

“A Face Mask Detector to Control Covid19 Using Machine Learning Technique”

Apurva Rajkumar Laddha, K.K. Chhajed

ABSTRACT

Corona virus disease 2019 has become a major health problem. It is spreading very widely due to its contact transparent behavior. So WHO declared to wear mask in crowded areas as a prevention method. Some of the areas the diseases become widely spread out due to improper wearing of facial mask. So to overcome this problem we required an efficient mask monitoring system. By the development of machine learning and image processing analysis introduce methods for mask detection. By using image processing analysis and machine learning method is used for find out mask detection. Face mask detection can be done through various methods. Mainly convolutional neural network method is used rapidly. The accuracy and decision making is very high in CNN compared to others. Here we are discussed about various deep learning techniques used for face mask detection.

Key Words: Corona virus disease 2019, Face mask detection, CNN, Machine learning

Date of Submission: 10-12-2021

Date of acceptance: 24-12-2021

I. INTRODUCTION

Since the end of 2019, infectious coronavirus disease (COVID-19) has been reported for the first time in Wuhan, and it has become a public damage fitness issue in China and even worldwide. This pandemic has devastating effects on societies and economies around the world causing a global health crisis. It is an emerging respiratory infectious disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). All over the world, especially in the third wave, COVID-19 has been a significant healthcare challenge. Many shutdowns in different industries have been caused by this pandemic. In addition, many sectors such as maintenance projects and infrastructure construction have not been suspended owing to their significant effect on people's routine life.

By now, the virus has rapidly spread to the majority of the countries worldwide. The last statistics (04/05/2021) provided by the World Health Organization (WHO) show 152,543,452 confirmed cases and 31,985,288 deaths. According to the centers for Disease Control and Prevention (CDC), coronavirus infection is transmitted predominantly by respiratory droplets produced when people breathe, talk, cough, or sneeze with common droplet size 5–10 μm but aerosol emission increases when humans speak and shout loudly.

Therefore, to prevent rapid COVID-19 infection, many solutions, such as confinement and lockdowns, are suggested by the majority of the world's governments. However, this COVID-19 management inefficacy can be additionally explored with game-theoretic scenarios beyond the public goods game. In particular, some researchers have focused on the hesitancy of governments in enacting difficult but necessary virus containment measures (e.g., stay-at-home orders and lockdowns), as well as noncooperation for reasons other than free riding. For instance, authors in argued that because strict stay-at-home measures can greatly impact people's livelihoods, the cost of staying home (coupled with lockdown fatigue) can end up outweighing the risk of infection from going out. As individual-level decisions have a direct impact on the society-level effectiveness of stay-at-home orders, governments may refrain from implementing them because of anticipated low rates of compliance, especially from socioeconomically disadvantaged individuals who do not have the luxury of staying home. Some governments may have also been hopeful that herd immunity from recoveries and vaccinations would allow them to avoid imposing such unpopular measures altogether.

With rising numbers of cases and stretched health facilities, as well as the lack of a vaccine throughout 2020 and difficulties associated with achieving herd immunity for COVID-19, government inaction became increasingly unviable. Hence, to increase people's adherence to strict regulations, authors in suggested using social programs such as emergency relief funds and unemployment insurance to lower the costs of compliance, particularly for lower-paid workers.

However, the technique of tracking massive businesses of humans is turning into more difficult. The tracking technique includes the detection of everyone who isn't carrying a face mask. Here we introduce a masks face detection version that is primarily based totally on pc imaginative and prescient and deep getting to know. The proposed version may be incorporated with surveillance cameras to obstruct the COVID-19 transmission

through permitting the detection of humans who're carrying mask now no longer carrying face mask. The version is integration among deep getting to know and classical gadget getting to know techniques.

II. LITERATURE REVIEW

In the recent past, various researchers and analysts mainly focused on gray-scale face image (Ojala, Pietikainen, & Maenpaa, 2002). While some were completely built on pattern identification models, possessing initial information of the face model while others were using AdaBoost (Kim, Park, Woo, Jeong, & Min, 2011), which was an excellent classifier for training purposes. Then came the Viola-Jones Detector, which provided a breakthrough in face detection technology, and real-time face detection got possible. It faced various problems like the orientation and brightness of the face, making it hard to intercept. So basically, it failed to work in dull and dim light. Thus, researchers started searching for a new alternative model that could easily detect faces as well as masks on the face. [12]

In the past, many datasets for face detection were developed to form an impression of face mask detection models. Earlier datasets consisted of images fetched in supervised surroundings, while recent datasets are constructed by taking online images like Wider Face (Yang, Luo, Loy, & Tang, 2016), IJB-A (Klare et al., 2015a), MALF (Yang, Yan, Lei, & Li, 2015), and Celeb A (Klare et al., 2015b). Annotations are provided for present faces in these datasets as compared to earlier ones. Large data-sets are much more needed for making better training and testing data and perform real-world applications in a much simpler way. [13] This calls for various deep learning algorithms which can read faces and mask straight from the data provided by the user.

Face Mask detection models have many variations. These can be divided into several categories. In Boosting-based classification, boosted cascades with easy features were embraced using the Viola-Jones face detector (Jones, Viola, & Jones, 2001), which was 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 this category were very effective in detecting face masks.

In Deformable Part Model-based classification, the structure and orientations of several different faces are modelled using DPM. In 2006 Ramanan proposed a Random forest tree model in face mask detection, which accurately guesses face structures and facial poses. [15] Zhang, Zhang, Li, and Qiao (2016), one of the renowned researchers made a DPM-based face mask detector using around 30,000 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, Ren, Wei, Cao, and Sun (2014). Typically, DPM-based face mask detection models can achieve majestic precisions, but it may be tolerant from the very towering cost of computation due to the use of DPM.

In Convolutional Neural Network-based classification, face detector models learn directly from the user's data and then apply several deep learning algorithms on it (Ren, He, Girshick, & Sun, 2015). In the year 2007, Li, Lin, Shen, Brandt, and Hua (2015) came up with Cascade CNN.

In Yang, Yan et al. (2015), Yan et al. came up with the idea of features aggregation of faces in the face detection model. In further research works, Ojala et al. (2002) upgraded the AlexNet architecture for fine-tuning the image dataset. For uninhibited circumstances, Zhu et al. (2017) propose a Contextual Multi-Scale Region-based Convolutional Neural Network (CMS-RCNN), which brought a significant 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. (2016) prepared a grid loss layer. As technology advanced, further CNN-based 3D models started coming up; one was proposed by Li et al. (2015). It was a learning structure for face mask detection models. [16] Several other works were done in the sphere of pose recognition, gender estimation, localization of landmarks, etc.

The Face mask detection model named SSD MNV2 has been developed 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 image classification and fine-tuned MobileNet V2 classifier has been used, MobileNet V2 classifier has been an improvement over MobileNet V1 architecture classifier as it consisted of 3 3 convolutional layer as the initial layer, which is followed by 13 times the previous building blocks. [18] In contrast, MobileNet V2 architecture is made up of 17, 33 convolutional layers in a row accompanied by a 1 convolution, an average layer of max pooling, and a layer of classification. The residual connection is a new addition in the MobileNet V2 classifier.

In the year 2018, Suma S L applied a actual time face popularity set of rules the use of Linear Binary Pattern Histogram (LBPH) and Viola Jones set of rules. This technique includes com fusion and popularity. is achieved the use of Viola Jones set of rules is implemented is for Face detection, characteristic extraction is achieved via way of means of LBPH approach and Euclidean Distance Classifier is used for face popularity. [1] These

paintings have popularity charge of approximately “85%-95%”. These paintings can be similarly amended to choose in all situations such as brightness, in case of twins, beard and carrying goggles.

In the year 2017, Li Cuimei applied a human face detection set of rules the use of 3 vulnerable classifiers including Har cascade classifier. Skin hue histogram, Eye detection and Mouth detection are the 3 classifiers followed via way of means of this technique. This yields sufficiently excessive detection. The proposed technique generates a function prediction value (PPV) to approximately 78.18% - 98.01%. This may be amended to locate human faces handiest of more than one races and decrease the put off for detecting and spotting diverse faces among distinct photos of humans with variant in mild and historical past situations.

In the year 2017, SouhailGuennouni put into effect a face detection device via way of means of collating with Har cascade classifiers and part orientation matching. Edge orientation matching set of rules and Har-like characteristic choice blended cascade classifiers are the 2 strategies used on this device.[2] This set of rules produces a higher matching however the detection pace is relatively less.

In the year 2015, Jiwen Lu the use of getting to know CBFD proposed a face popularity device. The face representation and popularity is applied thru Compact Binary Face Descriptor (CBFD) characteristic getting to know technique even as coupled CBFD is accomplished for heterogeneous face matching via way of means of minimizing the modality hole of characteristic level. Collating with different Binary Codes Learning strategies, CBFD extracts compact and discriminative characteristic, consequently produces a higher popularity charge of approximately 93.80% is obtained.[4] In this painting, characteristic is discovered handiest from one unmarried layer. This device can reap higher overall performance via way of means of Learning Hierarchal functions in deep networks.

III. PROPOSED SYSTEM ANALYSIS AND DESIGN

3.1 Analysis

The proposed system focuses on how to identify the person on image/video stream wearing face mask with the help of computer vision and deep learning algorithm by using the OpenCV, TensorFlow, Keras and library. To predict whether a person has worn a mask correctly, the initial stage would be to train the model using a proper dataset. After training the classifier, an accurate face detection model is required to detect faces, so that the MobileNetV2 model can classify whether the person is wearing a mask or not.

Dataset used

There are only a few datasets available for the detection of face masks. Most of them are either artificially created, which doesn't represent the real world accurately, or the dataset is full of noise and wrong labels. So, choosing the right dataset which would work best for the SSDMNv2 model required a little effort. The dataset used in for training the model in a given approach was a combination of various open-source datasets and pictures. Data were also collected using the dataset provided by the masked face recognition dataset and application The dataset contains pictures of people wearing medical masks and XML files containing their descriptions and masks. This dataset had a total of 678 images. The other Artificial mask The dataset includes 1,376 images separated into two classes with wearing masks, 690 pictures, and without wearing a mask, 686 pictures.

Approach of the proposed system

1. Train Deep learning model (MobileNetV2)

In this step dataset will be trained.

2. Apply mask detector over images/live video stream

In this step face mask detector will be applied to detect mass on the images and video streams captured by webcam.

3.2 System Design

3.2.1 Basic Idea

It is proposed to design a system that is capable of identifying whether a person's face is with or without a mask. For the system to work properly, it is necessary to use two databases: the first is for classifier training and consists of a large number of images of people who wear a face mask and others who do not. The second is used for training the facial recognition system, and here there are people with and without the biosafety material (face mask). The input data are obtained either from an image, or a video and the architecture used is MobileNet, with the aim of having a better precision and robustness.

For the classifier, MobileNet V2 architecture is used, as it uses smaller models with a low latency and low parameterization power. This improves the performance of mobile models in multiple tasks and benchmarks, resulting in a better accuracy. It also retains the simplicity and does not require any special operator to classify multiple images and various detection tasks for mobile applications. MobileNetV2 is 35% faster at object detection compared with the first version, when combined with Single Shot Detector Lite.

The major requirement for implementing this project using python programming language along with Deep learning, Machine learning, Computer vision and also with python libraries. The architecture consists of Mobile Net as the backbone, it can be used for high and low computation scenarios. Below figure depicts architecture of two phases of face mask detector that is training phase and testing phase.

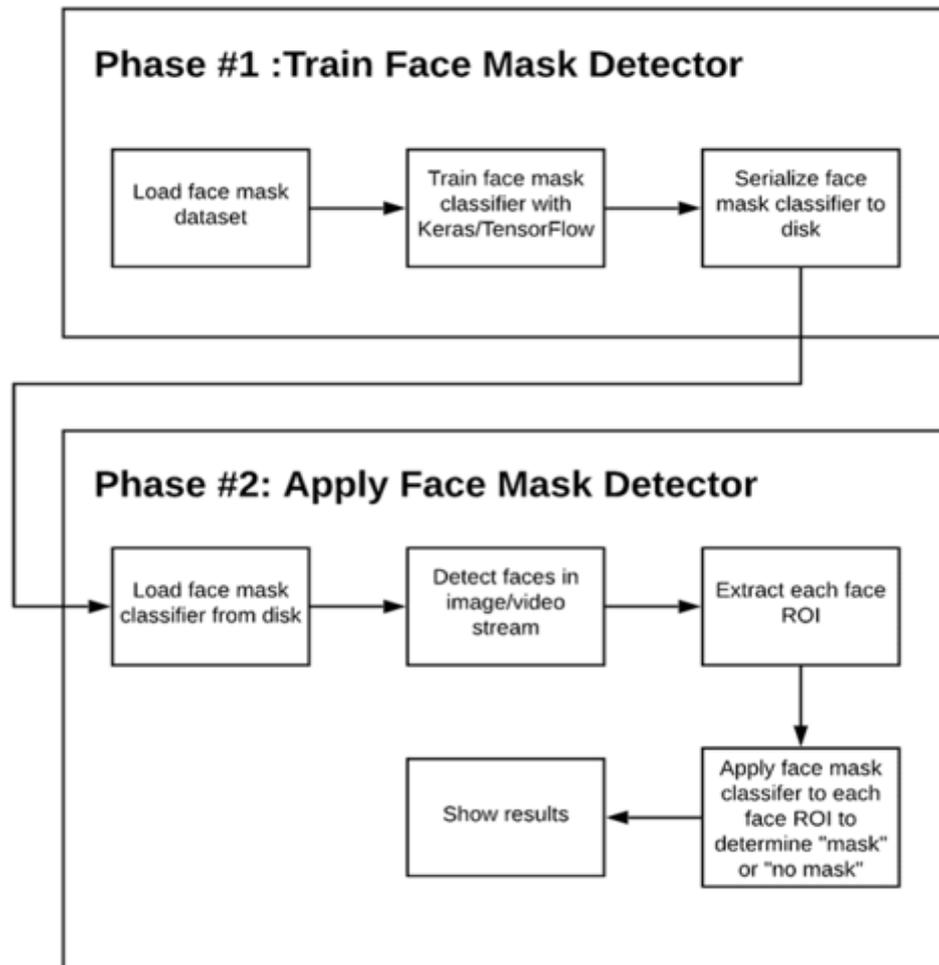


Fig. 3.1:Phases and individual steps for building a COVID-19 face mask detector with computer vision and deep learning using Python, OpenCV, and TensorFlow/ keras

In order to train a custom face mask detector, we need to break our project into two distinct phases, each with its own respective sub-steps (as shown by **Figure 3.1** above):

1. **Training:** Here we'll focus on loading our face mask detection dataset from disk, training a model (using Keras/TensorFlow) on this dataset, and then serializing the face mask detector to disk.
2. **Deployment:** Once the face mask detector is trained, we can then move on to loading the mask detector, performing face detection, and then classifying each face as with mask or without mask.

3.3 Modules of Proposed System:

Modules of the proposed system:

1. Datasets Collecting: model collect no of data sets with face mask and without masks. we can get high accuracy depends on collecting the number of images .
2. Datasets Extracting: model can extract the features using mobilenetv2 of mask and no mask sets.
3. Models Training: model will train the the model using open cv, keras (python library).
4. Facemask Detection: We can detect Preprocessing image and also detect via live video . If people wear mask, it will permit them, if not then it will give the buzzer to wear mask to prevent them from virus transmission.

The proposed system focuses on how to identify the person on image/video stream wearing face mask with the help of computer vision and deep learning algorithm by using the OpenCV, Tensor flow, Keras library.

3.3.1Working Methodology

Algorithms explaining the complete pipeline

The proposed methodology has been clearly explained using the two algorithms as shown below. First the images were pre-processed and were trained on the whole dataset. Second the model trained in the first part was used to detect the face mask with the appropriate accuracy. In Algorithm 1 shown below, images along with their pixel values were taken as an input, resized and normalized. Data augmentation technique was then applied on the images in order to get more accuracy. Data was then splitted into training and testing batches and MobilenetV2 model was applied on it. Adam optimizer was used to compile the whole model. In Algorithm 2 the model trained in previous part was then deployed on both classification on static images and on real time webcam. If the faces are detected then a boundingbox showing the face of the person wearing a mask is shown in the output.

1. Algorithm for training phase:

Following algorithm is for training phase of system. It involves images along with their pixel values were taken as an input, resized and normalized. Data augmentation technique was then applied on the images in order to get more accuracy. Data was then splitted into training and testing batches and MobilenetV2 model was applied on it. Adam optimizer was used to compile the whole model.

ALGORITHM 1 : Pre-processing and Training on Dataset

INPUT: Images along with their pixels values

OUTPUT: Trained Model

STEP 1: Load Images and their pixel values.

STEP 2: Process the images, i.e., resizing, normalization, and conversion to a ID array.

STEP 3: Load the Filenames and their respective labels.

STEP 4: Perform Data augmentation and then split data into training and testing batches.

STEP 5: Load MobilenetV2 model from Keras. Train it on training batches and compile it using Adam optimizer.

STEP6: Save the model for future use.

2. Algorithm for testing phase:

In Algorithm 2 the model trained in previous part was then deployed on both classification on static images and on real time webcam. If the faces are detected then a boundingbox showing the face of the person wearing a mask is shown in the output. If person is detected with mask then green box around the face is drawn and if person is detected without mask then red box around the person image is drawn.

ALGORITHM 2: Deployment of Face Mask Detector

INPUT: Choice of deployment and Files(optional).

OUTPUT: Images classified into the mask and no mask or Classification in Real-time.

STEP 1: Load saved classifier from disk. Also, load face detector from OpenCV.

STEP 2: If the choice is classification on image:

Load Image(s)

STEP 2.1: Apply face detection model to Detect faces in an image

STEP 2.2: If Faces are detected:

Crop face to bounding box coordinates from face detection model

Get predictions from the face classifier model.

Show predictions and save resultant image.

Else:

Show no output

STEP 3: If the choice is classification in real-time:

Load real-time feed from OpenCV

Read the feed frame by frame.

STEP 3.1: Apply face detection model to Detect faces in Frames read in real-time

STEP 3.2: If Faces are detected:

Crop face to bounding box coordinates from face detection model

Get predictions from the face classifier model.

Show output in a real-time feed

Else:

Show normal feed

STEP 4: End stream when q is pressed.

IV. RESULT ANALYSIS

By preserving a reasonable proportion of different classes, the dataset is partitioned into training and testing set. The dataset comprises of 1420 samples in total where 75% is used in training phase and 25% is used in testing phase. The training and testing dataset contains 686 and 680 images respectively. The developed architecture is trained for 20 epochs since further training results cause over fitting on the training data. Over fitting occurs when a model learns the unwanted patterns of the training samples. Hence, training accuracy increases but test accuracy decreases. Graph. 4.1 and Graph. 4.2 show the graphical view of accuracy and loss respectively. The trained model showed 99% accuracy.

In the accuracy curve of training and testing is shown for about 20 epochs. It is realized that the training and testing accuracy are almost identical. This means the model has a decent generalization ability for previously unseen data and it does not cause over fitting of the training data. In loss curves of training and testing phases are shown. Here, it is evident that the training loss is decreasing over increasing epochs.

Depicts the receiver operating characteristic (ROC) curve of the proposed framework. This illustrates the prediction ability of the classifier at different thresholds. Two parameters are plotted in the ROC curve; one is the true positive rate (TPR) and other is the false positive rate (FPR) measured using (1) and (2) respectively. TPR and FPR are calculated for different threshold and these values are plotted as ROC curve. The area under the ROC curve (AUC) measures the performance of the binary classifier for all possible thresholds.

$$\text{True Positive Rate} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (1)$$

$$\text{False Positive Rate} = \frac{\text{False Positive}}{\text{True Negative} + \text{False Positive}} \quad (2)$$

$$\text{Accuracy} = \frac{Tp + Tn}{(Tp + Fp + Fn + Tn)}$$

Where Tp = True positive,
 Tn = True negative,

Fp = False positive,
 Fn = False negative

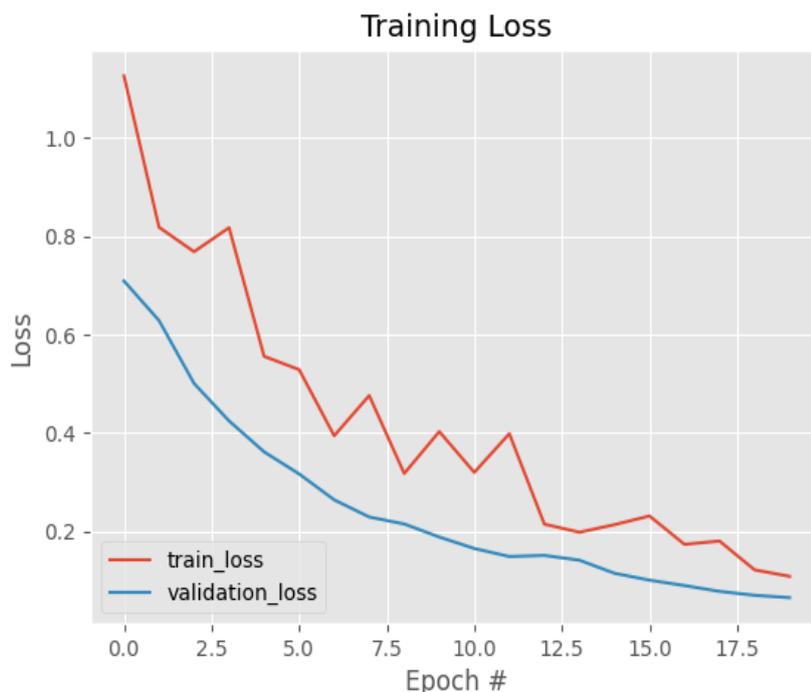
In above formulas, True positive values refer to image which were labelled true and after prediction by model gave true result. Likewise, for True negative refers to images which were labelled true but after prediction resulted in false result. False positive refers to images which were labelled false and after prediction resulted in false hence false positives. False negative refer to images which were labelled false and after prediction resulted in true hence false negatives.



Graph. 4.1: Accuracy of the developed system for training and testing phase.

We train the model using the training data and check its performance on both the training and validation sets (evaluation metric is accuracy). The training accuracy comes out to be 100% whereas the validation accuracy is 98% approx. Validation accuracy will be usually less than training accuracy because training data is something

with which the model is already familiar with and validation data is a collection of new data points which is new to the model.



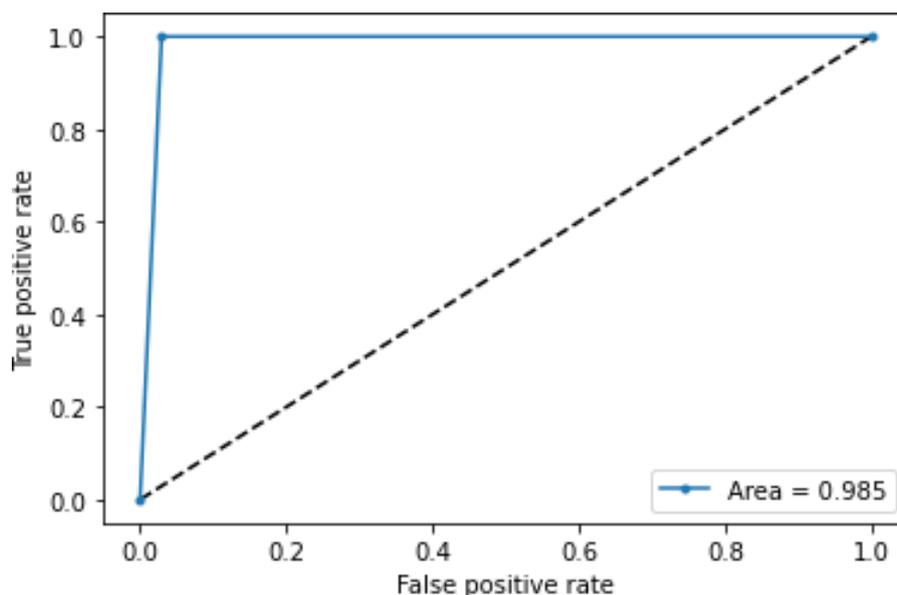
Graph.4.2: Loss of the developed system for training and testing phase.

The training loss indicates how well the model is fitting the training data, while the validation loss indicates how well the model fits new data. The average accuracy of our model is '96 %' for predicting if a person is wearing a mask or not on a validation dataset, as shown in Graph. 5.1. The red curve shows the training accuracy, which is nearly equal to 99%, whereas the blue line represents the accuracy of the validation dataset. The training loss curve corresponding to training and validation is shown in Graph. 5.2. Here, the red line shows the loss in the training dataset less than 0.1, whereas the blue line depicts training loss on the validation dataset.

Table 4.1 : Comparison Of Accuracy Between Different Models

Architecture Used	Year	Accuracy (%)	Percentage Improvement
LeNet – 5	1998	84.6	+9.37%
AlexNet	2012	89.2	+3.73%
SSDMNV2 (Developed method)	2020	92.64	+0%
MobileNetV2	2021	96.04	+4% (Approx)

in above table 4.1 architecture used in our project MobileNetV2 gives accuracy for face mask detection which is 96.04% approximately that it can vary and it is better than previous architecture used. MobileNetV2 model gives improvement over previous results of other architectures.



Graph 4.3: ROC of the classification network.

Above ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters: True Positive Rate. False Positive Rate.

V. CONCLUSION

Deep learning-based face mask detection has been a research hotspot in recent years. This project starts on generic facemask detection which provide base architectures for other related tasks. With the help of this the three other common tasks, namely object detection, face detection and pedestrian detection, can be accomplished. Authors accomplished this by combing two things: Object detection with deep learning and OpenCV and Efficient, threaded video streams with OpenCV. The camera sensor noise and lightening condition can change the result as it can create problem in recognizing the object. The end result will be a deep learning-based object detector system which will detect whether the person wear the mask or not.

VI. FUTURE SCOPE

Human recognition with face mask has various applications in different domains. The various methodologies discussed in this paper can be based on the particular demands of the application. As every approach has its very own pros and cons we need to determine the best approach according to the necessity. Face detection is gaining the interest of marketers. It can be used at various domains like airports where this system can be of great importance at airports to detect travellers whether they are wearing mask or not. Travellers data can be captured as videos in the system at the entrance. Hospitals – This system can be integrated with CCTV cameras and that data may be administered to see if their staff is wearing mask or not. Offices – This system can help in maintaining safety standards to prevent the spread of Covid- 19, to detect whether the person is wearing mask or not. The scope of this system extends to security systems of wide range right from Malls, hospitals, IT companies and in many such public areas.

Finally, the work opens interesting future directions for researchers. Firstly, the proposed technique can be integrated into any high-resolution video surveillance devices and not limited to mask detection only. Secondly, the model can be extended to detect facial landmarks with a facemask for biometric purposes.

REFERENCES

- [1]. P. A. Rota, M. S. Oberste, S. S. Monroe, W. A. Nix, R. Campagnoli, J. P. Icenogle, S. Penaranda, B. Bankamp, K. Maher, M. Chenet et al., “Characterization of a novel coronavirus associated with severe acute respiratory syndrome,” *science*, vol. 300, no. 5624, pp. 1394–1399, 2003.
- [2]. Z. A. Memish, A. I. Zumla, R. F. Al-Hakeem, A. A. AlRabeeah, and G. M. Stephens, “Family cluster of middle east respiratory syndrome coronavirus infections,” *New England Journal of Medicine*, vol. 368, no. 26, pp. 2487–2494, 2013.
- [3]. Y. Liu, A. A. Gayle, A. Wilder-Smith, and J. Rocklöv, “The reproductive number of covid-19 is higher compared to sar coronavirus,” *Journal of travel medicine*, 2020.
- [4]. Y. Fang, Y. Nie, and M. Penny, “Transmission dynamics of the covid-19 outbreak and effectiveness of government interventions: A data driven analysis,” *Journal of medical virology*, vol. 92, no. 6, pp. 645–659, 2020.
- [5]. N. H. Leung, D. K. Chu, E. Y. Shiu, K.-H. Chan, J. J. McDevitt, B. J. Hau, H.-L. Yen, Y. Li, D. K. M., J. Ip et al., “Respiratory virus shedding in exhaled breath and efficacy of face masks.”

- [6]. S. Feng, C. Shen, N. Xia, W. Song, M. Fan, and B. J. Cowling, “Rational use of face masks in the covid19pandemic,”*The Lancet Respiratory Medicine*, 2020.
- [7]. Z. Wang, G. Wang, B. Huang, Z. Xiong, Q. Hong, H. Wu, P. Yi, K. Jiang, N. Wang, Y. Peiet al., “Masked facerecognition dataset and application,”*arXiv preprint arXiv:2003.09093*, 2020.
- [8]. Z.-Q. Zhao, P. Zheng, S.-t. Xu, and X. Wu, “Object detection with deep learning: A review,”*IEEE transactions on neural networks and learning systems*, vol. 30, no. 11, pp. 3212–3232, 2019.
- [9]. A. Kumar, A. Kaur, and M. Kumar, “Face detection techniques: a review,”*ArtificialIntelligenceReview*, vol. 52,no. 2, pp. 927–948, 2019.D.-H. Lee, K.-L. Chen, K.-H. Liou, C.-L. Liu, and J.-L. Liu, “Deep learning and control algorithms of direct perception for autonomous driving,2019
- [10]. Huaizheng Zhang, Han Hu, GuanyuGao, Yonggang Wen, Kyle Guan, “Deepqoe: A Unified Framework for Learning to Predict Video QoE”, *Multimedia and Expo (ICME) 2018 IEEE International Conference on*, pp. 1- 6, 2018.
- [11]. B. QIN and D. Li, Identifying facemask-wearing condition using image super-resolution with classification network to prevent COVID-19, May 2020, doi: 10.21203/rs.3.rs-28668/v1.
- [12]. M.S. Ejaz, M.R. Islam, M. Sifatullah, A. SarkerImplementation of principal component analysis on masked and non-masked face recognition 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT) (2019), pp. 15, 10.1109/ICASERT.2019.8934543
- [13]. Jeong-Seon Park, You Hwa Oh, Sang ChulAhn, and Seong-Whan Lee, Glasses removal from facial image using recursive error compensation, *IEEE Trans. Pattern Anal. Mach. Intell.* 27 (5) (2005) 805–811, doi: 10.1109/TPAMI.2005.103.
- [14]. C. Li, R. Wang, J. Li, L. Fei, Face detection based on YOLOv3, in:: *Recent Trends in Intelligent Computing, Communication and Devices*, Singapore, 2020, pp. 277–284, doi: 10.1007/978-981-13-9406-5_34.
- [15]. N. Ud Din, K. Javed, S. Bae, J. YiA novel GAN-based network for unmasking of masked face *IEEE Access*, 8 (2020), pp. 4427644287, 10.1109/ACCESS.2020.2977386
- [16]. A. Nieto-Rodríguez, M. Mucientes, V.M. BreaSystem for medical mask detection in the operating room through facial attributes *Pattern Recogn. Image Anal. Cham* (2015), pp. 138-145, 10.1007/978-3-319-19390-8_16
- [17]. S. A. Hussain, A.S.A.A. Balushi, A real time face emotion classification and recognition using deep learning model, *J. Phys.: Conf. Ser.* 1432 (2020) 012087, doi: 10.1088/1742-6596/1432/1/012087.
- [18]. Sammy v. militante,Nanettev.dionisioReal time face mask recognition with alarm system using deep learning 2020 11th IEEE control and system graduate research colloquiu