Machine Learning-based System for Monitoring Social Distancing and Mask Wearing

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Abstract— Coronavirus is a large family of viruses known to cause diseases ranging from the common cold to more serious diseases, and the methods for controlling epidemics of such viruses are difficult to deal with. One of the most dangerous things about COVID-19 is the speed with which it spreads. Therefore, we introduced a smart machine learning-based system for monitoring social distancing and mask wearing. The proposed system is used to monitor people and identify those who violate the rules of mask wearing or do not observe social distancing. It will help to control the epidemic, reduce the spread of COVID-19 and stress the importance of social distancing. The experimental results of the proposed system illustrate its robustness and accuracy.

Keywords— Covid‐19; deep learning; Social Distancing; Mask Wearing.

I. INTRODUCTION

The World Health Organization (WHO) declared the spread of COVID-19 to be a pandemic. To stop the further spread of the virus, a concerted global effort is required. A pandemic is characterised as occurring over a wide geographic area and affecting an exceptionally high proportion of the population. Therefore, we must work hard in many ways to stop its spread. The COVID-19 epidemic has affected all the world's countries, so everyone should raise their awareness and start to do some things regularly. To reduce the spread of COVID-19, the government, social authorities, and workplaces must strictly follow the necessary rules for mask wearing and observing social distancing. Artificial intelligence (AI) and machine learning (ML) techniques are effective tools that can be used to help ensure mask wearing and social distancing. In this research, we use ML to ensure and monitor social distancing and mask wearing. The proposed system will monitor people and identify those who violate the rules of mask wearing and social distancing. The main motivations of this research are to contribute to overcoming the COVID-19 pandemic and to mitigate the spread of COVID-19 by introducing a smart learning-based system to monitor people and identify those who violate the rules of mask wearing and social distancing. The proposed

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system consists of two sub-systems: the surveillance system (SS) and the contact recognition system (CRS). The SS consists of two stages: the monitoring stage (MS) to monitor social distancing and the detection stage (DS) to detect mask wearing. The proposed CRS is used to recognise who is not maintaining social distance. To implement the proposed SS and CRS, several ML and image processing algorithms and techniques have been used, including face mask detection, object detection, and object tracking. The rest of this paper is structured as follows: Section 2 presents the background and literature review, Section 3 presents the proposed system, Section 4 illustrates the system experimentation and testing, Section 5 presents a systems evaluation and comparison with reference studies, and Section 6 provides the conclusion.

II. LITERATURE REVIEW

Many applications, algorithms and techniques have been introduced to address COVID-19 using AI and ML. In this section, we review the previous works that study the use of AI and ML to reduce the effects of the COVID-19 epidemic. We divide these works into three categories. The first addresses AI and ML technology in COVID-19 detection and classification, the second addresses AI and ML technology in COVID-19 contact tracing, and the third addresses AI and ML technology for mask detection.

Many systems have been introduced in the literature concerning AI and ML technology for COVID-19 detection and classification. In 2021, M. Faisal et al. [1] proposed two- and three-classifier diagnosis systems for classifying COVID-19 cases using transfer-learning techniques. In 2022, F. Albogamy, M. Faisal, et al. [2] introduced a COVID-19 Period Detection System (CPDS) that is used to detect the symptoms periods or classes: the healthy period (before the appearance of COVID-19 symptoms), the first six days of symptoms (COVID-19 positive cases from Day 1 to Day 6), and infection more than six days after the appearance of symptoms (COVID-19 positive cases from Day 6 onward). T. Mahmud, M. Rahman, and S. Fattah [3] used the ML to define COVID-19 using x-ray pictures. They trained several models such as SVM, ResNet101, ResNet50, ResNet18, VGG-19, and VGG-16. The performance was extracted by ResNet50 with 92.6% accuracy and 92.63% F-score, an average accuracy of 95.79%, and an F-score of 95.92% for SVM. Another study [4] used several ML models with data containing four classes (normal, pneumonia, other diseases and COVID-19). The performance was measured by AlexNet models with 98.82% accuracy, VGGNet with 90.13% accuracy, and RestNet with 85.98% accuracy. In [5], an automatic predictor for diagnosing COVID-19 cases was used to auto-distinguish between people with the COVID-19 virus and healthy people based on x-ray pictures. The data is divided into two-class classifications, normal and COVID-19 cases, and the research includes seven traditional methods of learning (KNN, DT, SVM, ANN, RBF, CN2) and five CNN deep learning models (MobileNetV2, RestNet50, GoogleNet, DarkNet, Xception) revealed. The results are that the two best models are ANN and SVM, which can be applied in diagnosing whether a patient is infected with the COVID-19 virus or not. All models work well, but the best accuracy is RestNet50 with 98.8% accuracy and F1 98.8%. The SVM model had an average accuracy of 95% and F1 of 93% by using a CNN and ML methods. In [6], they introduced a new standard dataset, which consists of two-class classification (normal and COVID-19) cases of x-ray. A comprehensive set of tests revealed that the SRC-Dalm-based compact classifier achieved the highest accuracy of 98.52%. Moreover, DenseNet-121 outperformed other deep networks with 99.37% accuracy, thanks to the CNN algorithm. Another study [7] compared the efficiency and the performance of deep learning-based CNN models like ResNet, InceptionV3, and Xception with three classes (normal, COVID-19, and pneumonia). The models ResNet, InceptionV3, and Xception had accuracy results of 97%, 96%, and 93%, respectively. A. Narin, C. Kaya, and Z. Pamuk [8] introduced five CNN-based models (ResNet152, ResNet101, ResNet50, ResNetV2, Inception-ResNetV2, and InceptionV3) to identify COVID-19 infected patients using x-ray images. The researchers used five-fold cross-validation to introduce three separate binary class classifications. The ResNet50 had the highest accuracy for the two-class classification (COVID-19 and normal) with 96.1% accuracy and 83.5% F1, the two-class classification (COVID-19 and viral pneumonia) achieved 99.5% of accuracy and 98.7% of F1, and the two-class classification (COVID-19 and bacterial pneumonia) achieved 99.7% accuracy and 98.5% F1. Another study [9] used the ResNet50-v2 and Xception to classify x-ray pictures using three classes (COVID-19, normal, and pneumonia). The Xception model had an average accuracy of 91.31%, while the ResNet50V2 model had an average accuracy of 89.79%. In [10], to predict COVID-19, they used ML algorithms and x-ray images through three classes (normal, COVID-19, and pneumonia). The Random Forest model generated the best results, with accuracy and F1 measured at 97.3% and 97.3%, respectively. The second best was XGBoost, which had 97.7% accuracy and a 97.7% F1 score. To detect COVID-19 infection, in [11] they used datasets containing x-ray pictures. These were divided into two classes (COVID-19 and normal), and five pretrained models were used based on deep learning (Xception + SVM, Xception + DT, Xception + RF, Xception + ADAboost, Xception + Bagging). An efficient diagnostic approach with machine features and in-depth learning of classification was used to improve diagnostic accuracy further. The accuracy of the diagnosis reached 99.33% with Xception + SVM. Concerning using AI and ML technologies for contact tracing, several studies have been introduced in the literature. In general, contact tracing is used to identify individuals that may have been in contact with an infected person and alert them to the possibility of infection. Currently, smartphone and mobile applications are used for the contact-tracing process. Several countries around the world are investigating contact-tracing apps. On 26 April 2020, COVIDSafe [12] was launched in Australia, developed by Australian authorities as a contact-tracing app and used to slow the spread of COVID-19. COVIDSafe collects personal details such as name, mobile number, and age. Tabaud is a smartphone app that is used for contact tracing in Saudi Arabia [13], developed by the National Information Center (NIC) of the Saudi Data and Artificial Intelligence Authority (SDAIA) in cooperation with the Ministry of Health (MoH). Tabaud provides two basic services: notifying people if they have had contact with others with confirmed COVID-19 cases during the past 14 days and sending their health reports to the MoH to provide the necessary medical support. BeAware-Bahrain is a smartphone app used for contact tracing in the Kingdom of Bahrain [14], developed by the government of the Kingdom of Bahrain. It provides many services, such as COVID-19 test appointments, tracing the movement of isolated cases, and alerting users to get tested once they have been in contact with a positive case. Corona-Warn-App is a smartphone app used for contact tracing in Germany. Corona-Warn-App has been developed by the Robert Koch Institute, the German national public health institute [15]. Its main function is to help to break the infection chains by notifying people who have recently been close to someone who tested positive for COVID-19. Many other studies in the literature are available for contact tracing. F. Luca, C. Wymant et al. [16] introduced a contact-tracing app that is used to estimate the contacted people and immediately notify contacts of positive cases. These apps can achieve epidemic control if used by enough people. By targeting recommendations to only those at risk, epidemics could be contained without resorting to mass quarantines ("lockdowns") that are harmful to society. R. Chris, M. Roman et al. [17] used graph theory to track infectious disease epidemics in farm animals in which the epidemics were driven by the shipment of animals between farms.

Face mask detection and classification systems have become essential during the COVID-19 pandemic. Concerning the use of AI and ML technologies for face mask monitoring and detection, S. Teboulbi, S. Messaoud, et. al. used DensNet, InceptionV3, MobileNetV2, and VGG-16 ML models for detection; their best result and accuracy was with the VGG-16: For mask cases, its accuracy was 99%, its F1 score was 99%, its precision was 99%, and the recall was. For without-mask cases, the results were 99% accuracy, 99% F1 score, 98% precision, and 99% recall. Another study was introduced by A. Oumina, N. El Makhfi, and M. Hamdi [18] for face mask detection using transfer-learning techniques. The best result was for the VGG-16 with 97.84% accuracy, 98.13% F1 score, 98.4% precision, and 97.87% recall for mask cases using the RMFD dataset [19]. M. Loey, G. Manogaran, et.al. [20] introduced a hybrid model for facemask detection. They used the ML-based architecture Resnet50 for features extraction and the classical AI models like support vector machines and decision trees for facemask detection. They trained the models using the RMFD dataset [19]. B. Zoph, V. Vasudevan et al. [21] introduced a model for face mask detection using an image compression method (FMM) to compress collected images. Then, they used the Viola-Jones Haar-like object detector to detect the human face in the compressed image. Then they extract the facial features using LBP. Finally, they used the k-NN for image classification.

III. PROPOSED SYSTEM

In this study, we introduced a smart machine learning-based system for monitoring social distancing and mask wearing. The proposed system is used to monitor people to identify those who violate the rules of mask wearing and social distancing. The proposed system consists of two sub-systems: the SS and CRS. The SS consists of two stages: the MS to monitor social distancing and the DS to detect mask wearing. The proposed CRS is used to recognise who is not maintaining social distance. To implement the proposed SS and CRS, several ML and image processing algorithms and techniques have been used, such as mask detection, object detection, and object tracking. The proposed system starts by using cameras to scan an area to detect people who are not wearing masks, then monitors for anyone who violates social distancing, then moves the control to the CRS to recognise who is not keeping the social distance, as illustrated in Figure 1.

Figure 1: Proposed system

As mentioned before, the SS consists of two stages. The DS is used to detect mask wearing, and the MS is used to monitor social distancing. MS and DS use several ML and image processing algorithms and techniques, using pre-mounted cameras to monitor people and detect mask violations, as illustrated in Figure 2.

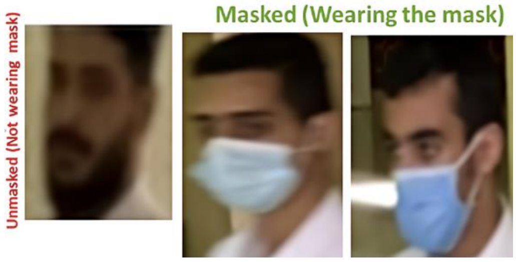


Figure 2: Snapshot of the proposed SS system

This step needs to be done before recognising who is not maintaining social distance because we need to find all the frames of the area, using object detection algorithms with the help of YOLO [22] Version 3 (You Only Look Once) algorithm in the proposed SS system. The proposed CRS is used to recognise people who are not maintaining social distance (less than two metres from others) in closed areas such as schools, universities, airports, and supermarkets, as illustrated in Figure 3.

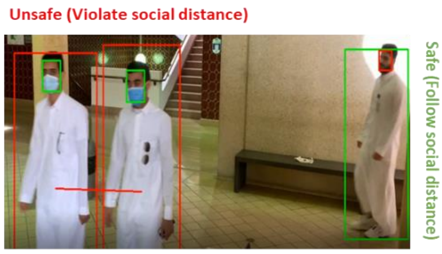


Figure 3: Snapshot of the proposed CRS system

Figure 4 shows the workflow of the proposed system. This starts with the initialisation step, in which all the parts will power on. Then the control moves to the SS system, which works using cameras mounted in several places to monitor everyone. The SS is used to monitor the area to check if everyone is wearing a mask. At the same time, the system checks if everyone is following social distance rules. If everyone is wearing a mask and maintaining social distance the system returns to the SS. If not, then the system moves to the proposed CRS to find everyone without a mask who was within a two-metre range before going back to the SS system.

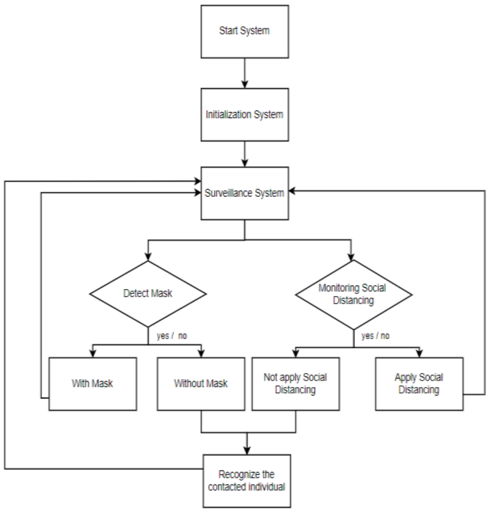


Figure 4: Proposed system workflow

IV. PROPOSED SYSTEM IMPLEMENTATION

As we mentioned, the proposed system consists of two sub-systems, SS and CRS, and the SS consists of two stages, the MS and the DS. The SS system is used to monitor social distancing and to detect mask wearing over video footage coming from cameras using YOLO-v3 along with DBSCAN [23] clustering and ResNet50 [24], a face mask classifier model for identifying people not wearing a face mask. To aid the training process, augmented masked faces are generated (using facial landmarks) and blurring effects (frequently found in video frames) are imitated. Human detection and tracking are generally considered the first two processes in a video surveillance pipeline and can feed into higher-level reasoning modules such as action recognition and dynamic scene analysis [18]. In this study, we used the YOLO for real-time human detection, which was pretrained on the COCO dataset. YOLO has been used for obtaining the bounding boxes of individual persons in a video frame with a resolution of 320x320 for faster processing speed, but lower accuracy, while a resolution of 512x512/608x608 can be used for even better detection accuracy, but with lower speed. The accurate detection of human faces in arbitrary scenes is the most important process involved in the MS stage of the SS system. Once faces can be located exactly in any scene, the recognition step is no longer so complicated. The proposed system used the Dual Shot Face Detector (DSFD) [25] for detecting faces. The common face detectors methods, such as the Haar-Cascades or the MTCNN, are not efficient in this particular case as they cannot detect faces that are covered or have low resolution. The DSFD method we used is good at detecting faces in a wide range of orientations. As we are working from video frames, we will probably encounter blurred faces and DSFD will certainly not miss any of those. This blurriness could be due to rapid movement, faces being out of focus or random noise during capturing. Therefore, we need to add some kind of blurring effect randomly to some parts of our training data. In the proposed SS, we used three types (Motion Blur for Mimics Rapid Movement, Average Blur for Mimics Out of Focus), and Gaussian Blur for Mimics Random Noise. For face mask classification, pretrained models ResNet50 and Inception-3 were used to classify whether the face is masked properly or not. In this study, we trained the ResNet50 and Inception-3 [26] using the dataset called Flickr Diverse Faces (FDF) [27]. This dataset consists of 1.5 million faces with a large diversity in terms of facial pose, age, ethnicity, occluding objects, facial painting, and image background. Moreover, it contains faces in various orientations and lighting conditions.

V. PROPOSED SYSTEM EXPERIMENTATION AND TESTING

In this section, we test the proposed system in a real environment (college building) and discuss the two parts of the system, the SS and CRS. The execution of the system will check if a person is wearing a mask or not and if the person is maintaining social distance or not. At startup, the system will monitor the covered area and then check all the people present, giving each one a frame and extracting the **Faces** (the face of each person), the **Persons** (the full picture of the person), and the **Frames** (the person in a frame that shows the classification), as illustrated in Figure 5 and Figure 6. The input of the proposed system is a video of people moving. Some of them are wearing a mask and some are not, while some of them are maintaining social distance and some are not, as illustrated in Figure 5.

Figure 5: Snapshot of the proposed system input

The output of the proposed system is illustrated in *Figure 6*. One of the three people is not wearing a mask and is called 'Unmasked', while two are wearing masks and are called 'Masked'.

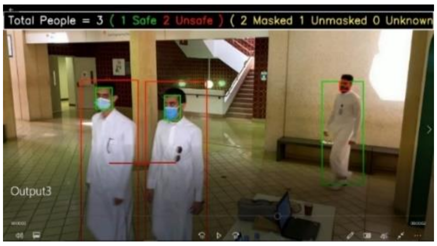


Figure 6: Result of the proposed system

One of them is observing social distance and is called 'Safe', while two are not, so they are called 'Unsafe'. The result is labelled as '*Total people (3) = (1 Safe, 2 Unsafe) (2 Masked, 1 Unmasked)*'. As we can see in Figure 6 and Figure 7, the system gives each one a frame coloured by its state: Red means breaking the rules green means following the rules. As mentioned, the system extracts the Faces (the face of each person), the Persons (the full picture of the person), and the Frames (the person in a frame that shows his classification), as illustrated here:

a) The extracted persons in the video.

b) The extracted person in a frame that shows his classification.

Figure 7: Output of the proposed system

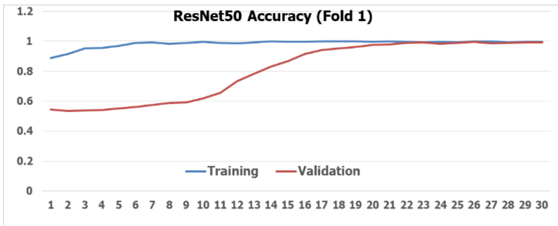
The experimentation with the proposed system is available at the following link (https://youtu.be/m1SU318tTVg).

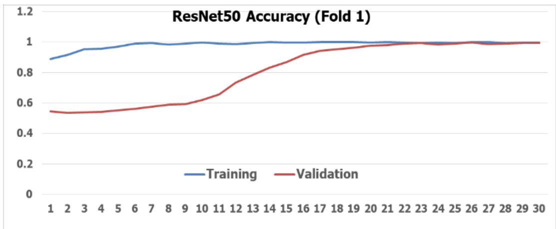
VI. SYSTEMS EVALUATION AND COMPARISON

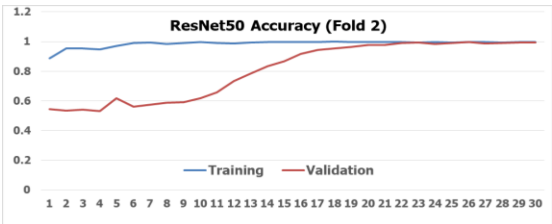
In the mask detection system of the proposed CRS, we used 30 epochs to train the ML models, Inception-V3 and ResNet50. As illustrated in Table 1, the performance metrics of the CNN architectures (Inception-V3 and ResNet50) were tested with masks and without masks. The ResNet50 outperformed the Inception-V3 with the following performance metrics: 99.2% accuracy, 99% F1 score, 100% precision, and 98% recall for mask cases, and 99.3% accuracy, 99% F1 score, 98% precision, and 100% recall for without-mask cases. We performed two-fold cross-validation with 30 epochs for both Inception-V3 and ResNet50 models and took the overall average of the results. Figure 8 and Figure 9 illustrate the learning performance accuracy of ResNet50 in one-fold cross-validation, with 30 epochs. The training and validation loss decreased to the point of stability with a minimal gap between the two final loss values in all folds.

Table 1: performance metrics of the proposed mask Detection system of the CRS system

		F1	Accuracy	Precision	Recall	Support
ResNet50	With Mask	99%	99.2%	100%	98%	33
	Without Mask	99%	99.3%	98%	100%	23
Inception-3	With Mask	96%	97%	98.5%	97%	30
	Without Mask	96%	97%	96%	98.5%	26







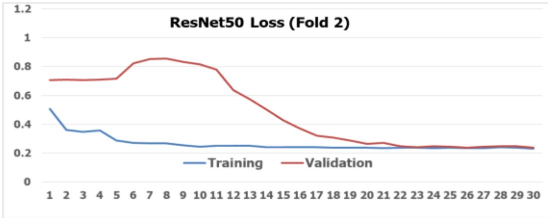


Figure 8: Learning performance of training and validation learning curves of ResNet50 for 30 epochs.

In comparison, the best results of the reference study [18] using the VGG-16 were 99% accuracy, 99% F1 score, 99% precision, and 98% recall for mask cases, and 99% accuracy, 99% F1 score, 98% precision, and 99% recall for without-mask cases.

In addition, the best results of the reference study [18] using the VGG-16 were 97.84% accuracy, 98.13% F1 score, 98.4% precision, and 97.87% recall for mask cases using the RMFD dataset [19].
As illustrated in Table 2 , we compared our system and two other systems from the previous literature [18, 28] for mask detection and showed the results of the comparison in the. In the proposed system, we used two models, ResNet50 and Inception v3, and used the COCO as a dataset. The ResNet50 of the proposed system outperformed the reference studies with the following performance metrics: 99.2% accuracy, 99% F1 score, 100% precision, and 98% recall for mask cases, and 99.3% accuracy, 99% F1 score, 98% precision, and 100% recall for without-mask cases.

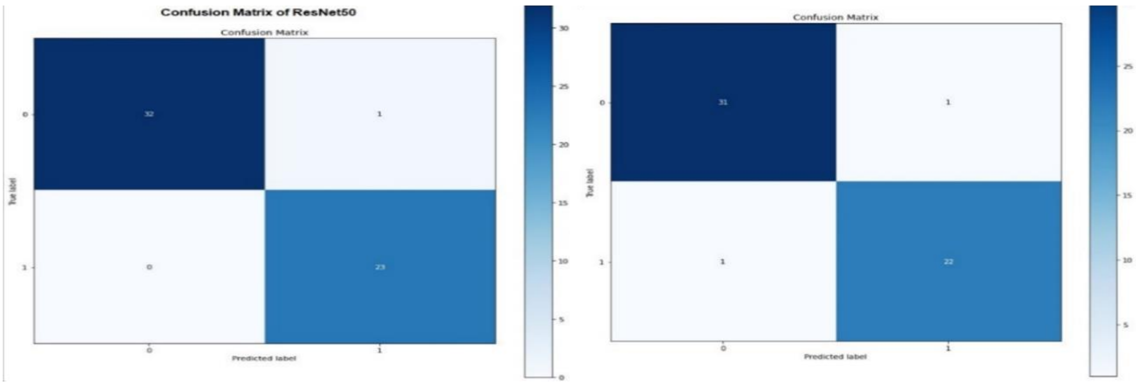


Figure 9: The confusion matrices of one fold of ResNet50 and Inception-V3 with 30 epochs

Table 2: System comparison

		F1	Accuracy	Precision	Recall	Support
ResNet50 (our model)	With Mask	**99**	**99.2**	**100**	**98**	33
	Without Mask	**99**	**99.3**	**98**	**100**	23
Inception-3 (our model)	With Mask	96	97	98.5	97	30
	Without Mask	96	97	96	98.5	26
DensNet [18]	With Mask	92	91	92	91	524
	Without Mask	89	91	88	90	390
InceptionV3 [18]	With Mask	84	88	83	85	524
	Without Mask	78	88	80	77	390
MobileNetV2 [18]	With Mask	96	95	95	96	524
	Without Mask	94	95	95	94	390
VGG-16 [18]	With Mask	99	99	99	98	524
	Without Mask	99	99	98	99	390
MobileNet [28]	With Mask	-	97.84	98.04	97.84	33
	Without Mask	-	97.84	97.08	97.79	33
Paper model [28]	With Mask	98.13	97.84	98.40	97.87	33

VII. Conclusion

In this paper, we proposed a real-time smart machine learning-based system for monitoring social distancing and mask wearing. The proposed system consists of two sub-systems, SS and CRS. The proposed system is used to monitor people in public places such as schools, universities, airports, and supermarkets to identify those who violate the rules of mask wearing and social distancing. We executed and tested the proposed system at King Saud University, Saudi Arabia. The experimental results of the proposed system illustrated its robustness and accuracy. In the future, we plan to enhance the system by adding more features like detecting high temperatures and analysing socially distanced people to understand their behaviour better. Therefore, the system can be integrated with governance systems to get real-time alarms. In addition, we plan to create an easy-to-use graphical user interface.

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