A Training Report

On

Real-Time Face Mask Detection

Submitted in partial fulfilment of requirements for the award of the

Degree of

Bachelor of Technology

In

Computer Science & Engineering

Submitted By

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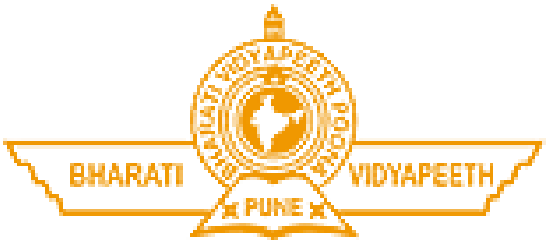

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June, 2020

CERTIFICATE

I hereby certify that the work which is being submitted in this report titled **"Real Time Face Mask Detection"**, in partial fulfilment of the requirement for the award of certification of "In-House Summer Training in Machine Learning and Deep Learning" submitted in Bharati Vidyapeeth's College of Engineering, New Delhi, is an authentic record of my own work carried out under the supervision of "Name of the Supervisor" and refers to other researchers work which are duly listed in the reference section.

The matter presented in this report has not been submitted for the award of any other certificate of this or any other institution.

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This is to certify that the statements made above by the candidates are correct and true to the best of our knowledge.

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Internal Examiner

External Examiner

CANDIDATES DECLARATION

I hereby declare that the work presented in this report entitled "**Real Time Face Mask Detection**", in partial fulfilment of the requirement for the award of the degree **Bachelor of Technology** and submitted in **Department of Computer Science & Engineering, Bharati Vidyapeeth's College of Engineering**, , **New Delhi** (**Affiliated to Guru Gobind Singh Indraprastha University**) is an authentic record of my own work carried out during the period from June July 2019 under the guidance of **Dr. Preeti Nagrath, Dr Rachna Jain, Dr Ashish Gupta, Mrs Nitika Sharma.**

The work reported in this has not been submitted by me for award of any other degree of this or any other institute.

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ORGANIZATION INTRODUCTION

The paper is organized in the following way:

Section 1 – Introduction of Project – "Real Time Face Mask Detection":

In this section we introduced the topic and the technology used in our project like OpenCV DNN, TensorFlow, Keras and MobileNetV2 architecture which is used as an image classifier. This model works very well not only for images having frontal faces with masks but also for frontal faces without masks. This paper also keeps complete attention towards removal of various inaccurate predictions which occurred in various other proposed models.

Section 2 – Literature Review:

In this section discusses the similar work proposed and completed in the domain of face mask detection.

Section 3 – Dataset Used:

In this section we described the face mask detection dataset used to train this model. Dataset used was made by merging data from various sources, like, Open Source Images, Kaggle dataset of Medical Masks Dataset, Artificial dataset by Prajna Bhandary and masked face detection dataset.

Section 4 – Methodology:

In this section we discussed the methodology adopted and technology used by us to build this Face mask detection model. Here pretrained model have been used which is further used to detect masks in static images and real time live webcam.

Section 5 – Result and Conclusion:

In this section we have shown our experimental results along with a comparison table.

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Preface

This report is prepared to fulfill the requirements of the B tech. Program of "Bharati Vidyapeeth's College Of Engineering on "Real Time Face Mask Detection". We have chosen this topic because it is a very important solution towards this Corona Virus Pandemic situation which has gained roots in many parts of the world. We would like our model to be used by the researchers and analysts to detect people with masks and people without masks so that we can prevent corona virus from spreading among others.
The prime focus of our Face mask Detection model is to detection model is to detect people with mask in real time video or webcams. This model has the potential to be used for safety purposes. We aim to use a pre-trained model on which deep learning and computer vision pipelines have been used and implemented. So basically this project has been divided into two parts, in the training part mask detection model will be trained using the dataset provided. and in the application part we will load our trained model to perform mask detection. We fine tuned our MobileNetV2 architecture on the dataset and obtained accuracy of about 92%, this architecture is extremely organized and can be applied on embedded devices (ex. NVIDIA Jetson Nano, Raspberry pi).

Detection of face masks is an extremely challenging task for the present proposed models of face detectors. This is because faces with masks have varied accommodations, various degrees of obstructions and diversified mask types.

Even after having such extraordinary and exceptional results in the existing face detectors, still there is high rising scrutiny in the development of more advanced face detectors as for existing models event analysis and video surveillance is still a challenging job. Several reasons were found for the poor achievement of existing face mask detection model as compared to the normal ones, two of them were First due to lack of a good datasets with proper masked faces and facial recognition, Secondly, the presence of masks on the face brings an undeniable kind of noise which further deteriorates the detection process.

In Chapter we discussed the similar work proposed and completed in the domain of face mask detection. In Chapter 3 we described the face mask detection dataset used to train this model. Dataset used was made by merging data from various sources, open source, kaggle dataset of Mask Detection Dataset, Artificial dataset by prajna bhandary and masked face detection dataset. In Chapter 3 we discussed the methodology adopted and technology used by us to build this Face mask detection model. Here pretrained model have been used which is further used to detect masks in static images and real time live webcam. In section 5 we have shown our experimental results along with a comparison table.

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Abstract

Face mask detection had seen a major progress in the fields of Computer vision and Image processing and since the rise of covid-19 pandemic this is today's necessity. Many face detection models have been created using several different algorithms and classifiers. We are training our covid-19 mask detector using deep learning, Tensorflow, Keras and opencv. This model has the potential to be used for safety purposes. We aim to use a pre-trained model on which deep learning and computer vision pipelines have been used and implemented. Dataset used in this model has been made manually by collecting from several different resources and applying the technique of data augmentation on it so that a large dataset can be easily created. After the model is trained we'll proceed further to test our model on static images and real time webcam. So basically this project has been divided into two parts, in the training part mask detection model will be trained using the dataset provided. and in the application part we will load our trained model to perform mask detection. We fine tuned our MobileNetV2 architecture on the dataset and obtained accuracy of about 96%, this architecture is extremely organized and can be applied on embedded devices (ex. NVIDIA Jetson Nano, Raspberry pi). We will be compiling our model using Adam Optimizer and we will use Binary Cross Entropy as a loss function. The output images are preprocessed for removing unwanted errors and will make a rectangle box around the mask or the face. The dataset provided in this model can be used by other researchers for further advanced models such as those of face recognition, facial landmarks and facial part detection process which will be our future research area.

Chapter 1
Introduction

What Is COVID-19?

A coronavirus is a kind of common virus that causes an infection in your nose, sinuses, or upper throat. Most coronaviruses aren't dangerous.

In early 2020, after a December 2019 outbreak in China, the World Health Organization identified SARS-CoV-2 as a new type of coronavirus. The outbreak quickly spread around the world.

COVID-19 is a disease caused by SARS-CoV-2 that can trigger what doctors call a respiratory tract infection. It can affect your upper respiratory tract (sinuses, nose, and throat) or lower respiratory tract (windpipe and lungs).

It spreads the same way other coronaviruses do, mainly through person-to-person contact. Infections range from mild to deadly.

SARS-CoV-2 is one of seven types of coronavirus, including the ones that cause severe diseases like Middle East respiratory syndrome (MERS) and sudden acute respiratory syndrome (SARS). The other coronaviruses cause most of the colds that affect us during the year but aren't a serious threat for otherwise healthy people.

Is there more than one strain of SARS-CoV-2?

It's normal for a virus to change, or mutate, as it infects people. A Chinese study of 103 COVID-19 cases suggests the virus that causes it has done just that. They found two strains, which they named L and S. The S type is older, but the L type was more common in early stages of the outbreak. They think one may cause more cases of the disease than the other, but they're still working on what it all means.

How long will the coronavirus last?

It's too soon to tell how long the pandemic will continue. It depends on many things, including researchers' work to learn more about the virus, their search for a treatment and a vaccine, and the public's efforts to slow the spread.

More than 100 vaccine candidates are in various stages of development and testing. This process usually takes years. Researchers are speeding it up as much as they can, but it still might take 12 to 18 months to find a vaccine that works and is safe.

Symptoms of COVID-19

The main symptoms include:

- Fever
- Coughing
- Shortness of breath
- Trouble breathing
- Fatigue
- Chills, sometimes with shaking
- Body aches
- Headache
- Sore throat
- Loss of smell or taste
- Nausea
- Diarrhea

Coronavirus Prevention

Take these steps:

Wash your hands often with soap and water or clean them with an alcohol-based sanitizer. This kills viruses on your hands.

Practice social distancing. Because you can have and spread the virus without knowing it, you should stay home as much as possible. If you do have to go out, stay at least 6 feet away from others.

Cover your nose and mouth in public. If you have COVID-19, you can spread it even if you don't feel sick. Wear a cloth face covering to protect others. This isn't a replacement for social distancing. You still need to keep a 6-foot distance between yourself and those around you. Don't use a face mask meant for health care workers. And don't put a face covering on anyone who is:

- Under 2 years old
- Having trouble breathing
- Unconscious or can't remove the mask on their own for other reasons

Don't touch your face. Coronaviruses can live on surfaces you touch for several hours. If they get on your hands and you touch your eyes, nose, or mouth, they can get into your body.

Clean and disinfect. You can clean first with soap and water, but disinfect surfaces you touch often, like tables, doorknobs, light switches, toilets, faucets, and sinks. Use a mix of household bleach and water (1/3 cup

bleach per gallon of water, or 4 teaspoons bleach per quart of water) or a household cleaner that's approved to treat SARS-CoV-2. You can check the Environmental Protection Agency (EPA) website to see if yours made the list. Wear gloves when you clean and throw them away when you're done.

There's no proof that herbal therapies and teas can prevent infection.

Can a face mask protect you from infection?

The CDC recommends that you wear a cloth face mask if you go out in public. This is an added layer of protection for everyone, on top of social distancing efforts. You can spread the virus when you talk or cough, even if you don't know that you have it or if you aren't showing signs of infection.

Surgical masks and N95 masks should be reserved for health care workers and first responders, the CDC says.

Figure 1: Corona-virus

Source

https://img.webmd.com/dtmcms/live/webmd/consumer_assets/site_images/article_thumbnails/other/1800x1200_virus_3d_render_red_03_other.jpg?resize=*:350px

Face Mask detection had turned up to be an astonishing problem in the field of image processing and computer vision. Face detection has various use cases ranging from face recognition to capturing facial motions which at the former needs the face to be detected with a very high precision.

Due to the rapid advancement of machine learning algorithms, the jeopardies of face detection technology seems to be well addressed yet. This technology is more relevant in today's era because this application is used to detect faces not only in static images and videos but also in real time inspection and supervision. With the advancements of convolution neural networks and deep learning very high accuracy in images can be achieved [1].

Face Mask detection has become a very trending application due to Covid-19 pandemic, which demands for a person to wear face masks, keep social distancing and use hand sanitizers to wash your hands. While other problems of social distancing and sanitization have been addressed uptill now, the problem of face mask detection has not been addressed yet.

This paper proposes a model for face detection using Opencv DNN [2], Tensorflow, Keras and MobileNetV2 architecture [3] which is used as an image classifier. This model works very well not only for images having frontal faces with masks but also for frontal faces without masks. This paper also keeps complete attention towards removal of various inaccurate predictions which occurred in various other proposed models.

Detection of face masks is an extremely challenging task for the present proposed models of face detectors[4 - 8]. This is because faces with masks have varied accommodations, various degrees of obstructions and diversified mask types. They are used to facilitate auto-focusing [9], human computer interaction [10] and image database management [11].

Even after having such extraordinary and exceptional results in the existing face detectors, still there is high rising scrutiny in the development of more advanced face detectors as for existing models event analysis and video surveillance is still a challenging job. Several reasons were found for the poor achievement of existing face mask detection model as compared to the normal ones, two of them were First due to lack of a good datasets with proper masked faces and facial recognition, Secondly, the presence of masks on the face brings an undeniable kind of noise which further deteriorates the detection process. These issues have been studied in some existing research papers such as [12 - 14], still there is a great demand for a large dataset so that an efficient face mask detection model can be easily developed.

The main contributions of this paper are three folds.

1.) We provide a github repository to the self made dataset of masked faces including datasets taken from online resources. This dataset could be used for developing new face mask detectors and performing several applications.

2.) We proposed Opencv DNNs for face mask detection, which allows for real time detection with much resource usage. It is also able to detect faces in different orientations and

3.)Several provocations which we faced during development of this model have been taken into account in this paper, this may help the reader for developing more improved face mask detectors.

The upcoming section discusses the similar work proposed and completed in the domain of face mask detection. In section III we described the face mask detection dataset used to train this model. Dataset used was made by merging data from various sources, open source, kaggle dataset of Mask Detection

Dataset, Artificial dataset by Prajna Bhandary and masked face detection dataset. In section IV we discussed the methodology adopted and technology used by us to build this Face mask detection model. Here pretrained model have been used which is further used to detect masks in static images and real time live webcam. In section V we have shown our experimental results along with a comparison table.

Chapter 2

Literature Review

Main contributions in this research paper are the dataset created and the technology used. Some of the works done by researchers and analysts on face mask detection models have been mentioned in this section.

In the previous times various researchers and analysts mainly focused on grayscale face image. Some were [15] completely based on pattern recognition models, having initial information of the face model while others were using Adaboost [16], which was a good classifier for training purposes.

The Viola Jones Detector which provided a major breakthrough in face detection technology and real time face detection got possible. It faced various problems like the orientation and brightness of face, making it hard to intercept. So basically it failed to work in dull and dim light, so researchers started searching for a new alternative model which could easily detect faces as well as masks on the face.

In the past times many datasets for face detection have been developed to assess face detection models. Earlier datasets mainly consisted of images collected in supervised surroundings, while recent datasets are constructed by taking online images like WIDER FACE [20],IJB-A[18],MALF [17] and CelebA [19].

Annotations are provided in present face datasets as compared to earlier ones. Large datasets are much more needed for making a better training and testing dataset and perform real world applications in a much more simple way. This calls for the use of various deep learning algorithms which can read faces and mask straight from the data provided by the user

Face Mask detection models are grouped into different variations:

1.) Boosting-based categories: In this category, boosted cascades with easy haar features were embraced using the Viola Jones face detector [21], which we discussed above in this section. Then a multiview face mask detector was made motivated by the Viola Jones detector model. In addition to this, a face mask detector model was made using decision trees algorithms. Face mask detectors in the boosting-based category are often very effective in detecting face masks.

2.) DPM-based category: In this category, the structure and orientations of several different faces are modelled using DPM. In 2006 Ramanan proposed a Random forest tree model for face mask detection, which accurately guesses face structures and facial poses. Mathias et al. [22], one of the renowned researchers made a DPM-based face mask detector using 26, 000 faces divided into masks and without masks category. His work achieved an exceptional accuracy of 97.14%. Further models of face mask detectors were made by Chen et al. [23]. Typically, DPM-based face mask detection models can achieve majestic precisions but it may suffer from very towering computational cost due to the use of DPM.

3.) CNN-based category: These type of face detector models learn directly from the dataset provided by the user and then apply several deep learning algorithms on it [24]. In the year 2007 Li et al [25] came up with CascadeCNN. In [17] Yang et al. came up with the idea of features aggregation of faces in the face detection model. In further research works Farfade et al.[15] upgraded the Alexnet architecture for fine tuning the image dataset. For uninhibited circumstances Zhu et al. [6] proposes Contextual Multi-Scale Region-based Convolutional Neural Network (CMS-RCNN) which brought a great impact on the face detection models. To minimize the error on the substitute layers of CNN layers and dealing with the biased obstructions generated in the mask detection models Opitz et al. [13] prepared a grid loss layer. As the technology advanced further CNN-based 3D models started coming up, among them one was proposed by Li et al. [25]. It was an end to end learning structure for face mask detection models. Several other works were done in the fields of pose recognition , gender estimation , localisation of landmarks etc.

We have developed our Face mask detection model using deep neural network modules from OpenCV and tensorflow which contains a Single Shot Multibox Detector object detection model. Typical classification architectures like ResNet-10 which is used as a backbone architecture for this model and for image classification and fine tuning MobileNetV2 classifier has been used, MobileNetV2 classifier has been an improvement over MobileNetV1 architecture classifier as it consists of a 3×3 convolution layer as the initial layer, which is followed by 13 times the previous building blocks while MobileNet V2 architecture consists of 17 of these building blocks in a row followed by a 1×1 convolution, an average max pooling layer, and a classification layer. **Residual connection** is a new addition in MobileNetV2 classifier.

Face detection as one of the important research directions of computer vision has been extensively studied in recent years. From the development process of face detection, we can simply classify previous work as handcraft feature based and neural networks based methods.

1.) Handcraft Feature Based Methods

With the appearance of the first real-time face detection method called Viola-Jones [4] in 2004, face detection has begun to be applied in practice. The well-known Viola-Jones can perform real-time detection using Haar feature and cascaded structure, but it also has some drawbacks, such as large feature size and low recognition rate for complex situations. To address these concerns, a lot of new handcraft features are proposed, such as HOG [5], SIFT [6], SUFT [7], and LBP [8], which have achieved outstanding results. Apart from the above methods, one of the significant advances was Deformable Part Model (DPM), proposed by Felzenszwalb et al. [9]. In the DPM model, the face is represented as a set of deformable parts, and the improved HOG feature and SVM are used for detection, achieving remarkable performance. In general, the advantages of handcraft features are that the model is intuitive and extensible, and the disadvantage is that the detection accuracy is limited in the face of multiobjective tasks.

2.) Neural Networks Based Methods

As early as 1994, Vaillant et al. [10] first proposed using neural network to detect faces. In this work, Convolutional Neural Networks (CNN) is used to classify whether each pixel is part of a face and then determine the location of the face through another CNN. After that, the researchers did a lot of research based on this work. In recent years, the deep learning approaches has significantly promoted the development of the computer vision technology, including face detection. Li et al. [11] proposed a cascade CNN network architecture for rapid face detection, which is a multiresolution network structure that can quickly eliminate background regions in the low-resolution stage and carefully evaluate challenging candidates in the last high resolution stage. Ranjan et al. [12] proposed a deformation part model based on normalized features extracted by deep convolutional neural network. Yang et al. [13] proposed a method called Convolutional Channel Feature (CCF) by combining the advantages of both filtered channel features and CNN, which has a lower computational cost and storage cost than the general end-to-end CNN method.

Recently, witnessing the significant advancement of object detection using region-based methods, researchers have gradually applied the R-CNN series of methods to face detection. Qin et al. [14] proposed a joint training scheme for CNN cascade, Region Proposal Network (RPN), and Fast R-CNN. In [15], Jiang et al. trained the Faster R-CNN model by using WIDER dataset and verified performance on

the FDDB and IJB-A benchmarks. Sun et al. [16] improve the Faster R-CNN framework through a series of strategies such as multiscale training, hard negative mining, and feature concatenation. Wu et al. [17] proposed a different scales face detection method based on Faster R-CNN for the challenge of small-scale face detection. Liu et al. [18] proposed a cascaded backbone branches fully convolutional neural network (BB-FCN) and used facial landmark localization results to guide R-CNN-based face detection. The neural networks based methods are already the mainstream of face detection because of its high efficiency and stability. In this work, we propose a G-Mask scheme, which achieves fairly progress in face detection task compared to the original architecture.

3.) Improved Mask R-CNN

- Network Architecture

The proposed method is extended from the Mask R-CNN [23] framework, which is the state-of-the-art object detection scheme and demonstrated impressive performance on various object detection benchmarks. The proposed G-Mask method consists of two branches, one for face detection and the other for face and background image segmentation. In this work, the ResNet-101 backbone is used to extract the facial features of the input image, and the Region of Interest (RoI) is rapidly generated on the feature map through the Region Proposal Network (RPN). We also use the Region of Interest Align (RoIAlign) to faithfully preserve exact spatial locations and output the feature map to a fixed size. At the end of the network, the bounding box is located and classified in the detection branch, and the corresponding face mask is generated on the image in the segmentation branch through the Fully Convolution Network (FCN) [31]. In the following, we will introduce the key steps of our network in detail.

- Region Proposal Network

For images with human faces in our daily life, there are generally some face objects with different scales and aspect ratios. Therefore, in our approach, Region Proposal Network (RPN) generates RoIs by sliding windows on the feature map through anchors with different scales and different aspect ratios. The largest rectangle in the figure represents the feature map extracted by the convolutional neural network, and the dotted line indicates that the anchor is the standard anchor. Assume that the standard anchor size is 64 pixels, and the three anchors it contained represent three anchors with aspect ratios of $1:1$, $1:2$, and $2:1$. The dot-dash line and the solid line represent the anchors of 32 and 128 pixels, respectively. Similarly, each of them also has three aspect ratios anchors. For traditional RPN, the above three scales and three aspect ratios are used to slide on the feature map to generate RoIs. In this paper, we use 5 scales (16^2, 32^2, 64^2, 128^2, and 256^2) and 3 aspect ratios ($1:1$, $1:2$, and $2:1$), leading to 15 anchors at each location, which was more effective in detecting objects of different scales.

- RoIAlign Layer

G-Mask, unlike the general face detection methods, has a segmentation operation, which requires more refined spatial quantization for feature extraction. In the traditional region-based approaches, RoIPool is the standard operation for extracting small feature map from RoIs, which have two quantization operations that result in misalignments between the RoI and the extracted features. For traditional detection methods, this may not affect classification and localization, while for our approach, it has a great impact on prediction of pixel-accurate masks, as well as for small object detection.

In response to the above problem, we introduced the RoIAlign layer, following the scheme of [23]. Suppose the feature map is divided into 2×2 bins. It can be seen that the RoIAlign layer cancels the harsh quantization operations on the feature map and uses bilinear interpolation to preserve the floating-number coordinates, thereby avoiding misalignments between the RoI and the extracted features.

Chapter 3
Work Carried Out

3.1 Dataset Procurement and Cleaning

There are only a few datasets available for the detection of face masks. Most of them are either artificially created which doesn't represent real world accurately or the dataset is full of noise and wrong labels. So, to choose the right dataset which would work best for the proposed approach required a little effort.

The dataset used in for training the model in given approach was a combination of various open source dataset and pictures which included data from Kaggle's the Medical Mask Dataset by Mikolaj Witkowski and Prajna Bhandandary dataset available at PyImageSearch. Also data was collected using the dataset provided by Masked face recognition dataset and application [27].

The Kaggle dataset contains pictures of people wearing medical masks along with XML files containing their description and the location of masks. This dataset had a total of 678 images. The other Artificial mask dataset was taken from 'Prajna Bhandary' from PyImageSearch. The dataset includes 1,376 images separated into two classes with mask, 690 images and without mask, 686 images. The dataset from Masked face recognition and application contained a lot of noise and a lot repetitions were present in the images of this dataset. Since a good dataset dictates the accuracy of the model trained on it so the data from the above specified datasets were taken. They were then processed and also all the repetitions were removed manually. The data cleaning was done manually to remove the corrupt images which we found in our dataset. Finding these corrupt images was a tricky task but due to valid efforts we divided the work and cleaned the data set with mask images and without mask images. Making a clean dataset was a vital part. As it is well known, identifying and correcting errors in a dataset removes negative effects from any predictive model. The artificial dataset created by Prajna Bhandary took normal images of faces and applied facial landmarks. Facial landmarks allowed to locate facial features of a person like eyes, eyebrows, nose, mouth, and jawline. This used an artificial way to create a dataset by including a mask on a non-masked person image but those images were not again used in the artificial generation process. The use of non-face mask samples, involved the risk of the model becoming heavily biased. It was a risk to use such a dataset but we included more images from various other sources which would in fact consist of person images with mask and unmasked which compensated for the error correction.

In the end we got an dataset which included 5521 images having label "with_mask" and "without_mask" also contained 5512 images to make a balanced dataset. A databatch created using this dataset is shown in

Figure 1 and the distribution between the two classes is visualized in Figure 2. The created dataset can also be used for detecting assailants who cover their faces while performing unlawful deeds. The Dataset has been made made available at: https://github.com/TheSSJ2612/Real-Time-Medical-Mask-Detection/releases/download/v0.1/Dataset.zip

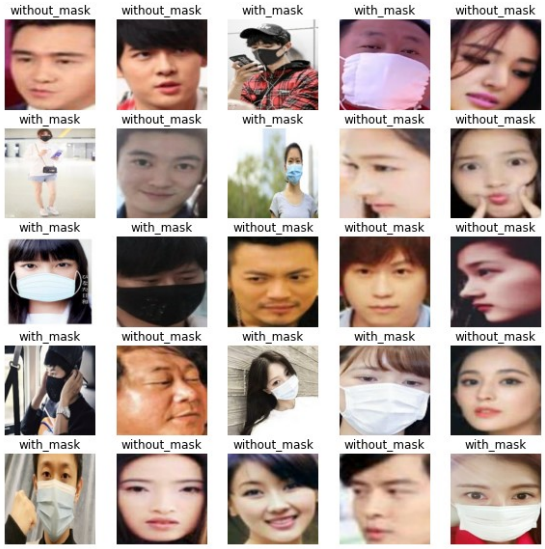

Figure 2: Dataset with mask and without mask

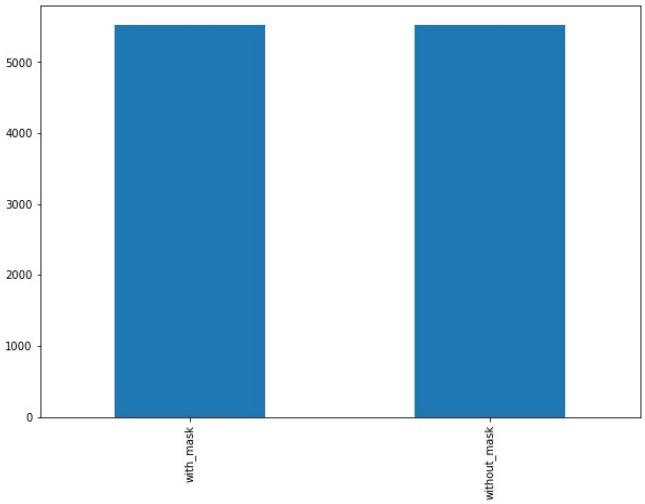

Figure 3: Bar Graph of with mask and without mask

3.2 Methodology Pipeline

To correctly identify whether a person has worn a mask, the first step would be to train the model using a proper dataset. Details about the dataset have been discussed above in section 3. After training the classifier, an accurate face detection model to detect faces is required so that the proposed model can classify whether the person is wearing a mask or not. The task in this paper is to maximize the accuracy for mask detection without being too resource heavy. For doing this task DNN module was used from OpenCV which contains a SSD (Single Shot Multibox Detector) object detection model with ResNet-10 as its backbone architecture. This approach helps in detecting faces in real time even on embedded devices like Raspberry Pi. The following classifier uses a pretrained model MobileNetV2 to predict whether the person is wearing a mask or not. The approach used in this paper is depicted in the flow diagram in Figure 3.

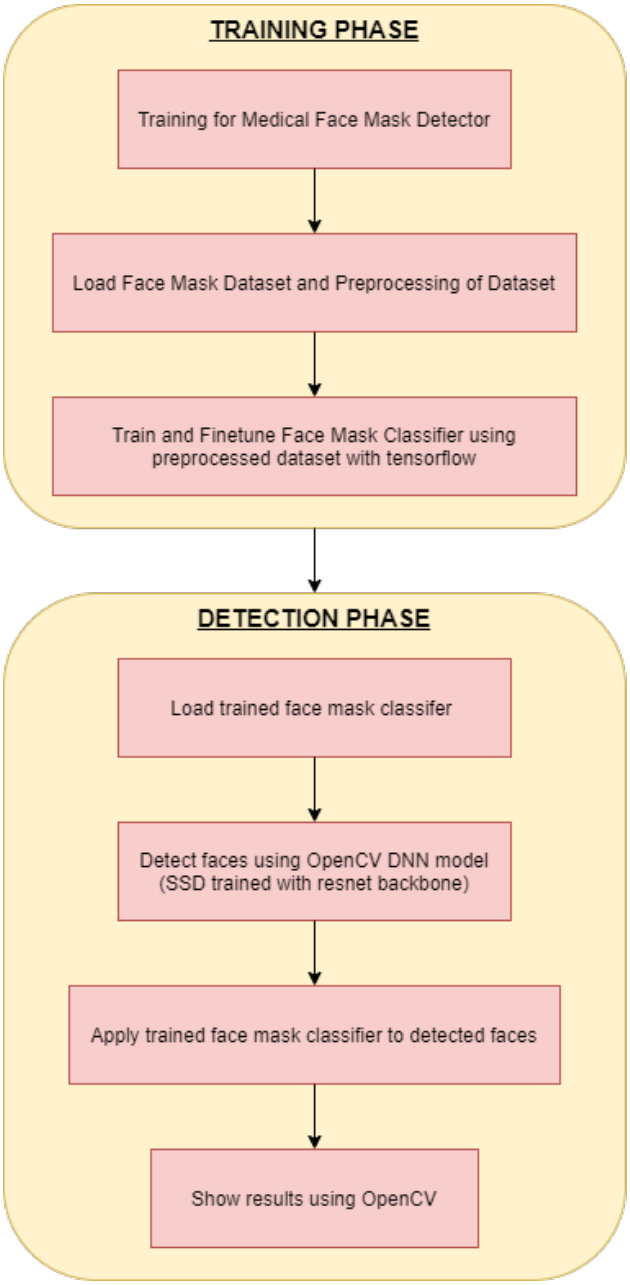

Figure 4: Architecture of our proposed work

3.2.1 Face Detection using OPEN-CV DNN

This model is included in the Github repository of OpenCV starting from version 3.3. It is based on Single Shot multibox Detector (SSD) and uses ResNet-10 architecture as the backbone. The images from which the model is trained have not been disclosed. Two versions of the model are made available by OpenCV:

1. Original Caffe Implementation (Floating point 16 version)
2. Tensorflow Implementation (8 bit quantized version)

We have used the caffemodel for our implementation for the proposed approach to detect faces for the detection of facial masks. For this the caffemodel and prototxt files were loaded using *cv2.dnn.readNet("path/to/prototxtfile", "path/to/caffemodelweights").* After applying the face detection model we get the output of the number of faces detected, the location of their bounding boxes, and the confidence score in those predictions. These outputs are then used as input for the face mask classifier. Using this approach to detect faces allows for real time detection with much resource usage. It is also able to detect faces in different orientations, i.e, left, right, top, and bottom with good accuracy. It is also able to detect faces of different scales, i.e., big or small.

3.2.2 Classification of images using MobileNetV2

MobileNetV2 is a Deep Neural Network which we have deployed for our classification problem. Pretrained weights of ImageNet were loaded from Tensorflow. Then the base layers are frozen to avoid impairment of already learned features. Then new trainable layers are added and these layers are trained on our collected dataset so that it can learn the features to classify a face wearing a mask from a face not wearing a mask. Then the model is finetuned and then the weights are saved. Using pretrained models helps us to avoid unnecessary computational costs and helps us take advantage of already biased weights.

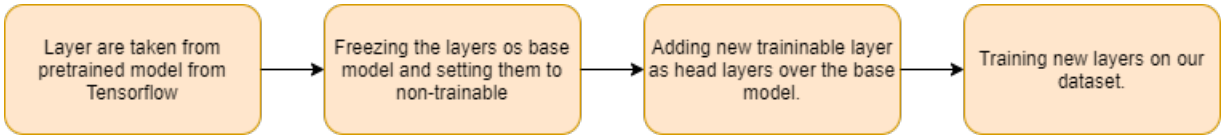

Figure 5: Pipeline of using Pretrained Model

3.2.2.1 Architecture of MobileNetV2

MobileNetV2 is a Convolutional Neural Network (CNN) based deep learning model which uses the following layers.

Table 1: MobileNet V2 Architecture

Input	**Operator**	**Expansion rate of the channels**	**Number of input channels**	**Repetitions**	**Stride**
224^2 x 3	Conv2d	-	32	1	2
112^2 x 32	bottleneck	1	16	1	1
112^2 x 16	bottleneck	6	24	2	2
56^2 x 64	bottleneck	6	32	3	2
28^2 x 32	bottleneck	6	64	4	2

14^2 x 64	bottleneck	6	96	3	1
14^2 x 96	bottleneck	6	160	3	2
7^2 x 160	bottleneck	6	320	1	1
7^2 x 320	Conv2d 1x1	-	1280	1	1
7^2 x 1280	Argpool 7x7	-	-	1	-
1 x 1 x 1280	Conv2d 1x1	-	K	-	

3.2.2.1.1 Convolution Layer

This layer is the building block of CNN. It works on a sliding window mechanism, which helps in extracting features from an image. This helps us to generate feature maps. The convolution of two matrices, one being the input image matrix of size X*Y*Z and convolutional kernel of size k*k*Z with stride size s and padding e gives us the output of size $(\frac{X-k+2e}{s}+1) \times (\frac{Y-k+2e}{s}+1) \times f$ where Z is the depth of image, and f is the number of filters. The Output of convolution C between matrices P of size (X, Y) and Q of size (A, B) can be expressed as:

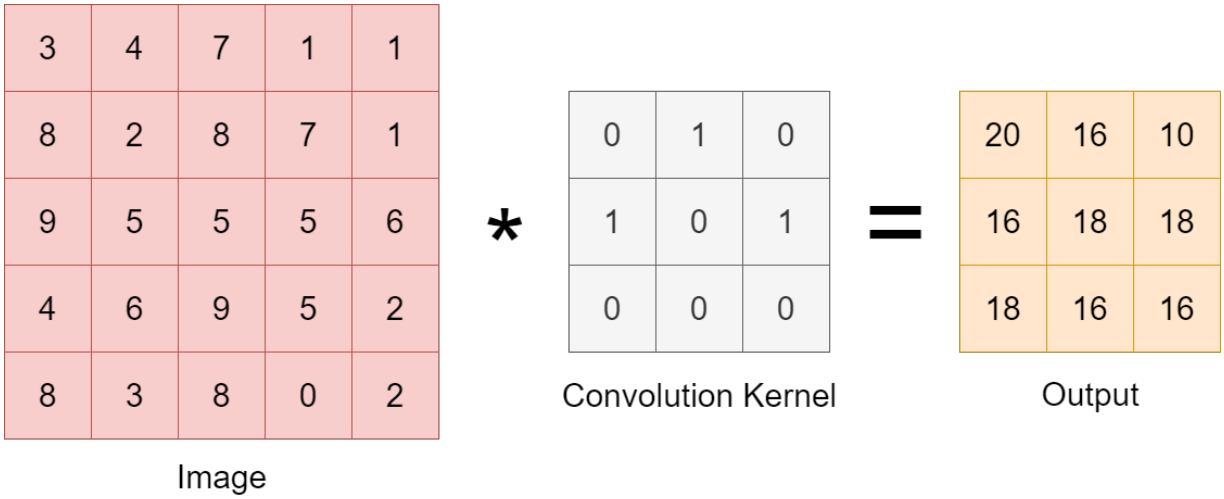

Figure 6: Convolutional Operation

$$C(i,j) = \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} P(x,y) * Q(i-x, j-q) \quad (1)$$

Where $0 \leq i \leq X + A - 1$ and $0 \leq j \leq Y + B - 1$. Figure 5 shows the convolutional operation.

3.2.2.1.2 Pooling Layer

Applying the pooling operations helps us to speed up the calculations by allowing us to reduce the size of the input matrix. Different kind of pooling operations can be applied out of which some are explained below:

a.) Max Pooling: It takes the maximum value present in the selected region where the kernel is currently at as the value for output of matrix value for that cell. Figure shows the max-pooling operation.

b.) Average Pooling: It takes the average of all the values that are currently in the region where the kernel is at and takes this value as the output for the matrix value of that cell.

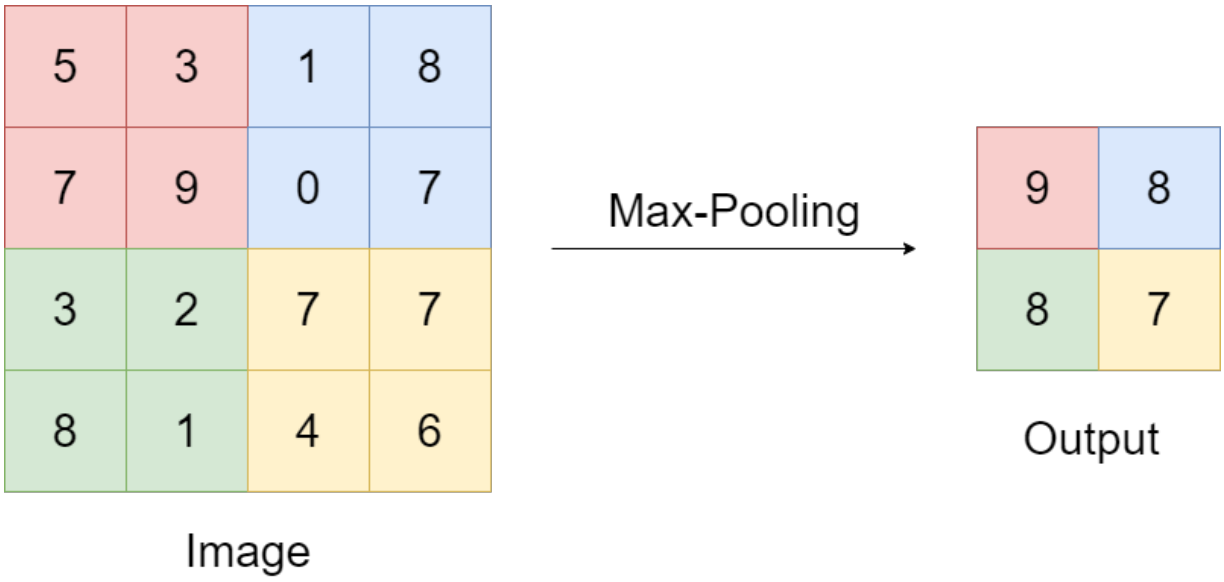

Figure 7: Max-Pooling Operation

3.2.2.1.3 Dropout Regularisation

This helps in reducing the overfitting which may occur while training by dropping random biased neurons from the model. These neurons can be a part of hidden layers as well as visible layers. The likelihood for a neuron to be dropped can be changed by changing the dropout ratio.

3.2.2.1.4 Non-Linear Layer

These layers usually follow the convolutional layers and are also called activation layers. Most commonly used Non-linear functions include different kinds of Rectified Linear Unit (ReLU), i.e.,

Leaky ReLU, Noisy ReLU, Exponential ReLU, etc., sigmoid function as well as tanh functions. Figure 7 shows different kinds of activation functions.

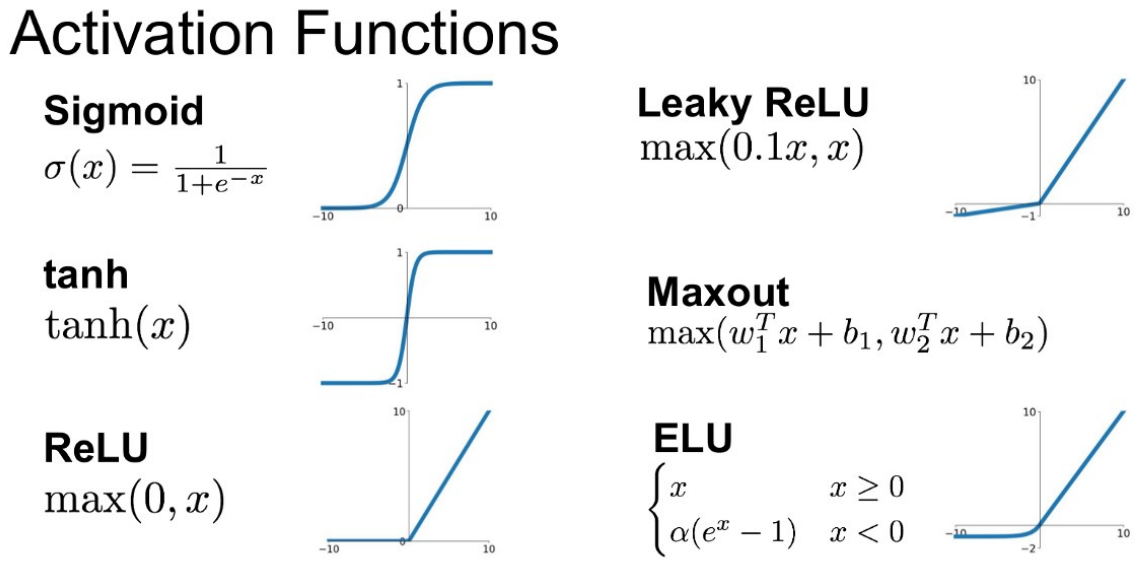

Figure 8: Different Activation Functions
*(source: https://miro.medium.com/max/1400/1*ZafDv3VUm60Eh10OeJu1vw.png)*

3.2.2.1.5 Fully-Connected Layer

These layers are added at the end of the model and have full connections to activations layers. These layers help us to classify the given images in multi-class or binary classification. Softmax is an example of activation functions used in these layers and it gives the result of predicted output classes in terms of probability.

3.2.2.1.6 Linear Bottlenecks

As multiple matrix multiplications can't be diminished to a single numerical operation so we apply non-linear activation functions like Relu6 in our neural networks so that several discrepancies can be removed easily. Through this we can build a multilayer neural network. Since Relu activation function abandons the values which are less than 0. To challenge the loss of information, dimensions of the network can be increased by increasing the number of channels.

For a reversed residual block layers of the blocks are compressed and the contrary procedure is done as done above. This is done at the point where the skip connections are linked, this could affect the execution of the network. To deal with this, the concept of linear bottleneck was introduced in which before adding the block to initial activation the last convolution of the residual block is given a linear output.

3.3 Algorithms explaining complete pipeline

ALGORITHM 1: Preprocessing and Training the dataset

```
Sorted_Alphanumerically(List)
{
Sort the given list in lexicographical order
}
Preprocessing(Image)
{
Convert image to array tensor
Resize image to 224 x 224 x 3 for our model
Normalize the created tensor to values between -1 and 1 for faster calculations
Return image
}
Load_files(path to folder)
{
Load all files and their paths and labels in a list
Preprocessing(input images)
Sort the list using Sorted_Alphanumerically()
Convert labels to numerical values
Convert list to Numpy array for faster calculations
}
Train_Test_Split(data_array)
{
Split the data into the ratio of 0.2, i.e., 80% data for training and 20% data for testing
Create train and test batches
Return data_batches
}
Data_Augmentator(data_batches)
{
Augment training data using techniques like rotation, shearing, flipping, etc.
}
 Create_Model()
{
Load pretrained MobileNetV2 as base model
Train its head while not training the base layers to avoid losing learned features
Compile the model with Adam optimizer using binary cross entropy loss function
Return the model
}
 Train_and_Save_Model(createdmodel)
{
Set the values for epochs
Give callbacks like tensor board to log metrics
Train model
Save the model on disk
}
Visualize_Model(modelpath)
{
Plot accuracy and loss curves
Print classification report results
Make predictions on test batches
Plot confusion matrix and roc curves
}
```

Algorithm 1 exlains the procedure of preprocessing the data and then training on data. First we define a function name sorted_alphanumerically to sort the list in lexicographical order. The a function preprocesssing is defined which takes the folder to dataset as input then it loads all the files from the folder resizes the images according to model. Then the list is sorted using sorted_alphanumerically and then the images are converted into tensors. Then the list is converted to numpy array for faster calculation. After this the process of data augmentation is applied to increase the accuracy after training the model. Then data batches are created. Then pretrained MobileNetV2 is loaded from Keras and new head is created to learn new features while leaving the base layers as it is. Then the model is trained by giving data batches as input and callbacks like tensorboard are giving to log the metrics. Then the model is saved after training for future use. Also we can use visualize_model function to visualize the metrics obtained from the model.

ALGORITHM 2: Deployment of Face Mask Detector

```
Detect_mask_image(Input_file)
{
Load face detector model and mask classifier model
Detect faces in image using face detector model
If face are detected
{
Pass cropped faces to mask classification model
Get predictions from model
Show the predictions on image and save the resultant image
}
Else
{
Give output no faces detected
}
}
Detect_mask_realtime()
{
Load face detector model and mask classifier model
Start Real time feed
Pass the feed through face detection model
If faces are detected
{
Pass cropped faces to mask  classification model
Get predictions from model
}
If predictions are returned from model
{
Show output in playback output of real time stream
}
End stream when q is pressed
}
Load_Image_or_RealTime(choice)
{
Check whether selected choice is real time detection or mask detection on image
If Choice = Image
{
Load Image
Detect_mask_image(Input_File)
}
If Choice = RealTime
{
Detect_mask_realtime()
}
```

Algorithm 2 explains the procedure for using the trained model classifier to detect masks on faces from static images or Real time video feed. The choice is taken from user. If user selects image then the path will be provided for the image where after a little preprocessing the face is detecting using face detector model. If face are found then the model for mask classifier to detect whether mask is worn or not. If no faces are detected then no output is shown. If real time feed is chosen then the real time feed is taken using OpenCV. Then each frame gotten is processed dynamically in almost real time just like images are processed and then the output is shown using OpenCV.

Figure 8 shows the explains the algorithms used in our approach with graphical representation.

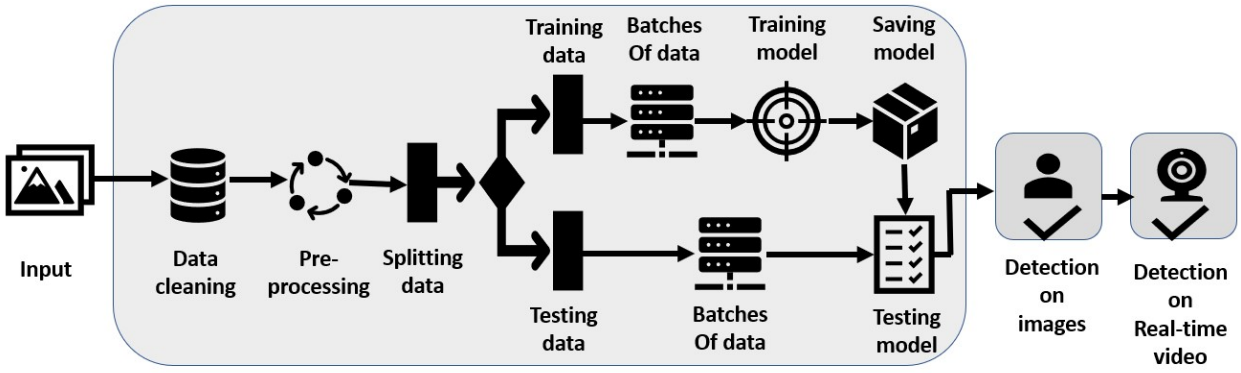

Figure 9: Explanation of Algorithms

Chapter 4

Experimental Result and Comparison

To solve the binary classification, deep learning model problem int this paper, Keras is used to make classification model in this paper, which is an advanced-level artificial neural networks API. The evaluation metrics used in this paper are accuracy, area under the ROC (Receiver Operating Characteristics) curve, confusion matrix, classification report and comparison of models. The accuracy gives us the level of correct prediction of masked person identified by the machine by the proposed model as shown in Figure 9. The Roc curve compares a model's true positive rate (tpr) from a model's with false positive rate (fpr) as shown in Figure 12. The model's roc accuracy score is close to the ideal roc curve but not the same. Confusion matrix shown in Figure 11 depicts a matrix to compare the labels, model prediction and actual labels it was supposed to predict. It is showing where the model is getting confused. Classification report shown in Table 2 explains the level of accuracy, precision, recall and f1 score of our model. The average accuracy of our model is '93%' for predicting if a person is wearing a mask or not on a validation dataset as shown in Figure 9. The training loss curve corresponding to training and validation is shown in Figure 10.

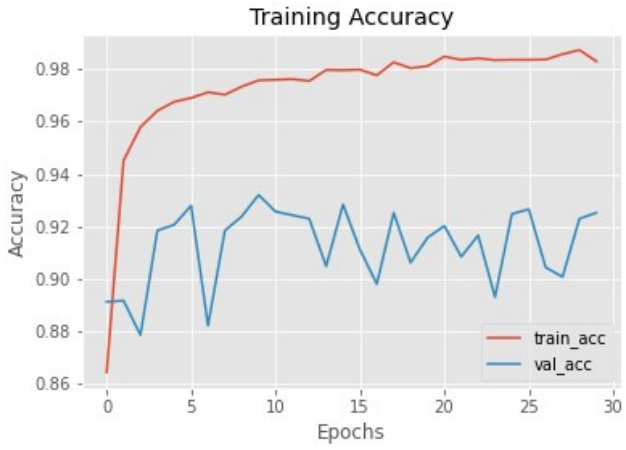

Figure 10: Training accuracy curve on train validation dataset

Figure 11: Training loss curve on train and and validation dataset

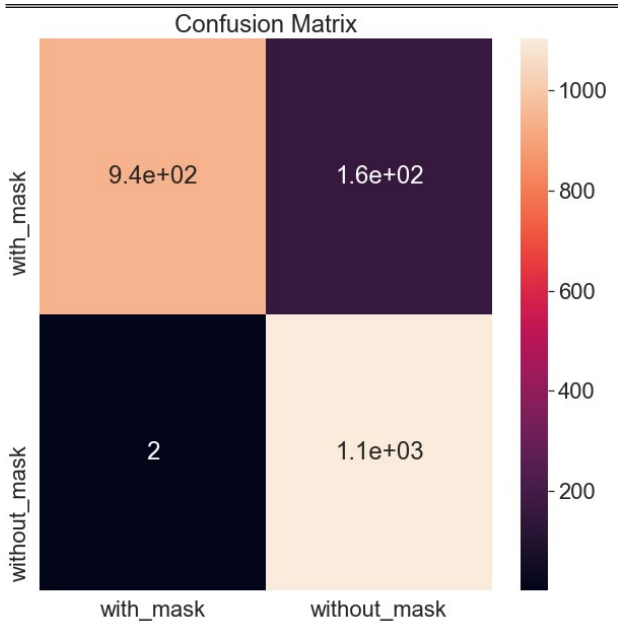

Figure 12: Confusion matrix

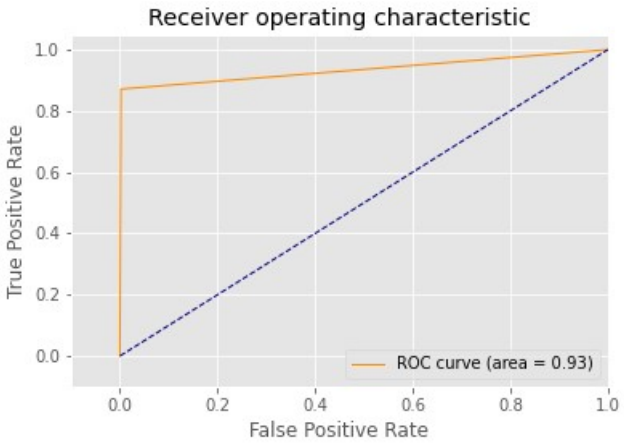

Figure 13: Roc curve

The plots are based on model accuracy, the pyplot command style function that makes matplotlib work like MATLAB. In Figure 9 the red curve shows the training accuracy which is nearly equal to 98%, whereas the blue line represents training accuracy on the validation dataset. Like the previous plot the Figure 10 represents training loss where the red curve shows loss in training dataset less than 0.1, whereas the blue curve shows training loss on the validation dataset. The confusion matrix is plotted with help of heatmap showing a 2D matrix data in graphical format. It has successfully identified 941 true positives, 163 false negatives, 2 false positive and 1103 true negative out of 2209 images used for validation. The Roc curve in Figure 12 shows graphical representation of true positive rate and false positive rate. The roc accuracy score showing 93% predicts the correctness of predicting the model values.

Figure 13 shows the predictions on some images. These are the predictions made on 12 test images by our model using MobileNetv2. The rectangular green box depicts the correct way of wearing a mask with accuracy score on the top left while the red rectangular box represents the incorrect way of wearing a mask. The model learns from the pattern of train dataset and labels and then makes predictions. The classification report of our model is shown in Table 2.

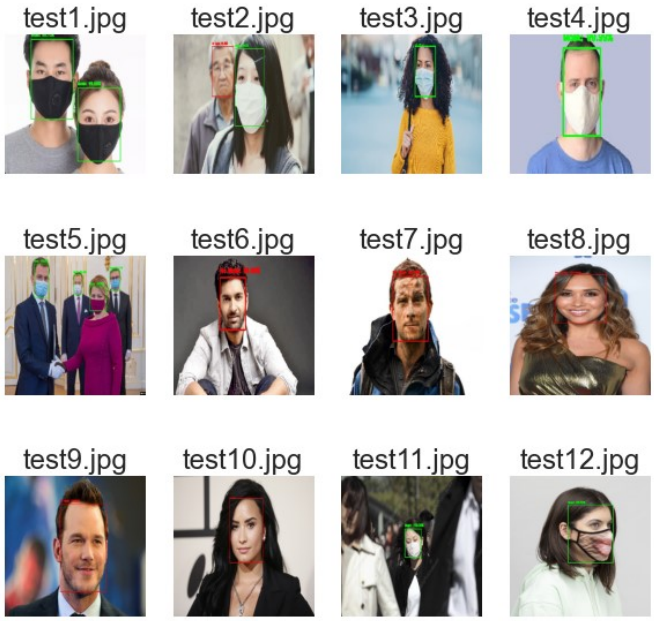

Figure 14: Predictions on test images

Table 2: Classification Report

	Precision	**recall**	**F1 Score**	**support**
with mask	1.00	0.85	0.93	1104
without mask	0.87	1.00	0.93	1105
accuracy			0.93	2209
Macro average	0.94	0.93	0.93	2209
Weighted average	0.94	0.93	0.93	2209

The proposed approach was also compared with different preexisting models by training them on the same dataset and the results from them have been shown in Table 3. In the end MobileNetV2 was chosen to be our model for the proposed approach even though it's accuracy is slightly less than VGG16 and ResNet - 50 since it is easy to deploy in real time even on embedded devices which is not possible with heavy models and to do real time detection using these models requires good computational power which might make it difficult to play in real life

Table 3: Comparison between different models

Method	**Year**	**Accuracy (%)**	**F1 Score**
LeNet -5	1998	85.6	0.86
AlexNet	2012	89.2	0.88
VGG -16	2014	93.21	0.92
ResNet - 50	2016	92.9	0.91
MobileNetV2	**2020**	**92.53**	**0.93**

Table : Weekly progress Report

Day	**Work Done**
Day 1	**Finalization of project idea**
Day 2	**Dataset Extraction and cleaning**
Day 3	**Write the code and compile the models**
Day 4	**Written the research paper**
Day 5	**Written the training report**
Day 6	**Prepared the presentation of our project**
Day 7	**Demonstration of the project idea**

Chapter 5

Conclusions, Summary and Future Scope

In our face mask detection model, we successfully performed both the training and development of the image dataset which were divided into categories of people having masks and people not having masks. The technique of opencv deep neural networks used in this model generated fruitful results. We were able to classify our images accurately using Mobilenetv2 image classifier which is one of the uniqueness of our model.

Many existing researches faced problematic results while some were able to generate better accuracy with their dataset. The problem of various wrong predictions have been successfully removed from our model as the dataset used was collected from various other sources and images used in the dataset was cleaned manually to increase the accuracy of our results. Real world applications are a much more challenging issue for the upcoming future. We believe that our proposed face mask detection model will help the concerned authorities in this great pandemic situation which had largely gained roots in most part of the world, the dataset provided in this model can be used by other researchers for further advanced models such as those of face recognition, facial landmarks and facial part detection process which will be our future research area.

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APPENDIX:

- https://github.com/TheSSJ2612/Real-Time-Medical-Mask-Detection