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A Fast and Accurate System for Face Mask Detection in Public Places

Nourin Naushad[1], Shibu Kumar K. B[2]
[1, 2]Computer Science and Engineering, APJ Abdul Kalam Technological University

Abstract: Changes in the way of life of everybody around the world. In those progressions wearing a cover has been indispensable to each person. Location of individuals who are not wearing veils is a test because of Outbreak of the Coronavirus pandemic has made different the enormous number of populaces. The COVID-19 pandemic has reshaped life. Numerous of us are remaining at home, staying away from individuals in the city and changing every day propensities, such as going to class or work, in manners we never envisioned. While we are changing old practices, there are new schedules we need to receive. Most importantly is the propensity for wearing a veil or face covering at whatever point we are in a public space. Veils and face covers can forestall the wearer from communicating the COVID-19 infection to other people and may give some assurance to the wearer. All-inclusive cover use can altogether diminish infection transmission locally by forestalling anybody, including the individuals who are accidentally conveying the infection, from communicating it to other people. Along these lines, the significance of wearing veil and its identification is exceptionally clear. Face veil recognition frameworks are currently progressively significant, particularly in keen medical clinics for viable patient consideration. They're likewise significant in arenas, air terminals, stockrooms, and other swarmed spaces where pedestrian activity is weighty and security guidelines are basic to defending everybody's wellbeing. Face veil recognition framework can guarantee our security and the security of others. This task can be utilized in schools, clinics, banks, air terminals, and so forth as a digitized examining instrument. The procedure of recognizing individuals' countenances and isolating them into two classes in particular individuals with covers and individuals without covers is finished with the assistance of picture handling and profound learning. With the assistance of this task, an individual who is expected to screen individuals can be situated in a far off region furthermore, still can screen productively and give directions appropriately. Different libraries of python like Open CV, Tensor Flow and Keras are utilized. In Deep Learning Convolution Neural Networks is a class Deep Neural Networks which is used to prepare the models in this task.

Keywords: Deep Learning, Open CV, Tensor Flow, Keras, Computer Vision.

I. INTRODUCTION

The pattern of brandishing face cover openly is rising due to the Covid-19 pandemic wherever in the world. Since individuals will not wear veil to protect their well-being from air contamination. Coronavirus spreads chiefly from individual to individual through respiratory drops. Respiratory drops travel into the air when we hack, wheeze, talk, yell, or sing. These drops can at that point land in the mouths or noses of individuals who are close to you or on the other hand they may inhale these beads in veils are a straightforward hindrance to help forestall our respiratory beads from arriving at others. Studies show that covers lessen the shower of drops when worn over the nose and mouth. We should wear a veil, regardless of whether we don't feel debilitated. This is on the grounds that few investigations have discovered that individuals with COVID-19 who never foster indications (asymptomatic) and the individuals who are not yet appearing manifestations (pre-suggestive) can in any case spread the infection to others. Wearing a veil ensures those around us, on the off chance that we are contaminated yet not appearance manifestations. It is particularly imperative to wear a cover at the point when we are inside with individuals we don't live with furthermore, when we can't remain in any event 6 feet separated since COVID-19 spreads predominantly among individuals who are in close contact with one another from individual to individual through respiratory drops. Respiratory drops travel into the air when we hack, wheeze, talk, yell, or sing. These beads can at that point land in the mouths or noses of individuals who are close to you or then again, they may inhale these drops in veils are a basic boundary to help forestall our respiratory drops from arriving at others. Studies show that covers diminish the shower of beads when worn over the nose and mouth. We should wear a veil, regardless of whether we don't feel wiped out. This is on the grounds that few examinations have discovered that individuals with COVID-19 who never foster manifestations (asymptomatic) and the individuals who are not yet appearing indications (pre-suggestive) can in any case spread the infection to others.

Wearing a cover secures those around us, on the off chance that we are tainted however not appearance indications. It is particularly critical to wear a veil at the point when we are inside with individuals we don't live with also, when we can't remain at any rate 6 feet separated since COVID-19 spreads principally among individuals who are in close contact with each other from one individual to another through respiratory beads. Respiratory beads travel into the air when we hack, sniffle, talk, yell, or sing. These beads can at that point land in the mouths or noses of individuals who are close to you or then again, they may inhale these drops in veils are a basic boundary to help forestall our respiratory beads from arriving at others. Studies show that veils diminish the shower of drops when worn over the nose and mouth. We should wear a veil, regardless of whether we don't feel wiped out. This is on the grounds that few examinations have discovered that individuals with COVID-19 who never foster side effects (asymptomatic) and the individuals who are not yet appearing side effects (pre-suggestive) can in any case spread the infection to others. Wearing a cover secures those around us, in the event that we are tainted yet not appearance indications. It is particularly critical to wear a cover at the point when we are inside with individuals, we don't live with what's more, when we can't remain in any event 6 feet separated since COVID-19 spreads basically among individuals who are in close contact with each other. In a world doing combating against the Novel Coronavirus Sickness (COVID-19) pandemic, innovation has been a lifeline. With the guide of innovation, 'telecommute' has subbed our typical work schedules and has gotten a part of our everyday lives. In any case, for a few areas, it is difficult to adjust to this new standard. As the pandemic gradually settles and such areas become anxious to continue face to face work, people are as yet incredulous of getting back to the workplace. 65% of workers are currently restless about getting back to the workplace (Woods, 2020). Various investigations have shown that the utilization of face covers decreases the danger of viral transmission just as gives a feeling of security. Be that as it may, it is infeasible to physically uphold such an approach on huge premises and track any infringement. PC Vision gives a superior option in contrast to this. Utilizing a mix of picture characterization, object identification, object following, and video investigation, here fostered a hearty framework that can identify the presence and nonappearance of face covers in pictures just as recordings. In this paper, propose a CNN design, where the main stage distinguishes human appearances, while the subsequent stage utilizes a lightweight picture classifier to arrange the faces recognized in the principal stage as all things considered 'Cover' or 'No Mask' faces and draws jumping boxes around them alongside the distinguished class name. This calculation was further reached out to recordings too. The distinguished faces are then followed between outlines utilizing an item following calculation, which makes the location strong to the commotion because of movement obscure. This framework would then be able to be incorporated with a picture or video catching gadget like a CCTV camera, to follow security infringement, advance the utilization of face veils, and guarantee a safe work space.

II. RELATED WORK

Generally, most of the projects specialize in face construction identity recognition when wearing mask. During this project, the focus is on recognizing the people that wearing mask, or not help in decreasing the transmission and spreading of covid-19. The scientist has proven that wearing a mask help in minimizing the spreading rate of Covid-19. R. Ranjan, V. M. Patel, and R. Chellappa proposed" Hyperface: A deep multitask learning framework for face detection, landmark localization, pose estimation, and gender recognition," [1] in which present an algorithm for simultaneous face detection, landmarks localization, pose estimation and gender recognition using deep convolutional neural networks (DCNN). The main disadvantage of this system is its computational burden. A. Kumar, R. Ranjan, V. M. Patel, and R. Chellappa proposed" Face alignment by local deep descriptor regression," [2] in which this paper discuss about different modules involved in designing an automatic face recognition system. Feature matching via local descriptors is one of the most fundamental problems in many computer visions tasks, as well as in the remote sensing image processing community. For example, in terms of remote sensing image registration based on the feature, feature matching is a vital process to determine the quality of transform model. While in the process of feature matching, the quality of feature descriptor determines the matching result directly. At present, the most commonly used descriptor is hand-crafted by the designer's expertise or intuition. However, it is hard to cover all the different cases, especially for remote sensing images with nonlinear grayscale deformation. One of the disadvantages is that it still faces many challenges, like pose variation, illumination variation etc. A. Bansal, R. Ranjan, C. D. Castillo, and R. Chellappa proposed "Deep features for recognizing disguised faces in the wild," [3] in which this paper presents an approach for general face verification and evaluated it on the Disguised Faces in the Wild challenge. This is an extremely challenging face verification problem. The aim of a face verification system in such cases is to be able to identify disguises and reject impersonators. Building such a system will be extremely helpful in law enforcement applications. One of the problems is performance only under controlled scenarios. D. Yi, Z. Lei, S. Liao, and S. Z. Li proposed" Learning face representation from scratch" [4], Pushing by big data and deep convolutional neural network (CNN), the performance of face recognition is becoming comparable to human.

Using private large scale training datasets, several groups achieve very high performance on LFW, i.e., 97 to 99%. While there are many open source implementations of CNN, none of large-scale face dataset is publicly available. The current situation in the field of face recognition is that data is more important than algorithm. This paper proposes a semi-automatic way to collect face images from Internet and builds a large-scale dataset containing about 10,000 subjects and 500,000 images, called CASIA Web Face. S. Yang, Y. Xiong, C. C. Loy, and X. Tang. proposed "Face detection through scale-friendly deep convolutional networks," [5] This paper presents framework to detect faces with very large-scale variance. A deep CNN model is built for the pedestrian detection, which consists of 10 convolutional layers, 4 max pooling layers, and 1 fully connected layer for classification. Do not encode the position and orientation of object is one of its drawbacks. facial recognition system is a biometric technology used for mapping the facial features, patterns, and/or texture of an individual from a digital image or live video feed for the purpose of identity storage and verification. The system specifically uses a combination of mathematical analysis and artificial intelligence, particularly machine learning algorithms, for the collection, storage, and retrieval of biometric data, as well as other sensing imaging techniques to include photometry and LiDAR or light detection and ranging, among others. Rajeev Ranjan, Ankan Bansal, Jingxiao Zheng, Hongyu Xu, Joshua Gleason, Boyu Lu, Anirudh Nanduri, Jun-Cheng Chen, Carlos D. Castillo, and Rama Chellappa, proposed" A Fast and Accurate System for Face Detection, Identification, and Verification" [6]. In this paper, describe a deep learning pipeline for unconstrained face identification and verification which achieves state-of-the-art performance on several benchmark datasets. Here provide the design details of the various modules involved in automatic face recognition: face detection, landmark localization and alignment, and face identification/verification. Also propose a novel face detector, deep pyramid single shot face detector (DPSSD), which is fast and detects faces with large scale variations (especially tiny faces). Additionally, here propose a new loss function, called crystal loss, for the tasks of face verification and identification. Crystal loss restricts the feature descriptors to lie on a hypersphere of a fixed radius, thus minimizing the angular distance between positive subject pairs and maximizing the angular distance between negative subject pairs. Also provide evaluation results of the proposed face detector on challenging unconstrained face detection datasets.

Yongqiang Li; Shangfei Wang; Yongping Zhao; Qiang Ji proposed" Simultaneous Facial Feature Tracking and Facial Expression Recognition" [7] The tracking and recognition of facial activities from images or videos have attracted great attention in computer vision field. Facial activities are characterized by three levels. First, in the bottom level, facial feature points around each facial component, i.e., eyebrow, mouth, etc., capture the detailed face shape information. Second, in the middle level, facial action units, defined in the facial action coding system, represent the contraction of a specific set of facial muscles, i.e., lid tightener, eyebrow raiser, etc. Finally, in the top level, six prototypical facial expressions represent the global facial muscle movement and are commonly used to describe the human emotion states. In contrast to the mainstream approaches, which usually only focus on one or two levels of facial activities, and track (or recognize) them separately, this paper introduces a unified probabilistic framework based on the dynamic Bayesian network to simultaneously and coherently represent the facial evolvement in different levels, their interactions and their observations. Advanced machine learning methods are introduced to learn the model based on both training data and subjective prior knowledge. Given the model and the measurements of facial motions, all three levels of facial activities are simultaneously recognized through a probabilistic inference. Extensive experiments are performed to illustrate the feasibility and effectiveness of the proposed model on all three level facial activities. B. QIN and D. Li, proposed" Identifying facemask-wearing condition using image super-resolution with classification network to prevent COVID-19" [8], the authors developed a face mask wearing condition identification method. They were ready to classify three categories of face mask-wearing. The categories are face mask- wearing, incorrect face mask-wearing and no face mask-wearing. C. Li, R. Wang, J. Li, L. Fei proposed" Face detection based on YOLOv3, in Recent Trends in Intelligent Computing, Communication and Devices" [9], the authors used the YOLOv3 algorithm for face detection. YOLOv3 uses Darknet-53 because the backbone. Prior detection systems repurpose classifiers or localizers to perform detection. They apply the model to an image at multiple locations and scales. High scoring regions of the image are considered detections. Here uses a totally different approach. Here applies a single neural network to the full image. This network divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities. Sheshang Degadwala, Sagar Pandya, Vidisha Patel, Shraddha Shah, Udita Doshi [10] proposed" Areview on real time face tracking and identification for surveillance system" [10] The demand of smart cameras for various applications in surveillance for security purpose is growing rapidly. However, till now, the processing required for real time face detection prohibits integration of the complete application into a small sized camera. The Real Time Face Tracking and Identification for Surveillance System proposed in this research work has come up with a simple and an efficient approach to satisfy the processing requirements and enable fast and accurate face detection.

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The core functionality of Real Time Face Tracking and Identification for Surveillance System is to allow tracking and recognition of human faces in a video stream and thereby provide a centralized, cost effective and robust mechanism of securing business and government premises.

A. MobileNetV2

MobileNetV2 is that the latest technology of mobile visual recognition, including classification, object detection and semantic segmentation. The classifier uses deep intelligent separable convolution, its purpose is to significantly reduce the complexity cost and model size of the network, so it's suitable for mobile devices, or devices with low computing power. In MobileNetV2, another best module introduced is that the reverse residual structure. The nonlinearity within the narrow layer is removed. Maintain because the backbone of feature extraction, MobileNetV2 achieves the simplest performance in object detection and semantic segmentation. For MobileNetV2 classifier, ADAM optimizer has been applied to see performance.

III.PROPOSED SYSTEM

A. Data Collection

The dataset pictures for covered and unmasked faces were collected from images dataset offered within the public domain the masked one obtained from the factitious generated by me through the picture redaction tool and few from collected from the public domain. Within the data set consist of 800 with masked face and 750 are while not masked face. The data set is collected for the training the face mask detection model. The downside of face mask detection is all regarding face detection. However, before face mask detection to faithfully notice a face and its landmarks. This can be basically a segmentation problem and in sensible system, most finding this task. After all the particular detection supported option extracted from these facial landmarks is barely a minor step. The dataset pictures for covered and unmasked faces were collected from images dataset offered within the public domain.

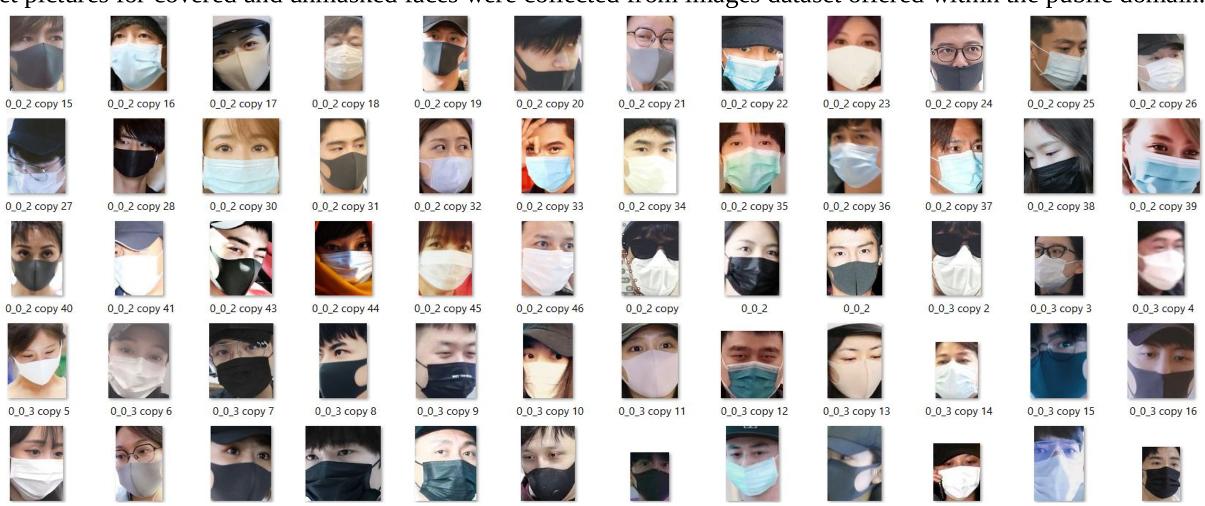

Fig. 1 Face Mask Detection Dataset with Mask

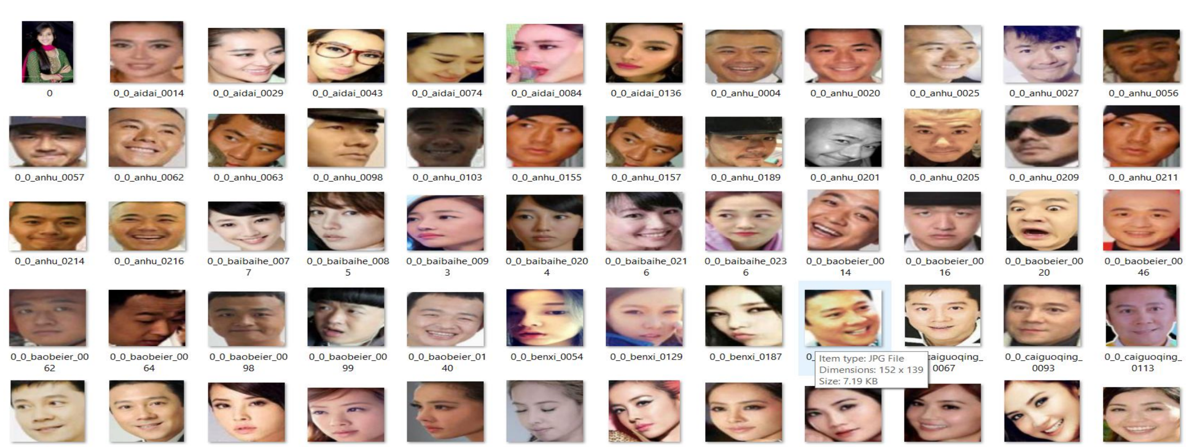

Fig. 2 Face Mask Detection Dataset Without Mask

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B. Methodolgy

FACE DETECTION: The downside of face mask detection is all regarding face detection. However, before face mask detection is possible, on should be able to faithfully notice a face and its landmarks. This can be basically a segmentation problem and in sensible system, most of the trouble goes into finding this task. After all the particular detection supported option extracted from these facial landmarks is barely a minor step.

TABLE I

Categories	Labelled	Total Image Count
With face mask	Yes	800
Without face mask	No	750

C. Splitting the Data

In this step, we divide the data into training set, and the training set will contain the image on which the CNN model will be trained and test set and the images on which the model will be tested. In this case, we use split size=0.8, which means that 80% of the total images will enter the training set, and the remaining 20% of the images will enter the test set.

Table III

Set	Labelled	Total Image Count
Training	Yes	1129
Test	Yes	301
Training	No	1121
Test	No	300

After segmentation, we see that the required image percentage has been allocated to the training set and test set as described in table II.

D. Building the Model

In the next step, we will use Conv2D, MaxPooling2D, Flatten, Dropout, and dense to build a sequential CNN model. In the last dense layer, we use the "SoftMax" function to output vector that gives the probability of each of the two categories.

Fig. 3 Building the model

Here, we use "ADAM" optimizer and binary cross entropy as our loss function because there are only two types. In addition, you can even use MobileNetV2 to get better accuracy. After setting up the model, let us create "train generator" and "validation generator" to make it fit our model in the next step. We see a total 2250 images in the training set and a total 551 images in the test set.

This is the main step in which we put images into training set a test set to use the sequence model built by the Keras library. I have trained the model for 20 epochs. However, we can train more epochs to obtain higher accuracy, so as to avoid overfitting. We see that after the 20th epoch, our model has accuracy of 97.86% on the training set and 99.22% on the test set. This mean that it is well-trained without any overfitting.

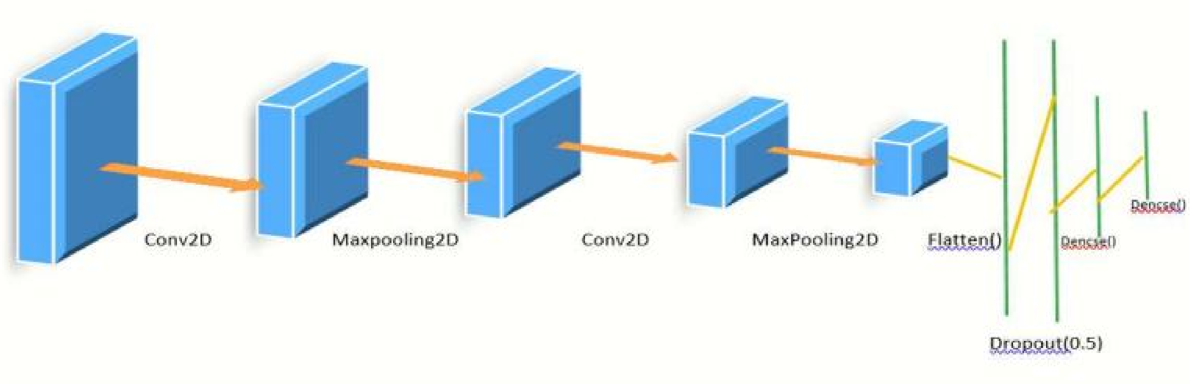


Fig. 4 CNN Model for Face Mask

E. Importing the Face Detection Program

From now on, we plan to use it detect whether we are wearing a mask through the pc's webcam. For this, first of all, we need to implement face detection model.

MobileNetV2 is predicated on thought of mobileV1, using deeply intelligent separable convolution as an efficient building piece. However, V2 introduced two new features building:

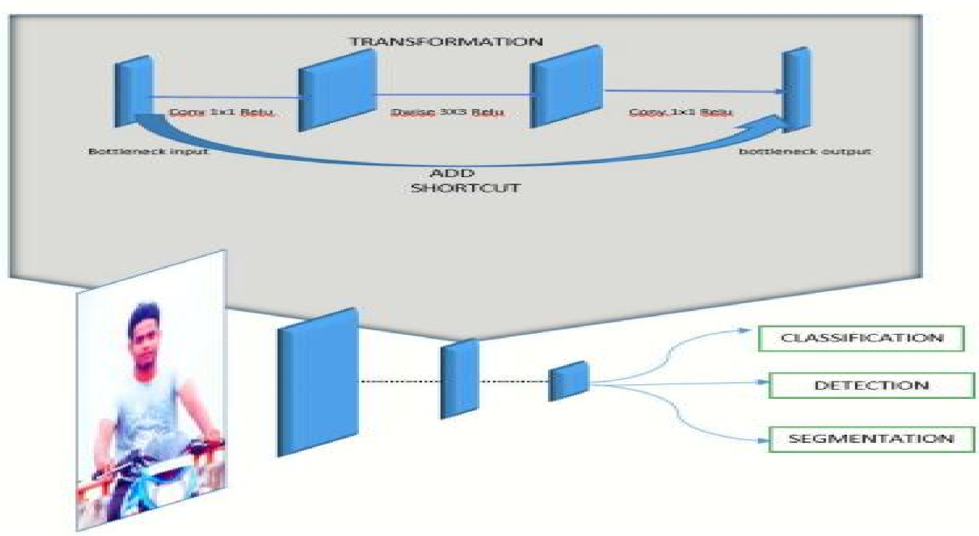


Fig. 5 MobileNetV2 Building Block

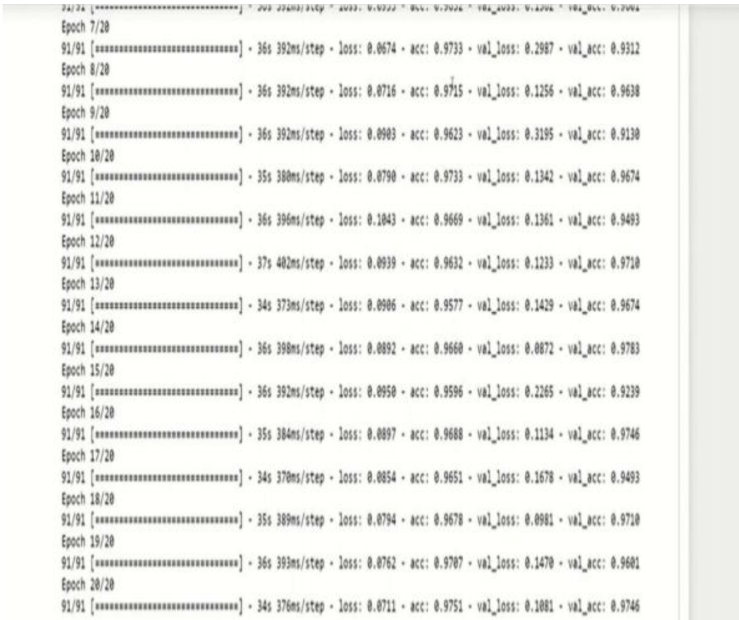
A typical MobileNetV2 architecture has multiple layers below. In python, we will use the model library in tensorflow to make a MobileNetV2 model. the load of every layer within the model is predefined consistent with the Image net data set. the load indicates padding, stride, kernel size, input channel and output channel. Select MobileNetV2 because the algorithm for building models which will be deployed on mobile device. A customized fully connected layer was developed that contains for consecutive layers on top of the MobileNetV2 model.

The layers are:

1) Average pooling layer with 7x7 weights
2) Linear layer with Reactivation function
3) Dropout layer
4) Linear layer with SoftMax activation function with the results of 2 values

F. Experimental Results

The experimental result of system performance is evaluated with the MobileNetV2 classifier ADAM optimizes.



```
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
```

Fig. 6 Compilation screen for training script of facemask detection.

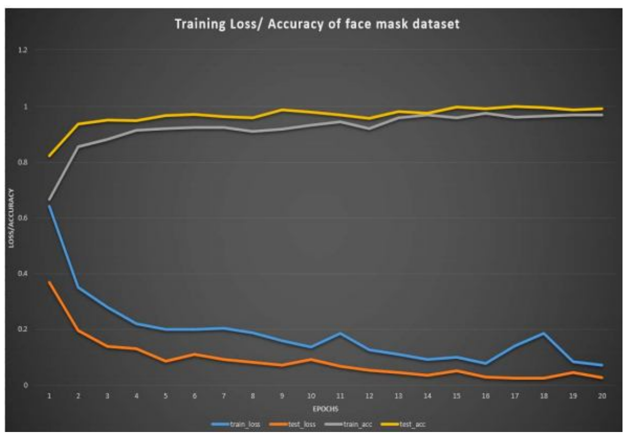
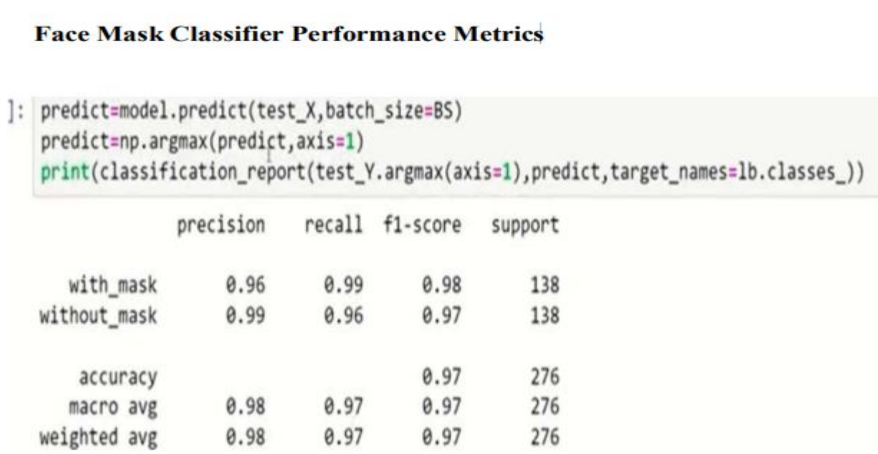


Fig.7 Training Loss/Accuracy curves of face mask detection dataset



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:Face Mask Classifier Performance Metrics

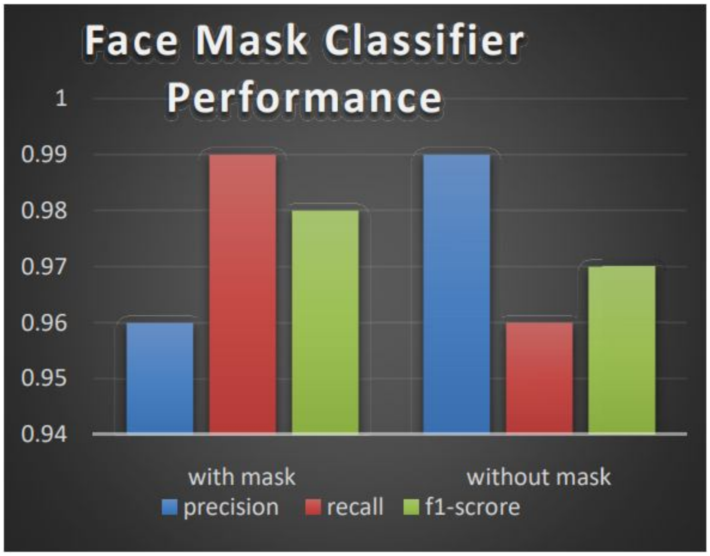


Fig 9: Performance Metrics Histogram graph

G. Final Results

Combining all the elements of our architecture, we tend to observation system. Mobile NetV2, classifier employed in this system. The resultant system performance and has the potential to detect face mask in image with multiple face over a large vary angles. It was observed that all three models show good results on images taken from a very short distance, having no more than two people in the image. However, it was noticed that as the number of people in the images increases, the performance of Dlib becomes subpar. Dlib also struggles to detect masked or covered faces.

Combining all the components of our architecture, we thus get a highly accurate and robust Face Mask Detection System. The resultant system exhibits high performance and has the capability to detect face masks in images with multiple faces over a wide range of angles. The detected face ROIs in a given frame are tracked over a predefined number of frames so that the ROI coordinates for the faces are stored even if the detector fails to detect the object during the transition between frames.

Fig 10: Detect face with mask from image

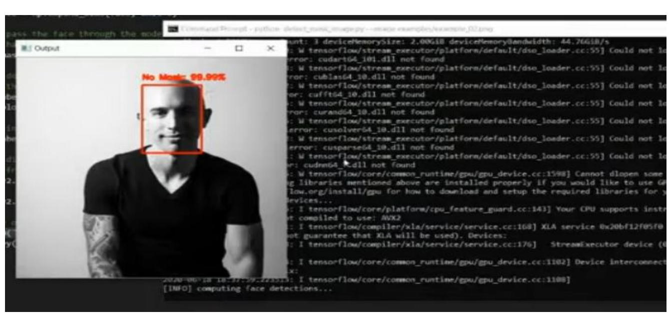


Fig 11: Detect face without mask from image

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H. Face Mask Detect from real time Image

Fig12S: Detect face with mask or without mask in real time video stream

IV. CONCLUSIONS

As the innovation are blossoming with arising patterns the accessibility so we have novel face cover indicator which can add to general wellbeing care division. The design comprises of MobileNetV2 classifier and ADAM analyzer as the spine it tends to be utilized for high and low calculation situations. Our face veil identification is prepared on CNN model furthermore, we are utilized Oven CV, Tensor Flow, Keras and python to distinguish whether individual is wearing a veil or not. The model was tried with picture and genuine time video transfer. The exactness of model is accomplished and, the advancement of the model is nonstop cycle. This particular model could be utilized as use instance of edge examination.

V. ACKNOWLEDGMENT

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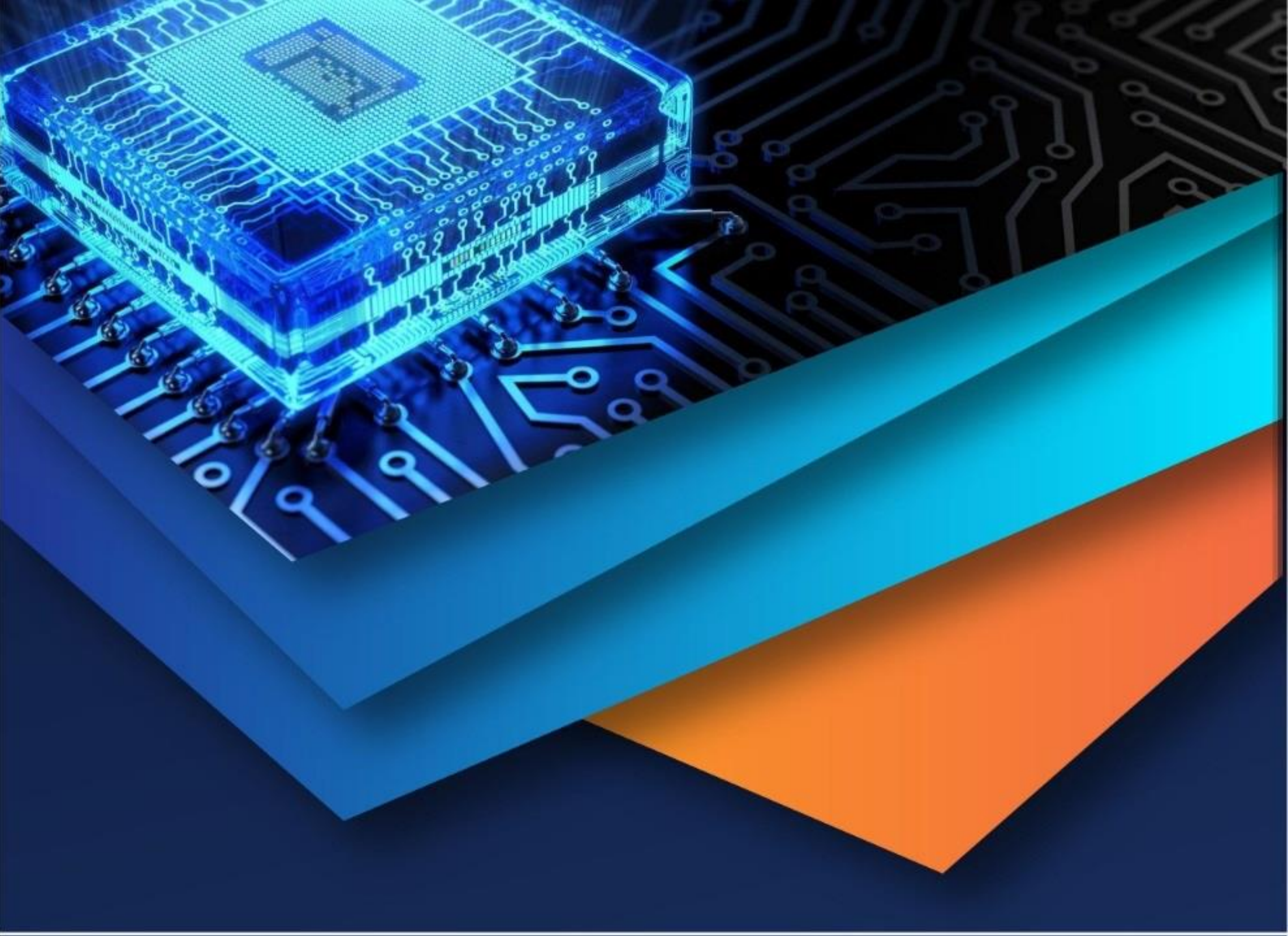

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