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Research Article

IoT and AI Based Recognition and Classification of Covid 19 Persons in Public Place

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Abstract

One of the computer vision application is human face detection. There have been several studies in the field of image processing on the face. Previously, several researchers studied facial recognition. In this paper, we identified the covid-19 patient roaming in public places during quarantine time, which has been identified by using IOT and AI techniques with core concept of Human face detection. This is the new idea in this covid -19 conditions for Human face detection. In district wise, day by day regular covid -19 positive cases are stored in the cloud by using an IoT mechanism. The storable data's such as name, mobile number, address with photos (with different poses). These personal details are properly stored and retrieved from the cloud database. The store and retrieve process are handled by using IoT with Raspberry Pi. In CCTV with face detection system is used to observe the actual situation and detect any human presence on the video. We set up the cameras in important places that are connected to the cloud server to forward the covid 19 affected and non-covid person's faces. In this recognition, processes are handled by using AI techniques and the classification of covid positive and normal case by using convolution neural network (CNN). The roaming persons are captured in the camera continuously, AI technique will match and classify the face with already stored database (testing center data). In this classification process, If AI recognizes the covid positive patient, raspberry pi will follow the classified personal data that will directly send a message to the government health care unit, they

will take legal action against the person. This experiment, we have conducted by using OpenCV with python platform. This proposed model will minimize the covid 19 spread in public, and also decrease the mortality rate due to covid disease.

Keyword: Raspberry pi, convolution neural network, COVID-19, Human face detection and recognition.

1 Introduction

COVID-19 is mostly spread through salivary drops made when close contact people sneeze or cough. Respiratory droplets can form when breathing, although they are not well-planned airborne. It might potentially spread by fomite transmission [1]. Contacting a fomite (contaminated surface) and then contacting the body's mucous membranes, such as the mouth, nose, or eyes, may allow the pathogen to enter the body. This is why it is essential to thoroughly and regularly wash your hands. It is most transmissible when individuals are sick, although it can spread before signs show [2]. COVID-19 can survive for up to 72 hrs on surfaces. The time between exposure and the start of symptoms ranges from two to fourteen days, with a five-day average. Infection-prevention strategies include regular hand cleaning, social distancing (keeping a bodily distance from others, particularly those with symptoms), covering coughs and sneezes with a tissue or inner elbow, and keeping unclean hands away from the face [3]. The international community is looking at new ways to prevent the virus's spread. The virus mostly spreads among people who are in close proximity to each other (within 6 feet) over an extended period of time. Real-time scheduling and optimization techniques can help prevent an excessive number of people from congregating in a certain area (e.g., supermarkets, hospitals) while maintaining a sufficient Quality-of-Service level in the context of social distance. Figure 1 illustrates a range of social distance scenarios that may be addressed using scheduling and optimization techniques [4].

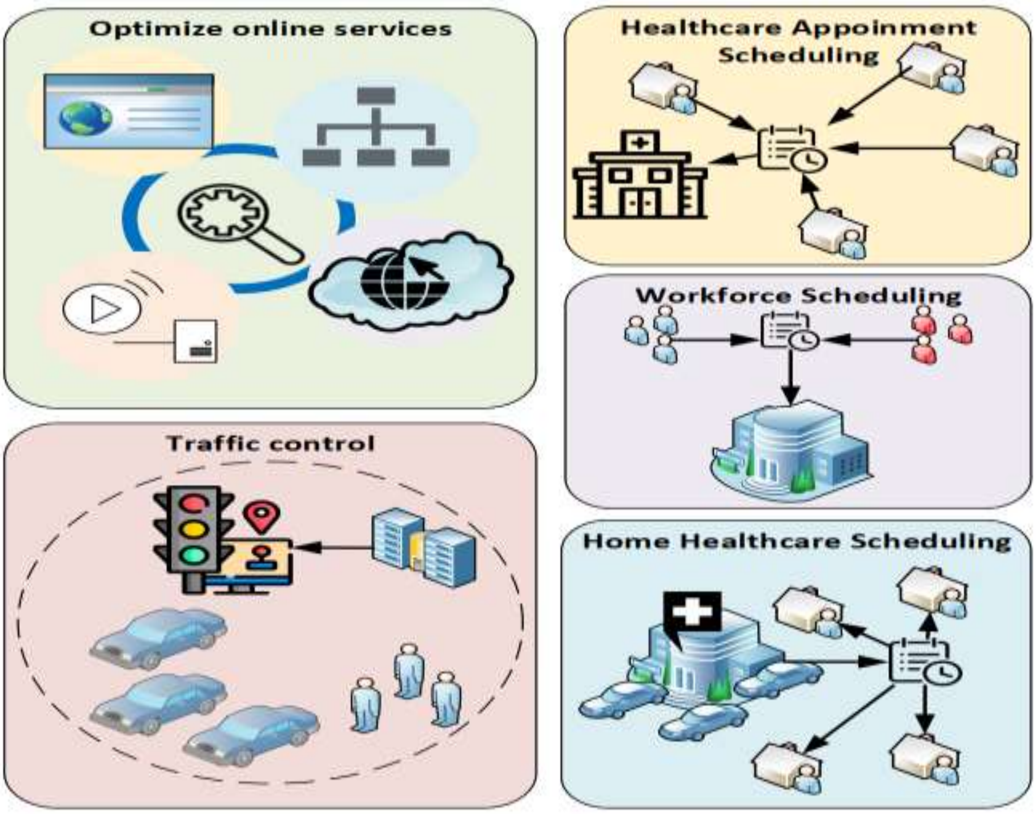

Figure 1: Scheduling and optimization for several social distancing scenarios

Droplets from an infected person's nose or mouth disperse into the air and infect people around them when they sneeze, cough, or talk. The droplets reach the lungs through the respiratory system as well, where they begin to harm lung cells. According to recent study, people who show no symptoms but are infected with the virus help spread the infection [5]. As a result, even if no symptoms are evident, it is critical to maintain a distance of at least 6 feet from people. Social distancing is connected with efforts to prevent viral spread by reducing physical contact between humans in public areas, avoiding crowd gatherings, and keeping a sufficient space between individuals. Throughout the previous two decades, computer vision, machine learning, AI, deep learning and IoT have all showed promising results in a range of real-world situations. Artificial intelligence developments have made facial detection tasks more successful. One subset of computer vision applications is human face detection. Face detection is based on recognising and finding a human face picture in an image, regardless of its size, position, or condition [6 and 7].

Face recognition is a technological development that is becoming more important in a number of sectors, such as security, control systems, and the presence system. When people are sick it is most contagious, though it can break out before symptoms appear [8]. Up to 72 hours COVID-19 on surfaces can survive. The time from exposure to symptoms is two to 14 days, with an average of 5 days. Careful hand washing, social distance's, especially those with symptoms (keeping physical distance from others), cough and tissue- or internal elbow-covering sneezes, and unclean hands from the face include infection prevention [9]. Computer vision technology instructs computers on how to evaluate and interpret visual data such as digital photographs and videos. As a result of recent breakthroughs in AI, computer vision has enabled computers to properly detect and categorize individuals (e.g., in pattern recognition and deep learning) [10].

2 Literature survey

This evaluation looked at numerous studies involving COVID-19 and the Internet of Things, medical imaging, and different software applications.

Tian et al. [11] have projected the Temporally Deformable Alignment Network, which addresses the problem of video frame temporal alignment by using deformable convolutions rather than computing optical flow. Xue et al. [12] have projected the task-oriented flow, which assessed the optical flow field and used a flow image as a motion depiction. Su et al. [13] describe a deep learning method for fusing adjacent frames for video deblurring, which eliminates the necessity for precise temporal alignment. To improve mean average accuracy, Najibi et al. [14] have offered a Single Stage Headless (SSH) face detector that includes context layers into detection modules. Meanwhile, when applying detectors to actual systems, real-time is critical.

Hassan et al. [15] proposed for the use of AI-based algorithms to limit physical connections between persons in order to minimize the range of the COVID-19 virus and extra illnesses. They use bipartite graph and Hopcroft-Karp network methods to evaluate the risk of crowds in public places using simulated and collected data. First, the collected and simulated data are graphed, and graph nodes and links are discovered. The Hopcroft-Karp method is applied to the resulting bipartite graph. The extreme number of matching sets and driver nodes are found. Lastly, the findings may be used to make choices about hazardous networks and driver nodes for public safety drives. According to experimental data, using network procedures reduces the spread of the COVID-19 virus in public by 67 percent.

The combination of IoT and ML [16] led in an unique notion of an medical IoT to fight COVID-19 spread. The study's objective was to develop a method for monitoring COVID-19 patients. It also advocated for preserving a physical barrier among healthcare staff and patients. The system may communicate a patient's biological data to the right doctor while also allowing contact between the patient and healthcare professionals. As part of this system, patients must dress biological sensors, as well as cameras for observing and touchscreen screens for communication with physicians or nurses. The data obtained is then evaluated using machine learning techniques and computer vision skills. Arduino and Raspberry Pi are among the hardware components used to control and organise sensors, cameras, and touchscreens. According to the researchers, this low-cost technology enables healthcare practitioners to give remote services to patients. Real-time data from IoT strategies alerts healthcare authorities in time to respond to a serious scenario in a patient.

2.1 Face Recognition Challenges

Automatic Face Recognition is regarded as a challenging topic since most searches are conducted solely among faces going to the same or diverse classes. Furthermore, in most situations, only a few sample face photos are available to train the system, and when training and test images are taken under changed situations, the results are poor. Researchers have encountered difficulties as a result of the classifiers' sensitivity to lighting, posture, emotion, age, resolution fluctuation, and occlusion issues. As a result, current research have been categorized based on the influence of face recognition approaches to meeting some of the aforementioned problems, namely, partial face identification and low resolution face recognition.

3 Proposed method

To prevent the virus from spreading from one infected person to another, the infected individual or those who have had direct contact with them must be quarantined in limited locations or at home. Computer vision's facial recognition capabilities can assist in enforcing this rule by analyzing pictures or videos from cameras to identify these persons (i.e., to check whether they breach the self-isolation requirements or not). If these individuals are discovered in public, the authorities can be alerted and necessary action can be taken. We employed Convolution Neural Networks in this suggested model to identify and classify human faces. Using an IoT method, the covid -19 positive instances recorded are saved in the cloud. A dataset including full-face pictures of the isolated persons must be created. The face recognition algorithm initially learns from this dataset before analyzing photos from public surveillance cameras to determine their looks. The proposed model diagram is depicted in figure 2 below.

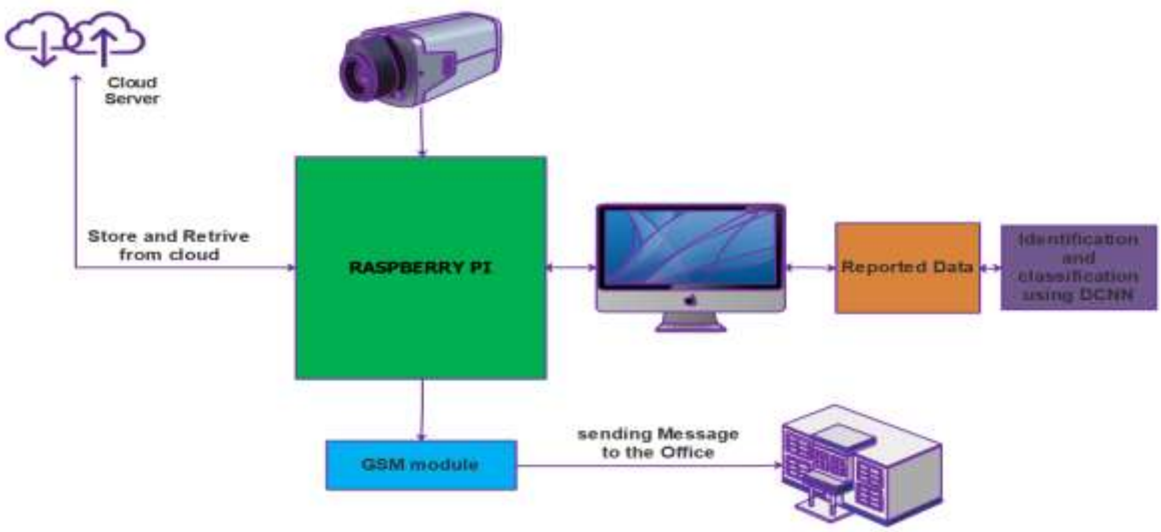

Figure 2: Proposed Methodology Flow Diagram

3.1 Dataset

The system installation, like other surveillance cameras, employed a camera with a frame rate of 30 frames per sec (30 fps). This camera is set up to record at 1920x720 resolution with a color depth of 16 bits per pixel. The detection accuracy and storage efficiency of a sample video captured for 1263 seconds (4000 frames) have been investigated. This video has been checked by hand, frame by frame. It contains 2300 face frames and 2700 body-embedded frames, for a total of 5000 motion frames. These findings served as the foundation for our analysis. Figure 3 depicts the various frames samples obtained from the video.

Figure 3: figures extracted from video frame

Table 1: Specification of personal data

Covid positive case persons record format
Name
Sex
Age
Address
Place
Phone number
Specific id for the person

3.2 Cloud storage

Because Wi-Fi technology is extensively implemented in interior locations, it may be regarded as a viable option to practice in cloud storage. A wireless transmitter, called as a wireless right of entry point, is required in a Wi-Fi system to broadcast the covid person data to cloud storage. Wi-Fi enabled wireless strategies are currently working on IEEE 802.11 specifications. Wi-Fi 6 (802.11) is the most recent version of Wi-Fi standards, providing high speed and dependable connections.

3.3 Raspberry Pi

It is a credit card-sized computer that can be plugged into any HDMI or RCA video input device and requires a keyboard to operate. Once configured, the HDMI and keyboard are no longer necessary for operation because it may be controlled by alternative ways such as ssh for command line border.

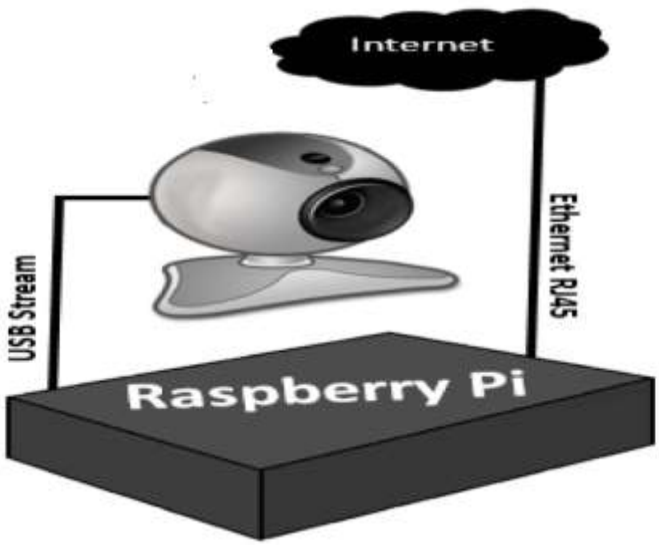

Figure 2: Raspberry Pi construction model

The Raspberry Pi tracks Linux-based OS, and there is a customized version of the Linux-based as Raspian that can run virtually any Linux-compatible apps. As a result, in this project, we utilized 'python' and 'wput,' a python script for motion discovery and wput for saving the files on an external server.

3.4 IoT

The Internet of Things has been used extensively in studies on COVID-19. With IoT devices, we can simply monitor individuals, particularly patients in hospital places, at home, or even on the streets. The Internet of Things (IoT) provides a framework for the health industry to gather, exchange, process, and store patient information. A patient history folders, wearable gadgets, medical imaging devices, physicians, and nurses can all provide medical data. Incorporating IoT into our life provides several benefits for individuals, businesses, and people on a daily basis. New concepts in loT are emerging in areas like as health, safety, and security. Integrating loT into security systems may be highly helpful, and this project seeks to integrate loT in security systems to detect motion. Another significant benefit that this system will have over others is that it will make the user's system lightweight, which is now feasible but not without machine-to-machine communication. There is no need for machines at both ends in this scenario to get the required output. As a result, for residential users, this system will be extremely useful due to its low energy usage and inexpensive cost. The project's goal is to simplify motion detection and provide a user-friendly interface that sends quick notifications when motion is detected.

3.5 Convolution neural network

The construction of a typical CNN is seen in Figure 4. CNN is currently constructed with a five layers: The first layer is the image's input phase, the second layer is the first convolution phase, and the third layer is the first sub-sampling phase. The fourth layer is the second convolution phase, while the fifth layer is the second sub-sampling phase. The initial kernel value is chosen at random from a certain location. When an image is loaded into the first layer, it separates features into six maps by convoluting from that picture in the second layer. In the third layer, subsampling reduces the sizes of six maps. The picture is constructed as a single vector at the last layer by a repeating procedure, and when all 12 maps are patched together, the feature vector for input is achieved. For image size changes, the input picture in the first layer is 28*28 in size, and when kernel size of convolution as 5*5 is conducted in the second layer of convolution, that utilizes entirely overlapping kernel and image. As a consequence, the output picture is 24*24 pixels in size since the result image is ‘the original image size-(k -1)'. In the third layer, pooling, a type of non-linear downsampling, is performed. Pooling divides the input picture into a collection of non-overlapping rectangles and returns the maximum for each of these sub-regions. The role of the pooling layer is to gradually lessen the spatial size of the image to lessen the amount of network parameters and calculations.

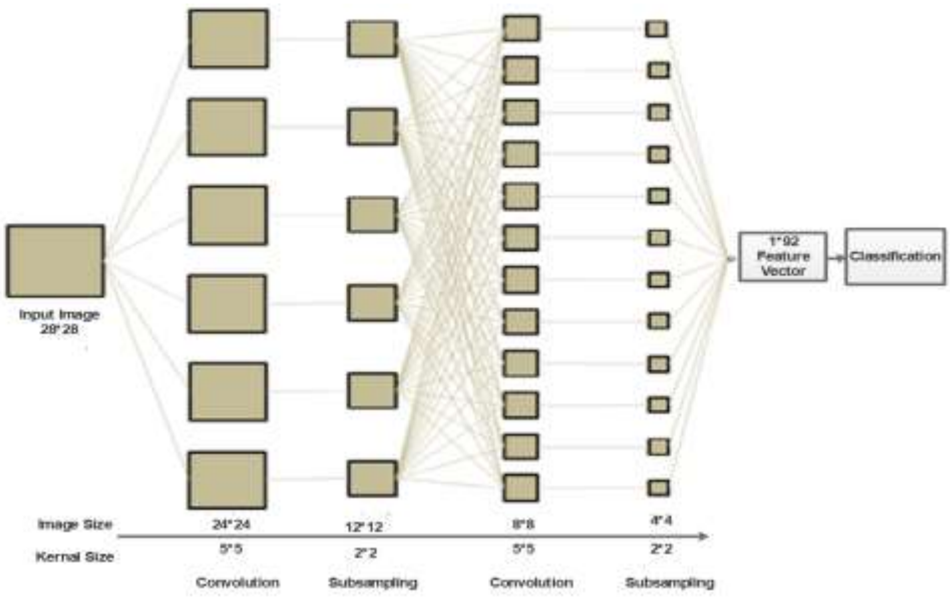

Figure 4: The architecture of convolution neural network

Translation invariance is provided via the pooling process. Because the kernel size is 2 ×2.at this point, the picture size is decreased by half to 12 ×12. CNN structures can be designed in a variety of ways. The sum of convolution layers or sub-sampling layers, for example, can be raised or decreased, and the sum of feature maps in the conv. layer can also be adjusted.

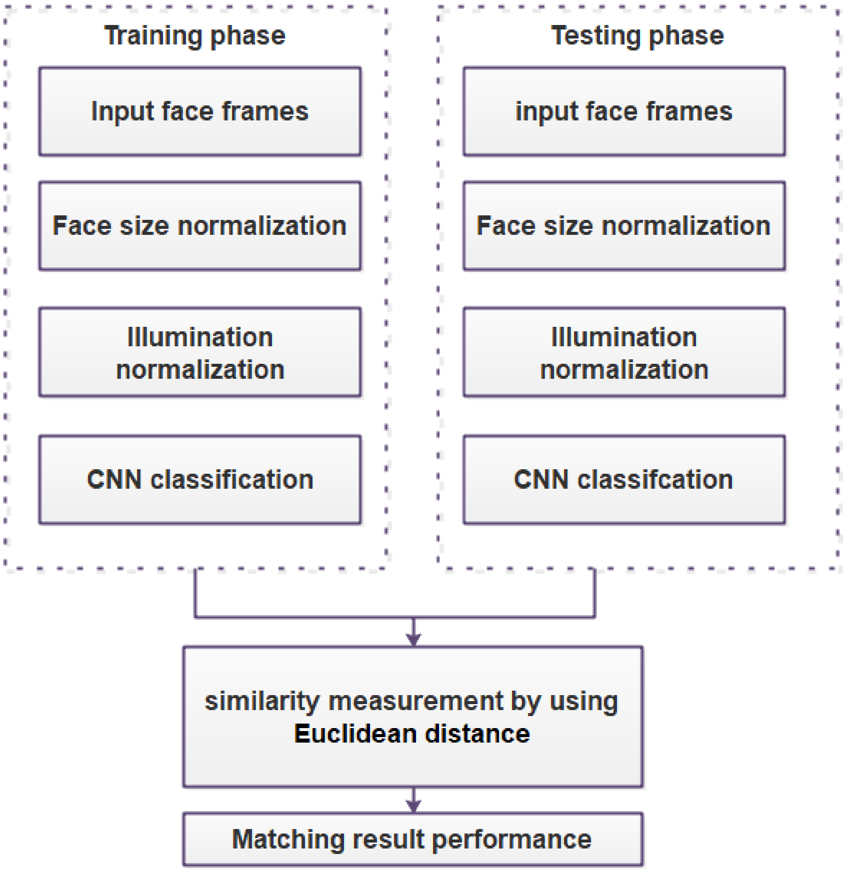

Figure 5: The proposed CNN-based face recognition overall flow diagram

As training data for the proposed face recognition system, a face picture by distance is used. A technique for using the face image by expanse as a training method gets the face image by advancing from 1 m to the extreme distance where the user may directly recognize the face from the camera. Histogram equalization is the process of changing the image's histogram such that it appears evenly in all grayscale regions. The intensities on the histogram can be better dispersed with this modification. This permits areas with poor local contrast to gain contrast. This is accomplished by histogram equalization, which effectively spreads out the maximum frequent intensity standards. When specifying the function for converting the image's pixel value. A method for obtaining a facial image by real distance through a camera by moving a person directly in different positions while the camera's location is fixed. CNN were employed for facial recognition, whereas Euclidean distance was utilized to quantify similarity. The image Euclidean distance deliberates the spatial relationship among the pixels of diverse images and can certainly be embedded in existing image recognition procedures that are based on Euclidean distance. When comparing extracted face pictures by distance, the sizes of the removed face images differ. A technique that uses real distance to create a face picture has the benefit of getting an accurate short and long-distance facial image. However, it has the difficulty of requiring more user involvement when compared to the technique employing a single distance face image.

4 Result and discussion

We created a face verification program that consists of two parts: face detection in public human photos and face identity verification. This experiment was carried out using OpenCV on a Python environment. This suggested model would lessen the range of covid 19 in the general public as well as the death rate owing to covid illness. In the instance of the face detector, we choose to use a CNN and Euclidean distance method over customizable characteristics. Even though the exactness attained in the adaptive scheme are greater, the major objective of this trial was to build a real-time system, and the adaptive scheme's temporal presentation was still insufficient to meet this real-time constraint. This requirement for real-time has also justified the use of a feature extraction technique in the verification stage (to decrease data storage).

Also, our face detector is limited to faces with modest rotations, despite the fact that the real-world application is set up to collect enough frontal images of each individual. Recognition was also assessed online, with the recognition outcomes and video being recorded in order to manually assess the online categorization accuracy. Recognition rate for roughly 2000 test photos from the gallery's 47 topics. In this test, we also discovered that the classifier would advantage substantially from integration, which was not implemented at the time. The application's frame rate with all three functional engines and this gallery of 47 subjects was around 15 fps. To speed up the system, prototype selection systems used to the NN classifier might also be used. In particular, all faces were created with no problem. If a face meets one of the conditions in Table 2, we add the associated difficulty rating. Annotations with difficulty ratings greater than 2 were disregarded. In addition, any pictures with more than 1000 annotations were deleted.

Table 2: Struggle Value Task Policy

Blur		**Illumination**	**Expression**	**Occlusion**		**Pose**
High Blur	**Normal Blur**	**High Expression**	**High Illumination**	**Heavy Occlusion**	**Partial Occlusion**	**Different Pose**
1	0.5	1	1	1	0.5	1

4.1 Evaluation Metrics

The projected method performance is evaluated and analysis by using different parametric measures, which are includes as sensitivity (SE), specificity (SP), Precision (P) and Accuracy (AC). The mathematical expression of following metrics as:

$$P = \frac{tp}{tp+fP} \tag{1}$$

$$SE = \frac{tp}{tp+fn} \tag{2}$$

$$SP = \frac{tn}{tn+fp} \tag{3}$$

$$\mathrm{AC} = \frac{tp+tn}{tp+fp+tn+fn} \tag{4}$$

Where,

$TP = True\ positive$

$TN = True\ Negative$

$FP = \ False\ Positive$
$FN = False\ Negative$

Table 3: performance analysis of proposed model with different condition

Different frames	Sensitivity	Specificity	Precision	Recall
Person (with mask)	61.20	62.35	61.55	68.51
Person (without mask)	71.56	70.15	76.99	72.56
Day time	81.54	79.56	83.56	75.87
Evening time	70.56	71.24	75.49	76.11
Night time	51.64	53.69	54.87	56.58
Average	67.30	67.39	70.492	69.92

In table 3 and figure 5 represent that the performance measure of proposed model using different metrics. The performance are evaluated by using different condition, which are indicated in table 3. In this different condition, Day time frames are achieved the better performance. An average performance of Sensitivity as 67.30%, Specificity of 67.39%, Precision of 70.49% and recall of 69.92% respectively.

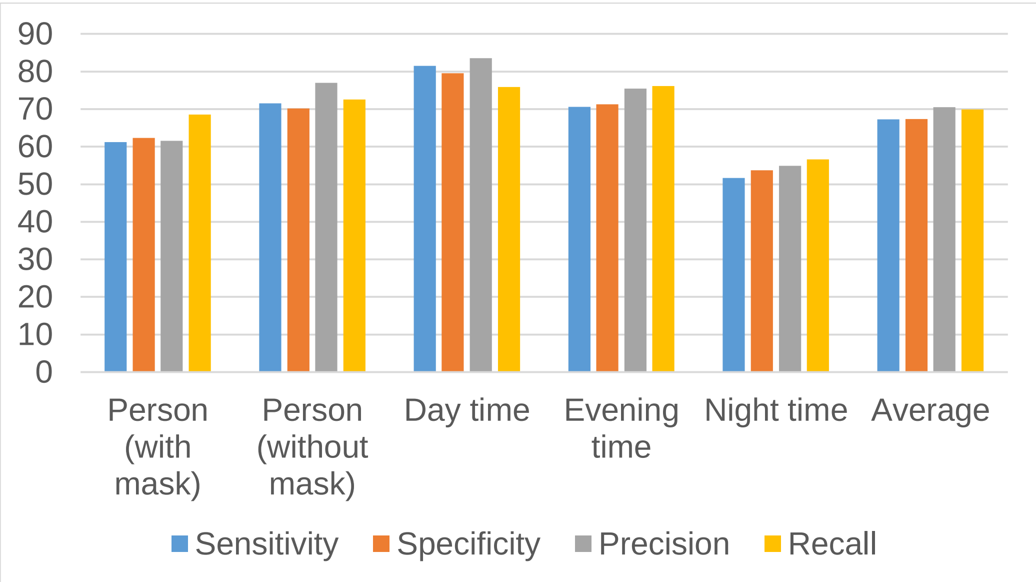

Figure 5: Graphical representation of proposed methodology performance

In table 4 and figure 6 represent that the Detection Accuracy performance calculation of proposed method with condition, in this conditions, Person (with mask) at reached the 63.56%, Person (without mask) 75.69%, Day time 81.55%, Evening time 78.14% and Night time 58.25%. Finally the average accuracy of 71.43% respectively.

Table 4: performance analysis of detection accuracy at different frames

Different frames	Detection Accuracy

Person (with mask)	63.56
Person (without mask)	75.69
Day time	81.55
Evening time	78.14
Night time	58.25
Average	71.43

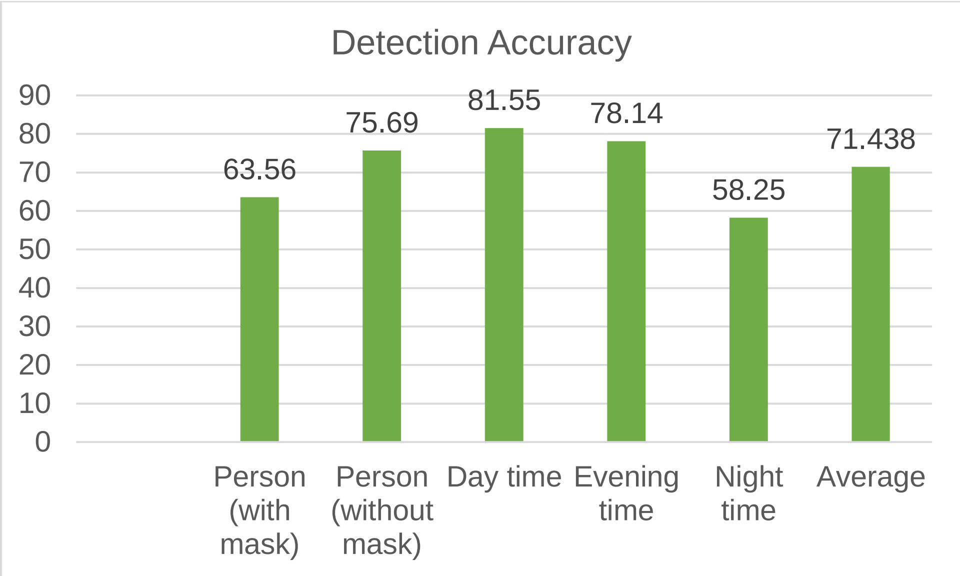

Figure 6: Graphical representation of Detection Accuracy of proposed

5 Conclusion

In conclusion, our model is the first that combines subject independence with robustness in terms of diversity in face pictures in terms of appearance and position. We set up the cameras in important places that are connected to the cloud server to recognize the covid 19 affected and non-covid person's faces. In this recognition, processes are handled by using AI techniques and the classification of covid positive and normal case by using convolution neural network (CNN). In this experimentation, We examined about 2000 test pictures from the gallery's 47 topics with various lighting and posture conditions such as Person (with mask), Person (without mask), Day, Evening, and Night. The findings indicate extremely excellent accuracies in real-world testing, and we also obtained a detection performance, attaining rates close to 15 frames per second. Although the accuracies attained in the adaptive scheme are greater, the major objective of this research was to build a real-time scheme, and this performance was still insufficient to meet this real-time constraint. Further, we will implement better resolution camera to capture the video and also will implement the better recognition model to improve the performance of the model.

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