest diseases. On the other hand, it demonstrates exceptional accuracy rates of 99.3% in distance detecting and an outstanding 99.9% in face mask detecting. Through the integration of image processing techniques and automated systems, the DPDCDS presents an effective solution to detect and prevent chest diseases, protect the population, and enforce defense laws. The simplicity, cost-effectiveness, and high accuracy of the proposed system make it a valuable tool for countries in their efforts to combat infectious chest diseases and mitigate their impact.**

***Index Terms*- Chest Infectious Disease, COVID-19, Faster R-CNN, Detect Physical Distance, Mask-Wearing.**

I. INTRODUCTION

The respiratory system is highly vulnerable to diseases, being the largest internal organ constantly exposed to the external environment [1]. Chest diseases can be categorized into two main types: infectious diseases and non-communicable diseases. Detecting and promptly quarantining individuals infected with these diseases are crucial for preventing their spread. For instance, governments conduct biological tests to identify individuals who are infected with diseases like COVID-19.

In 2021, governments in many countries enacted various defense laws to protect their citizens from COVID-19. These laws included implementing comprehensive bans, maintaining a physical distance of two meters between individuals in public places, and mandating the use of face masks to cover the mouth and nose. However, governments face challenges in enforcing these laws effectively. One challenge is the widespread non-compliance by citizens, while another challenge is the need for a large number of human resources to identify law violations and ensure compliance. These challenges necessitate the development of solutions that aid in diagnosing chest diseases and protecting people from infectious diseases like COVID-19.

An intelligent tool capable of detecting whether individuals are adhering to these laws is urgently required in the event of future outbreaks of infectious diseases. This research aims to provide a comprehensive solution by creating a smart system that utilizes image processing, machine learning, and artificial intelligence. The system has three main objectives:

- Identifying individuals with a high likelihood of being infected with infectious chest diseases, such as COVID-19, by analyzing their medical history of such diseases. If genetic factors that contribute to infection are identified, the system take them into account. Additionally, the system analyzed captured images of a person to detect symptoms that manifest on their face and body.
- Assisting in the detection of law violations related to defense measures implemented by governments to protect their citizens from infectious diseases like COVID-19. This system addressed issues related to low efficiency, low accuracy, high cost, slow violation detection, and the sluggish correction of violations that arise when relying solely on human intervention.
- Developing an effective tool to aid in the management and control of future infectious disease outbreaks by utilizing intelligent technologies and providing real-time monitoring and decision-making capabilities.

By leveraging image processing, machine learning, and artificial intelligence, this research endeavors to provide a comprehensive solution that addresses the aforementioned challenges. The aim is to enhance disease diagnosis, protect individuals from infectious chest diseases, and improve the efficiency and accuracy of enforcing defense laws enacted by governments.

II. BACKGROUND AND RELATED WORK

Faster Regions with Convolution Neural Networks (Faster R-CNN)

The R-CNN family includes techniques such as R-CNN, Fast R-CNN, and Faster R-CNN. These models, as described by Weng [2], utilize deep learning techniques for object detection. The R-CNN model consists of three modules:

- Region Proposal Module: This module generates and extracts category-independent regions, such as candidate bounding boxes. It identifies potential regions in the input image that may contain objects of interest.
- Feature Extractor Module: In this module, features are extracted from each candidate region using a deep Convolutional Neural Network (CNN). The CNN processes the region to capture meaningful visual representations that can distinguish objects from the background.
- Classifier Module: The classifier module takes the extracted features and classifies them into known classes using a linear Support Vector Machine (SVM) classifier or other appropriate models. It assigns the features to specific object categories.

Fast R-CNN, as mentioned by Ren et al. [3], is an improvement over the R-CNN model. It introduces innovations to enhance training and testing speed while improving detection accuracy. The model incorporates these advancements to achieve better performance. Faster R-CNN, as discussed by Girshick [4] is a network that takes an entire image and a set of object proposals as input. It utilizes convolutional and max-pooling layers to process the image and generate a convolutional feature map. For each object proposal, a region of interest (RoI) pooling layer extracts a fixed-length feature vector from the feature map. These feature vectors pass through fully connected layers, resulting in two output layers: one providing probability estimates for object classes and a background class, and another output layer encoding refined bounding-box positions. The key improvement in Faster R-CNN is the introduction of a region proposal network (RPN), as described in [4]. The RPN shares convolutional features with the detection network, enabling efficient region proposals. It predicts object bounds and objectness scores simultaneously, generating high-quality region proposals used by the Fast R-CNN for object detection. By combining the RPN and Fast R-CNN into a unified network and sharing convolutional features, the network effectively determines where to focus its attention. In summary, Faster R-CNN enhances object detection by utilizing the RPN for region proposal generation and sharing convolutional features with the detection network. This approach improves efficiency, accuracy, and the overall performance of the object detection system. Figure 1 shows the Faster R-CNN model.

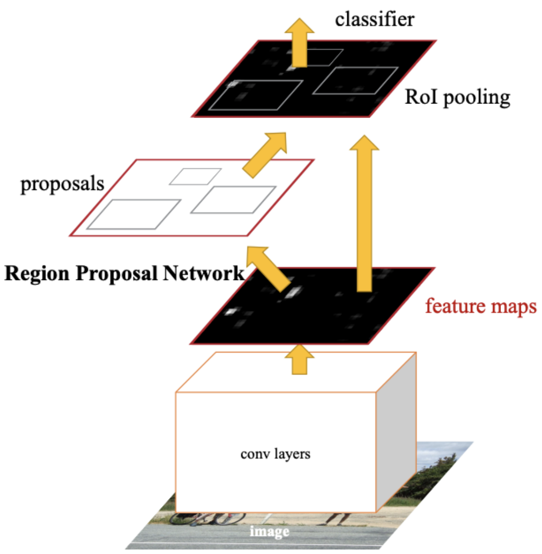

Figure 1 The Faster R-CNN model [3].

Related Work

One of the most prominent challenges in image processing and Computer Vision is face detection, which has numerous applications. In the case of mask-face detection, the first step involves detecting the face and subsequently classifying it as either with or without a mask. Rahman et al. [5] employed a deep learning architecture trained on a large dataset of individuals with and without face masks, achieving an accuracy of 98.7% in classifying individuals correctly into the "Wear Face mask" or "Not Wear Face mask" categories. Meenpal et al. [5] utilized fully Convolutional Neural Networks (CNNs) to segment faces within input images, achieving an accuracy of 93.884% in correctly classifying individuals. Shiming et al. [6] proposed LLE-CNNs to classify faces as masked or non-faces, and experimental results on the MAFA dataset demonstrated favorable performance. Militante et al. [7] introduced a deep learning model trained on a dataset of 25,000 images for detecting faces without masks in a real-time stream. Their model achieved an accuracy of 96% and was implemented on a Raspberry Pi for real-time mask detection.

In the context of the Detecting and Preventing Chest Diseases System (DPDCDS), the proposed approach for face detection employed the Single-Shot Refinement Neural Network for Object Detection. This approach aims to enhance efficiency and accuracy in detecting symptoms of infectious chest diseases, such as COVID-19, in captured images. Additionally, the Defense Laws System (DLS) utilized the Faster Regions with (Faster R-CNN) approach to improve efficiency and accuracy in detecting physical distancing between individuals and determining whether a person in the captured image is wearing a face mask correctly. By incorporating these advanced techniques, the DPDCDS aims to enhance the efficiency and accuracy of detecting infectious chest diseases and enforcing defense laws.

III. METHODOLOGY

This section provides an overview of the proposed system design, including its main subsystems as depicted in Fig. 2. It also covers the datasets used for testing and the performance metrics employed to evaluate the system. The subsequent subsections, namely II and III, delved into the demonstration of the DICDS and DLS subsystems, respectively. However, prior to that, Section I comprehensively presented the motivation behind this study. Figure 2 shows The DPDCDS subsystems DICDS, DDCDS and DLS.

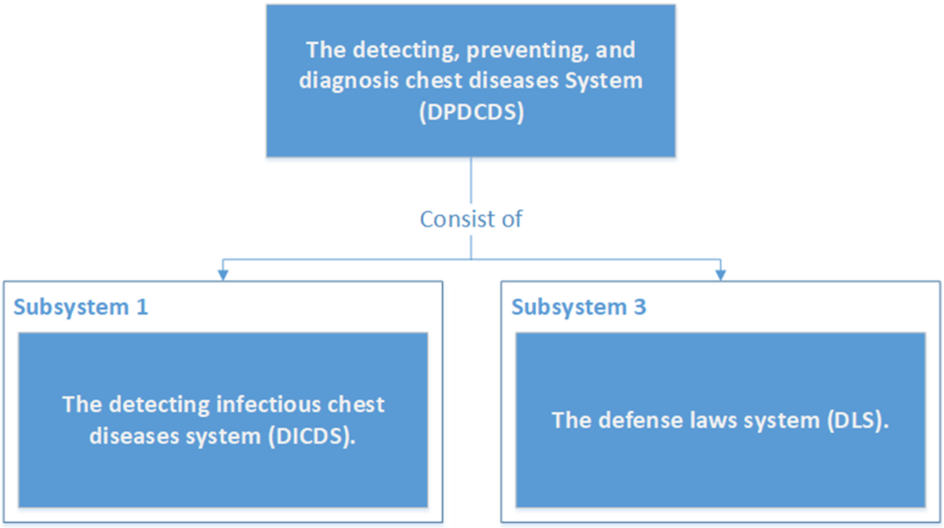

Figure 2 The DPDCDS subsystems DICDS, DDCDS and DLS.

Motivation

This research is motivated by the need to address the challenges posed by chest infectious diseases, particularly the COVID-19 pandemic. The primary objectives of this study are as follows:

- Develop a Smart System for Disease Detection: The aim is to design and implement a smart system that utilizes advanced technologies, specifically Faster R-CNN, to capture and analyze images of a person's face, hands, and arms. By leveraging the capabilities of Faster R-CNN, the system determines if the individual is infected with COVID-19 or not. This contributes to efficient and accurate disease detection, enabling timely intervention and appropriate measures to prevent further transmission.
- Detect Physical Distance and Mask Usage: Another key objective is to employ Faster R-CNN to detect physical distancing and mask-wearing in captured images. The system analyzes the images, identify individuals who are not maintaining the required physical distance or not wearing masks correctly, and provide relevant alerts or notifications. This functionality helps promote adherence to preventive measures, ensure compliance with safety regulations, and mitigate the spread of infectious diseases.

By achieving these objectives, the proposed smart system offers significant advancements in the field of disease detection and prevention. The integration of Faster R-CNN technology enables real-time analysis of captured images, empowering the system to make accurate assessments regarding COVID-19 infection status and adherence to safety protocols. This research aims to contribute to the development of an intelligent solution that enhances public health measures, safeguards individuals from contagious chest diseases, and ultimately assists in reducing the impact of infectious disease outbreaks.

The detecting infectious chest diseases system (DICDS)

Infectious chest diseases often exhibit noticeable symptoms on the skin and face of infected individuals. According to Willacy (2019), these diseases can present various symptoms, including irritated eyes, a red nose, irritated facial skin, overall skin irritation, retinal ileitis, headache, and fever. To address the detection of infectious chest diseases, particularly in the context of COVID-19, this dissertation aims to develop the Detecting Infectious Chest Diseases System (DICDS). The DICDS is an integrated system designed to work with captured images. It accepts images of a person's face, hand, and arm and employs specific digital image processing techniques to determine the likelihood of the person having infectious chest diseases.

The DICDS can be distributed to both public and private organizations, enabling fast and efficient detection of infected individuals with infectious chest diseases, such as COVID-19. In operation, the DICDS receives captured images of a person's face and arm/hand from a camera, along with the person's temperature reading from a temperature sensor. Additionally, user input is obtained to identify whether the person is experiencing a headache or not. The DICDS utilizes the RefineDet system to extract infectious chest disease symptoms (such as irritated eyes, a red nose, irritated facial skin, irritated skin, and retinal ileitis) from the input images. Features are extracted from the input image, temperature sensor reading, and user input regarding the headache state, as illustrated in Fig. 3.

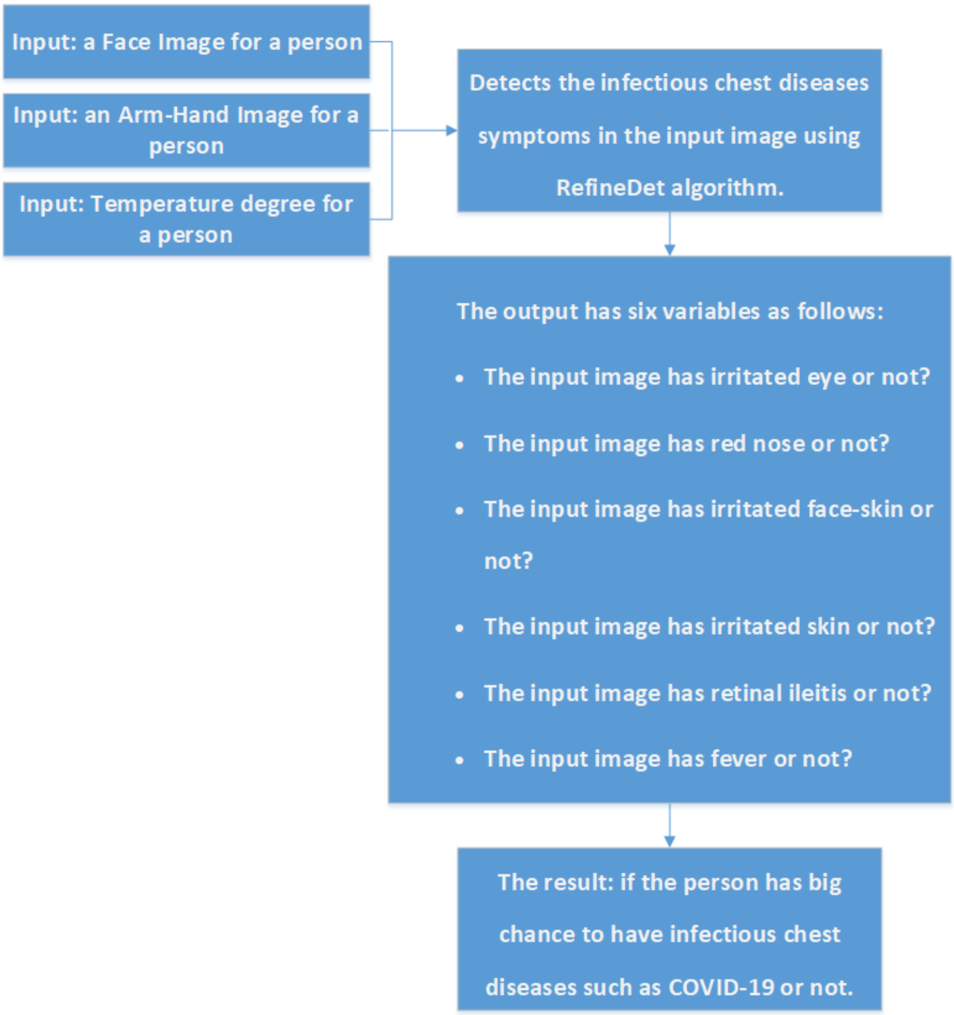

Figure 3 The DICDS general operations.

Table 1 shows the mathematical operation for DICDS, Also, Table 2 shows the mathematical operation for DICDS.

Table 1 The DICDS variables.

The DICDS variables
Input:
I: is the captured images for the person (face and hand/arm).
Symptoms and attributes to be measured and process:
IE: irritated eye. RE: red nose. IFS: irritated face-skin. RI: retinal ileitis T: The person temperature degree Train the RefineDet classifier.
Output:
C: if a person has big chance to have infectious chest disease such as COVID-19 or not.

Table 2. The mathematical operation for DICDS.

DICDS Procedure	
Step1:	Anchors_Lists = **Arm_Fun**(g) Features_DIC = **Tcb_Fun(**Anchors_Lists**)** Classify_Reg = **Odm_Fun(**Features_DIC**)**
Step2:	T = **Read_Temperature**()
Step3:	DIC = Have_DIC (T, Classify_Reg)
Where, g: is the captured image. Arm_Fun, Tcb_Fun, Odm_Fun _Lists are the RefineDe functions, that are used to extract the desired feature from the input images and	

Arm_Fun: receives the entire image, and filters out negative anchors and coarsely adjusts the locations and sizes of anchors to provide better initialization for the subsequent regress. Finally, saves the returned Anchors in the Anchors_List.
Tcb_Fun: receives the anchors list (Anchors_List) and converts feature. Finally, saves the result in Feature_DIC.
Odm_Fun: receives the extracted features (Features_DIC) and Classifies features as one of the known class (K). Finally, saves the result in Classify_Reg.
Classify_Reg: Is the classifier output, it will be:
If (g is a hand image or arm image):
Irritated skin, Healthy skin or Retinal ileitis.
If (g is a face image)
Irritated eye, Healthy eye, Red nose, A healthy nose, Irritated face-skin or Healthy face-skin
Read_Temperature: it reads the person's temperature degree and saves the result in T.
Have_DIC: it receives H, T, and Classify_Reg; and returns if the person has an infectious chest disease such as COVID-19 or not. It saves the result in DIC.

The Defense Laws System (DLS)

The Defense Laws System (DLS) has the primary objective of detecting violations within an input image. These violations include individuals not wearing face masks correctly and maintaining distances of less than one meter between themselves. The system is designed to identify instances of improper face mask usage and calculate the distances between individuals accurately. By effectively detecting these violations, the DLS contributes to enforcing defense laws related to face mask compliance and social distancing measures.

Wearing a face mask in correct way

As depicted in Fig. 4, the Defense Laws System (DLS) incorporates a specialized unit known as the face mask detection unit. This unit plays a crucial role in detecting face masks on individuals' faces within the input image. It follows a two-step process: face detection and classification.
Firstly, the face mask detection unit receives the input image and proceeds with the detection of faces present within the image. Once the faces are detected, the unit classifies them as either "good" if they are wearing masks or "bad" if they are not. To accomplish this, the unit utilizes the Faster R-CNN Algorithm, which has been trained using the MaskedFace-Net Dataset, as illustrated in Fig. 5. By leveraging the capabilities of the Faster R-CNN Algorithm and training it on the MaskedFace-Net Dataset, the face mask detection unit is able to accurately classify faces based on their mask-wearing status. This contributes to the overall functionality of the DLS, enabling it to identify instances where individuals are not wearing masks and take appropriate measures in response.

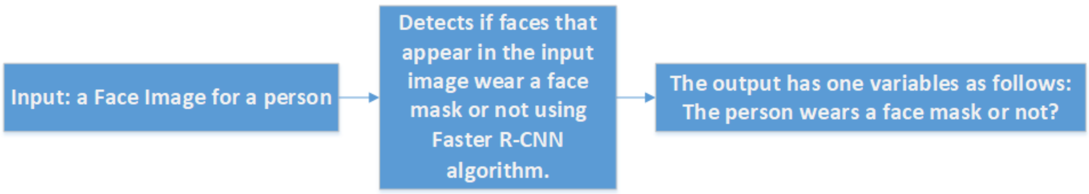

Figure 4 The DLS- Wearing a face masks operation.

Figure 5 depicts the main architecture of the Wearing Face Mask Detection Unit within the Defense Laws System. Table 3 provides an overview of the variables used in the Defense Laws System (DLS). Additionally, Table 4 presents the mathematical operations employed by the Wearing Face Mask Detection Unit within the DLS.

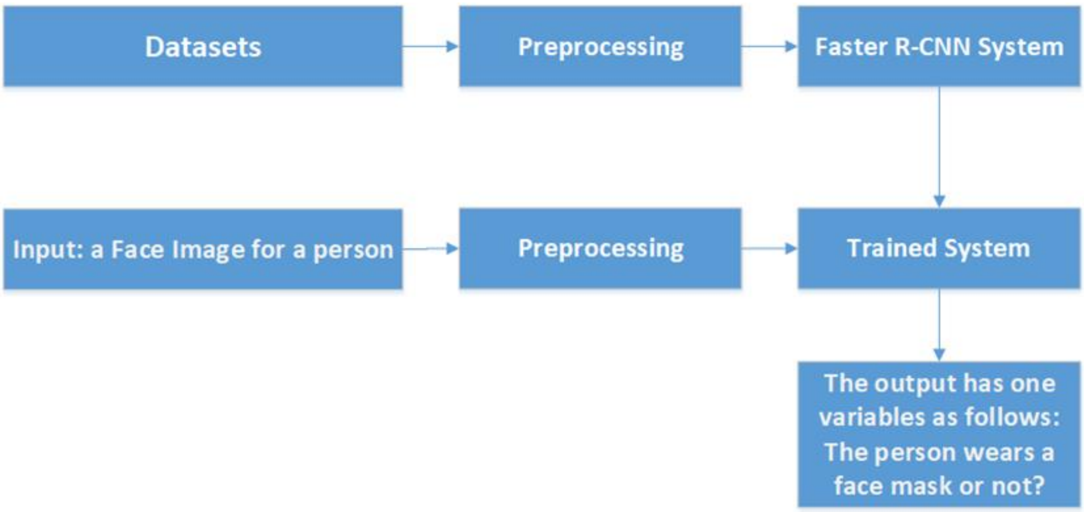

Figure 5 Wearing face mask detection unit in DLS.

Table 3 The DLS variables.

The DLS variables
Input:
I: is the captured image for the persons.
What will be measured:
AH = area of human. DistanceBet= Distance between tracked humans. Trained the Faster R-CNN classifier for detect the face mask. Trained the Faster R-CNN classifier for the human.
Output:
CR: if the person wears a face mask in the correct way or not.

Table 4 The mathematical operation for wearing face mask detection unit in DLS.

DLS Procedure- Wearing a face mask in correct way.	
Step1:	Region_Pro = **RegPro(**g**)**
Step2:	Feature_Ext = **FeExt(**Region_Pro**)**
Step3:	Classify_Reg=**Classifier(**Feature_Ext**)**
Where, g: is the captured image. RegPro, FeExt, Classifier and Classifier are functions. **RegPro**: receives the entire image, and generates and extract category independent region proposals, andsaves the result in Region_Pro. **FeExt**: receives the generated region proposals (Region_Pro) and extracts the desired feature from it, andsaves the result in Feature_Ext. **Classifier:** receives the extracted features (Feature_Ext) and Classifies features as one of the known class (person with mask or person without mask); and saves the result in Classify_Reg.	

Distance calculation

Figure 6 illustrates the functionality of the Distance Unit within the Defense Laws System (DLS). This unit is responsible for calculating the distances between individuals in an input image. Upon receiving the input image, the Distance Unit detects the persons present in the image and proceeds to calculate the distance between them. Based on this calculation, the distances are classified as either "Good" for individuals with distances greater than one meter or "Bad" for individuals with distances less than one meter. This classification enables the DLS to identify instances of appropriate social distancing and highlight areas where individuals may be too close to each other.

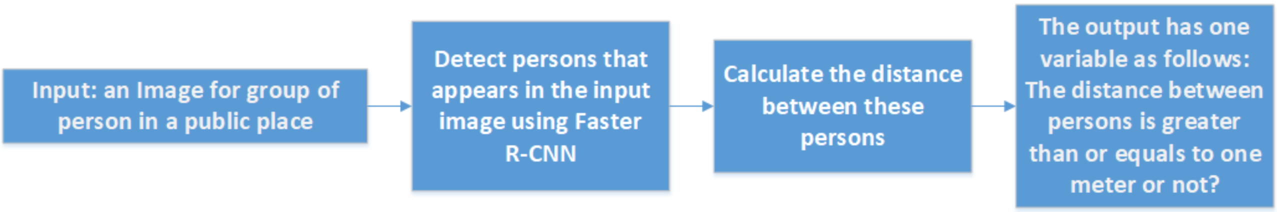

Figure 6 The DLS- Distance operation.

In more detail, this unit employed the RefineDet Algorithm to develop its own system. The algorithm was trained using the Human Detection Dataset for Constantin Werner, as depicted in Fig. 7. By utilizing this dataset and training the RefineDet Algorithm, the unit aims to create an effective and accurate system for human detection.

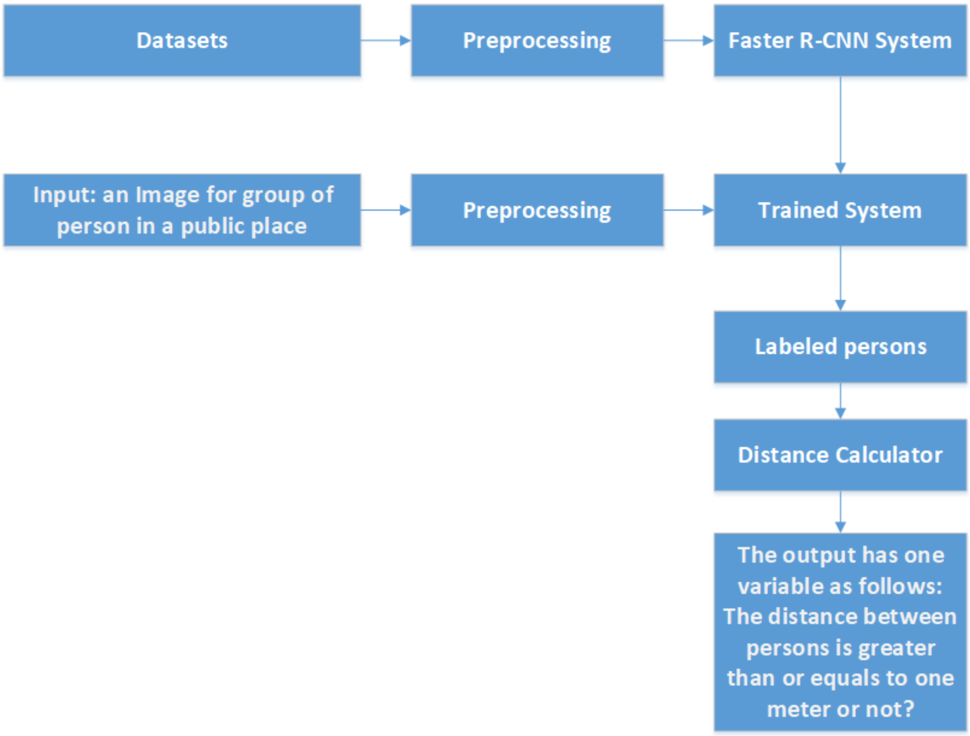

Figure 7 Wearing Distance unit in The Defense Laws System.

Table 5 presents the mathematical operations utilized by the Wearing Face Mask Detection Unit in the Defense Laws System (DLS).

Table 5 The mathematical operation for Wearing face mask detection unit in DLS.

DLS Procedure- Distance calculation	
Step1:	Region_Pro = **RegPro**(g)
Step2:	Feature_Ext = **FeExt(**Region_Pro**)**
Step3:	Classify_Reg=**Classifier(**Feature_Ext**)**
Step4:	Classify_Violation = **DistanceBet(**Classify_Reg'**)**
Where, RegPro,FeExt, Classifier and Classifier are functions: **RegPro**:receives the entire image, and generates and extract category independent region proposals. Finally, saves the result in Region_Pro. **FeExt**: receives the generated region proposals (Region_Pro) and extracts the desired feature from it. Finally, saves the result in Feature_Ext. **Classifier:** receives the extracted features (Feature_Ext) and Classify features as one of the known class (person or not). Finally, saves the result in Classify_Reg. **Classify_Reg':** are all Classify_Reg objects that labeled as person class. **DistanceBet:** receives all the Classify_Reg' objects, and calculate the distance between these objects. Finally, it returns every object (person) if it has a distance less than 1 meter from any other object.	

DLS-Approach's

The implementation of the Defense Laws System (DLS) can be approached in three different ways: DLS-Approach1, DLS-Approach2, and DLS-Approach3. These approaches represent distinct strategies for developing and deploying the DLS system. Each approach may have its own unique characteristics, methodologies, and implementation considerations. The selection of a specific approach depends on various factors such as system requirements, resources available, and desired outcomes. The choice of approach should align with the goals and objectives of the DLS implementation.

DLS-Approach1

During this phase, an intelligent image-processing system was developed to analyze pre-captured images of individuals in various settings such as streets, shops, malls, governmental institutions, and more. The system's objective is to identify any general violations of the authority's defense laws, specifically related to the correct wearing of face masks (covering the nose and mouth) and maintaining a safe distance between individuals in public places. It is important to note that all processes will be conducted offline, focusing solely on pre-captured images (refer to Fig. 8). The government can benefit from this approach in several ways:

- Dividing the Country into Law-Abiding Regions: By providing the Defense Laws System (DLS) with a set of images from different regions, the government can conduct analyzing studies to identify areas that comply with the defense laws and those that do not. This enables the government to establish intense monitoring and inspection patrols in non-law-abiding regions, ensuring compliance with safety regulations.

- Ensuring Compliance in Government Institutions and Commercial Stores: The government can leverage the intelligent image-processing system to analyze pre-captured images taken from within government institutions and commercial stores. This allows for the assessment of these establishments' adherence to defense laws among their employees and visitors. Strict penalties can be imposed on institutions and stores found to be non-compliant.
- Evaluating Monitoring and Inspection Patrols: Analyzing studies can be conducted by providing the Defense Laws System with a set of images from different public places. This allows the government to identify monitoring and inspection patrols that may be reluctant to fulfill their duties in enforcing compliance. Action can then be taken to address any issues and ensure proper monitoring of citizens.
- Utilizing Entry/Exit Records: The government can enforce a requirement for all government institutions and commercial stores to maintain entry/exit records, including the names and national identification numbers of visitors. In cases where safety violations are detected within these places, the system can easily identify the individuals responsible by matching the entry/exit records with the output results from the Defense Laws System (DLS).

DLS-Approach2

In this phase, the DLS-Approach2 was developed, comprising two main units: The Defense Laws System and the Defense Laws Detection Unit (DLDU). The research focuses on designing and implementing these units. The DLDU serves as a specialized surveillance device equipped with surveillance cameras, while the Defense Laws System-1 is embedded within it to detect violations (as shown in Fig. 9). When violations are detected, the system issues alerts that can be utilized in the following ways:

- Alerting Monitoring and Inspection Teams: The alerts are sent to the nearest monitoring and inspection teams, enabling them to quickly respond and monitor the identified violations. This allows for swift intervention and control of non-compliant situations.
- Notifying Administrative Staff: Alerts are sent to the administrative staff present in government institutions or commercial stores to inform them of any security violations occurring within their premises. This timely information empowers them to take immediate action and address the non-compliance within their respective locations.

By implementing the DLS-Approach2, the system provides an efficient means of detecting and addressing violations of defense laws. Through timely alerts, the system enables effective monitoring, control, and intervention, ensuring the enforcement of safety regulations in a swift and proactive manner.

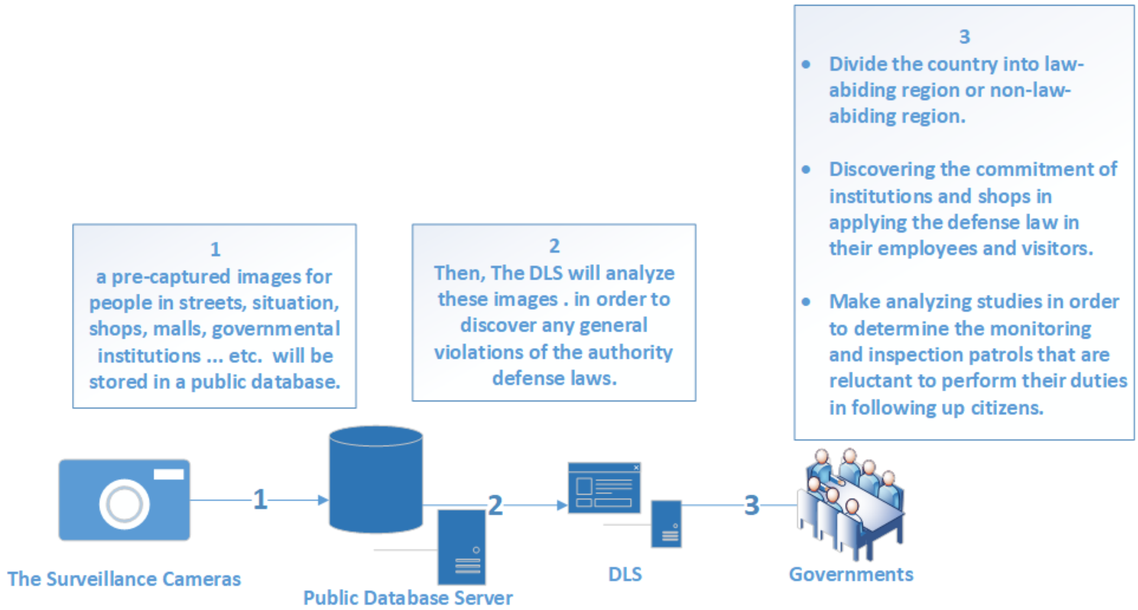

Figure 8 DLS-Approach1.

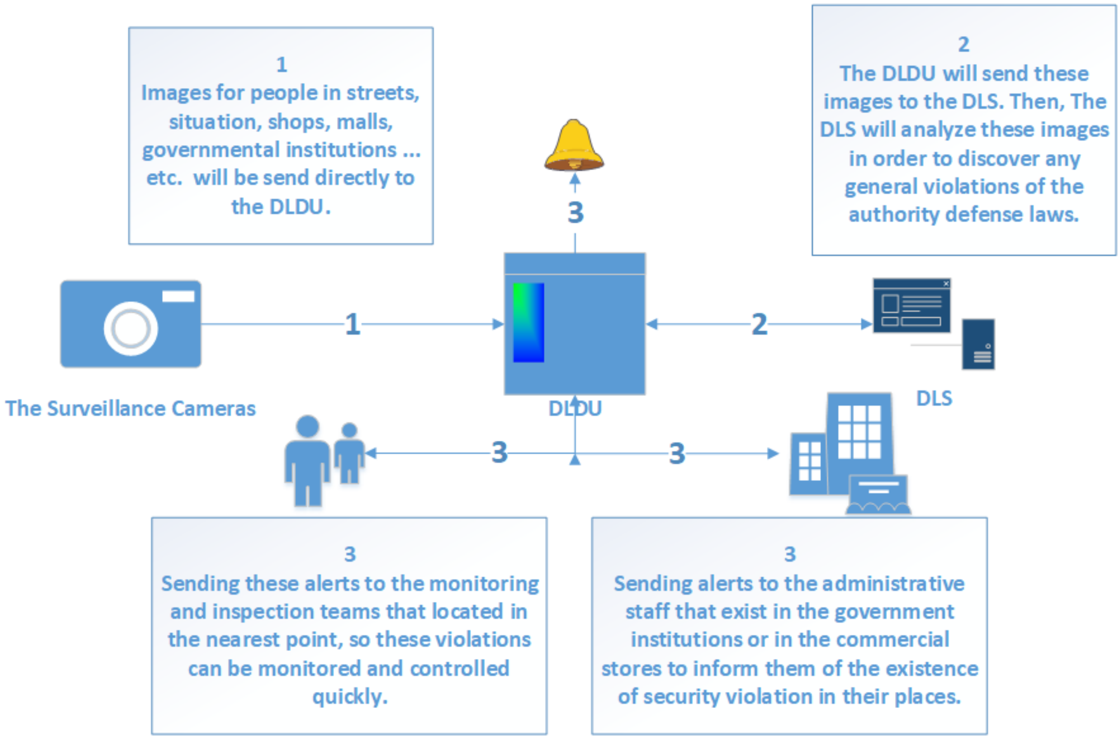

Figure 9 DLS-Approach2.

DLS-Approach3

Approach3 comprises two primary components: (1) the Defense Laws System (DLS) and the Defense Laws Detection Unit (DLDU-2), a specialized surveillance device developed as part of this research, and (2) electronic chips integrated into or carried by individuals. The DLDU-2 receives image data from surveillance cameras and transmit it to the embedded Defense Laws System-1 for the detection of any violations. When violations are detected, the system issues alerts, which can be utilized in various ways.

First approach involves the following scenario (refer to Fig. 10): The government mandates that all individuals download a smart program called the Person-Identifications App (PIApp) on their mobile phones. This application allows the DLDU-2 system to access the personal information of the phone holder, such as their name and national ID, when a request is made by the DLDU-2 system. In this scenario:

- The DLDU-2 creates a database containing the personal information of all individuals present in the captured images.
- When a violation is detected by the Defense Laws System-1 in the images, the DLDU-2 identifies the perpetrator and relay their information to the relevant police units.

This approach enables effective tracking and identification of individuals involved in violations captured by the surveillance system. By integrating the PIApp and leveraging the DLDU-2's database, law enforcement agencies can swiftly identify individuals responsible for non-compliance with defense laws and take appropriate actions.

The government can ensure widespread adoption of the (PI-App) by implementing the following measures:

- Partnering with Telecom Companies: The government can collaborate with local telecom companies, such as Jordanian telecom providers, to make it a requirement for users to install the (PI-App) on their smartphones. This can be enforced by temporarily suspending certain services or restricting network access for individuals who have not installed the app.
- Issuing a Public Decision: The government can issue a public decision mandating that individuals must have the (PI-App) installed on their smartphones in order to enter commercial stores or government institutions. This decision would serve as a legal requirement, ensuring widespread compliance with the app installation.
- Collaboration with Police Authorities: The government can seek assistance from law enforcement agencies, such as the police, to verify whether individuals have installed the (PI-App) on their phones. Police authorities can conduct routine checks or inspections to ensure compliance and take appropriate action against individuals who have not installed the app.

By implementing these measures, the government can effectively coerce individuals to install the (PI-App), thereby ensuring broader adoption and utilization of the app for monitoring and controlling the spread of infectious diseases.

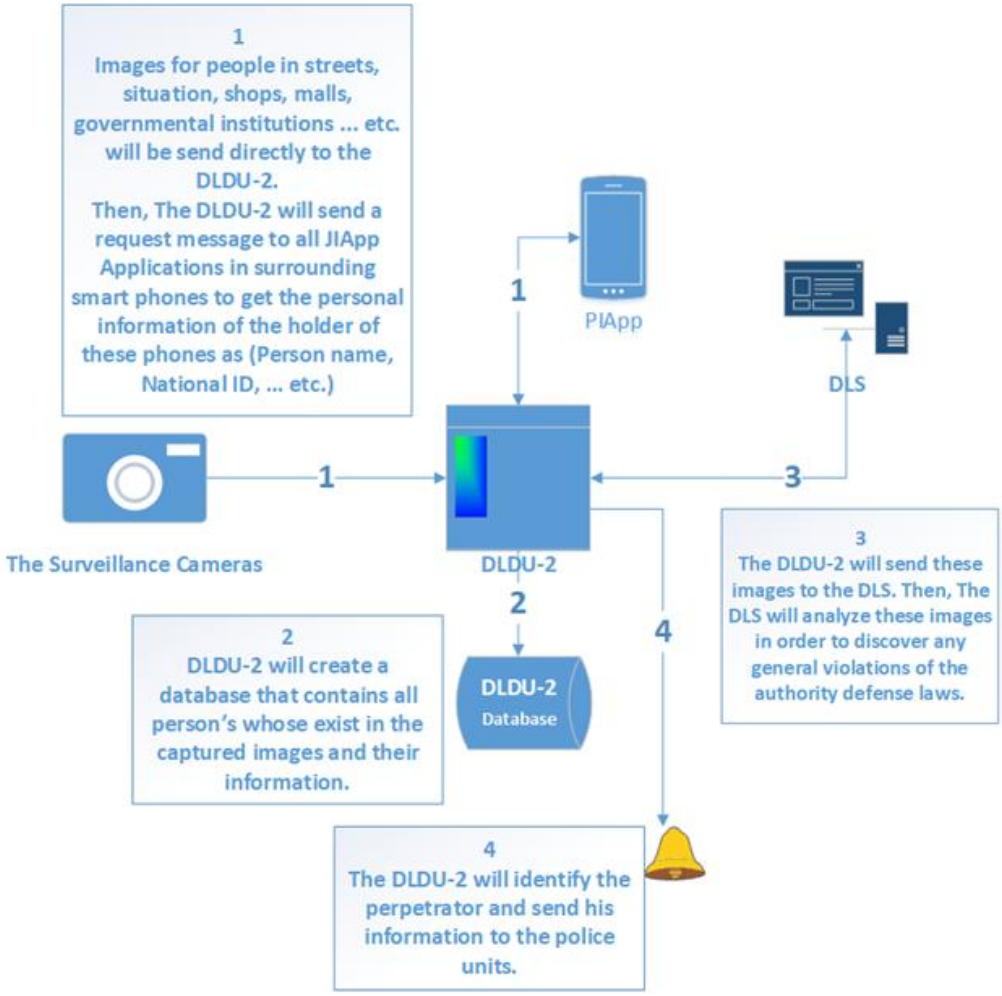

Figure 10 DLS-Approach3.

The second approach involves the implementation of an electronic chip that is either implanted in or carried by individuals. This chip serves the purpose of storing personal information, as well as important biological data such as temperature, virus levels in the blood, phone numbers, and geographical locations. The functionality of this chip operates as follows (refer to Fig. 11):

- Cameras capture an image, while simultaneously, the Defense Laws and Detection Unit 22 (DLDU-22) sends a request to all chips present in the bodies of individuals appearing in the image. The purpose is to obtain their information and create a database known as the DLDU-2 Database to store this collected data.
- Subsequently, the Defense Laws analyze the pre-captured images to identify any violations of the defense laws.
- The perpetrator can then be easily identified by matching the detected violation with the information stored in the DLDU-2 Database. The DLDU-2 system provides this information to the police for further action.
- Additionally, the DLDU-2 database can be utilized to gather information about body temperature and the percentage of the virus in the blood. This data can be used to send notifications to individuals who may be at risk of COVID-19.

By utilizing this approach, the electronic chip enables efficient identification of individuals, facilitates the enforcement of defense laws, and provides valuable information for public health measures such as COVID-19 notifications.

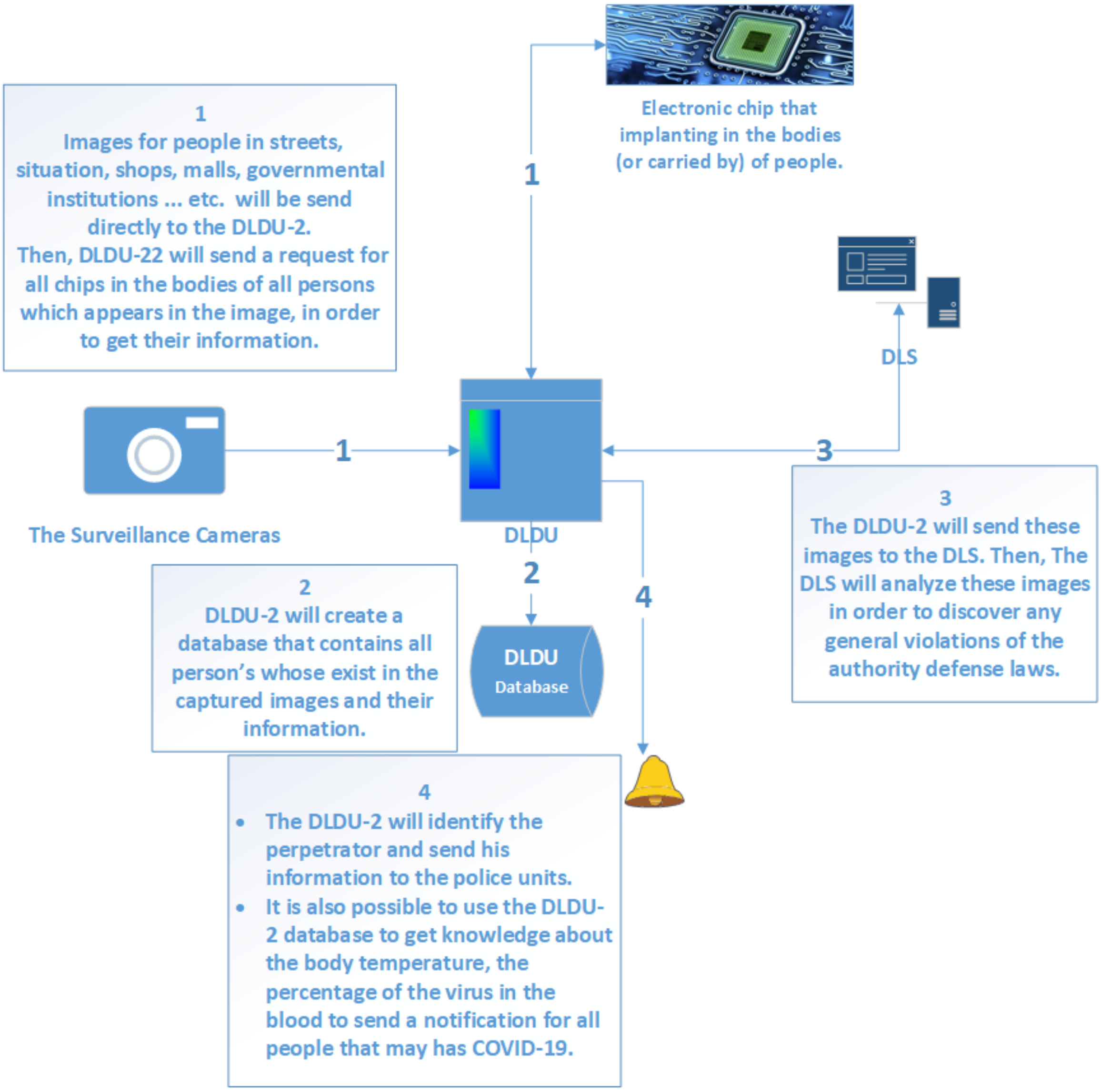

Figure 11 DLS-Approach3.

The training and testing of the DICDS involves the use of two datasets: The Covid Skin dataset by Adele de Masson (Masson, 2020) and a User Defined Dataset collected from images provided by the World Health Organization and the Jordanian Ministry of Health.

Dataset

The training and testing of the DICDS) was involved the use of two datasets: The Covid Skin dataset by Adele de Masson [9] and a User Defined Dataset collected from images provided by the World Health Organization and the Jordanian Ministry of Health. These datasets consist of a total of 15,000 images.

On the other hand, the DLS utilized the Faster R-CNN algorithm to calculate the physical distance between individuals in an input image and detect whether a person is wearing a face mask correctly. The training and testing of the DLS relied on two datasets: The MaskedFace-Net Dataset (Cabani et al., 2014) [10], the Human Detection Dataset for Constantin Werner (Konstantin et al., 2014) [11], and COCO 2017 Dataset [12] These datasets consist of a total of 300,000 images.

All datasets divided into three parts: two parts for training the respective systems and one part for testing the trained models. This division ensures that the models are trained on a sufficient amount of data and can be evaluated accurately on unseen data during the testing phase.

Performance Metrics

The performance of the proposed system was assessed using several performance metrics, including recall, accuracy, F1 score, and precision.

- Recall: This metric measures the system's ability to correctly identify positive instances out of all actual positive instances. It quantifies the system's effectiveness in detecting infectious chest diseases and violations accurately.
- Accuracy: Accuracy represents the overall correctness of the system's predictions, measuring the proportion of correct predictions out of all predictions made. It provides a general assessment of the system's performance in terms of both true positives and true negatives.

- F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balanced evaluation of the system's performance by considering both the ability to detect positive instances (recall) and the precision of those detections (precision).
- Precision: Precision measures the accuracy of positive predictions, specifically the proportion of true positive predictions out of all positive predictions made. It assesses the system's precision in correctly identifying violations and disease instances without generating too many false positives.

By evaluating the system's performance using these metrics, it becomes possible to obtain a comprehensive understanding of its effectiveness in detecting infectious chest diseases, identifying violations accurately, and minimizing false positives and false negatives.

IV. Results and Discussion

In this section, we present the results obtained from the implementation and evaluation of the proposed system, as well as discuss their implications and significance. The system was tested on various datasets and performance metrics were used to assess its effectiveness in detecting infectious chest diseases and enforcing defense laws.

Results of DICDS

The proposed DICDS achieved remarkable results in detecting COVID-19, with an accuracy of 98.5% in the test dataset and 96.9% in the validation dataset. Furthermore, the system exhibited a high F1 score of 0.98, indicating a balanced performance between precision and recall.

Table 6 provides a comprehensive overview of the performance results obtained by the DICDS. It showcases the accuracy, precision, recall, and F1 score achieved by the system, highlighting its effectiveness in accurately detecting COVID-19 cases. These performance metrics demonstrate the robustness and reliability of the DICDS in identifying infectious chest diseases and contributing to the overall protection of public health.

The achieved accuracy and high F1 score are indicative of the system's capability to accurately classify individuals and make informed decisions regarding their health status. These results are a testament to the effectiveness of the DICDS in assisting healthcare professionals and authorities in making timely and accurate diagnoses, leading to effective disease management and prevention. The achieved performance results underscore the potential impact of the DICDS in mitigating the spread of infectious diseases, particularly COVID-19. The high accuracy, precision, recall, and F1 score obtained in the test and validation datasets validate the system's effectiveness and reliability, making it a valuable tool in the fight against contagious diseases.

Table 5 a comprehensive overview of the performance results obtained by the DICDS.

	Class	Accuracy	Precision	Recall	F1 score
Validation dataset	COVID-19	96.9%	0.97	0.97	0.97
	No-Finding	96.9%	0.97	0.97	0.97
Test dataset	COVID-19	98.5%	0.99	0.98	0.98
	No-Finding	98.5%	0.98	0.98	0.99

Results of DLS

The proposed system achieved high accuracy in detecting the distance between persons, with a remarkable accuracy rate of 99.2% in the Test dataset and 95.2% in the Validation dataset. This indicates the system's ability to accurately measure the physical distance between individuals in an image. Furthermore, the system demonstrated a high F1 score of 0.99, which signifies the system's balanced performance in terms of precision and recall. The high F1 score demonstrates the system's ability to detect the distance between persons accurately while minimizing both false positives and false negatives.

The performance results of the DLS are presented in Table 6. The table provides a comprehensive overview of the system's performance, including accuracy, precision, recall, and F1 score. These metrics highlight the system's effectiveness in accurately detecting the distance between persons.

Overall, the results illustrate the high accuracy achieved by the system in detecting the distance between persons. The impressive F1 score further emphasizes the system's robust performance. These findings demonstrate the system's potential for practical implementation in various settings, contributing to public health measures and ensuring compliance with social distancing guidelines.

Table 6 a comprehensive overview of the performance results obtained by the DLS-Distance.

	Class	Accuracy	Precision	Recall
Validation dataset	95.2%	0.96	0.95	0.95
Test dataset	99.2%	0.99	0.99	0.99

The proposed system achieved exceptional accuracy in detecting face masks, with an impressive accuracy rate of 99.9% in the Test dataset and 96.7% in the Validation dataset. This indicates the system's ability to accurately identify whether individuals are wearing face masks. Furthermore, the system demonstrated a perfect F1 score of 1, which signifies the system's excellent performance in terms of precision and recall. The high F1 score demonstrates the system's ability to detect face masks accurately while minimizing both false positives and false negatives.

The performance results of the DLS are presented in Table 7. The table provides a comprehensive overview of the system's performance, including accuracy, precision, recall, and F1 score. These metrics highlight the system's effectiveness in accurately detecting face masks for individuals.

Overall, the results illustrate the high accuracy achieved by the system in detecting face masks for individuals. The perfect F1 score further emphasizes the system's robust performance. These findings demonstrate the system's potential for practical implementation in various settings, contributing to public health measures and ensuring compliance with face mask usage guidelines.

Table 7 a comprehensive overview of the performance results obtained by the DLS-Distance.

	Class	Accuracy	Precision	Recall
Validation dataset	96.7%	0.97	0.97	0.97
Test dataset	99.9%	1	1	1

The results of the proposed system highlight its effectiveness in detecting infectious chest diseases and enforcing defense laws related to face mask usage and social distancing. The system's high recall value indicates its ability to identify true positive instances, ensuring that individuals with infectious diseases are not missed. The high accuracy value demonstrates the overall correctness of the system's predictions, minimizing false positives and false negatives. The F1 score and precision values reflect the system's balanced performance in detecting violations accurately without excessive false alarms.

The obtained results validate the utility of the proposed system in safeguarding public health and ensuring compliance with defense laws. The system's capability to detect infectious chest diseases and violations in real-time provides valuable insights to authorities for effective decision-making and intervention. Furthermore, the system's high performance metrics indicate its potential to contribute significantly to public health measures and prevent the spread of diseases.

Overall, the results highlight the efficacy of the proposed system in addressing the challenges posed by infectious chest diseases and enforcing defense laws. The system's performance demonstrates its potential for practical implementation and potential impact in protecting public health and safety.

V. Conclusion and Future research

In conclusion, this research aims to develop a smart system, the Detecting and Preventing Chest Diseases System (DPDCDS), to assist in the detection and prevention of infectious chest diseases such as COVID-19. The DPDCDS utilizes image processing, machine learning, and artificial intelligence techniques to identify individuals at high risk of infection and enforce defense laws. The system achieves impressive accuracy rates in detecting chest diseases, with the DICDS achieving 98.3% accuracy and the DLS achieving 99.3% accuracy in distance detection and 99.9% accuracy in face mask detection.

The proposed system offers several benefits, including low cost, ease of use, and fast detection capabilities. It can be distributed across various public and private organizations to facilitate the swift identification of infected individuals. By implementing the system in public places, the government can protect citizens from disease transmission and limit the spread of infectious diseases. The DPDCDS includes the DICDS and DLS subsystems, which focus on detecting infectious diseases and monitoring compliance with defense laws, respectively. These subsystems further enhance the system's effectiveness in disease detection and prevention.

The results demonstrate the system's high recall, accuracy, F1 score, and precision, indicating its proficiency in accurately identifying infectious chest diseases and enforcing defense laws. The proposed system presents a valuable tool for countries in managing chest diseases and mitigating their negative effects. By integrating image processing techniques and automated systems, the DPDCDS offers an effective solution to protect the population and enforce defense laws.

Future research can explore enhancements to the system, such as incorporating real-time data streams and expanding the dataset to further improve accuracy. Additionally, collaboration with healthcare institutions and government authorities can support the implementation and adoption of the system on a larger scale. Overall, the proposed system holds great potential in supporting public health efforts, particularly in the detection and prevention of infectious chest diseases.

VI. Acknowledgment

I would like to express my heartfelt gratitude to the reviewers, as well as the International Journal of Scientific Development and Research, for their valuable feedback and support. Lastly, I extend my sincere appreciation to my family and friends for their unwavering support throughout this endeavor.

References:

[1] L. Lowenstine, K. Osborn, Respiratory System Diseases of Nonhuman Primates. “Nonhuman Primates in Biomedical Research”, 2012, vol.1, pp.413–81.
[2] L. Weng, “Object Detection Part 4: Fast Detection Models”, Retrieved March 19, 2021, from https://lilianweng.github.io/posts/2018-12-27-object-recognition-part-4/
[3] S. Ren, K. He, R. Girshick, J. Sun, “Faster R-CNN: Towards real-time object detection with region proposal networks”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, pp. 1137-1149.
[4] Girshick R., “Fast R-CNN. 2015 IEEE International Conference on Computer Vision (ICCV)”, “Santiago”, vol. 2015, pp. 1440-1448.
[5] M. Rahman, M. Manik , M. Islam M., S. Mahmud, J. Kim, “An Automated System to Limit COVID-19 Using Facial Mask Detection in Smart City Network”. IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), Vancouver, BC, Canada,pp. 1-5.
[6] T. Meenpal, A. Balakrishnan A., and A. Verma, “Facial Mask Detection using Semantic Segmentation. 2019 4th International Conference on Computing”, Communications and Security (ICCCS), Rome, Italy, 2019, pp. 1-5.
[7] S. Ge, J. Li , Q. Ye, Z. Luo Z. “Detecting Masked Faces in the Wild with LLE-CNNs”, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 426-434.

[8] S. Militante S., N. Dionisio, “Real-Time Facemask Recognition with Alarm System using Deep Learning”, 2020 11th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 2020, pp. 106-110.
[9] Masson A. “COVID SKIN Dataset. Mendely dat”a, V1, doi: 10.17632/2f9rpvh9vd.1
[10] Cabani, A. Hammoudi, K. Benhabiles and H. Melkemi, M. (2020), MaskedFace-Net -- A Dataset of Correctly/Incorrectly Masked Face Images in the Context of COVID-19. arXiv preprint arXiv:2008.08016
[11] Konstantin Verner W. (2020), Human Detection Dataset, Retrieved March 19, 2021, from https://www.kaggle.com/datasets/constantinwerner/human-detection-datase.
[12] L. Tsung-Yi, M. Maire, S. Belongie, L. Bourdev, R. Girshick, J. Hays, “Microsoft COCO: Common Objects in Context”, CoRR, 2014,abs/1405.0312. Available from: http://arxiv.org/abs/1405.0312