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Real-Time Identification of COVID Norm Violations Based on Machine Learning

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Abstract: Corona virus disease -2019 (COVID-2019) has influenced many people's habits and encouraged some measure of vigilance in daily life. This paper presents a machine learning technique for detecting and recognizing COVID-19 norm violators, aimed at helping the administration in a populous country like India implement preventive guidelines. Persons are localized using the Faster Region Convolution Neural Network (R-CNN) model, social distance is measured using a height-width comparison, and a modified Faster R-CNN model is used to identify FaceNet in the proposed framework. Following detection, the program uses a face recognition library based on FaceNet to identify the offenders. Results from evaluating the suggested approach against both comparison datasets and real-world data show that it strikes a better balance between accuracy and complexity than the most recent developments. Because of the complexity of the COVID-19 pandemic, this method provides a simple alternative for monitoring and implementing preventative recommendations.

Keywords: *COVID-19, Norm Violations, Faster R-CNN, FaceNet, person localization, face recognition*

1. Introduction

The creation of a more advanced form of transportation will include Real-time detection of COVID refers to the application of technology and methodologies to swiftly and correctly identify the presence of COVID-19, the illness caused by the SARS-CoV-2 virus, in humans. This real-time identification is critical for successful disease management, contact tracking, and quick action to prevent the spread of the virus [1]. The detection of SARS-CoV-2 RNA in samples is often accomplished by Polymerase Chain Reaction (PCR) testing. Viral sequences may be amplified and tracked in patient samples using real-time PCR, allowing for speedy diagnosis. The virus may be detected quickly and reliably due to its high sensitivity and specificity. Real-time polymerase chain reaction testing is normally performed in dedicated labs [2]. Rapid antigen testing uses a lateral flow technique to identify viral proteins in patient samples. Infected people may be identified rapidly with the use of these tests, which can provide findings in a matter of minutes. Rapid antigen tests are useful for screening large populations, doing triage, and identifying possible cases quickly, although they are not as sensitive as PCR testing [3]. The quick detection of COVID-19 is possible using molecular-based assays like the loop-mediated isothermal amplification (LAMP) and the nucleic acid amplification test (NAAT). These methods are comparable to polymerase chain reaction (PCR) in that they amplify and identify viral genetic material, but they need less complex apparatus. They may be done at the patient's bedside or other convenient location, and the findings are available quickly [4]. Antibodies generated by the immune system in response to a COVID-19 infection are detectable by serological testing. These tests may be used to detect the presence of the virus in the bodies of people who have been exposed to it in the past, even if their symptoms were moderate or nonexistent at the time. It takes time for the body to generate antibodies that may be detected by a serological test, making them less useful for the rapid detection of current illnesses [5]. Chest X-rays and CT scans are useful for detecting lung abnormalities caused by COVID-19. With the use of these imaging techniques, instances of COVID-19 may be better diagnosed and monitored. However, they are not utilized alone but rather in combination with other techniques for diagnosis [6]. The healthcare facility, available resources, and illness progression all factor into the particular diagnostic procedures and techniques employed for real-time diagnosis of COVID. To reliably and accurately identify COVID-19 instances in real-time, it is essential to adhere to the criteria and recommendations of healthcare authorities and specialists [7]. COVID norm breaches are any activities or behaviors that go against the established rules and regulations designed to stop the development of COVID-19. There are serious consequences for public

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health when these rights are violated, either on an individual or a societal level [8]. COVID norm breaches are any activities or behaviors that go against the established rules and regulations designed to stop the development of COVID-19. There are serious consequences for public health when these rights are violated, either on an individual or a societal level [9]. Although machine learning may be used for the analysis and identification of patterns in many different forms of data, including human behavior, it is vital to keep in mind that machine learning does not have any built-in ethical or normative frameworks. Algorithms used in machine learning are fed data, and then they use that data to produce predictions or classifications. However, it is usually up to human judgment, and interpretation of rules, regulations, and social norms to determine whether or not a norm breach has occurred [10]. With the use of labeled datasets containing instances of norm violations, machine learning algorithms may be taught to recognize particular behaviors or acts that may be indicative of norm violations. To illustrate, machine learning algorithms may be taught to spot instances of non-compliance with mask rules or social distance norms by labeling a dataset with such information [11]. Inheriting biases from the training data might provide discriminating or unjust results when using machine learning algorithms. The training data should be varied, representative, and unbiased, thus it's important to pay close attention to these factors [12]. Using machine learning algorithms to examine real-time data and spot behaviors or activities that point to non-compliance with COVID-19 rules or procedures is what's meant by "real-time identification of COVID norm violations based on machine learning." Although the ethical and practical concerns raised previously must be taken into account, machine learning can aid in the detection of norm breaches in some settings [13].

2. Related Works

The study [14] proposes a framework to curb the spread of infectious illnesses. Leveraging certain current and future technologies, such as machine learning and the Internet of Vehicles, the proposed architecture comprises a physical distance notification system. Each vehicle has a camera system that can flip between thermal and visual imaging. The study, [15] presents a methodology for real-time monitoring of COVID-19 procedures to identify any violations as they occur. Additionally, we have developed a web application that employs the suggested methodology to monitor ongoing compliance with COVID-19 regulations. The suggested model has been successfully evaluated on a dataset of 1376 photos, demonstrating its ability to perform well in a variety of challenging settings. The research introduces a machine learning model for identifying individuals who are not properly protecting themselves from the virus by wearing protective gear or maintaining an appropriate distance. The number of those who break the SOP is also included. The suggested model enhances its detection capabilities by first using the Single Shot Multi-box Detector as a feature extractor, then using Spatial Pyramid Pooling (SPP) to incorporate the derived features [16]. The study [17] proposes an advanced learning and computer vision-based method that focuses on real-time robotized observation of people to identify unmasked faces in public spaces to create a safe atmosphere that leads to open safety. Therefore, the suggested remedy benefits society by saving time and aids in reducing the transmission of coronavirus. In the suggested system, face detection is handled by a single-shot multi-box detector, while face mask classification is handled by a fine-tuned MobileNetV2. The system has a small footprint (low resource needs) and may be integrated with existing CCTV cameras to identify instances of face mask abuse. 14,535 photos are used to train the system, 5,000 of which have erroneous masks, 4,781 with masks, and 4,742 without masks. The major motivation for amassing such a dataset was to create a face mask identification algorithm that is capable of recognizing a wide variety of masks worn in a variety of positions [18]. The study, [19] provides an approach to automatically determine whether a person is hiding their identity behind a mask. Using the MobileNetV2 model, we develop a transfer learning strategy for detecting face mask violations in digital media. Additionally, the suggested method can pinpoint the region associated with face mask detection with a fair degree of certainty. The ultimate goal of the research is to develop an automated facial recognition and mask detection system based on a Graphics User Interface that operates in real-time. Principal Component Analysis (PCA) and the HAAR Cascade Algorithm are the methods used by the suggested technique [20]. The research offers a comprehensive analysis of how various models of face detection and face mask categorization fare against one another. Precision, recall, F1-score, support, sensitivity, specificity, and accuracy are some of the measures of system performance used to prove the system's usefulness in real-world scenarios [21]. In the paper, [22] propose a real-time, machine learning-based framework to automate the monitoring of social distancing through object detection and tracking to aid in the identification of individuals who violate government-mandated social distance requirements (critical during the COVID-19 pandemic in public places).

3. Methodology

We have created a comprehensive system that begins with pinpointing individual users and ends with the identification of those responsible for violations. It uses a Convolution Neural Network (CNN)-based face recognizer, an HCI calculator, a modified faster R-CNN and FaceNet model, and more. The planned task may be completed with the help of the four components when they are combined. This section provides an overview of each component module.

3.1. Faster R-CNN and FaceNet

The Faster R-CNN and FaceNet algorithm's design, training, and loss functions are all summarized in this section.

3.1.1. Structure

CNN is a popular machine-learning solution utilized in many machine vision systems and image interpretation programs. While there are other object identification algorithms to choose from, Faster R-CNN provides the best balance between accuracy and resource requirements. The goal of this work is to speed up algorithms like Region CNN (R-CNN) and Faster R-CNN which are notoriously slow. It has a two-pronged approach to object detection:

Section 1: Faster R-CNN as a region proposal algorithm, uses anchors as reference boxes for generating proposals. Predictions are made at the layers of classification level as to whether or not each proposition is an object or background, and then the boundary parameters are predicted at the regression coefficient network stage.

Section 2: Rapid-fire CNN Reconstruction As a detection device, RPN's suggestion parts are sent to the Fast R-CNN algorithm, which uses a region of interest pooling layer to reduce the maps of features before approving that reduced map's results through fully connected layers and into a softmax layer for categorization and a regression layer for boundaries forecasting.

3.1.2 Learning and Regression Functions

Minimizing the loss value initiates the RPN training process, which begins with a random selection of an image from the training dataset and the assignment of labels to each of its 256 anchors. After that, the picture is fed into RPN as an input to make anchor-based proposal predictions, and the loss value is measured and propagated to alter the weights assigned to the convolution kernels. The following equation (1) illustrates the interplay between Faster R-CNN's two losses the classification loss "L_{cls}" (for categories) and the regression loss "L_{reg}" (for bounding box locations).

$$L\left(p_{i,}t_i\right) = \frac{1}{N_{cls}}\sum_i \quad L_{cls}(p_{i,}p_{*\,i} + \lambda\frac{1}{N_{reg}}\sum_i \quad p_{*\,i}\, L_{reg}(t_{i,}t_{*\,i}) \qquad (1)$$

3.1.3. Using an HCI Calculator for Social Distance Monitoring

Camera calibration is essential for determining the physical separation of two subjects in a video. When footage is retrieved from a closed-circuit television (CCTV) camera placed in the monitoring area, the coordinates are projected from three dimensions (3D) to two dimensions (2D), creating a perspective-distorted image. Therefore, a transformation based on inverse perspective mapping is used to set the camera's focus. The latter is used in IPM to convert two-dimensional (x, y) coordinates to three-dimensional (3D) parameters through Equation (2).

$$[x\ y\ 1]^T = K\ R\ T[X\ Y\ Z\ 1\ ]^T \qquad (2)$$

In this equation, K, R, and T stand for the camera's focusing parameters, rotational matrix, and translation matrix, correspondingly.

3.2. FaceNet

FaceNet is a machine learning network trained specifically on the job of identifying human faces. Faces with comparable traits will be clustered together in this high-dimensional environment that has been created specifically for this purpose. Successful uses of this concept include recognizing people in photographs and movies. FaceNet's CNN architecture is in charge of deducing useful characteristics from photos of people's faces. As the input face pictures are processed via successive layers of convolution and pooling procedures, a hierarchical representation of the faces is gradually learned. A triplet loss function is used throughout FaceNet's model training process. The triplet loss evaluates how dissimilar three face embeddings are from one another: an anchor face, a positive face (with the same identity as the anchor), and a negative face (with a different identity). The objective is to optimize the learned feature space such that the distance between the anchor and positive faces is minimized, while the distance between the anchor and negative faces is maximized. FaceNet optimizes the CNN's settings during training by learning to reduce the triplet loss. FaceNet is often trained using large-scale face datasets with tagged identities. FaceNet learns to encode faces in a manner that permits successful face recognition by being fed a large dataset of face photos and trained to discriminate between various people. FaceNet be used to identify people by comparing their faces to a database of already-identified people for COVID-19 norm violation detection. When FaceNet is included in the proposed framework, the model may aid in the identification of norm violators by comparing their identified faces with a database of approved persons.

3.3. HCI (γ) calculation

Faster R-CNN and FaceNet's usage of the phrase "high centroid index" (HCI) to describe instances of norm breaches is unusual. But we can explain Faster R-CNN, FaceNet, and norm breaches as they pertain to this problem. Methodology for detecting objects, faster R-CNN blends machine learning with region proposal techniques. The system has two primary parts: an RPN (region proposal network) and a DN (detection network). The RPN suggests possible bounding boxes, and the detection network sorts through the suggestions and adjusts the bounding box coordinates accordingly. FaceNet is a specialized machine-learning model for identifying human faces. It learns to map face photos to a high-dimensional feature space in which similar faces are clustered together and dissimilar ones are spread apart. Uses for FaceNet include identification, verification, and even grouping similar faces. When particular norms, regulations, or expectations are broken, we call it a norm breach. When a system has trouble detecting an item or identifying a face, for example, owing to occlusion, poor illumination, position variation, or low picture quality, this may be considered a violation of the norm. It seems that the term HCI may be special to a certain study or research environment that is not well-known or often utilized. It would be beneficial to add more details or define the particular context or publication you are alluding to provide a more precise explanation or interpretation. The suggested approach determines the social distance between two people once they have been geographically located using the Faster R-CNN and FaceNet model. This technique begins by identifying the individual inside the picture and creating bounding boxes around them. The two bounding boxes' Euclidean centroid distance D is calculated. Fig. 1 provides a clear representation of the proposed framework's process flow. Based on the fundamental notion that maintaining social distance would not contribute to COVID propagation, complexity is decreased. By only applying the mask identification method to bounding boxes that contravene our Customized Faster R-CNN and FaceNet model for mask identification, the complexity of the whole framework is decreased. By mainly training the specialized Faster R-CNN and FaceNet model on correct social distance analyzer data, we were able to reduce the algorithm's difficulty. A bespoke model is developed using an early Faster R-CNN and FaceNet model with the express purpose of detecting masks.

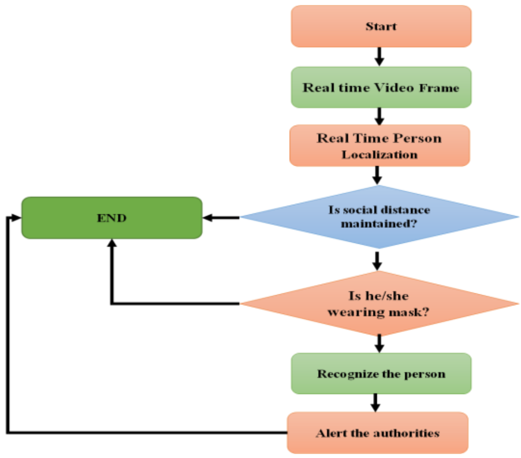

Fig.1. Methodology suggested for observing COVID standards

4. Results and discussion

In this subsection, we describe in further detail the simulation outcomes of the proposed system using benchmark and real-time data. The suggested pipeline is trained on many benchmarks, such as Microsoft Common Objects in Context (MSCOCO), and evaluated on traditional and internet video formats. To run our models, we have chosen Python as our programming platform of choice. Modeling of type Faster R-CNN and FaceNet (including pretrained and custom-trained variants) execute in a chained way. An unaltered version of the frame was fed into the Faster R-CNN and FaceNet model to identify faces. The initial phase of the four-fold modules was the usage of a pre-trained version of Faster R-CNN and FaceNet for people (human) identification, which was then followed by a social distance analyzer.

4.1. Accuracy

A difference between the result and the true number is caused by inadequate precision. The percentage of actual outcomes reveals how balanced the data is overall. Accuracy is assessed using an equation (3).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

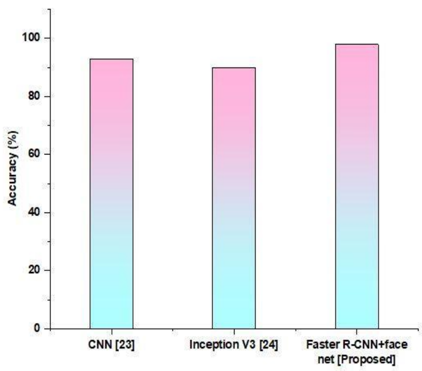

Fig.2. Comparison of Accuracy

Fig.2. and Table 1 shows the comparable values for the accuracy measures. When compared to existing methods like 8, which has an accuracy rate of 93%, and Inception V3, which has an accuracy rate of 90%, the recommended method's Faster R-CNN and FaceNet value is 98%. The suggested Faster R-CNN and FaceNet perform well in classifying COVID Norm Violations with more accuracy than previous methods.

Table 1. Numerical outcomes of Accuracy

Methods	***Accuracy (%)***
CNN [23]	93
Inception V3 [24]	90
Faster R-CNN+ FaceNet [Proposed]	98

4.2. Precision

The most crucial standard for accuracy is precision, it is clearly defined as the percentage of properly categorized cases to all instances of predicatively positive data. Equation (4) is used to compute the precision.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

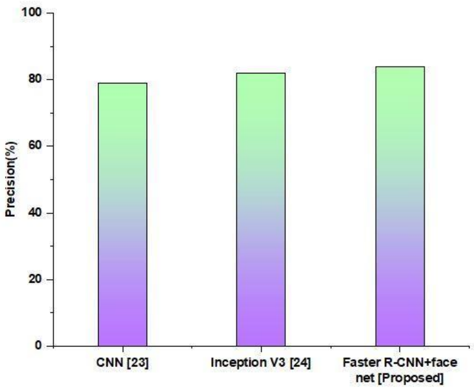

Fig.3. Comparison of Precision

Comparable values for the precision measures are shown in Fig.3 and Table 2. This proves the suggested strategy may provide performance results that are superior to those obtained by the current study methods. The precision of the proposed approach Faster R-CNN and FaceNet is 84%, which performs better than existing outcomes. Include CNN, and Inception V3 precision rates are 79% and 82%.

Table 2. Numerical outcomes of Precision

Methods	***Precision (%)***
CNN [23]	79
Inception V3 [24]	82
Faster R-CNN+FaceNet [Proposed]	84

4.3. Recall

The potential of a model to identify each important sample within a data collection is known as recall. The recall is calculated using equation (5).

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

Fig.4 and Table 3 shows the comparative data for the recall metrics. Recall rates for CNN 89%, Inception V3 92%, and Faster R-CNN and FaceNet 96%.The proposed method performed better than the current results with a recall of 96%.

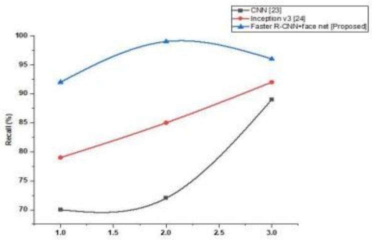

Fig.4. Comparison of Recall

Table 3. Numerical outcomes of Recall

	Recall (%)		
	CNN [23]	***Inception v3 [24]***	***Faster R-CNN+FaceNet [Proposed]***
1	70	79	92
2	72	85	99
3	89	92	96

We determined the optimal height for the camera to be 3 meters, and we preserved the angle factor at 0.5 by experimentation and error. The HCI architecture presented here specifies a range (trial and error) of values for the threshold. The absence of a mask may be readily identified by our processing workflow. The difficulty of using the mask detection model was reduced by limiting its use to situations in which social distance is not strictly enforced. Training the specialized Faster R-CNN and FaceNet model resulted in a loss of 0.3. Our HCI module can properly calculate the social distance when evaluated on unrestricted real-time movies (with authors in the scene) in various scenarios, validating the significance of the proposed approach. The green window represents a favorable situation in which one can maintain social distance, whereas the orange and red windows represent medium and high-risk situations, respectively (Fig. 4). After calculating social distance, a mask detection model was developed using Faster R-CNN and FaceNet and inception V3 as training data. Once calculating social distance, we used Faster R-CNN and FaceNet and inception V3 to train our mask detection model. Following instructions, the Faster R-CNN model had a loss of 0.355, whereas the inception V3 model had a loss of 1.19. In Fig. 7 and Table 4, we can see how the mAP values of the proposed framework compare to those of the already available options. The Corporate Social Responsibility Dashboard (CSRD) is a tool for monitoring and analyzing the output of social distance, mask detection, and facial recognition machine learning models in real-time. Informing individuals (business personnel) by SMS and email to various locations is another capability included in CSRD. Together with the colored bounding boxes, you can see the frames from the studied videos. Boundary boxes in red indicate that our system successfully identifies rule breakers. Despite our algorithm's remarkable effectiveness in finding offenders, it is not without flaws. The many lighting and illumination problems that arise at night are a big negative. Additionally, human localization in the dark is not investigated; doing so would be a great addition to future research. It is deteriorating mAP if the height and breadth of a person's bounding box are not similar.

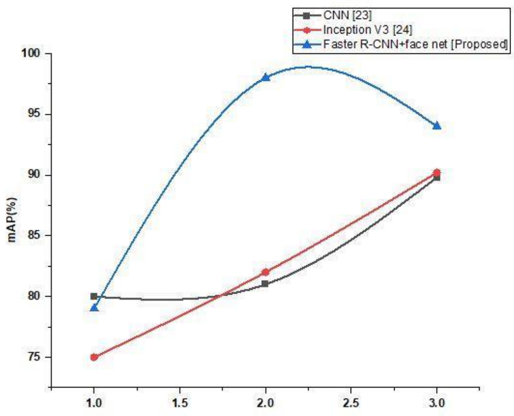

Fig.7. Comparison of mAP

Table 4. Numerical outcomes of mAP

	CNN [23]	*Inception V3 [24]*	*Faster R-CNN+FaceNet [Proposed]*
1	80	75	79
2	81	82	98
3	89.8	90.2	94

5. Conclusion

In this paper, we present a framework for a system to identify offenders of the COVID standards. The suggested approach takes a restricted or unrestricted video and uses IPM transformation, the HCI factor, and a FaceNet/Faster R-CNN customization to identify any infractions. The intruder is identified by the facial recognition system once they have been seen. In addition, the suggested framework helps the user learn about the breakdown of lawbreakers in a given area. Therefore, the setup works well in a free-form space and may be included in a complex system in which CCTV is installed at a fixed height. When it comes to identifying instances of COVID rule violations, the suggested machine learning-based methodology performs much better than prior efforts. When applied to the problem of planning and controlling movement in response to COVID norm violations, the system achieves remarkable results, with an accuracy of 98%, a precision of 84%, and a recall of 96% thanks in large part to the use of the suggested Faster R-CNN and FaceNet method [25]. In the future, information on those who break the law may be sent to the appropriate authorities through secure channels of communication. When Faster R-CNN and FaceNet are used for people location and mask detection, more complexity is created, which will be mitigated by the use of simultaneous techniques.

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