

Facemask Detection using MobileNet, Keras, and OpenCV

Bulagakula Ruthvick¹, Eperu Sai Teja Reddy²

^{1,2}Student, Panimalar Institute of Technology, Chennai.

Abstract - Coronaviruses, a large family of viruses, have recently become extremely prevalent, infectious, and hazardous to the whole human population. It transmits from person to person by exhaling the infectious breath, which leaves droplets of the virus on various surfaces, which are then breathed by another person, who also becomes infected. As a result, protecting ourselves and those around us from this scenario has become critical. We may take measures such as keeping social distance, washing hands every two hours, using sanitizer, maintaining social distance, and, most importantly, wearing a mask. The wearing of masks in public has grown quite widespread all around the world. Due of its enormous population density in a short region, India is the most impacted. This article presents a technique for detecting whether or not a face mask is used in an office or any other workplace where a large number of individuals come to work. For this, we utilised a convolutional neural network. The model has been trained on a real-world dataset and has been tested with live video streaming with high accuracy. The model's accuracy is further tested using different hyper parameters and numerous persons at various distances and locations of the frame.

Key Words: Conventional neural network

1.INTRODUCTION

Since the advent of the new coronavirus virus, public use of face masks has become common in China and other countries across the world. According to the Health Centre's advice, we now know from recent research that a large number of people with coronavirus have no symptoms ("asymptomatic") and that even those who ultimately acquire symptoms ("pre-symptomatic") can spread the virus to others before they display symptoms. "This means that the virus can transmit between persons engaging in close proximity, such as speaking, coughing, or sneezing, even if those people do not have symptoms." . The most current research also indicates the presence of a new type of corona virus, the mutant corona virus, in which the virus's structure has altered and it has become mutant. The new strain is not even detectable with the RT-PCR technique that we now employ. As a result, it is unavoidable for individuals in a densely populated nation like India to put on masks and carry on with their job. Nobody can keep track of whether or not everyone entering the workplace is wearing a mask. Face mask detection became necessary as a result. The Convolutional Neural Network is employed in this article. It is a deep neural network model that can analyse any visual imagery. It receives visual data as input, collects all of the

data, and sends it to the layers of neurons. It has a fully linked layer that processes the final output, which provides the prediction about the picture. The MobileNetV2 architecture is utilised for the Convolutional neural network model. The MobileNet model is a network model that uses depth wise separable convolution as its fundamental unit. Its depth wise separable convolution contains two layers: depth wise convolution and point convolution [1]. It is built on an inverted residual structure with residual connections between the bottleneck levels. As a source of non-linearity, the intermediate expansion layer filters features using lightweight depth wise convolutions. The MobileNetV2 design has an initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers. Figure 1 depicts the MobileNetV2 framework utilised in the model presented in this study.

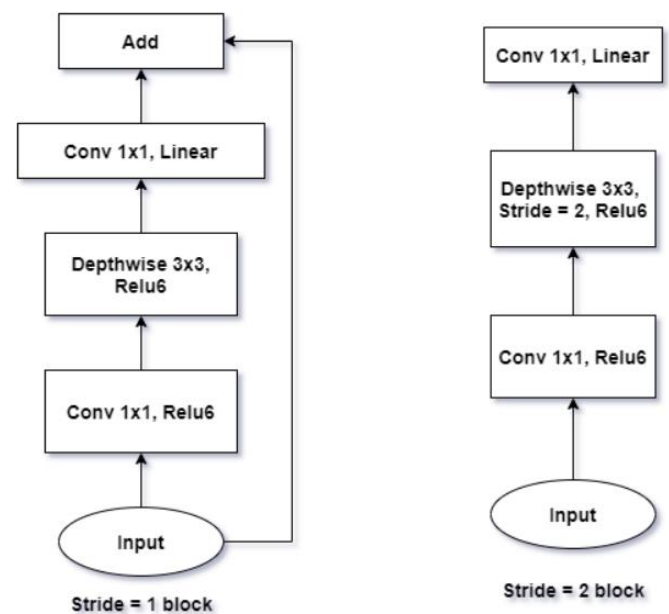


Figure-1: MobileNetV2

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

2. RELATED WORK

They presented a pre-trained MobileNet with a global pooling block for face mask identification in [3]. The pre-configured MobileNet captures a shading image and generates a multi-dimensional component map. The suggested model's global 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 suggested model on two publicly available datasets. On DS1 and DS2, respectively, our suggested model achieved 99 percent and 100 percent exactness. Overfitting is avoided in the proposed model because to the use of a global pooling block. Furthermore, the suggested model outperforms previous models in terms of the number of boundaries as well as preparation time. However, this model is incapable of detecting numerous face masks at the same time. The [5] article employs a competent and powerful item location computation to automatically detect the appearances with or without veils, making the plague avoidance task more intelligent. They acquired a large data set of 9886 images of people with and without face covers and physically identified them, after which they used multi-scale preparation and picture error approaches to improve YOLOv3, an article recognition computation, to determine whether a face is wearing a veil. According to our findings, the enhanced YOLOv3 calculation model's mean Average Precision (mAP) was 86.3 percent. This job can successfully and naturally detect if people are wearing veils, reducing the need for HR to check for openly put coverings and having a high functional application esteem. Tensorflow, Keras, and OpenCV are three Python libraries used to construct and build the model presented here. The model we utilised was a convolutional neural network called MobileNetV2. Transfer Learning is the way of employing MobileNetV2. Transfer learning is the process of utilising a previously trained model to train your current model and obtain a prediction, which saves time and simplifies the process of training various models. The hyper parameters : learning rate, number of epochs, and batch size are used to fine-tune the model. The model is trained on a set of pictures divided into two categories: with and without mask. There are 1915 pictures in the collection with masks and 1918 images without mask. I Using the extracted dataset to train the model ii) Putting the mode into operation We used the above-mentioned libraries to construct a model in the article. We ran the model under various situations and with various hyper parameters, the results of which are presented in the next section. We input the dataset into the model first, then execute the training algorithm to train the model on the provided dataset. Then, using the object detection method, we execute the detection software, which turns on the video stream and grabs the frames constantly from the video stream with an anchor box. This information is sent through the MobileNetV2 model layers, which classify the picture as having a mask or not. A green anchor box appears if the person is wearing a mask, and a red anchor box appears if the person is not wearing a mask, with the

accuracy for the same labelled on the anchor box. The flow of the Face Mask Detection model utilised in this work is shown in Figure 2.

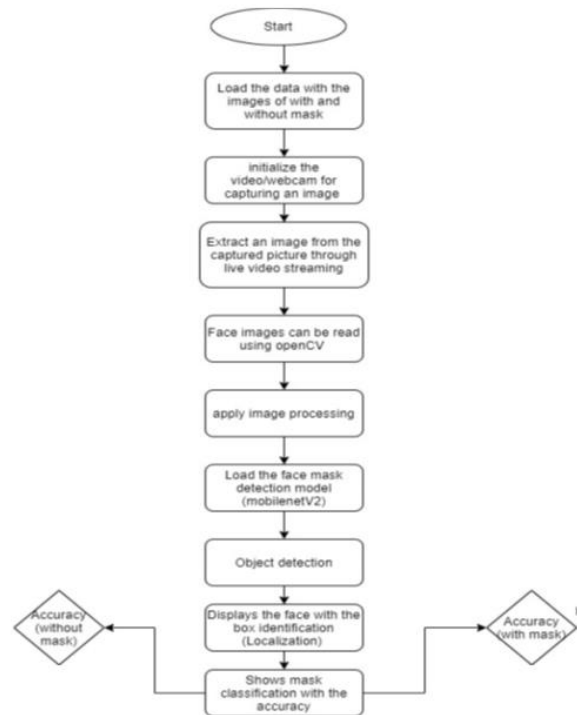


Figure-2: Flow of Face Mask Detection Model

3. RESULT

We evaluated the model in three distinct settings, and the table below shows the outcomes of those scenarios with a consistent number of epochs (20) and batch size 32 for all three scenarios. For obtaining a smooth picture, we utilised Average Pooling. Table 1 displays the outcomes of a comparison of several hyperparameters and scenarios.

```
[INFO] evaluating network...
```

	precision	recall	f1-score	support
with_mask	0.99	0.99	0.99	383
without_mask	0.99	0.99	0.99	384
accuracy			0.99	767
macro avg	0.99	0.99	0.99	767
weighted avg	0.99	0.99	0.99	767

```
[INFO] saving mask detector model...
```

Table -1: Result Comparison Table

The first model, according to the aforementioned results, is the best of all the models. Below is a graphic of the best model from our study. It plots the number of epochs vs loss or

accuracy for training loss, validation loss, training accuracy, and validation accuracy. The plot shows that the training and validation accuracy increases as the number of epochs grows, whereas the training and validation accuracy falls. Furthermore, the validation accuracy is better than the training accuracy, indicating that the model is not overfitted. Figure 3 depicts the relationship between the number of epochs and the loss or accuracy.

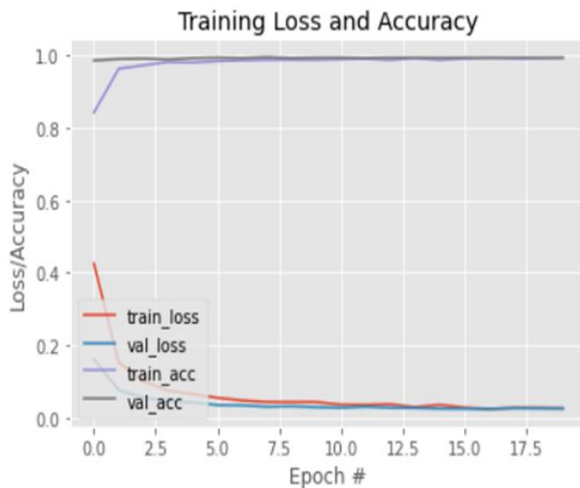


Figure-3: Graph of Number of epochs vs loss or accuracy.

Below image describes the accuracy of no mask and mask

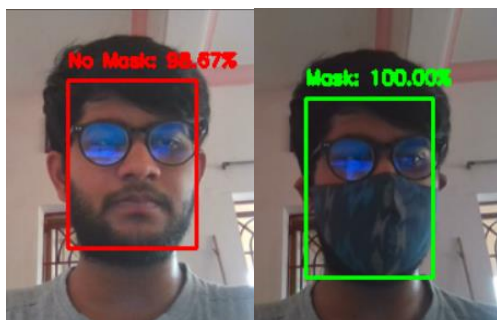


Figure-4: Applied model in realtime

4. CONCLUSION

Measures should be done to slow the spread of the COVID-19 pandemic. In neural organisations, we showed a facemask detector utilising Convolutional Neural Networks and motion learning methods. We used a dataset with 993 masked faces photos and 1918 exposed faces pictures to train, validate, and test the model. These images were compiled from a variety of sources, including Kaggle and RMFD databases. On photos and live video transmissions, the model was induced. We evaluated metrics such as precision, accuracy, and recall to pick a base model, and the best exhibition was MobileNetV2 architecture, which had 99 percent precision and 99 percent recall. MobileNetV2 is also

more computationally efficient, making it easier to integrate the model into other frameworks. This face mask detector may be deployed at a variety of locations, including shopping malls, airports, and other high-traffic areas, to screen individuals in general and prevent the spread of infection by determining who is following basic standards and who is not.

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," 4 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

[5] Changjin Li, Jian Cao, and Xing Zhang. 2020. Robust Deep Learning Method to Detect Face Masks. In <i>Proceedings of the 2nd International Conference on Artificial Intelligence and Advanced Manufacture</i> (<i>AIAM2020</i>). Association for Computing Machinery, New York, NY, USA, 74–77. DOI:<https://doi.org/10.1145/3421766.3421768>