Face mask detection using Tensorflow and OpenCV

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***Abstract*—In the current situation of COVID-19 - an airborne infectious disease - face mask has become an integral part of our lives. Many health organizations suggests that wearing a face mask is one of the best preventive measures against COVID-19 since it eliminates cross-contamination. In this paper we have proposed a face mask detection model built using Tensorflow along with real time detection using OpenCV. This model can classify images into three which are 'with mask', 'without mask' and 'without properly'. The proposed model has its initial layers taken from MobileNet-v2 which is a light weight image classification model upon which a few layers are added on to produce the final model. The data-set for the model has three categories which are 'with mask', 'without mask', and 'without properly' which totals to 3855 images . The real time detection was done by feature extraction from the region of interest (RIO) of an image or a frame from the video and classified it into one of the above mentioned categories. This was done using functions and libraries under Tensorflow and OpenCV This model has achieved a training accuracy of 98.56% and validation accuracy of 98.33%.**

I. Introduction

COVID-19 pandemic has become a rise of concern for the human community these days. To prevent the spread of this disease, an effective and protective measure is to use a face mask in public areas. As a result ,there is a need to build the face mask detector which will ensure whether a person is wearing a mask or not. During the COVID-19 pandemic, face masks have been used as a public as well as personal health control measure against the transmission of corona virus. Their use is intended as personal protection to prevent infection and as source control to limit transmission of the virus in a community or health care setting. But most people are neglecting and not following this strictly. So, it becomes important for us to ensure people are wearing face masks.

Most people are aware about the benefits of using a face mask and carry a mask with them but they are not wearing it properly which defeats the whole purpose of wearing them. So there is also a need to monitor whether people are wearing face mask properly or not.

The existing solutions are quite accurate but it consists of only two categories ,that is, it checks whether a person is wearing a mask or not (with mask and without mask) but does not check the third category of people who do not wear the mask properly .The proposed model takes into account the third category (not properly worn) also which is more relevant in the present day. The model make sures a person is wearing a mask properly or not and uses transfer learning and python scripts to train the model.

This project aims to build a face mask detector using concepts of Convolutional Neural Networks (CNN) and OpenCV so that we can ensure public safety guidelines such as wearing face masks are followed. Keeping this project as simple and versatile as possible so that, later it can be integrated with embedded systems for applications in airports, railway stations and other public places to keep a check on people.

II. Literature Survey

Generally, most of the publications focuses on whether people are wearing a face mask or not. In this project we have introduced a new category where it identifies people who are not wearing the mask properly. In [5] the authors proposed a transfer learning model using ResNet and used standard machine learning algorithms for classification. They achieved an accuracy 99.49% in SMFD, and 100% in LFW using SVM classification model for classification.

In [7], the authors used the YOLOv3 algorithm for face detection. YOLOv3 uses Darknet-53 as the backbone. The proposed method achieved 93.9% accuracy. It was trained on CelebA and WIDER FACE dataset . The testing was the FDDB dataset. Javed et al [6] presented an interactive method called MRGAN. The method depends on getting the

TABLE I: Summary of Literature Survey

Authors	Methodology	Merits	Limitations	Dataset Used
M. Khalifa et al.	Transfer learning using ResNet and SVM	Works well on most datasets	Try most of classical machine learning methods to get lowest consume time and highest accuracy.	SMFD, LFW
C. Li et al.	YOLOv3 algorithm and Darknet-53	Have balanced the speed accuracy trade off very well	Can introduce more complex models for better and complex feature extraction.	CelebA, WIDER FACE
B. Qin et al.	SRCNet	Have included the third category of 'incorrect facemask wearing'	Does not perform well on low quality images.	FDDB
Shaik et al.	Deep learning and VGG-16	Classifies seven facial expressions and quite accurate	KDEF cannot be used in cross-cultural studies and is gender specific	KDEF
Kavitha et al.	Viola-Jones algorithm GMM	Works well on low dimensional face datasets	False detection due to face orientation.	AR face, MAFA

microphone area from the user and using the Generative Adversarial Network to rebuild this area. Shaik et al [8] used deep learning real-time face emotion classification and recognition. They used VGG-16 to classify seven facial expressions. The proposed model was trained on the KDEF dataset and achieved 88% accuracy. In [9] Kavitha et al proposed a Gaussian Mixture Model (GMM) which is applied for foreground detection to extract the region of interest (ROI).The accuracy obtained from this model was 97.50%.

III. Problem Statement

Wearing a face mask has become mandatory but unfortunately most of the people are not following it. For safety purposes there should be a system which ensures that everyone is wearing a mask and most importantly to check whether people are wearing it properly. The above problem was solved by using Tensorflow and OpenCV to build a face mask detector.

A. *Objectives*

- Build face mask detector : to build a face mask detector which is as accurate as possible.
- To check if people are wearing mask : to check whether people are wearing face masks as it stops the micro droplets expelled from cough or sneeze thus eliminating cross contamination.
- To check if people are wearing mask according to WHO standards : Many people although wearing a mask may not be wearing it properly which may lead to the further spread of the disease.

IV. Methodology

The methodology includes three phases. First creating the dataset for training our model, second building the face mask detection model with the help of Tensorflow/Keras and third real time detection using OpenCV.

A. *Dataset creation / characteristics :*

This project was conducted on a dataset consisting of 3855 images which includes three categories of 'with mask', 'without mask', and 'without properly' and it is still expanding. A large part of the dataset for the 'with mask' category was created manually by pasting a face mask on the 'without mask' category images. This was done by python scripts using OpenCV. For this Haar Cascade algorithm was

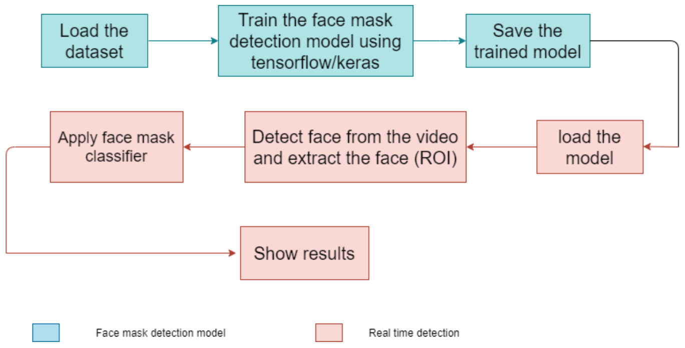
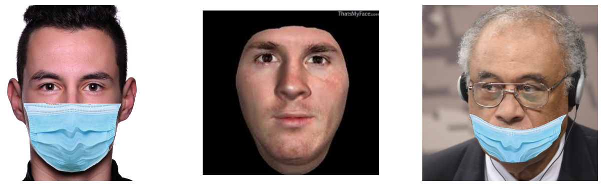

Load the dataset
Train the face mask detection model using tensorflow/keras
Save the trained model
load the model
Detect face from the video and extract the face (ROI)
Apply face mask classifier
Show results
Face mask detection model
Real time detection

Fig. 1: Flowchart

adopted which is basically a machine learning object detection algorithm which is used to identify objects in an image or video. Using the above algorithm we detect the face in the given image and compute the bounding box location of the face in the image. Once we know where in the image the face is, we extract the Face region of Interest(ROI) using Numpy slicing and from there, we apply facial landmarks which help us to localize the eyes , nose , mouth ,chin etc. Next an image of a mask with a transparent background is loaded. The script automatically applies the mask to the face using the facial landmarks. Hence creating a images with face mask. This process is repeated for all the input images, thereby creating the artificial data set. The dataset for the 'without properly' along with few images for 'with mask' categories was taken from 'https://github.com/cabani/MaskedFace-Net' making a total of 3855 images.



(a) with mask (b) without mask (c) without properly

Fig. 2: Sample images from the dataset

So finally we have 1447 of images under 'with mask' folder. 906 number of images under 'without mask' folder and 1502 number of images under 'without properly' folder .In the training section of our model we have data augmentation were we flip , resize the image in all possible ways so that our model gets trained well. Fig. 2 shows images of the data set.

B. Model building :

The model includes two parts, the base model and the head model. The base model is deep transfer learning neural network (MobileNet-v2) used as feature extractor and head model a customized model which is placed on top of the base model for better classification.

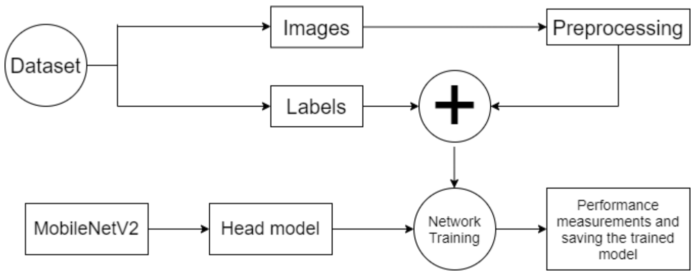


Fig. 3: Proposed model structure

MobileNet-v2 is a light weight convolutional neural network that has 53 layers. It contains initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers. MobileNet-v2 is based on inverted residual structure where the connections are between the bottleneck layers. The intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity. The final layers are removed from MobileNet-v2 and the head model is added on top of this for classification.

The head model consists of 5 layers which are, AveragePooling2D, Flatten, Dense, Dropout, Dense (output layer with softmax as activation function). This head model is added on top of the base model to produce the final model that we are going to train and classify images accordingly.

C. Real time detection and testing :

1) Testing of static images: Consists of three main parts

- Load an input image from the disk
- Detect faces in the images
- Apply our face mask detector to classify the face as 'with mask' or 'without mask' or 'without properly'

The python script requires three TensorFlow/Keras imports to (1) load our MaskNet model and (2) pre-process the input image. (3) OpenCV is required for display and image manipulations.

First the image is loaded from the disk with the trained deep learning model in memory. Image pre processing is done using 'preprocess_input' function which is imported from 'tensorflow.keras.applications.mobilenet_v2' library. Upon loading the image from disk a copy of the image is made and frame dimensions are grabbed for future scaling and display purposes. Pre-processing is handled by OpenCV's blobFromImage function. As shown in the parameters, the image is resized and mean subtraction is performed. Face detection is performed to localize where in the image all faces are. Once all the faces are detected in the image, we loop over the detections to find the probability of face detection. If the probability is greater than 0.5 the face is considered else it is rejected. Once the faces are identified in the image, the bounding box value for a particular face is computed and then extract face ROI via Numpy slicing, pre-processing the ROI and perform the mask detection to predict 'with mask' or 'without mask' or 'without properly'.

```
face = frame[startY:endY, startX:endX]
face = cv2.cvtColor(face, cv2.COLOR_BGR2RGB)
face = cv2.resize(face, (224, 224))
face = img_to_array(face)
face = preprocess_input(face)
```

Fig. 4: code for RIO and pre-processing

2) Real time video detection: Videos are basically made up of frames, which are still images and the face detection is applied for each frame in a video. So when it comes to detecting a face in still image and detecting a face in a real-time video stream, there is not much difference between them.

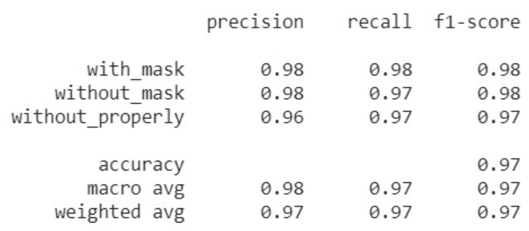
The trained face-mask detector model is loaded and the frames are captured from the webcam stream using OpenCV for which the read() function is used. We run a infinite loop to get all the frames until the user presses q to quit the program. The read() function returns, the actual video frame read (one frame on each loop).

In python script we have declared a function called as 'detect_and_predict_mask' function.

```
detect_and_predict_mask (frame, faceNet, MaskNet)
        blob = cv2.dnn.blogFromImage(frame, shape)
        detections = faceNet.forward()
        for i in detection.shape[2] {
                find confidence
                if confidence > 0.5 {
                        find RIO
                        find location
                        find predictions
                }
        }
        return (predictions, location)
```

Fig. 5: Pseudo code for detect_and_predict_maask function

This function detects faces and then applies our face mask classifier to each face ROI. Inside, we construct a blob, detect

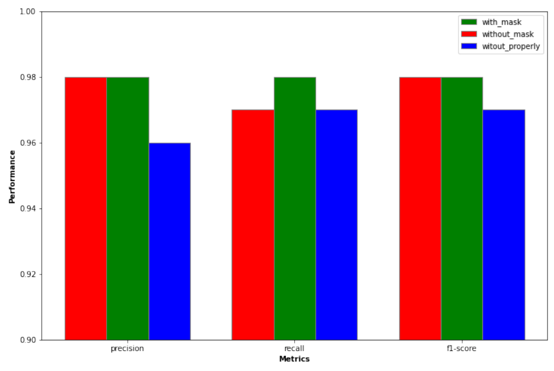


```
                 precision    recall  f1-score

      with_mask       0.98      0.98      0.98
   without_mask       0.98      0.97      0.98
without_properly      0.96      0.97      0.97

       accuracy                           0.97
      macro avg       0.98      0.97      0.97
   weighted avg       0.97      0.97      0.97
```

(a) Numeric representation



(b) Bar graph representation

Fig. 6: Classification report

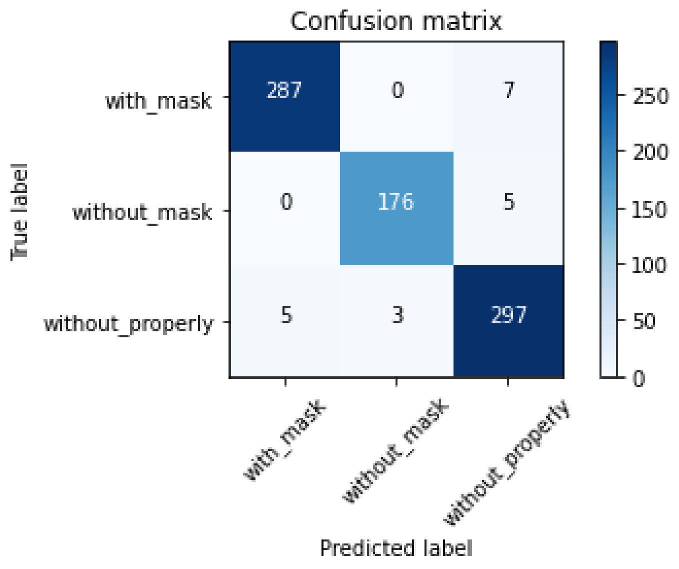


Fig. 7: confusion matrix

faces, and initialize lists, two of which the function is set to return. These lists include our faces (i.e ROIs) and locs(the face locations). Then we loop over the detections to find the probability of face detection. If the probability is greater than 0.5 we consider the face else we reject it. This is basically to filter out the weak detections. Inside this loop we also extract bounding boxes while ensuring bounding box coordinates do not fall outside the bounds of the image. Once the face ROIs is extracted and pre-processing is done, it is passed to the face mask detector. It performs the face mask detection to predict whether the person is wearing mask or not or not wearing properly.

V. Results and Analysis

A. *Results and analysis for the proposed model :*

All the computation required for model building was done on an i7 processor (4.4GHz) and the results obtained are from the above device. The different metrics used to evaluate the performance of the model were :

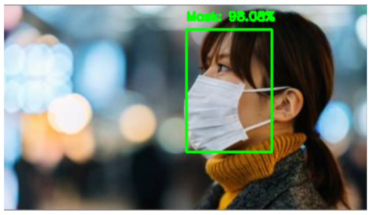
$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

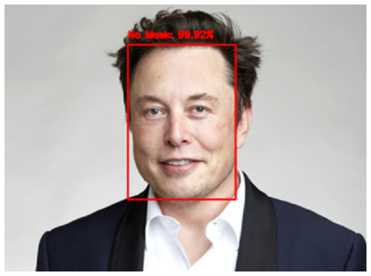
$$F1Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{3}$$

(where TN = True Negatives, FP = False Positives, TP = True Positives and FN = False Negatives)

Fig. 6 shows a very good performance of the proposed model. It shows the 'with_mask' category has precision of 0.98, recall of 0.98 and f1-score of 0.98, 'without_mask' category has precision of 0.98, recall of 0.97 and f1-score of 0.98, 'without_properly' has precision of 0.96, recall of 0.97



(a) with mask



(b) without mask

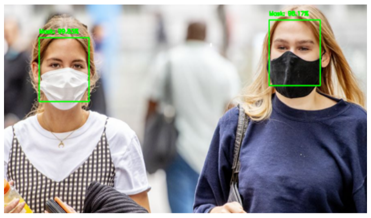
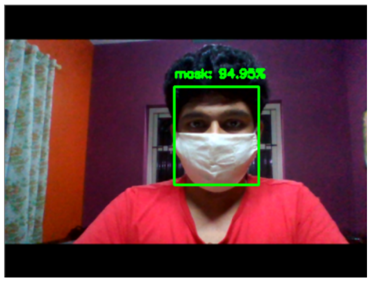
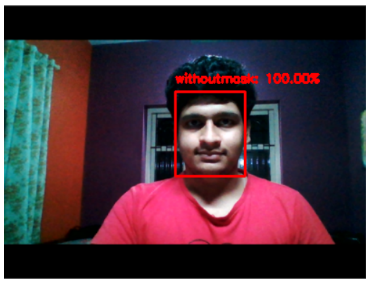

(c) multiple faces

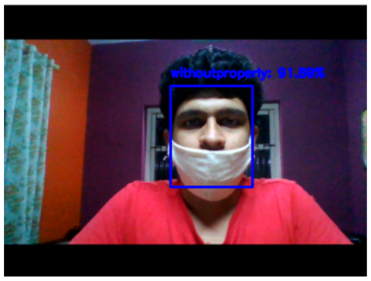
Fig. 8: Testing of static images



(a) with mask

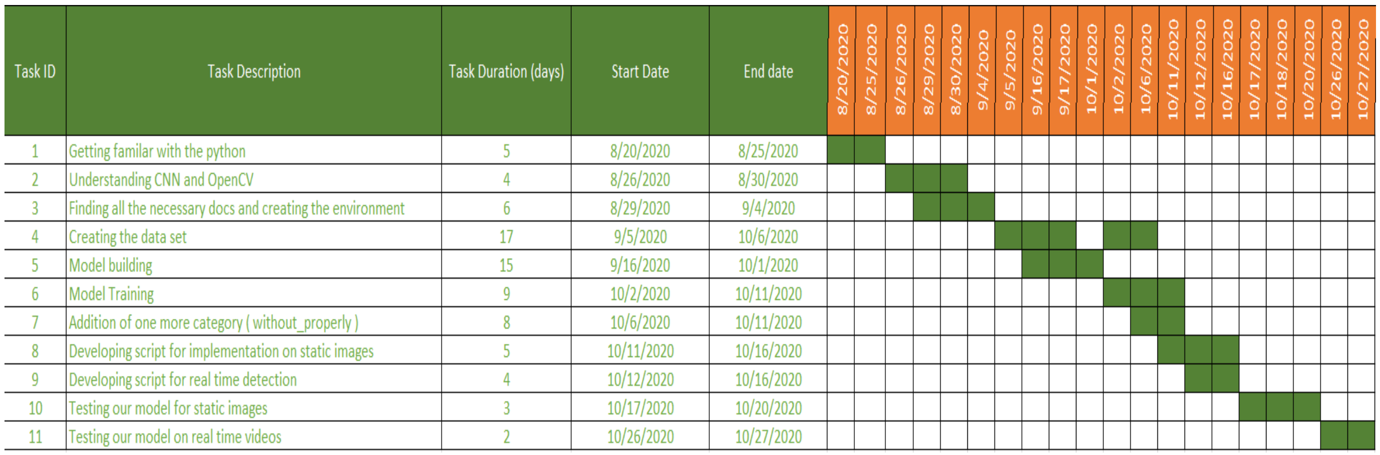


(b) without mask



(c) without properly

Fig. 9: Frames taken from real time detection using a web camera .



Task ID	Task Description	Task Duration (days)	Start Date	End date	8/20/2020	8/25/2020	8/26/2020	8/29/2020	8/30/2020	9/4/2020	9/5/2020	9/16/2020	9/17/2020	10/1/2020	10/2/2020	10/6/2020	10/11/2020	10/12/2020	10/16/2020	10/17/2020	10/18/2020	10/20/2020	10/26/2020	10/27/2020
1	Getting familar with the python	5	8/20/2020	8/25/2020	🟩	🟩																		
2	Understanding CNN and OpenCV	4	8/26/2020	8/30/2020			🟩	🟩	🟩															
3	Finding all the necessary docs and creating the environment	6	8/29/2020	9/4/2020				🟩	🟩	🟩														
4	Creating the data set	17	9/5/2020	10/6/2020							🟩	🟩	🟩		🟩	🟩								
5	Model building	15	9/16/2020	10/1/2020								🟩	🟩	🟩										
6	Model Training	9	10/2/2020	10/11/2020											🟩	🟩	🟩							
7	Addition of one more category (without_properly)	8	10/6/2020	10/11/2020												🟩	🟩							
8	Developing script for implementation on static images	5	10/11/2020	10/16/2020													🟩	🟩	🟩					
9	Developing script for real time detection	4	10/12/2020	10/16/2020														🟩	🟩					
10	Testing our model for static images	3	10/17/2020	10/20/2020																🟩	🟩	🟩		
11	Testing our model on real time videos	2	10/26/2020	10/27/2020																			🟩	🟩

Fig. 10: Gantt chart

and f1-score of 0.97. It is clearly seen that the scores of the 'without_properly' are the least in all the metrics used and this is a potential improvement area for the model.

Confusion matrices are another metrics that can be used to evaluate the model and also it provides insights to the performance of the proposed classification model.

From Fig. 7 it is pretty evident that the proposed model is able to predict/classify most images correctly (conclusion derived by observing the left to right diagonal of the confusion matrix which represents the correctly labeled predictions)

B. Results and analysis for real time detection

1) Testing on static images : For checking the whether our model works well or not. We have randomly collected around 10 images and have used them for testing and these images are put under a new folder called 'examples'. The class label is determined based on probabilities returned by the mask detector model and assign an associated color for the annotation.

Fig. 8 tells that the model can accurately predict and classify static images, while Fig. 8(c) points out that the model is quite robust and trained well as it can correctly predict images containing multiple faces also.

2) Real time video detection : For displaying the results , first the class label is determined based on probabilities returned by the mask detector model and assign an associated color for the annotation. The color will be green for with_mask, blue for without_properly and red for without_mask. The output is a label text along with the probability of detection, as well as a bounding rectangular box for the face using OpenCV. Fig. 9 presents the different frames captured during the real time detection using a computer web camera.

VI. Conclusion

Most countries are suffering from the COVID-19 pandemic and wearing a face mask has proven to be a very good countermeasure against the spread of corona virus. In this paper a face mask detection system has been proposed which was done using Tensorflow and OpenCV. Transfer learning technique was used which was the initial layers of MobileNet-V2 was used as feature extractor upon which further layers where added for classification purposes. Real time detection on static images and videos was done with OpenCV and other tensorflow libraries. The proposed model showed 99.56% training accuracy and 99.33% validation accuracy .

Induvidual contribution

The individual contribution of the team members are :

- Kausthub Thekke Madathil : Model building, analysis and plotting of the results, made necessary changes to include the third category 'without_properly' .
- Puttaraja : Artificial data set creation, python script for static image testing, preparation of PPT's for weekly presentation and report compilation.
- Sohanraj R : Data pre-processing, model building and analysis, final code documentation.
- Neeraj Mirji : Artificial data set creation, python scripts for testing static images and real time detection video, Output analysis and visualization of real time detection.

Fig. 10 shows the Gantt Chart illustrating the time line and the project's progress with respect to time.

Implemented/Base Paper

M. Loey, G. Manogaran, M. Hamed N. Taha, N. Eldeen 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 (2020), doi: https://doi.org/10.1016/j.measurement.2020.108288 was considered as the base paper.

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