



# Face Mask Detector

Divyansh Gupta | Vasudha Bahl

Department of Information Technology, Maharaja Agrasen Institute Of Technology, New Delhi, Delhi, India

## To Cite this Article

Divyansh Gupta | Vasudha Bahl. Face Mask Detector. *International Journal for Modern Trends in Science and Technology* 2021, 7 pp. 410-413. <https://doi.org/10.46501/IJMTST0712075>

## Article Info

Received: 19 November 2021; Accepted: 22 December 2021; Published: 29 December 2021

## ABSTRACT

Coronaviruses, a large family of different viruses, have recently become very common, contagious, and dangerous to the entire human population. It spreads from person to person by exhaling the infected breath, which leaves droplets of the virus on various surfaces, which are then inhaled by another person, who becomes infected as well. As a result, it has become critical to protect ourselves and those around us from this situation. We can take precautions like social distancing, hand washing every two hours, using sanitizer, maintaining social distance, and, most importantly, wearing a mask. The wearing of masks in public has become very common all over the world. Due to its extreme population density in a small area, India is the most affected and devastating condition. This paper proposes a method for determining whether or not a face mask is worn.

**KEYWORDS:** FACE MASK DETECTOR, MACHINE LEARNING, CNN, OPENCV

## INTRODUCTION

Since the outbreak of the new coronavirus disease, public use of face masks has become common in China and other countries around the world. According to the Health Centre's advisory, we now know from recent studies that a significant portion of people with coronavirus have no symptoms ("asymptomatic") and that even those who eventually develop symptoms ("pre-symptomatic") can transmit the virus to others before they show symptoms. "This means that the virus can spread between people who are interacting in close proximity — for example, speaking, coughing, or sneezing — even if those people are not experiencing symptoms." The most recent information also indicates the existence of a new strain of corona virus, the mutant corona virus, in which the virus's structure has changed and it has become mutant. The new strain is not even detectable using the current RT-PCR test.

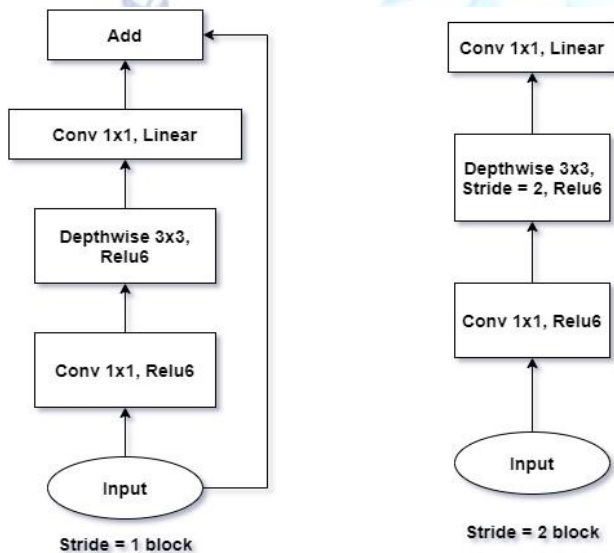
As a result, it is unavoidable for people in a densely

populated country like India to wear masks and continue working. Nobody can keep track of whether or not everyone who enters the workplace is wearing a mask. As a result, the need for Face mask detection arose. The Convolutional Neural Network is used in this paper's model. It is a deep neural network model that is used to analyse visual imagery. It takes image data as input, captures all of the data, and sends it to the neural layers. It has a fully connected layer that processes the final output, which represents the image prediction. The MobileNetV2 architecture is used in this Convolutional neural network model. The MobileNet model is a network model that uses depth wise separable convolution as its fundamental unit. It has two layers in its depth wise separable convolution: depth wise convolution and point convolution [1].

It is based on an inverted residual structure, with residual connections between bottleneck layers. As a source of non-linearity, the intermediate expansion

layer filters features using lightweight depth wise convolutions. The MobileNetV2 architecture includes an initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers. Figure 1 depicts the MobileNetV2 framework used in the model discussed in this paper.

The model is then subjected to further testing with various hyper parameters. The hyper parameters tested are learning rate, which is a tuning parameter used in optimization models that determines the step size of the model and aids in the reduction of the loss function. It is a critical hyper parameter because it determines whether the model converges or overshoots. Other hyper parameters used include batch size, epochs, and so on. The model has used OpenCV to accomplish the goal of using the video stream to capture the frames in the video stream.



## RELATED WORK

They proposed a pre-trained MobileNet with a global pooling block for face mask detection in [3]. The pre-configured MobileNet captures a shading image and generates a multi-dimensional component map. The proposed model's worldwide pooling block converts the element map into an element vector of 64 highlights. Finally, the softmax layer employs paired order with the 64 highlights. We tested our proposed model on two publicly available datasets. On DS1 and DS2, respectively, our proposed model achieved 99 percent and 100 percent exactness. The proposed model's use of a global pooling block prevents the model from overfitting. Furthermore, the proposed model outperforms existing models in terms of the

number of boundaries as well as preparation time. However, this model is incapable of detecting face masks for multiple faces at the same time.

The [5] paper employs a skilled and powerful item location calculation to naturally identify the appearances with or without veils, making the plague avoidance work more intelligent. They gathered a large data set of 9886 pictures of people with and without face covers and physically named them, after which they used multi-scale preparation and picture mistake techniques to improve YOLOv3, an article recognition calculation, to determine whether a face is wearing a veil.

The mean Average Precision (mAP) of the improved YOLOv3 calculation model was 86.3 percent, according to our analysis results. This work can successfully and naturally distinguish whether individuals are wearing veils, which reduces the pressing factor of conveying HR for checking covers openly and has a high functional application esteem.

## PROPOSED SYSTEM

Tensorflow, Keras, and OpenCV are Python libraries that were used to design and model the model presented here. We used the MobileNetV2 convolutional neural network model. The method of employing MobileNetV2 is known as Transfer Learning. Transfer learning is the process of using a previously trained model to train your current model and obtain a prediction, which saves time and simplifies the process of training different models. The model is fine-tuned using the hyper parameters: learning rate, number of epochs, and batch size. The model is trained on a dataset of images divided into two classes, with and without mask. The dataset contains 993 images with masks and 1918 images without masks.

- (i) Training the model with the taken dataset.
- (ii) Deploying the model

We created a model in the paper by combining the aforementioned libraries. We tested the model under various conditions and with various hyper parameters, and the results are presented in the following section. We start by feeding the dataset into the model, then we run the training programme, which trains the model on the given dataset. The detection programme is then run, which turns on the video stream and continuously

captures frames from the video stream with an anchor box using the object detection process. This is then passed through the MobileNetV2 model layers, which determine whether the image has a mask or not. If the person is wearing a mask, a green anchor box is displayed; if the person is not wearing a mask, a red anchor box is displayed, with the accuracy for the same tagged on the anchor box. The flow of the Face Mask Detection model used in this paper is depicted in Figure 2.

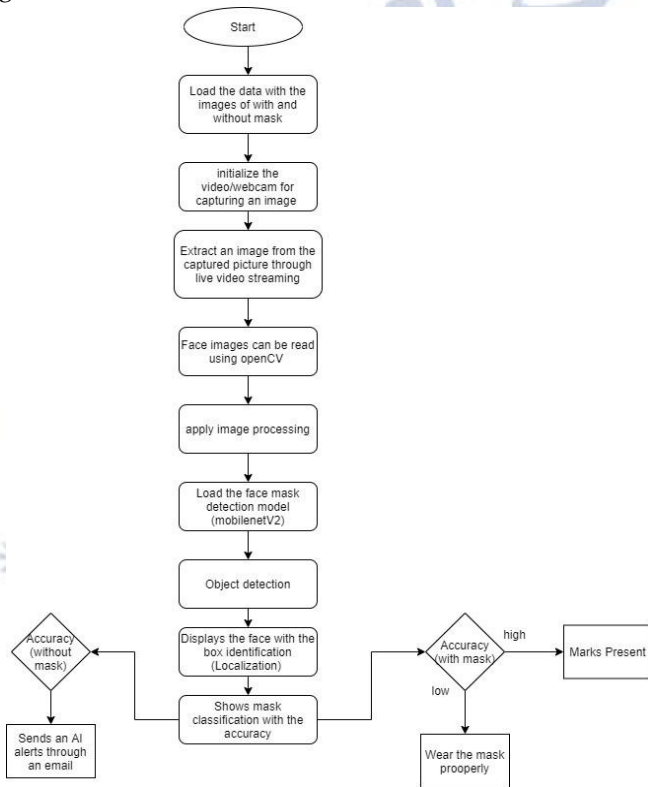


Figure 2. Flow of Face Mask Detection Model

The face mask recognition system employs AI technology to detect whether or not a person is wearing a mask. It can be linked to any surveillance system that is installed on your premises. The authorities or admin can use the system to confirm the person's identity. If someone enters the premises without wearing a face mask, the system sends an alert message to the authorised person. Detecting a person wearing a face mask has an accuracy rate of 95-97 percent, depending on the digital capabilities. The data has been automatically transferred and stored in the system, allowing you to run reports whenever you want.

## RESULTS

We tested the model for various scenarios, and the results are shown in the table below, with the number of

epochs 20 and batch size 32 remaining constant across all three scenarios. For capturing a smooth image, we used Average Pooling. Table 1 displays the results of a comparison of various hyper parameters and situations.

Table 1. Result Comparison Table

Model	Learningrate	With mask distance	Without mask distance	Blur image quality	Multiple people capturing
1	1e-4	161 cm	190 cm	Good	4 people
2	1e-3	155 cm	187 cm	Average	3 people
3	1e-2	146 cm	179 cm	Bad	3 people

According to the above results, the first model outperforms all others. Below is a plot of the best model from our research. It plots the training loss, validation loss, training accuracy, and validation accuracy for the number of epochs versus loss or accuracy. The plot clearly shows that as the number of epochs increases, the training and validation accuracy increases while the training and validation loss decreases. Furthermore, the validation accuracy is greater than the training accuracy, indicating that the model is not overfitting. Figure 3 depicts a plot of the number of epochs versus the loss or accuracy.

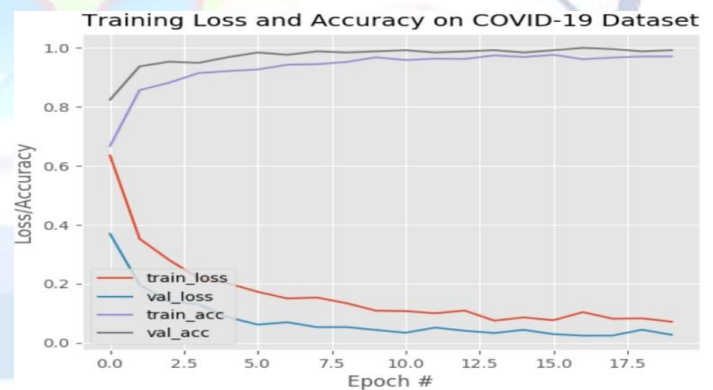


Figure 3. Graph of Number of epochs vs loss or accuracy.

## FUTURE WORK

The proposed model provides excellent accuracy for single faces with and without masks. It also has a high level of accuracy when used on multiple faces. It works on any mobile device simply by turning on the video stream, with no external hardware required. Further, we will work to improve the accuracy of multiple face mask detection, to classify faces into three categories, with mask, without mask, and improper mask, rather



than just the two with and without mask classes, by adding datasets with images of people wearing masks that do not cover their noses properly, and to detect the masked face using the FaceNet model of Convolutional Neural Network, as shown in [4], in order to further improve our model and add marking attestation.

## CONCLUSION

Measures should be taken to slow the spread of the COVID-19 pandemic. We demonstrated a facemask detector in neural organisations using Convolutional Neural Network and move learning techniques. We used a dataset of 993 masked faces pictures and 1918 exposed faces pictures to train, validate, and test the model. These images were taken from various assets such as Kaggle and RMFD datasets. The model was created using images and live video transfers. To select a base model, we evaluated measurements such as precision, accuracy, and recall and selected the MobileNetV2 architecture with the best exhibition of 99 percent precision and 99 percent recall.

It is also computationally efficient when using MobileNetV2, making it easier to introduce the model to inserted frameworks. This face mask detector can be deployed in a variety of settings, including shopping malls, airports, and other high-traffic areas, to screen people in general and prevent the spread of infection by determining who is and isn't following important rules.

## REFERENCES

- [1] A. G. Howard, M. Zhu, B. Chen et al., "Mobilenets: efficient convolutional neural networks for mobile vision applications," 2017, <https://arxiv.org/abs/1704.04861>.
- [2] Wei Wang, Yutao Li, Ting Zou, Xin Wang, Jieyu You, Yanhong Luo, "A Novel Image Classification Approach via Dense-MobileNet Models", *Mobile Information Systems*, vol. 2020, ArticleID 7602384, 8 pages, 2020. <https://doi.org/10.1155/2020/7602384>
- [3] I. B. Venkateswarlu, J. Kakarla and S. Prakash, "Face mask detection using MobileNet and Global Pooling Block," 2020 IEEE 4th Conference on Information & Communication Technology (CICT), 2020, pp. 1-5, doi: 10.1109/CICT51604.2020.9312083
- [4] M. S. Ejaz and M. R. Islam, "Masked Face Recognition Using Convolutional Neural Network," 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), 2019, pp. 1-6, doi: 10.1109/STI47673.2019.9068044