

Social distance and face mask detector system exploiting transfer learning

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ABSTRACT

As time advances, the use of deep learning-based object detection algorithms has also evolved leading to developments of new human-computer interactions, facilitating an exploration of various domains. Considering the automated process of detection, systems suitable for detecting violations are developed. One such applications is the social distancing and face mask detectors to control air-borne diseases. The objective of this research is to deploy transfer learning on object detection models for spotting violations in face masks and physical distance rules in real-time. The common drawbacks of existing models are low accuracy and inability to detect in real-time. The MobileNetV2 object detection model and YOLOv3 model with Euclidean distance measure have been used for detection of face mask and physical distancing. A proactive transfer learning approach is used to perform the functionality of face mask classification on the patterns obtained from the social distance detector model. On implementing the application on various surveillance footage, it was observed that the system could classify masked and unmasked faces and if social distancing was maintained or not with accuracies 99% and 94% respectively. The models exhibited high accuracy on testing and the system can be infused with the existing internet protocol (IP) cameras or surveillance systems for real-time surveillance of face masks and physical distancing rules effectively.

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1. INTRODUCTION

In recent years, plenty of research has been conducted to develop applications in the realm of computer vision, speech recognition, pattern recognition, and face recognition. Object detection deals with discovering and classifying the objects in an image [1], [2]. Machine learning and deep learning methods have been extensively used in statistical interpretation and extending their applications in computer vision and object recognition. There exist numerous applications of object detection that are evolving lately up such as face mask detection, and pedestrian detection [3]–[5]. Based on the application's point of view, object detection algorithms are ordered as: i) generic object detection and ii) application-oriented detection [6]–[9]. Furthermore, deep learning models are viewed in two forms based on the inferring speed and recognition efficiency: i) one-staged detectors such as the you only look once (YOLO) and ii) two-staged detectors such as the region-based convolutional neural networks (RCNN) [10], [11].

Previously, Jiang's [5] works suggested a one-staged Retina Face Mask detector to focus on detecting face masks. The paper by Matthias [8], concentrated on real-time face recognition and the intended

model was trained on huge datasets. It was capable of extracting facial features, before applying decision-making algorithms on them. A convolutional neural networks (CNN) model for face mask classifier employs the characteristics of transfer learning and combines them with classical machine learning techniques. Transfer learning involves the use of data from one task to be used as part of a second task. Besides, it also indicates the use of pre-trained models such as the ones trained on ImageNet and common objects in context (COCO) datasets, to be used as the starting point in an image processing application. The applications of deep learning, machine learning, OpenCV, TensorFlow, and PyTorch are defined in detail. Besides, real-time face mask detection from a live stream is attempted using a graphics processing unit (GPU) [9], [10]. Four steps have been performed in the paper by Ren *et al.* [11] that centered on region-based convolutional neural network (R-CNN) or regions with CNN features. Initially, it picks certain areas from an image as object candidate boxes and rescales them to a fixed size. Secondly, it works on the CNN for feature extraction of every individual region. Lastly, the category of boundary boxes is predicted based on the characteristics of every region while applying the support vector machine (SVM) classifier [12]. Fast R-CNN addresses this subject by considering the undivided image as the input to CNN to acquire features. Faster R-CNN advances the R-CNN nexus by compensating for exploration with a region proposal network to diminish the number of candidate boxes [13].

The social distancing detector requires person detection, followed by person tracking. Ahmed *et al.* [14] applied YOLOv3 to recognize people in the crowd. They accomplished an initial efficiency of 92% and then improved the accuracy to 98% by employing transfer learning. Wang *et al.* [15] has outlined two varieties of deep learning object detection models. One denotes the R-CNN-based and the other is the regression-based YOLO. The ‘you only look once’ YOLO model was reported by Redmon *et al.* [16]. It is a one-staged detector based on the CNN backbone [17], [18]. Wang *et al.* [19] applied the YOLOv3 algorithm with DarkNet-53 as a backbone for facial detection. The model was 90% accurate and was trained on 6,00,000 plus data. Rezaei *et al.* [20] extended a model based on YOLOv4 to detect unmasked faces and physical distancing. The model was trained on open and large databases and produced a precision of 99.8% for real-time detection on a GPU. Eventually, a structured YOLO-compact system for single class instant object acumen is procured based on YOLO-v3 [19]–[23]. It assumes a sampling layer approach to present an improved res tailback block and RFB-compact module. Hussain *et al.* [11], exhibited Viola and Jones's object detection system as an exemplar of supervised learning. Nonetheless, it served only for upright and frontal faces. In [24], [25] the system structure of the YOLO model is accustomed to YOLO-R. Later, [25], [26] recommended a multi-view face detector. The Voila-Jones framework is pre-trained to discover face and other objects. The implementation was carried out in MATLAB. It was presumed that Viola Jones exceeded the rest for face detection. The employment of locally linear embedding CNNs has been put forth in along with the use of the MAFA dataset. The prototype classifies faces while remaining covered with typical occlusions like hands, beard, or face masks of diverse types. This occurred as a finding that surpassed other diverse models by accomplishing a mean precision of 76.4% when face detection was tested on the masked faces (MAFA) test set.

A detailed comparative survey has been illustrated in [26], [27] regarding the suitable models for developing a face mask classifier and a person detection system. Many deep learning algorithms including single stage and double stage detectors are analyzed based on several datasets. The authors have concluded that MobileNetV2 classifier can be used to detect face masks [28]–[30]. Since the notion of social distancing and face mask detectors is quite contemporary, there is no preceding dedicated study for estimating inter-people distance measures in gatherings. It is discerned that computationally expensive models attain more prominent accuracy. Nevertheless, they cannot be stationed in a restrained environment with restricted sources. On the other hand, “You Only Look Once” uses regression ways to assess the dimensions and foretell probabilities of categories they belong to while contributing to vast advancements in pace and effectiveness. YOLOv3, a class of SSD can be trained on individual GPUs succeeding the issues encountered by other models. Nevertheless, the backbone of YOLO is one of the variants of CNN's-residual neural network (ResNet), densely connected convolutional network (DenseNet), DarkNet, or visual geometry group (VGG) that perform the task of feature extractors [31]–[33]. There are two separate systems to detect social distancing violation and the use of face masks.

However, there is a demand for expanding the functionality of the system by enabling concurrent detections, thereby assisting the surveillance. Stating the research gap, our work intends for a novel method of combining two distinct models that can serve as a face mask detector and social distance detector. It aims at delivering a platform-independent, real-time functionality of face mask and social distance detection using transfer learning. That is, the model developed for social distancing is reused as the starting point for the facemask classifier model. The system is believed to deliver accurate results in current scenario. Consequently, it is concluded that a MobileNetV2 classifier and YoloV3 is an effective approach for developing a face mask detector and social distance detector, respectively.

In a broader sense, the application is a combination of a face mask and a physical distance detector. The platform-independent nature of the application enables the client to use any platform for surveillance. The application can be consolidated with established surveillance hardware to monitor the gathering at the respective locations. The application can connect with the IP address of the camera and can run on any operating system with minimum hardware requirements.

2. RESEARCH METHOD

This paper put-forth a solution to perform real-time inspection of a gathering to track physical distancing and face mask norms. The approach used in working out this explication have been outlined in this section. This involves gathering of image datasets from Kaggle and UCI repository, training a MobileNetV2 model over the gathered dataset, person detection using the YOLOv3 weights and computing the distance between every person detected in the surveillance frame. Finally, the output consists of the MobileNetV2 classification of masked and unmasked faces and distance between every individual, which are compared with the threshold distance to verify that they are in a safe distance amidst the gathering.

2.1. Datasets and pre-processing

The dataset comprises of image data from COCO dataset containing 330,000 images, followed by 2,000 images annotated as 'masked' and 2,000 images annotated as 'unmasked'. The images were gathered via Kaggle and University of California, Irvine (UCI) repository. The stage prior to training and testing of the data is the pre-processing phase. This stage comprises of four steps, that includes image resizing, vectorization of the images, pre-processing using the model and hot encoding on class labels in case of the Face Mask classifier. Image resizing is a significant step in the pre-processing stage due to the efficacy of training models. The performance of the model is observed to be superior on smaller sized images. In this study, the images are resized to 224×224 pixels. This is followed by processing all the frames into an array, after which the MobileNetV2 classifier will be applied. The final step in this stage is to perform hot encoding on labels as the deep learning models cannot act on labels instantly. This requires the input image to be transformed into numerical labels, in order to be process the image. The dataset is divided into batches for training and testing, following the pre-processing stage. 80% of the dataset is used as training set while the persisting ones are used for validation. Each set contains images annotated as 'masked' and 'unmasked'.

2.2. Face mask classifier using MobileNetV2 model

The face mask classifier is trained using the pre-trained MobileNetV2 weights on ImageNet dataset. The bounding rectangles and class labels are determined for each individual captured in the frame, following which they undergo normalization considering the width and height of the image. In [24] represents the convolution blocks of MobileNetV2 as depicted in Figure 1.

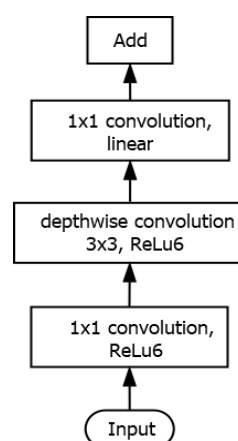


Figure 1. Convolution block of MobileNetV2

The block consists of two convolution layers with rectified linear unit (ReLU) and non-linearity, and a depth wise convolution layer. The image generator for the process of Image Augmentation was constructed to support the training. Using the transfer learning approach, additional layers and model parameters were added on top of the base MobileNetV2 model. The base model used the pre-trained weights on ImageNet

dataset. The base model is followed by the average pooling, dropout and dense layers. The final layer terminates with a SoftMax function as the application requires a binary classifier. To assure that the model fits well, we can validate it on the test dataset for a definite number of iterations or epochs.

2.3. Person detection using YOLOv3 model

We detect the faces using the dual shot face detector (DSFD) or retina face detector and apply the trained classifier on the faces detected. For social distancing detector, the persons are detected using the YOLOv3 model. YOLOv3 object detection is widely used to track the people in a surveillance footage. Each person in coordinates (x, y) are mapped to a feature space. For every pair of individuals, L2 norm is calculated and based on the spatial threshold, the violations are determined. The trained weights of YOLOv3 model using DarkNet53 code based on COCO dataset is used for the person detection. The model is trained on COCO dataset with 80 classes of objects. Figure 2 [19], [25] represents a schematic representation of the YOLOv3 architecture. The pipeline comprises of three parts, namely, the neck, backbone, and the head. A red green blue (RGB) image is taken as the input by the network. The backbone takes care of feature extraction. CSPDarkNet53 is an optimal choice for the backbone. YOLOv3 is capable of multi-class classification using logistic classifiers unlike the other versions of YOLO, that uses a SoftMax activation function. DarkNet53 was proposed as the backbone for the YOLOv3 network by Redmon *et al.* [16]. The backbone is responsible for the extraction of feature maps. The DarkNet53 contains residual blocks and up sampling layers for concatenation. Images are scaled thrice for every spatial location as YOLOv3 generates three predictions, overcoming the issues of detecting smaller objects efficiently. Each prediction is administered by bounding boxes and confidence scores. The coordinates, centroids and boxes are stored as separate sets and the coordinates are used for transfer learning.

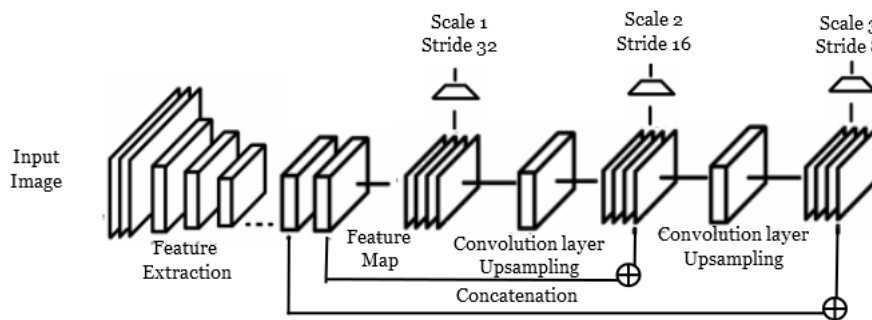


Figure 2. Schematic representation of YOLOv3 network architecture

2.4. Social distancing using Euclidean distance

The respective authority has the option of selecting the social distance to be maintained in their respective zone by controlling the threshold distance in pixels. This is based on the orientation of the camera and the calibration and absolute distance is fed into the model. The physical distancing model uses the concept of lens, which is radically convex, where the frame is captured on the screen. The distance measure between the optic center and the focus is called the focal length of the lens as shown in Figure 3. It is computed in millimeters (mm).

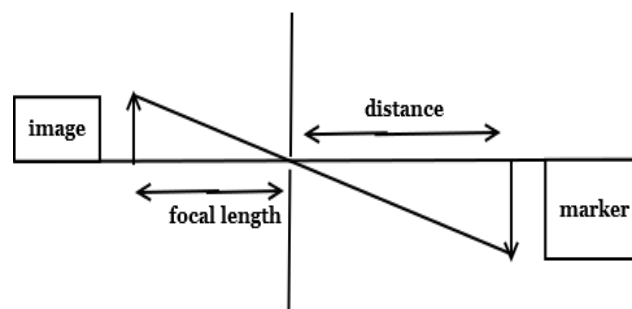


Figure 3. Visualization of the operation of a camera

Considering the coordinates of person A and person B, are (x_1, y_1) and (x_2, y_2) respectively in the conferred frame, we can say that:

$$\frac{\text{dimension of sensor}}{\text{focal length}} = \frac{\text{field dimension}}{\text{distance to field}} \quad (1)$$

the equation to derive the depth of an entity in a frame is as (2).

$$d = \frac{\text{object height} \times \text{focal length}}{\text{sensor height}} \quad (2)$$

Assuming the distance of the people from the camera is d_i , the estimated distance amid the pedestrians in the frame can be computed using the Euclidean distance given by (3).

$$\sqrt{\sum_{i=1}^n (q_i - p_i)^2} \quad (3)$$

Where, p and q are points in Euclidean space. Let the distance from camera of two persons be d_1 and d_2 . The physical distancing width w' can be formulated as (4).

$$w' = (|x_1 - x_2|) \times \text{pixel size} \quad (4)$$

The field width w can be obtained from (5).

$$w = \frac{\text{sensor width} \times w'}{\text{focal length}} \quad (5)$$

If person 1 is at coordinate $(0, d_1)$ and person 2 is at (w, d_2) , then physical distance d' is given by (6).

$$d' = \sqrt{(w - 0)^2 + (d_2 - d_1)^2} \quad (6)$$

If the computed distance is less than the threshold specified, the pair of individuals will be considered as violators. The threshold is not fixed and varies depending on the camera orientation. The lens used in this paper has a sensor width and sensor height of 10 mm and 9.8 mm respectively, thereby yielding a threshold distance of 142 pixels. The pixel size can be obtained using (7).

$$\frac{\text{sensor width}}{\text{image width}} + \frac{\text{sensor height}}{\text{image height}} \quad (7)$$

3. RESULTS AND DISCUSSION

The pipeline of how transfer learning takes place has an important role to play. The current work focuses on enhancing the performance of the violation detections with respect to face mask and social distancing rules. The steps involved in implementation of the proposed are as: i) requirements collected, this includes the data and pre trained YOLOv3 weights; ii) the functionalities are clearly defined and decomposed into modules; iii) develop person detection using the YOLOv3 model, iv) transfer learning, use the coordinates of the persons detected for face mask classifier; v) apply the MobileNetV2 model to perform face mask classification; and vi) use the centroids of persons obtained during person detection to compute the distance among them using Euclidean distance measure.

A distinct real-time state-of-art object inference models is the YOLO model, that processes the pictures at 30 frames per second on a Pascal Titan X. It is proven to have a mAP of 56% on the large-scale captioning COCO repository. YOLOv3 is 4 times faster and can easily set-off among the accuracy and speed. There is no requirement of re-training the model from scratch. YOLOv3 is capable of processing 45 frames per second on Pascal Titan X. The open-source pre-trained weights of YOLOv3 on the COCO datasets are available.

Figure 4 depicts the overall system architecture. We trained one model for classifying between a pair of classes Masked face and Unmasked face. The algorithms were trained on 3,000 pictures. The dataset was augmented to provide sufficient training data. The hyperparameters for training was set as: i) number of steps: length of training data/batch size; ii) batch size: 12; iii) initial learning rate: 0.0001; and iv) epochs: 30. To test the social distancing and face mask detector, the camera configurations used is as: i) focal length: 12 mm; ii) image sensor: ultra-wide with 5MP depth; and iii) camera height: variable.

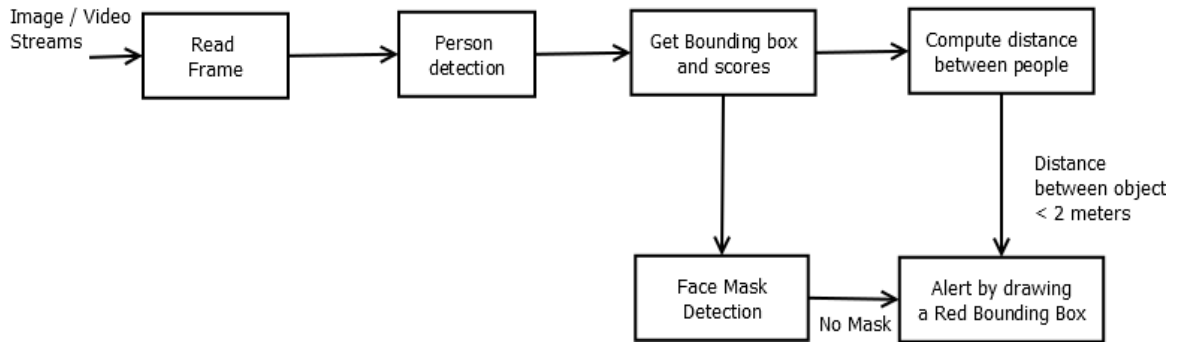


Figure 4. Overall system architecture

The MobileNetV2 classifier is qualified to classify among the masked and unmasked faces. The classifier model has a promising accuracy of 99%. Figures 5 and 6 depicts the classification report and the graph of validation loss and accuracy for both classes indicating that the overall system yields extremely good results without involving costly computations. The average FPS of the overall system is 35FPS on an NVIDIA Tesla K80 GPU, yielding significantly higher performance.

	precision	recall	f1-score	support
with_mask	0.99	1.00	0.99	312
without_mask	1.00	0.99	0.99	384
accuracy			0.99	696
macro avg	0.99	0.99	0.99	696
weighted avg	0.99	0.99	0.99	696

Figure 5. Classification report of MobileNetv2 model

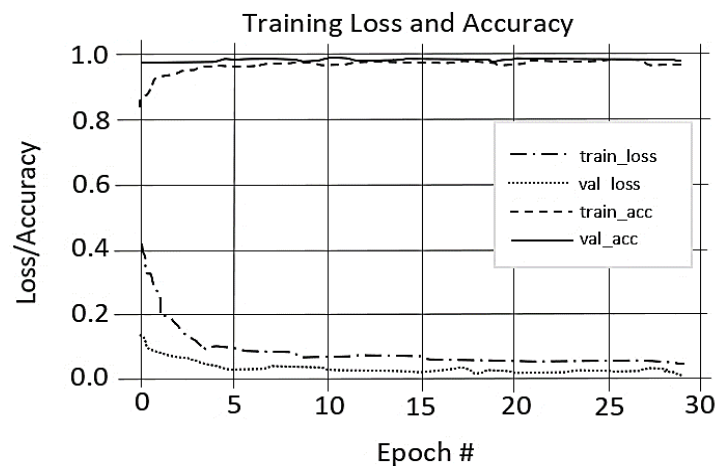


Figure 6. Accuracy and loss curves

From Figures 7(a) to 7(c), it is observed that the system can detect the violations related to face masks and social distancing. As the models exhibit high accuracy on testing, the system can be integrated with the existing surveillance system for real-time monitoring of face masks and social distancing rules effectively. Also, we can estimate that the overall system yields extremely good results of whether physical distancing and use of face mask is violated or not, without involving costly computations. The YOLOv3

yields an accuracy of 94% for pedestrian detection and MobileNetV2 face mask classifier yields an accuracy of 99%. The monitoring status of the frame shows the number of violations with respect to the face mask and physical distance rules. Also, the violations are notified using a red bounding box and an alarm. Besides, snapshots and footages of the processed frames are stored in the disk.



Figure 7. Inference of social distance and face mask detection on (a) surveillance footage 1, (b) surveillance footages 2, and (c) surveillance footage 3

4. CONCLUSION

The current work stresses on a real-time physical distancing detector and face mask classifier using Deep Learning. The proposed system aims at delivering a platform-independent, real-time functionality of face mask and physical distance detection. The drawbacks of existing models, such as CNN, RCNN and other two staged detectors were low accuracy due to the complex structures and redundancy of neurons. Besides, the integration of face masks and physical distance functionality was not feasible with previous models in real-time. After training, validation and testing the face mask detector under several circumstances, the detection using MobileNetV2 proved to be highly accurate. This along with YOLOv3 based physical distance detector is a well-integrated real time violation detection system. The detection of three classes namely, the masked faces, unmasked faces and the people happen simultaneously using transfer learning approach. The relative distance between the people is derived from the coordinates given by the person class that is detected by the YOLOv3 person detector. On observing the behavior of the system, it was concluded that this lightweight model can be infused with existing applications for real time surveillance to detect violations with respect to use of face mask and social distancing.

The future goals associated with current works include deployment of the application to cloud to make installation simpler. Observing the applications to integrate additional functionalities such as body temperature check. Additionally, the work may be revamped based on different indoor and outdoor circumstances. Different tracking and detection algorithms can be worked upon to help track the breaches on the face mask and social distancing threshold in a more feasible manner.





REFERENCES

- [1] L. Jiao *et al.*, "A survey of deep learning-based object detection," *IEEE Access*, vol. 7, pp. 128837–128868, 2019, doi: 10.1109/ACCESS.2019.2939201.
- [2] L. Liu *et al.*, "Deep learning for generic object detection: a survey," *International Journal of Computer Vision*, vol. 128, no. 2, pp. 261–318, Feb. 2020, doi: 10.1007/s11263-019-01247-4.
- [3] Z. Q. Zhao, P. Zheng, S. T. Xu, and X. Wu, "Object detection with deep learning: a review," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 11, pp. 3212–3232, Nov. 2019, doi: 10.1109/TNNLS.2018.2876865.
- [4] M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, "A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic," *Measurement*, vol. 167, Jan. 2021, doi: 10.1016/j.measurement.2020.108288.
- [5] M. Jiang, X. Fan, and H. Yan, "Retinamask: A face mask detector," *arXiv:2005.03950*, May 2020.
- [6] V. Vinitha and V. Velantina, "COVID-19 facemask detection with deep learning and computer vision," *International Research Journal of Engineering and Technology (IRJET)*, vol. 7, no. 8, pp. 3127–3132, 2020.
- [7] P. Khandelwal, A. Khandelwal, S. Agarwal, D. Thomas, N. Xavier, and A. Raghuraman, "Using computer vision to enhance safety of workforce in manufacturing in a post COVID world," *arXiv:2005.05287*, May 2020.
- [8] D. Matthias, C. Managwu, and O. Olumide, "Face mask detection application and dataset," *Journal of Computer Science and Its Application*, vol. 27, no. 2, Mar. 2021, doi: 10.4314/jcsia.v27i2.5.
- [9] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Jun. 2014, pp. 580–587, doi: 10.1109/CVPR.2014.81.
- [10] Z. Zou, Z. Shi, Y. Guo, and J. Ye, "Object detection in 20 years: a survey," *arXiv:1905.05055*, May 2019.
- [11] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017, doi: 10.1109/TPAMI.2016.2577031.
- [12] S. Yadav, "Deep learning based safe social distancing and face mask detection in public areas for COVID-19 safety guidelines adherence," *International Journal for Research in Applied Science and Engineering Technology*, vol. 8, no. 7, pp. 1368–1375, Jul. 2020, doi: 10.22214/ijraset.2020.30560.
- [13] H. Jiang and E. Learned-Miller, "Face detection with the faster R-CNN," in *12th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2017)*, May 2017, pp. 650–657, doi: 10.1109/FG.2017.82.
- [14] I. Ahmed, M. Ahmad, J. J. P. C. Rodrigues, G. Jeon, and S. Din, "A deep learning-based social distance monitoring framework for COVID-19," *Sustainable Cities and Society*, vol. 65, Feb. 2021, doi: 10.1016/j.scs.2020.102571.
- [15] Z. Wang *et al.*, "Masked face recognition dataset and application," *arXiv:2003.09093*, Mar. 2020.
- [16] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: unified, real-time object detection," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.
- [17] S. V. Militante and N. V. Dionisio, "Real-time facemask recognition with alarm system using deep learning," in *2020 11th IEEE Control and System Graduate Research Colloquium, ICSGRC 2020 - Proceedings*, Aug. 2020, pp. 106–110, doi: 10.1109/ICSGRC49013.2020.9232610.
- [18] M. Inamdar and N. Mehendale, "Real-time face mask identification using facemasknet deep learning network," *SSRN Electronic Journal*, 2020, doi: 10.2139/ssrn.3663305.
- [19] C. Li, R. Wang, J. Li, and L. Fei, "Face detection based on YOLOv3," in *Advances in Intelligent Systems and Computing*, vol. 1031 AISC, Springer Singapore, 2020, pp. 277–284.
- [20] M. Rezaei and M. Azarmi, "DeepSOCIAL: social distancing monitoring and infection risk assessment in COVID-19 pandemic," *Applied Sciences*, vol. 10, no. 21, p. 7514, Oct. 2020, doi: 10.3390/app10217514.
- [21] S. Ge, J. Li, Q. Ye, and Z. Luo, "Detecting masked faces in the wild with LLE-CNNs," in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, Jul. 2017, vol. 2017-Janua, pp. 426–434, doi: 10.1109/CVPR.2017.53.
- [22] M. S. Ejaz, M. R. Islam, M. Sifatullah, and A. Sarker, "Implementation of principal component analysis on masked and non-masked face recognition," May 2019, doi: 10.1109/ICASERT.2019.8934543.





- [23] S. A. Hussain and A. S. A. Al Balushi, "A real time face emotion classification and recognition using deep learning model," *Journal of Physics: Conference Series*, vol. 1432, no. 1, Jan. 2020, doi: 10.1088/1742-6596/1432/1/012087.
- [24] A. G. Howard *et al.*, "MobileNets: efficient convolutional neural networks for mobile vision applications," *arXiv:1704.04861*, 2017.
- [25] Y. Lu, L. Zhang, and W. Xie, "YOLO-compact: an efficient YOLO network for single category real-time object detection," in *2020 Chinese Control And Decision Conference (CCDC)*, Aug. 2020, pp. 1931–1936, doi: 10.1109/CCDC49329.2020.9164580.
- [26] S. V. Shetty, K. Anand, S. Pooja, K. A. Punnya, and M. Priyanka, "Social distancing and face mask detection using deep learning models: a survey," in *Asian Conference on Innovation in Technology (ASIANCON)*, Aug. 2021, pp. 1–6, doi: 10.1109/ASIANCON51346.2021.9544890.
- [27] Y. C. Hou, M. Z. Baharuddin, S. Yussof, and S. Dzulkifly, "Social distancing detection with deep learning model," in *8th International Conference on Information Technology and Multimedia (ICIMU)*, Aug. 2020, pp. 334–338, doi: 10.1109/ICIMU49871.2020.9243478.
- [28] S. Susanto, F. A. Putra, R. Analia, and I. K. L. N. Suciningtyas, "The face mask detection for preventing the spread of COVID-19 at politeknik negeri batam," *Proceedings of ICAE 2020 - 3rd International Conference on Applied Engineering*, Oct. 2020, doi: 10.1109/ICAE50557.2020.9350556.
- [29] G. J. Chowdary, N. S. Punn, S. K. Sonbhadra, and S. Agarwal, "Face mask detection using transfer learning of inceptionV3," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12581, Springer International Publishing, 2020, pp. 81–90.
- [30] A. N. Zereen, S. Corraya, M. N. Dailey, and M. Ekpanyapong, "Two-stage facial mask detection model for indoor environments," in *Advances in Intelligent Systems and Computing*, vol. 1309, Springer Singapore, 2021, pp. 591–601.
- [31] M. E. Rusli, S. Yussof, M. Ali, and A. A. A. Hassan, "MySD: a smart social distancing monitoring system," in *8th International Conference on Information Technology and Multimedia (ICIMU)*, Aug. 2020, pp. 399–403, doi: 10.1109/ICIMU49871.2020.9243569.
- [32] M. Botella-Campos, J. L. Gacía-Navas, A. Rego, S. Sendra, and J. Lloret, "A new system to detect coronavirus social distance violation," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 6, pp. 5034–5048, Dec. 2021, doi: 10.11591/ijece.v11i6.pp5034-5048.
- [33] G. Bathla, H. Aggarwal, and R. Rani, "A novel approach for clustering big data based on mapreduce," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, no. 3, pp. 1711–1719, Jun. 2018, doi: 10.11591/ijece.v8i3.pp1711-1719.

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