JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 07 Issue 01
2024
Research Article
https://doi.org/10.56979/701/2024

Alleviating the Risk of COVID-19: A Social Healthcare Face Mask Detection System Based on Deep Learning Techniques

Moosa Khan[1*], Muhammad Bilal Sharif[2], Muzammil Ahmad Khan[3], and Bilal Ahmed[4]

[1]Department of Computer Science, Govt. Degree College Lal Qilla Maidan Dir Lower, Pakistan.
[2]Department of Computer Science, University of Lahore, Pakistan.
[3]Department of Computer Engineering, Sir Syed University of Engineering and Technology, Karachi, Pakistan.
[4]Department of Software Engineering, University of Lahore, Pakistan.
*Corresponding Author: Moosa Khan. Email: kmoosa523@gmail.com

Received: January 11, 2024 **Accepted:** May 12, 2024 **Published:** June 01, 2024

Abstract: The purpose of a facemask detection-system is to ascertain in real-time whether or not an individual is wearing a face mask using an automated process. It commonly entails the utilization of Machine-Learning (ML), Deep-Learning (DL), and Computer-Vision (CV) approaches to examine images or video streams collected by cameras. The ability of the technology to distinguish between those wearing face masks and those who do not helps in the implementation of mask-wearing laws in a variety of settings, such as schools, hospitals, airports, and public transportation. One tactic being suggested to contain the spread is the wearing of face masks by persons in public areas. As a result, computerized face detection methods that are both successful and efficient are essential for such requirements. This article aims to design and implement an intelligent system that can detect faces that have been masked to mitigate the risk of COVID-19. MobileNetV2 makes integrating the system into devices with limited processing power easy. The photos are divided into two groups by this model: "with mask" and "without mask." During the model's development, it is trained and evaluated using a dataset of around 6,369 photos. The pre-trained MobileNetV2 model tha t we employed for this research achieved a 98.20% accuracy rate in terms of performance. Compared to VGG-16 and Inception-V3, the proposed system outperforms them in terms of its computational efficiency and accuracy. This work can be used as a digital verification tool in hospitals, colleges, banks, airports, and other public areas. This system can potentially improve public safety efforts and aid in preventing the spread of infectious diseases.

Keywords: Deep Learning; CNN; Real-Time Face Mask Detection; OpenC; MobileNetV2; COVID-19.

1. Introduction

A novel CORONAVIRUS-2019 called severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) emerged and rapidly spread worldwide. Millions have been infected, and as of October 31, 2022, approximately 6,593,789 have tragically died. Due to the epidemic's quick spread around the globe caused by COVID-19, people's regular lives have been significantly affected [1]. COVID-19, a new coronavirus that causes a respiratory illness, can also be spread by close physical contact with an infected person. According to the available evidence, SARS-CoV-2 is transmitted from person to person through saliva, respiratory secretions, or droplets expelled from the mouth and nose of infected patients, as well as through direct contact (with contaminated objects or surfaces). When a sick person talks, sings, or coughs, mucus, and other secretions are ejected from the lips and nose. Droplets can infect someone less than 1 meter away from an infected person if they enter their mouth, nose, or eyes [2]. By sneezing, coughing, or touching surfaces (tables, handrails, railings), sick individuals can transfer infectious droplets to objects and surfaces (called fomites). After touching these objects or surfaces, unwashed hands might infect others [3]. To stop the epidemic, people must always wear face masks [4]. Mask must be worn indoors outside of private residences as well as in all outdoor locations unless the nature of the area or the facts require permanent isolation [5]. An infected person can spread the virus to others by saliva, respiratory droplets, and nasal droplets discharged into the air when they cough, sneeze, or breathe out. To prevent the spread of these diseases, it's recommended that people maintain distance from one another and wear face masks. To achieve efficient and successful computer vision strategies, the goal is to develop a real-time application that can detect and track people in public, regardless of whether they're wearing face masks.

Computer-Vision technology and image processing have played a significant role in the development of face mask detection applications, ranging from facial recognition to facial motions that require precise facial movements to depict a face [6]. The correct method to wear a mask, according to the World Health Organization (WHO), is to adjust the mask so that it covers the mouth, nose, and chin [7]. If masks are not correctly fitted, they provide much less protection. Currently, a security officer is present in public areas to remind individuals to wear masks. It's important to find a solution that doesn't put guardians at risk or create overcrowding. We need a method that is both quick and effective. Computer vision is a subject that covers many different areas of study concerned with how computers acquire sophisticated information from digital images or recordings [8]. Masks have survived many pandemics. In addition, numerous studies have demonstrated that not only wearing masks but also wearing them correctly greatly reduces the spread of the virus. The discovery that the number of COVID-19 cases is correlated with the percentage of a country's population that is seen to be wearing face masks was the impetus behind the creation of an automatic face mask detector. In addition, the coronavirus pandemic has prompted a worldwide appeal for scientific assistance in the fight against the pandemic. Utilize modern technological advancements. Several solutions have been developed to prevent the spread of the pathogen [9].

The global COVID19 coronavirus epidemic has led to a rise in the popularity of mask use in public. Even before the arrival of Covid-19, people had to take precautions against air pollution by wearing masks. Unlike others who worry about how they look, these people aren't afraid to show their feelings, but they hide them by hiding their faces. It demonstrated that wearing a mask significantly reduces the likelihood of contracting COVID-19 [10]. To combat the spread of the highly contagious coronavirus, various preventative measures have been implemented. Among these measures are the basic practices of frequently washing one's hands, maintaining a safe physical distance from others, and avoiding touching one's face, particularly the eyes, nose, and mouth. However, a face mask is the most simple and effective preventative measure. Despite the clear benefits of wearing a face mask, many individuals need to adhere to this practice, leading to increased cases of COVID-19. Therefore, it may be necessary to identify and report those who refuse to comply with this important preventative measure. One method developed for this purpose is face mask detection, which involves identifying whether an individual is wearing a mask or not. This technique is similar to the object detection systems used in various other fields, and often involves the use of deep learning techniques. In conclusion, while various preventative measures can be taken to limit the spread of COVID-19, the use of a face mask is a simple and effective method that all individuals should embrace. By adhering to this practice and reporting those who refuse to comply, we can work together to limit the spread of this deadly virus and protect the health and safety of our communities [11-12].

To mitigate the risk of COVID-19, this article proposed a system that involves the creation of a classification model that can identify masks in facial images with a high degree of accuracy. If successfully developed, this technology could revolutionize our efforts to curb the spread of the virus. The proposed approach accurately and quickly detects face masks. The trained model is over 98.20% accurate. The model improves processing speed and precision. Due to its precision and computing efficiency, this approach could be used for real-time monitoring systems. This work can be used as a digital verification tool in hospitals, colleges, banks, airports, and other public areas. This project aims to develop a system that can accurately detect faces and determine whether individuals are wearing masks. To achieve this, we leverage the power of OpenCV, Keras/TensorFlow, and Deep Learning. Through real-time video and still image analysis, the proposed face mask recognition technology can swiftly and accurately identify the presence of face masks. This system can potentially improve public safety efforts and aid in preventing the spread of infectious diseases.

2. Literature Review

The research by [13] outlines a technique that distinguishes between people who are and are not wearing masks using “TensorFlow” and “OpenCV”. Using a bounding box to scan the subject's face, the approach determines whether or not the subject is wearing a face mask. It can recognize someone who is not wearing a mask and send them an email telling them to take the appropriate safety measures if their face is already registered in the system's database. To protect people's security and privacy, this only occurs if the person's face is already in the database. One important aspect of the method described in [14] is its ability to identify, in both static images and real-time video, if a human face is covered by a mask. Deep Learning (DL) was used to construct a face identification model. Object detection uses the Single Shot Detector (SSD) architecture because of its high-performance accuracy and efficiency. They have also used key ideas from transfer learning to train neural networks to identify whether or not a face mask is present in an image or video. The experimental results indicate that their model achieved perfect accuracy and nearly perfect performance on the test data.

[15] Provide an approach that used a three-way categorization based on whether or not a mask was worn appropriately and if it was there at all. The basis for this categorization is whether or not a mask is worn. They achieved a 98.6% accuracy rate with their Facemasknet DL method. Real-time processing of both still images and moving videos is possible with the Facemasknet. It is improper to wear a mask while one's lips and nose are visible. The suggested approach may reliably determine whether someone is mask-wearing to make sure he doesn't represent a threat to others by using CCTV video.

[16] Introduced a simplified approach that makes use of TensorFlow, Keras, “Open-CV”, and “Scikit-Learn”. The proposed method correctly identifies faces in photos and determines whether or not they are hidden. Masks and faces are tracked by it. Using two different datasets, the method obtains accuracy rates of 95.77% and 94.58%, respectively. There are 1376 images in Dataset 1, 690 of which feature people wearing masks and 686 of which do not. For clarity, faces in dataset 2 consist of 853 photos with either masks on or off. The suggested approach investigated optimal parameter values inside a sequential convolutional neural network model to accurately identify mask existence without overfitting.

DL approaches were employed by [17] in a recent work to precisely detect faces and facemasks. With a 224x224 pixel object resolution over a sample of 25,000 photos, their trained model demonstrated an astounding 96% accuracy rate. This project intends to reduce physical contact in public settings and lessen the transmission of sickness by utilizing such technologies.

In [18] the authors proposed a method for detecting whether or not a person is wearing a face mask. This is accomplished using image processing and DL. Python libraries such as Open CV, Tensor flow, and Keras are utilized. The model was evaluated using both images and a live video transmission. MobileNetV2 is the architecture utilized for the proposed endeavor, and it provides nearly 97% accuracy. [19] Presented the design, implementation, and performance evaluation of a real-time image sequence mask recognition system. A generic object detection network is used to train a detector of faces with and without masks with above 90% accuracy. A network with more parameters but longer calculation time can improve accuracy. Capturing a video sequence of people with and without facemasks in various contexts validates the detector. To improve real-time face mask identification, the authors of [20] collected mages that were used with and without filtering. The suggested method used a pre-trained convolutional neural network, MobileNetV2. The suggested model achieved a 98.95% detection rate for face masks. The method was effective even when the mask was held at an angle, and it employed an optimization function that combined learning loops and optimization procedures. [1] Developed a face mask detection model that can differentiate between "with mask" and "without mask" in static images and real-time videos. The Kaggle dataset is used for training and the evaluation of the model. In addition to reaching an accuracy rate that is 98%, the compiled dataset comprises of roughly 4,000 images.

In contrast with different models, the model that was developed is both accurate and efficient in terms of processing resources. This technology can be used as a digital examining device in schools, clinics, institutions, airport terminals, and a variety of other public or commercial spaces. [21] Present a method which automatically detects face masks and warns authorities. This solution leverages PC Vision and MobileNetV2 to help people wear masks and prevent Coronavirus transmission. Their research helps law enforcement determine if a suspect is wearing a mask and provides the victim's photo if not. This project uses the MobileNetV2 model and 3,918 mask-free and mask-wearing photos. Train stations, shopping complexes, companies, colleges, and airports can use the suggested system. The authors [22] presented A system that can observe if the necessary medical respirator is in the workplace or not. The objective is to minimize false positives when identifying faces with masks, while still being able to recognize the presence of a mask. The system will send alerts to medical staff who do not wear surgical masks. For identifying medical masks, two face signs are used: one for the person's face and one for the mask. The suggested model can find faces and surgical masks more than 95% of the time and gives false positives less than 5% of the time. [23] Proposed a model with two modules. The first module is designed to extract features using the ResNet-50 deep transfer model. The second module applies YOLO v2 to the detection of medical face masks. In this study, the system will examine a newly combined dataset consisting of two previously separate collections of medical facial mask images. The average IoU was employed as a proxy for the ideal number of anchor frames for object detection. The data shows that the Adam optimizer achieved the best overall detection accuracy, 81%, of any tested method.

2.1. Relevant Technologies

This section discusses some relevant technologies such as ML, DL, supervised learning, unsupervised learning and reinforcement learning.

2.1.1. Machine-Learning (ML)

Artificial Intelligence is linked with Machine learning approaches as subfield that involves training a model for prediction results. This technique uses algorithms to examine and understand big data interpretation, which leads to improve the accuracy and performance of the system [24].

2.1.2. Supervised learning

Machines predict output using labeled training data. Labeled data is input data that has been labeled with the appropriate label. In supervised learning, training data helps machines predict output appropriately. It uses the same concept students learn from teachers [25].

2.1.3. Unsupervised learning

It is the process of discovering latent patterns in unlabeled data using ML. Models trained on unlabeled data sets can behave autonomously [26]

2.1.4. Reinforcement Learning (RL)

RL is a type of ML that operates on the principle of feedback. It involves an agent interacting with a given environment by performing certain actions and receiving feedback about the outcomes of those actions. Over time, the agent learns how to make decisions that lead to desirable outcomes and avoid those that lead to negative ones. This process is continuous and iterative, with the agent refining its decision-making abilities through trial and error. Every good activity is rewarded and every bad action is punished. Reinforcement learning is unsupervised and uses feedback without labeled data. Without labeled data, the agent learns by experience [27].

2.1.5. Deep Learning (DL)

DL is a branch of artificial intelligence that falls under the umbrella of ML. It uses algorithms that are based on how the human brain is built and how it works to give computers understanding. Using DL, the computer model learns to classify things just by looking at pictures, reading text, or listening to sounds. Models that use DL can achieve the best level of accuracy and sometimes even do better than humans. Data science, which includes such disciplines as statistics and predictive modeling, uses DL. Data scientists can collect, analyze, and interpret huge amounts of data much more quickly and easily with the help of DL. Autonomous vehicles rely heavily on DL so that they can recognize and respond appropriately to traffic signals. This function enables voice command of electronic devices (such as smartphones, tablets, TVs, and wireless speakers) [28].

2.1.6. Convolutional neural network (CNN)

CNN is a type of deep neural network inspired by biological processes [29] with the help of a back-propagation algorithm. CNN can instantly and adaptively learn spatial hierarchies of features. CNN's shared kernels across all picture positions make it extremely efficient with its parameters. For these reasons, CNN is the best option for computer vision applications. DL technology has flourished with the vast increase in GPU computing capacity in recent years [30].

2.1.7. Pre-trained Model

A pre-trained model is one that has already been developed. Instead of starting from scratch to construct and train a model. Although pre-trained models rarely achieve perfect accuracy, they significantly reduce development time [31].

2.1.8. MobileNetV2 Algorithm

The MobileNet architecture requires very little processing capacity to function. This algorithm is more suitable for CPUs, embedded systems, and mobile devices that do not need a graphics processing unit. The first official version of MobileNet models is called MobilenetV1. The most recent version of the MobileNet model is called MobilenetV2. Deep neural networks have significantly fewer parameters than conventional neural networks. This facilitates the development of DL networks. It is suitable for embedded systems and mobile devices due to its low weight. MobilenetV2 is the upgraded version of Mobilenet1 which has increased its efficiency. Due to the importance of face mask identification in public places, the proposed study used MobileNetV2, a popular DL-based architecture, for effective face mask detection [32].

3. Materials and Methods

This section provides an extensive overview of the methodology used to predict whether a person has worn a mask. This prediction is crucial in preventing the spread of COVID19. To ensure that the model is accurate and effective, a well-curated dataset downloaded from Kaggle is utilized. The model is constructed using the MobileNetV2 algorithm in combination with OpenCV, Keras, and TensorFlow libraries. The construction of the model involved following steps.

- Data Collection
- Data Preprocessing
- Model Training
- Model Deployment.

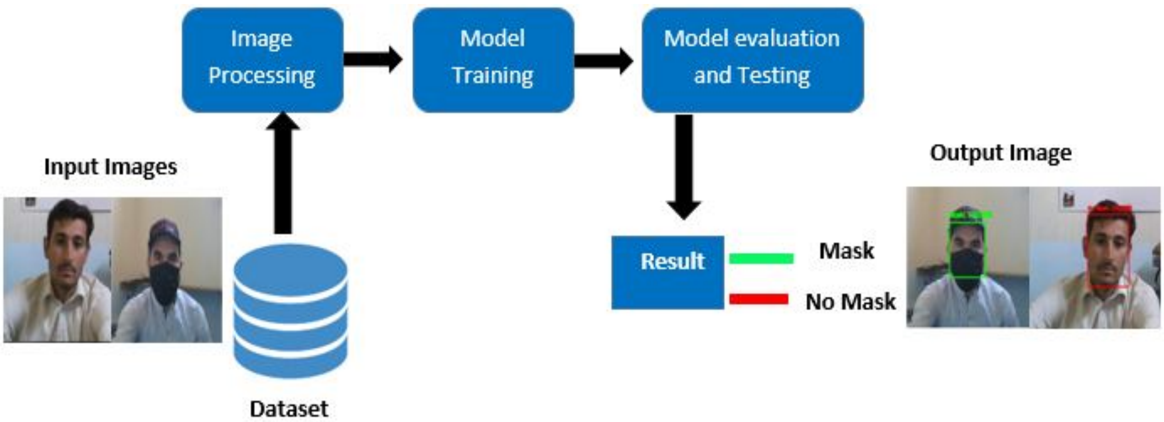

Figure 1. Proposed System

3.1. Data Collection

The first step is data collection to develop an accurate face mask detection model. For this system, the dataset is downloaded from Kaggle (34) the dataset includes a total of 6369 Images, with 3458 of them depicting individuals wearing face masks and the remaining 2911 images showing individuals without masks. To better organize the data, the dataset is separated into two into two distinct groups, one containing images of individuals wearing masks and the other of individuals not wearing masks, as shown in figures 2 and 3.

Figure 2. with mask images

Figure 3. Without mask images

3.2. Data Preprocessing

The reliability of the m ML model is heavily influenced by the dataset it is trained on. Tonsure the best possible results; the dataset undergoes a thorough data cleansing process to eliminate any bad images. Additionally, the images are scaled down to 96x96 pixels to reduce the computational load while producing accurate results. As seen in Figure 4, the labeled images are separated into two groups: with masks and without. The image array is converted into a Numpy array for effective computing following the labeling process. The preprocessing input capability of MobileNetV2 is also employed to enhance the generated dataset's optimization. After that, data augmentation methods are used to expand and improve the dataset. Using a data generator, combined with rotation, magnification, horizontal flip, and vertical flip, creates various versions of the same image. This procedure improves the model's capacity for precise prediction-making and helps to avoid over fitting. To ensure the dataset is thoroughly tested, a random selection of images from the entire dataset is used to create a training and test datasets in an 8:2 ratio. With the use of the stratify parameter, the total number of records in the training and deployment datasets is kept constant. This process improves the model's accuracy and ensures it can make reliable predictions.

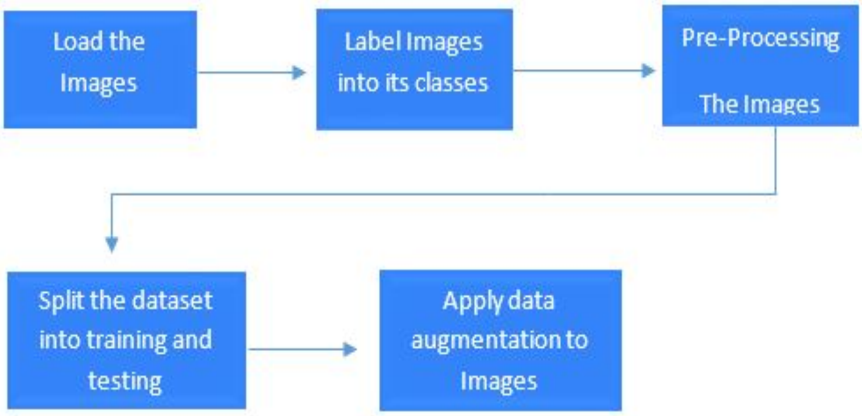

Figure 4. Data Pre-Processing

3.3. Data Augmentation

Data augmentation is a method for artificially increasing the diversity of training datasets. The effectiveness of the model's training is enhanced as additional data is included. MobileNetV2 training requires a vast number of data to be conducted properly. Since there isn't enough information to train the proposed model, data augmentation is used to tackle this problem. This method creates variations of an image by manipulating it in various ways, such as rotating, zooming, and flipping it horizontally and vertically. The suggested approach employs an image-based data augmentation process. To improve images, a particular image. Data Generator function is developed, which provides both test and train datasets.

3.4. Model Training

The proposed model is trained in this step. Training a DL model requires a significant investment of time and computing power. The success of the procedure significantly depends on the quality of training a labelled dataset is used for this task which included information like the percentage of people wearing masks. Figure 5 depicts how the dataset is initially imported, trained the model, and then saved it as "custom_4000_32_100.h5".

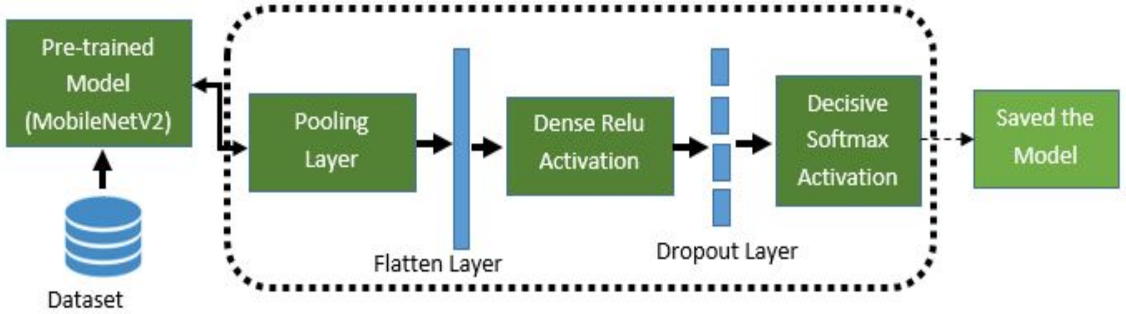

Figure 5. Model Training

3.5. Model Deployment

This is the final phase depicted in figure 6, in which the trained model is tested in two different ways: first with video and then with images. On video, the system will ascertain the presence or absence of a facial mask on an individual. This operation is accomplished using a laptop's camera; the system is able to detect a face mask. In the case of images, the image path is provided and then execute the model to detect face mask. Open CV is used for this process.

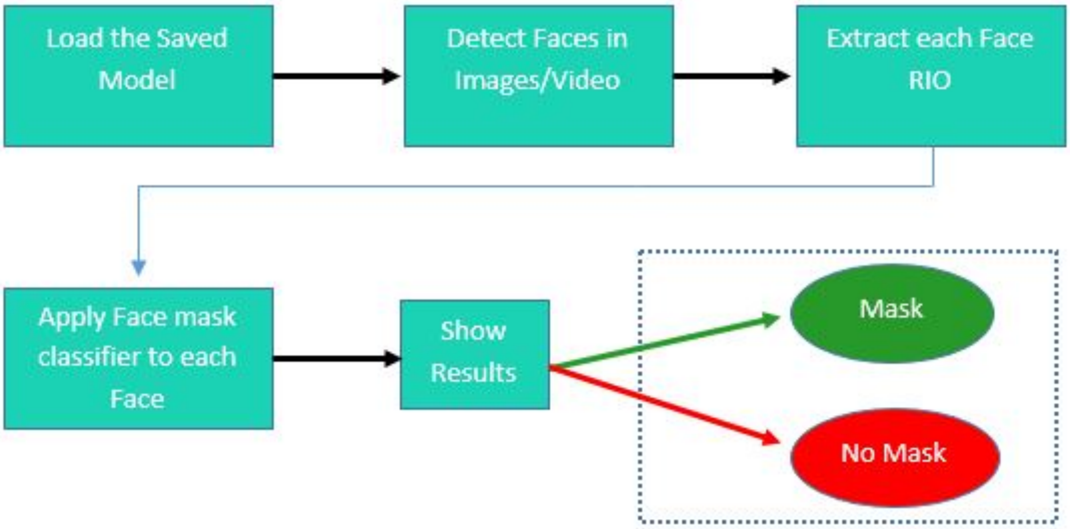

Figure 6. Model Deployment

3.6. Proposed Model Implementation

In the proposed project, the Python programming language is used to prepare, evaluate, and test the proposed model MobileNetV2. The image set is subjected to a series of preprocessing steps, data augmentation, and subsequent training with the pre-trained algorithm MobileNetV2. Jupyternote book is utilized for the operation of the model. The Batch Size, Learning Rate, Optimizer, and Epochs are listed in Table 1.

4. Experimental Results

In this section, the proposed model's results are discussed. The proposed model performs adequately with both static images and real-time videos. The model accurately categorized both mask-wearing and mask-less individuals. Figure 8 shows the results of the proposed system. In the provided illustration, there are two people. One of them did not wear a face covering, while the other did, demonstrating that the proposed model produces accurate results. The developed model has classified individuals who wore or did not wear face masks. Several experiments utilizing various hyper-parameter values, including epoch size, learning rate, and group size, the final outcomes presented in Table 1.

Table 1. Parameters of MobilenetV2

Parameter	Model	Batch Size	Epochs	Learning Rate	Optimizer	Loss Function
Detail	MobileNetV2	32	85	0.0005	Adam	Binary-crossentropy

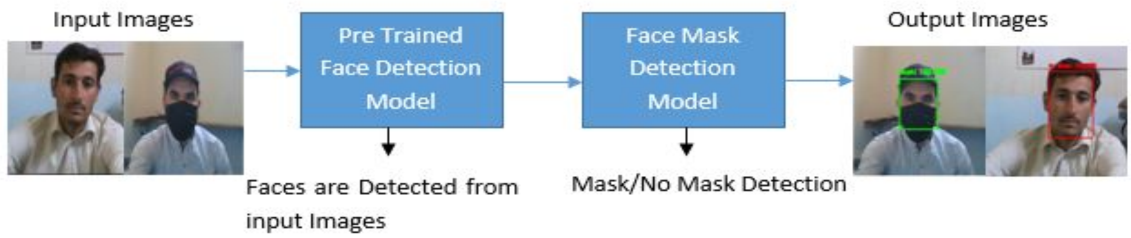

Figure 7. Face Mask Model Implementation Diagram

Table 2. The Report on Classification

	Precision	Recall	F1-score	Support
Macro avg	0.98%	0.98%	0.98%	1272
Weighted avg	0.98%	0.98%	0.98%	1272
without mask	0.96%	0.99%	0.98%	583
with mask	0.99%	0.97%	0.98%	689
Accuracy			98.20%	1272

Precision: measurement of data that how many positive forecasts are correct (true positive).
Recall is a metric that measuring how many +ve-positive-cases the classifier accurately predicted out of all the positive-cases in the dataset.
F1 score is a measure that integrates both precision and recall.
The formula for Precision, Recall, F1-Score and Accuracy is given below.
Evaluation of the model through variety of metrics, including Accuracy-measurement, Precision-results, Recall, and F1 score.

In this particular context, the abbreviations TP, TN, FP, and FN pertain to different classifications that are used in predictive models. When a model predicts that a particular instance belongs to a positive class and it is actually true, this is referred to as a true positive (TP). On the other hand, when a model predicts that an instance belongs to a positive class but it is actually false, this is called a false positive (FP). Similarly, when a model predicts that an instance belongs to a negative class and it is indeed true, this is referred to as a true negative (TN). Conversely, when a model predicts that an instance belongs to a negative class but it is actually false, this is called a false negative (FN). In summary, true positives and true negatives are correct predictions, while false positives and false negatives are incorrect predictions.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = TP/(TP+FN) \quad (2)$$

$$\text{F1-Score.} = \frac{2*(Precicsion*Recall}{Precision+Recall} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

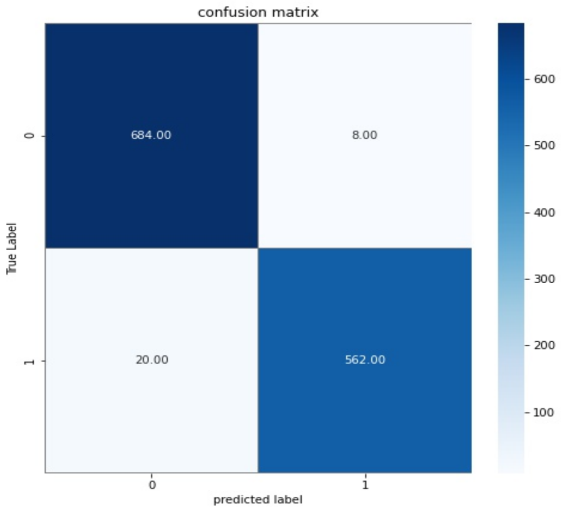

Figure 8. Confusion metric

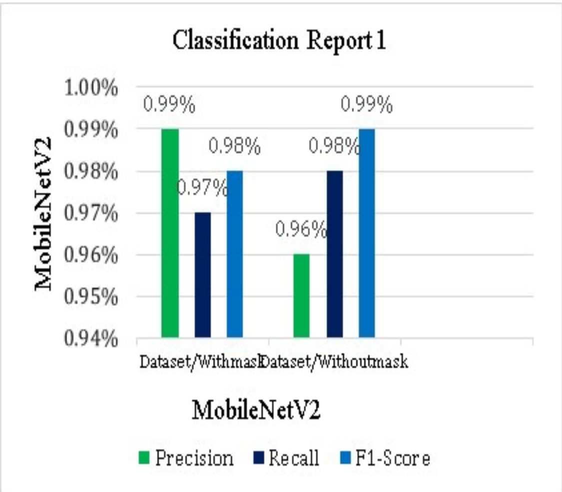

Figure 9. Classification report 1

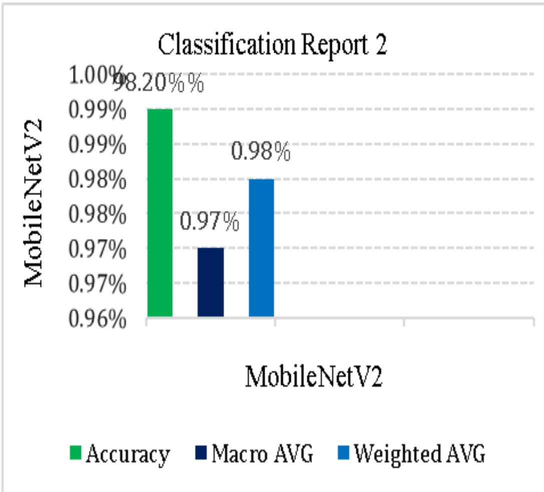

Figure 10. Classification report 2

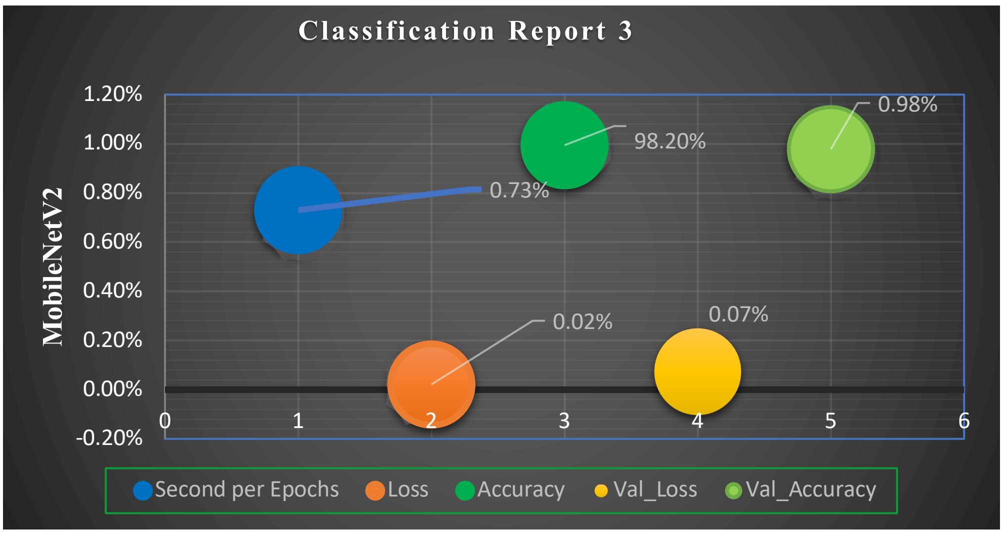

Figure 11. Classification report 3

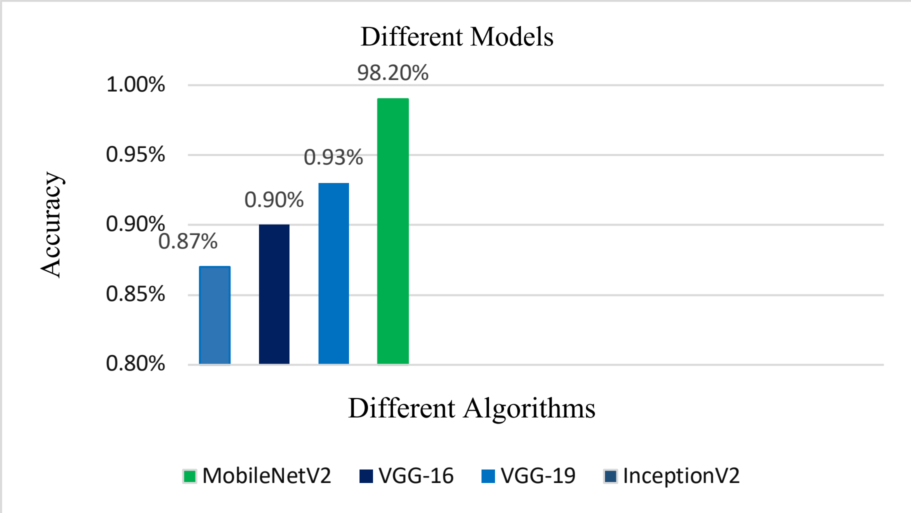

Figure 12. Different models

The proposed model accurately identifies masked individuals, establishing a high standard for prediction. In Fig. 13, which depicts the training accuracy, the model labored to acquire features until 40 epochs, after which the curve stabilized. After 85 epochs, the precision exceeded 98%. The green line in the graph shows the accuracy during training, whereas the blue line shows the accuracy during validation. Figure 14 also shows the loss curves in training and validation. After 85 epochs, the green line in the graph denotes a loss in the training set of less than 0.1, while the blue line in the figure reflects a loss in the validation set of less than 0.2.

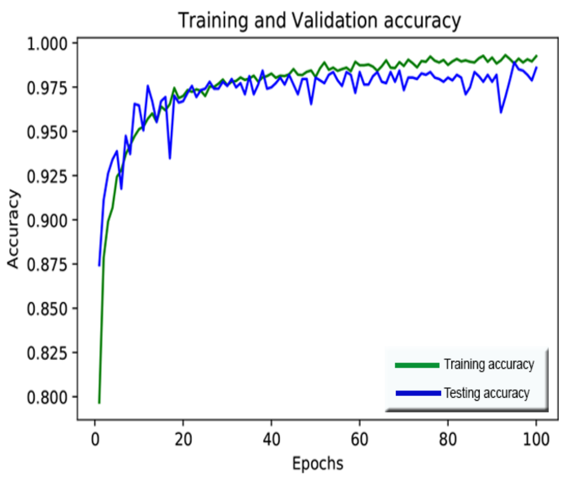

Figure 13. Accuracy results

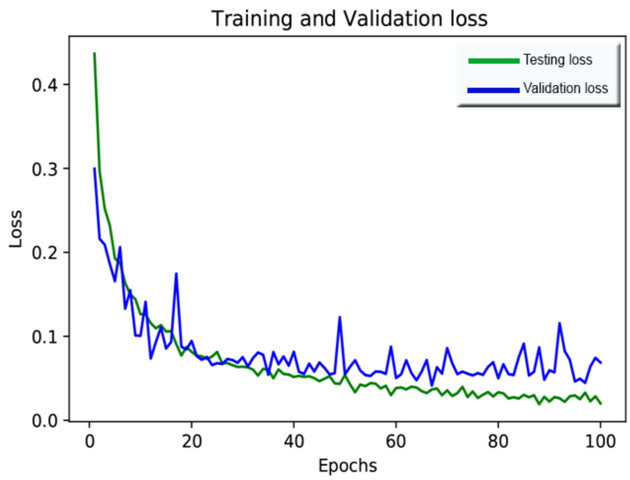

Figure 14. Results of test lost during model training

4.1. Model Testing

During this stage, the proposed model was evaluated on a variety of images, some of which are illustrated in Figures 15 and 16. It is worth noting that the model's performance is visually displayed through rectangular boxes in green and red colors. A green rectangular box is used to indicate that the individual in the image is correctly wearing a mask, while a red rectangular box is used to indicate that the individual is not wearing a mask. It is important to mention that the model's classifications are based on the training dataset, and these classifications are then utilized to make accurate predictions.

Figure 15. The output generated by the suggested model in the absence of a mask

Figure 16. The output generated by the suggested model in the presence of a mask

5. Conclusion

In this study, we designed and developed a "face-mask" identification system for virtual reality or real time videos and static photos that can automatically determine if a person is putting a mask or not on face. The system would work with both types of images. Keras, OpenCV, TensorFlow, and MobileNetV2 are the technologies that enable the proposed system to determine whether or not a "face-mask" is present; the model generates accurate and quick results. Greater than 98.20% accuracy can be achieved with the trained model. We compared the proposed model to other DL models the results showed that the proposed model was superior to Inception-V3 and VGG-16 VGG-19 in terms of the amount of time it took to process the data and accuracy. Due to its accuracy and computational efficiency, this approach is a leading candidate for a real-time monitoring system.

6. Future Work

In the future, other state-of-the-art technologies, such as Explainable AI, can be implemented with this system.

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