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A Convolutional Neural Network-based Method for Identifying COVID19 Face Masks

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ABSTRACT_ Changes in the lifestyle of everyone around the world. In those changes wearing a mask has been very vital to every individual. Detection of people who are not wearing masks is a challenge due to Outbreak of the Coronavirus pandemic has created various the large number of populations. This project can be used in schools, hospitals, banks, airports, and etc. as a digitalized scanning tool. The technique of detecting people's faces and segregating them into two classes namely the people with masks and people without masks is done with the help of image processing and deep learning. With the help of this project, a person who is intended to monitor the people can be seated in a remote area and still can monitor efficiently and give instructions accordingly. Various libraries of python such as OpenCV, TensorFlow and Keras. In Deep Learning Convolution Neural Networks is a class Deep Neural Networks which is used to train the models used for this project..

1.INTRODUCTION

Coronavirus sickness 2019 has impacted the world considerably. One significant safety approach for human beings is to put on masks in public settings. so many public provider carriers require consumers to employ the carrier just if they put on masks correctly. However, there are simply a few lookup research about face masks recognition relying purely on photo analysis. In this we offer, MobileNet Mask, it is a deep learning-based multi-phase face masks detection model for blocking human transmission of SARS-CoV-2. Two outstanding face masks datasets have been utilised to instruct and take a look at the model for detecting with and barring a face masks from the snap photographs and video stream. Experiment effects demonstrate that with 770 validation samples MobileNet Mask achieves an accuracy of ~ 93 percent and with 276 validation samples it attains an accuracy of roughly ~ 100 percent . The penalties demonstrated that our proposed technique is fairly exact have been identified as a virus. Loss of smell and taste was added as a compatible and defining symptom of this virus in a March 2020 update by the Council of State and Territorial Epidemiologists (CSTE) [3]. Moreover, various studies have indicated that the pandemic has affected us mentally, both because of the constraints to which we have been subjected in an effort to reduce the spread of SARS-CoV-2 and because of the repercussions left by the virus once the patient has recovered. Some persons are more likely to experience difficulties with their mental health due to demographic and psychosocial characteristics that are exacerbated by the epidemic. Stress, emotional disorders, sadness, anxiety, sleeping problems, panic attacks, and other mental health issues [4]. COVID-19 symptoms and its rapid spread among humans have both been the subject of research. Studies have shown that the prevalence of disease is greater in confined spaces with poor ventilation. This is because virus particles can disperse in airborne microdroplets, often known as aerosols. Humans create these aerosols when we vocalise (sing, laugh, etc.). Furthermore, their velocity increases when the flow is stronger, such as when we run or shout. The larger drops eventually hit the ground, but the nucleus, which is where the virus particle is, remains in the air and can be inhaled to infect someone else [5,6]. There is a high risk of contracting the virus through the air, so several countries have made wearing a mask when outdoors a must. Deaths and illnesses caused by COVID-19 have decreased as a result of the mask's widespread use. In addition, health care costs have been decreased, averting a complete breakdown of medical infrastructure [7]. Furthermore, mask use in conjunction with social isolation has helped to reduce the exponential growth rate of the disease's spread. In the first place, they serve to keep people from inhaling and spreading the aerosolized viruses they may have breathed in while talking, coughing, sneezing, etc. The mask's material, on the other hand, can trap the flammable particles within its pores. In addition, wearing a mask has been quite useful in reducing the spread of the disease from asymptomatic individuals to the general public [8]. New research confirms that the use of surgical masks significantly cuts down on the release of infectious particles. While coronavirus was found in 30%-40% of samples taken from people wearing face masks, neither the droplets nor the aerosols were infectious for those who wore them. Results from a study using breathed air samples from individuals infected with SARS-CoV and MERS-CoV show that the use of surgical masks significantly decreases the release of virus particles [9]. When wearing a surgical mask, exhaled air should leave the nose and mouth at a high velocity and be directed frontally, as recommended by the Centers for Disease Control and Prevention (CDC) [10,11]. Particles are 3-8 microns thick (1 micron = 0.001 mm) and hit the interior of the mask at close range. Bacteria and other particles are contained even if air leaks out the sides, since they are too thick to follow the flow lines of the air that escapes from the edges if the seal is properly adjusted. For masks to be effective, wearers must follow all basic hygiene guidelines, with the most important being that the mask completely covers the face, including the mouth and nose. With an incomplete, improper, or asymmetric fit, the possibility of infection is greatly increased [12]. It is crucial to regulate the proper application of masks because of their significance. As a result, the use of non-pharmaceutical products for controlling the spread of the virus has increased [13]. Due to the need for stricter regulation of masks in public or other venues frequented by a significant number of people, AI-based approaches have become increasingly important.

2.LITERATURE SURVEY

[1] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-resnet and the impact of residual connections on learning," in Thirty-first AAAI conference on artificial intelligence, 2017.

The adoption of extremely deep convolutional networks has enabled the most significant advancements in picture identification performance in the last few years. The Inception concept has been proven to be highly efficient at a low computational cost. This year's ILSVRC competition found that the usage of residual connections, along with a more traditional architecture, led in equivalent performance to the Inception-v3 networks. Are there any advantages to combining Inception architectures with residual connections? Training Inception networks with residual connections, as we demonstrate in this research, greatly increases training speed. According to the study, Inception networks with residual connections appear to outperform similarly priced Inception networks by a small percentage as well. Additionally, we demonstrate a variety of novel, more efficient Inception network topologies, both residual and non-residual, as an additional bonus. On the ILSVRC 2012 classification task, single-frame recognition is considerably improved. We go on to show that activation scaling stabilises the training of extremely large residual Inception networks. With an ensemble of three residual networks and one Inception-v4 network, we achieved a top-five error rate of 3.08 percent on the ImageNet classification (CLS) test set.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Image categorization with deep convolutional neural networks," in Advances in neural information processing systems (ed) (in Russian).

Our convolutional neural network was trained to classify the 1.2 million high-quality images in the ImageNet LSVRC-2010 contest into 1000 separate classes. Our top-1 and top-5 error rates of 37.5% and 17.0%, respectively, show that this is a significant improvement over the preceding state-of-the-art. The neural network is comprised of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To speed up training, we used non-saturating neurons and a GPU implementation of the convolution function. One of our new regularisation methods, called "dropout," proved to be particularly efficient at reducing overlays in the fully-connected layers. In the ILSVRC-2012 competition, a variant of this model came in first place with a top-5 test error rate of 15.3%, beating out the second-best entry's 26.23%.

[3] Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 1–9. "Going deeper with convolutions."

At ImageNet, we demonstrated a deep convolutional neural network architecture dubbed Inception that is capable of achieving the new state of the art in classification and detection (ILSVRC14). The most noticeable characteristic of this design is its

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ability to make the best use of available network bandwidth. We were able to increase the network's breadth and depth while keeping the same computational budget thanks to meticulous planning. Architectural decisions were influenced by Hebbian principles and multi-scale processing intuition in order to achieve the highest possible level of quality. We used a 22-layer deep network called GoogLeNet in our application for ILSVRC14 to evaluate the quality of classification and detection.

[4] ArXiv preprint arXiv:1409.1556 (A. Zisserman and K. Simonyan, "Very deep convolutional networks for large-scale image recognition").

We investigate how the depth of a convolutional network impacts the accuracy of the network in the setting of large-scale image recognition. A relatively small (3x3) convolution filter architecture was used to assess increasing network depth and discovered that extending the depth to 16-19 weight layers offered significant gains over prior-art settings. Based on these findings, our team took first and second place in the ImageNet Challenge 2014 classification and localization tracks, respectively. It is also possible to generalise the model to other datasets and obtain cutting-edge results on those datasets as well. Our best-performing ConvNet models have been made available to academics so that they can continue to investigate the use of deep visual representations in computer vision.

3.PROPOSED WORK

We propose, MobileNet Mask, which is a deep learning-based multi-phase face mask detection model for preventing human transmission of SARS-CoV-2. Two different face mask datasets along with more than 5,200 images have been utilized to train and test the model for detecting with and without a face mask from the images and video stream. Experiment results show that with 770 validation samples MobileNet Mask achieves an accuracy of ~ 93% whereas with 276 validation samples it attains an accuracy of nearly ~ 100%.

3.1 Face Mask Detector Training Phase

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It has been proposed that a two-phase face masks detection model be used to train our proprietary face masks detector. Our face mask detector model (github.com/chandrikadeb7/Face-Mask-Detection) has been constructed using the help of the Keras and TensorFlow libraries. In addition, a two-step approach is used to recognise face masks in both still images and live video feeds. Following Fig. 3, we provide our suggested two-part COVID-19 Face Mask Detector Model technique.

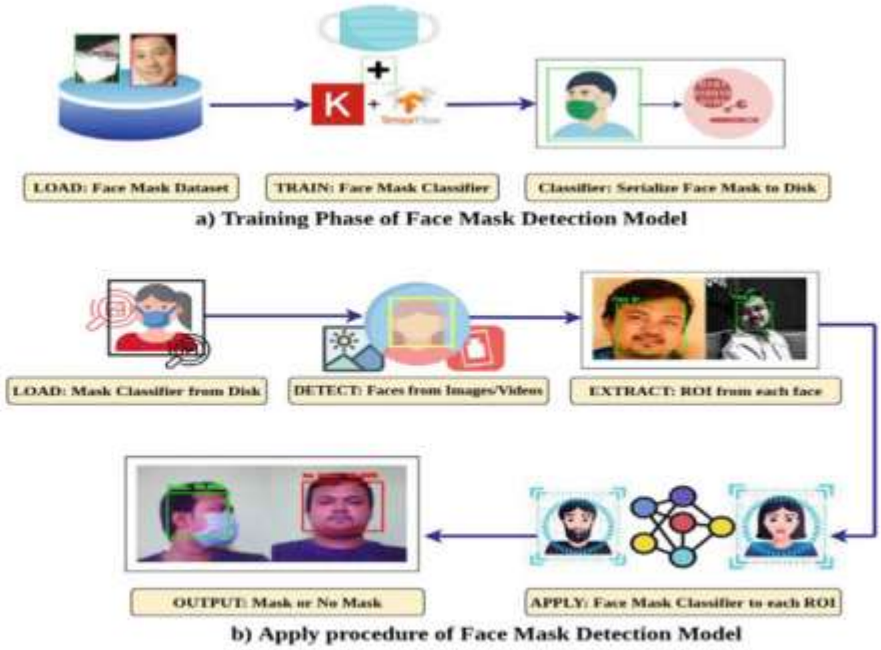

Fig. 3 Multiple stages and detailed phases for the development of a face mask detector model (images by the authors) **a** represent the training phase of face detection model whereas **b** shows how the apply procedure works in face detection model

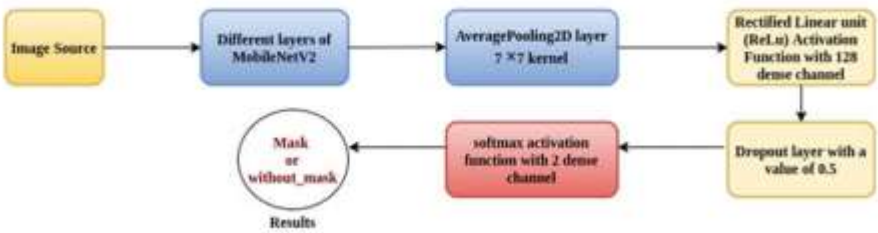

Fig. 4 Working procedure of customized fully connected layer of MobileNetV2 architecture

detection and then categorised primarily based on with_mask and without_mask. This exploration has used a deep mastering device involving TensorFlow and Keras to routinely classify face masks carrying situations.

To gain this goal, a fantastic tuned mechanism on MobileNetV2 [11] structure has been conducted. Several applications of machine/deep studying processes and photo processing libraries have been used in this lookup which include OpenCV, scikit-learn, matplotlib, numpy, and many greater to educate the masks detector. To set up a baseline mannequin that saves a sizable quantity of time, a three-step manner of fine-tuning has additionally been performed to put together the MobilenetV2 architecture. As our mannequin is for binary classification (mask and without_mask) problem, consequently we have used binary cross-entropy, decay agenda of a studying rate, and Adam optimizer to assemble our model. After the completion of the education phase, we evaluated the ensuing mannequin on the check set and generated a classification document for inspection. Finally, we serialized the face masks classification mannequin to the disk.

3.2 Face Mask Detector for Webcam/Video Stream

A two-fold procedure of detecting masks from a webcam or video flow is additionally applied. In order to pick out faces in the webcam a pre-trained mannequin supplied through the OpenCV framework used to be employed. The pre-trained mannequin is primarily based on Single-Shot-Multibox Detector (SSD) and makes use of the spine of a ResNet-10 Architecture. Following Fig. 5 indicates the step by using step working technique of face masks detection strategy from video data

Fig 5:Face Mask Detection Workflow For Webcam Or Video Stream

4.RESULTS AND DISCUSSION

The experimental result of system performance are evaluated with the MobileNetV2 classifier and ADAM optimize

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```
Epoch 7/20
91/91 [==============================] - 36s 392ms/step - loss: 0.0674 - acc: 0.9733 - val_loss: 0.2987 - val_acc: 0.9312
Epoch 8/20
91/91 [==============================] - 36s 392ms/step - loss: 0.0716 - acc: 0.9715 - val_loss: 0.1256 - val_acc: 0.9638
Epoch 9/20
91/91 [==============================] - 36s 392ms/step - loss: 0.0903 - acc: 0.9623 - val_loss: 0.3195 - val_acc: 0.9130
Epoch 10/20
91/91 [==============================] - 35s 380ms/step - loss: 0.0790 - acc: 0.9733 - val_loss: 0.1342 - val_acc: 0.9674
Epoch 11/20
91/91 [==============================] - 36s 396ms/step - loss: 0.1043 - acc: 0.9669 - val_loss: 0.1361 - val_acc: 0.9493
Epoch 12/20
91/91 [==============================] - 37s 402ms/step - loss: 0.0939 - acc: 0.9632 - val_loss: 0.1233 - val_acc: 0.9710
Epoch 13/20
91/91 [==============================] - 34s 373ms/step - loss: 0.0906 - acc: 0.9577 - val_loss: 0.1429 - val_acc: 0.9674
Epoch 14/20
91/91 [==============================] - 36s 398ms/step - loss: 0.0892 - acc: 0.9660 - val_loss: 0.0872 - val_acc: 0.9783
Epoch 15/20
91/91 [==============================] - 36s 392ms/step - loss: 0.0950 - acc: 0.9596 - val_loss: 0.2265 - val_acc: 0.9239
Epoch 16/20
91/91 [==============================] - 35s 384ms/step - loss: 0.0897 - acc: 0.9688 - val_loss: 0.1134 - val_acc: 0.9746
Epoch 17/20
91/91 [==============================] - 34s 370ms/step - loss: 0.0854 - acc: 0.9651 - val_loss: 0.1678 - val_acc: 0.9493
Epoch 18/20
91/91 [==============================] - 35s 389ms/step - loss: 0.0794 - acc: 0.9678 - val_loss: 0.0981 - val_acc: 0.9710
Epoch 19/20
91/91 [==============================] - 36s 393ms/step - loss: 0.0762 - acc: 0.9707 - val_loss: 0.1470 - val_acc: 0.9601
Epoch 20/20
91/91 [==============================] - 34s 376ms/step - loss: 0.0711 - acc: 0.9751 - val_loss: 0.1081 - val_acc: 0.9746
```

Figure 6: compilation screen for training script of face mask detection.

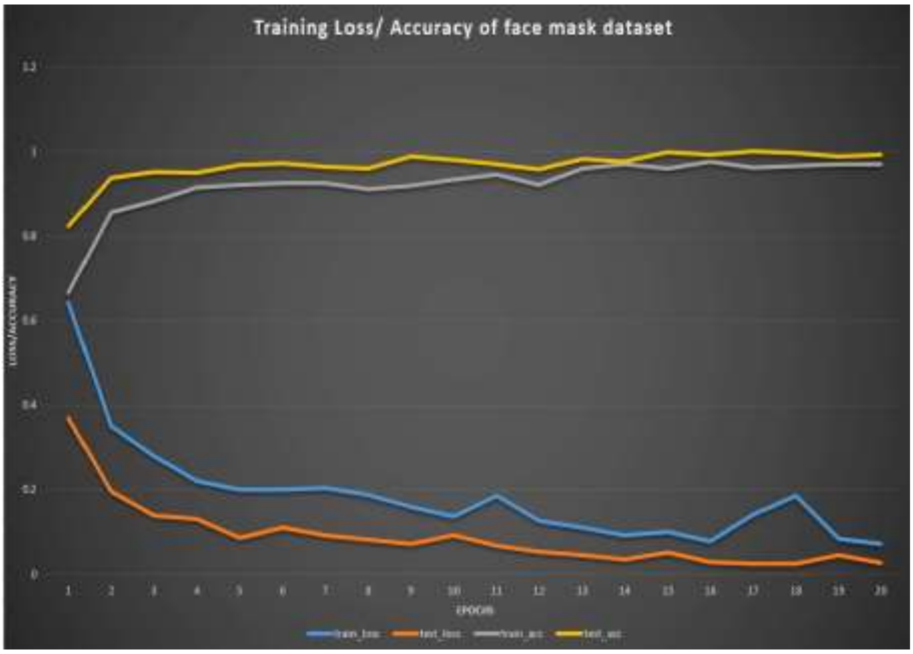

Figure 7: Training Loss/Accuracy curves of face mask detection dataset

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Face Mask Classifier Performance Metrics

```
predict=model.predict(test_X,batch_size=BS)
predict=np.argmax(predict,axis=1)
print(classification_report(test_Y.argmax(axis=1),predict,target_names=lb.classes_))
```

	precision	recall	f1-score	support
with_mask	0.96	0.99	0.98	138
without_mask	0.99	0.96	0.97	138
accuracy			0.97	276
macro avg	0.98	0.97	0.97	276
weighted avg	0.98	0.97	0.97	276

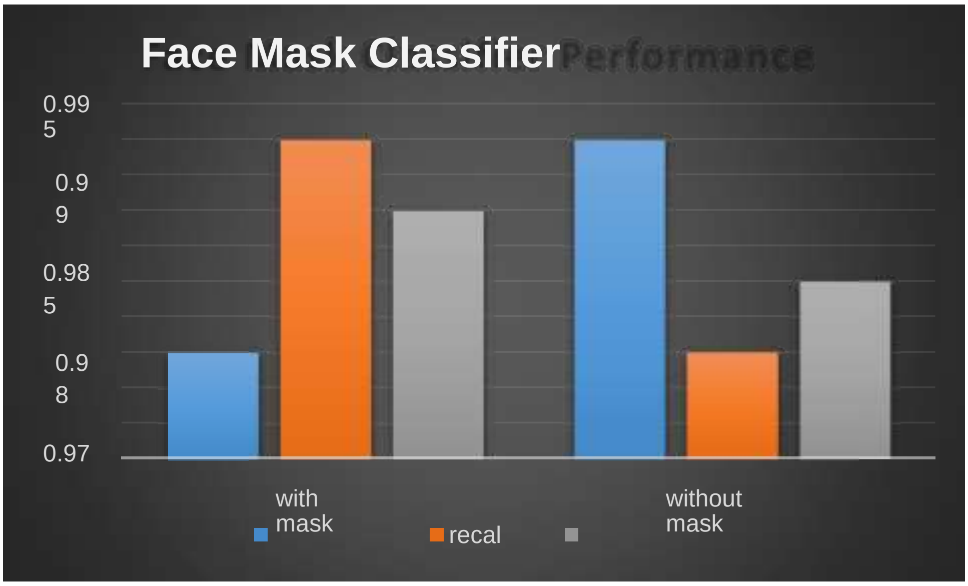

Fig 8 : Performance Metrics Histogram graph

Face mask detection from image :


Figure 9: Detect face with mask from imageFig 15: Detect face without mask from image

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Face mask detect from real time image:

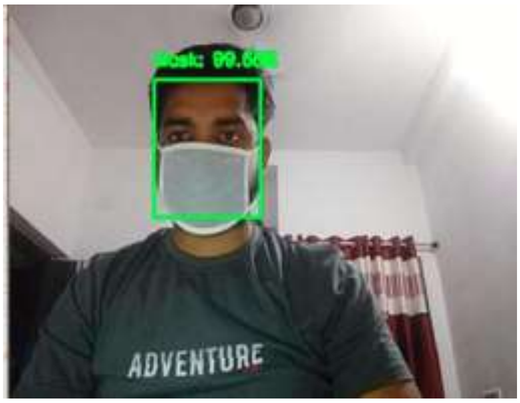

Figure 10: Detect face with mask or without mask in real time video stream

5.CONCLUSION

As the technology are blooming with emerging trends the availability so we have novel face mask detector which can possibly contribute to public health care department. The architecture consists of MobileNetV2 classifier and ADAM optimizer as the back bone it can be used for high and low computation scenarios. The our face mask detection is trained on CNN model and we are used OvenCV, Tensor Flow , Keras and python to detect whether person is wearing a mask or not . The model was tested with image and real- time video stream. The accuracy of model is achieved and, the optimization of the model is continuous process. This specific model could be used as use case of edge analytics..

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