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Face Mask Detection

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***Abstract*— The COVID-19 coronavirus pandemic is wreaking havoc on the world's health. The healthcare sector is in a state of disaster. Many precautionary steps have been taken to prevent the spread of this disease, including the usage of a mask, which is strongly recommended by the World Health Organization (WHO). In this paper, we used three deep learning methods for face mask detection, including Max pooling, Average pooling, and MobileNetV2 architecture, and showed the methods detection accuracy. A dataset containing 1845 images from various sources and 120 co-author pictures taken with a webcam and a mobile phone camera is used to train a deep learning architecture. The Max pooling achieved 96.49% training accuracy and validation accuracy is 98.67%. Besides, the Average pooling achieved 95.19% training accuracy and validation accuracy is 96.23%. MobileNetV2 architecture gained the highest accuracy 99.72% for training and 99.82% for validation.**

Keywords—face mask; max pooling; covid-19; average pooling; mask detection; MobileNetV2; CNN

I. Introduction

The term "novel coronavirus" refers to a modern type of coronavirus that has never been observed in humans before. Coronaviruses are a form of the virus that can trigger a variety of illnesses, from colds to life-threatening infections including Middle East Respiratory Syndrome to Severe Acute Respiratory Syndrome [1]. In December of this year, the first coronavirus- infected patient was discovered. COVID-19 has been a worldwide pandemic since that time [2]. Humans all around the world are in precarious conditions as a consequence of the pandemic. Every day, a huge amount of people become contaminated with the disease and suffer as a result of it. At the time of publication, almost 16,207,130 contaminated cases had been reported, with 648,513 dead [3]. This statistic is gradually growing. According to the World Health Organization (WHO), the most frequent signs of coronavirus are fever, dry cough, exhaustion, diarrhea, loss of taste, and smell [4]. Many researchers and developers are working with diseases for several years using machine learning and deep learning [5-9].

Jiang et al. [10] suggest Retina Facemask, a paradigm for detecting the face mask that combines it with a bridge entity elimination algorithm. The developed model includes a single- stage detector that uses a feature pyramid network to achieve slightly better precision and recall than the baseline result. To address the lack of datasets, they used a learning algorithm [11], well deep learning [12-16] methodology. Gupta et al. [17] suggested a model implement social distance utilizing smart communities and Intelligent Transportation Systems during the COVID-19 pandemic (ITS). Their model called for the installation of sensors in the city to monitor the movement of objects in real-time, as well as the development of a data-sharing network. Won Sonn and Lee [18] clarify how a smart city will aid in the control of coronavirus spread in South Korea. A time- space cartographer sped up the city's communication monitoring, which included patient movement, transaction background, mobile phone use, and cell phone position. CCTV cameras in residential building hallways have been monitored in real-time.

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In the paper [19-22], M. Loey et al. showed the performance of different machine learning algorithms in detecting face masks and various purposes. In this study, three datasets are used for feature extraction using ResNet50. For the classification process, the decision tree algorithm, support vector machine, and ensemble algorithms are used that gave high detection accuracy on each dataset.

The main objective of the paper [23] is to detect a person without a face mask and informing the authority to reduce the spread of COVID-19. The image used in the process is captured by CCTV cameras. After preprocessing the data, feature extraction and classification are done using CNN. The trained model shows an accuracy of 98.7%. The authors in the paper [24] designed a binary face classifier to detect faces irrespective of their alignment. In detect masks in arbitrary size input image VGG – 16 Architecture is used for feature extraction [25]. In this work, Gradient Descent is used for training the dataset while Binomial Cross-Entropy is used as a loss function. M.S. Ejaz et al. in [26], has implemented PCA for masked and non-masked facial image detection. Viola-Jones algorithm is used in the paper to detect face portion and at the same time, PCA to compute Eigenface and the nearest neighbor (NN) classifier distance is used for face recognition.

The rest of the document is formatted in the same way. This sector consists of the most current developments in the field of facial mask detection. The analysis technique for designing the whole structure is outlined in Section II. Section III examines the outcomes of the framework that has been created. Section IV concludes with a hypothesis and shortcomings, as well as suggestions for future work.

II. Research Methodology

CNN are a kind of deep neural network which is typically used in deep learning to examine visual imagery. A CNN is a Deep Learning algorithm that would take an image as input, assign meaning to different parts of the image, and differentiate between them. Because of their high precision, CNNs are used for image detection [27] and identification. The CNN uses a hierarchical model that builds a network in the shape of a funnel and then outputs a fully-connected layer where all the neurons are connected to each other and the data is stored. Artificial Intelligence has made important strides in bridging the difference between human and computer capabilities. Researchers and enthusiasts alike operate in a number of facets of the area to produce impressive performance. The field of computer vision is one of several such fields. The goal of this area is to allow machines to see and understand the environment in the same way that humans do, and to use that information for picture and video identification, image interpretation and labeling, media recreation, recommendation systems, natural language processing, and other functions are only a few examples.

In this paper, we used three deep learning methods for face mask detection, including Max pooling, Average

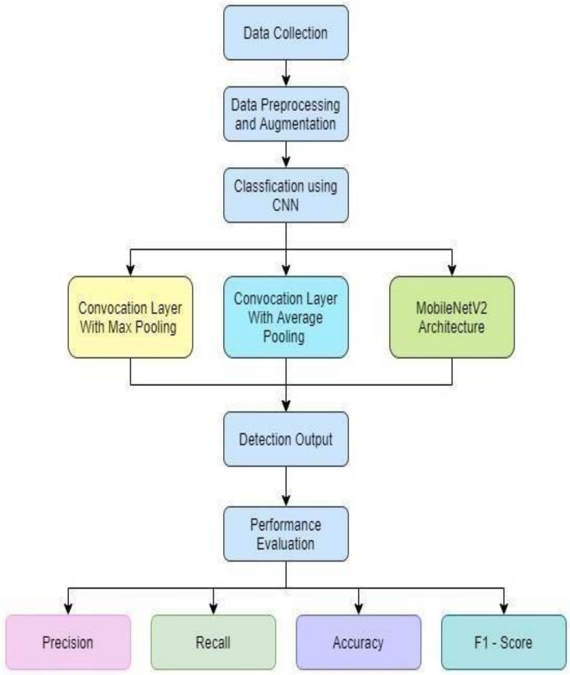

Fig. 1. Proposed model diagram.

A. Data Collection:

For mask detection, we used three different datasets with a total of 1340 photographs. Using mobile cameras, webcams, and CCTV video, another 120 photographs were taken. For detecting masks from video used CCTV footage and Webcam, both of the photos are in RGB. To avoid overfitting, we collected data from different datasets and generated our datasets, the Real-World Masked Face Dataset (RMFD) [28] and the Simulated Masked Face Dataset (SMFD) [29], which we used for training and testing purpose.

Fig. 2. Datasets images Samples.

B. Preprocessing and Augmentation of Data:

The images in the dataset are not all the same size, so preprocessing was required for this study. The training of deep learning models necessarily requires a large amount of data. We used Keras' Image Data Generator method to resize all of the images to 256 × 256 pixels. We normalized all images after converting them to 256 × 256. For faster calculation, images are converted to NumPy arrays. Increase the amount of data by rotating, zooming, shearing, and horizontal flipping. Images are gathered as well. The images are then resized to 128 x 128 for passing through the second convolution layer, and then to 64 x 64 for passing through the third convolution layer.

C. Proposed Convolution Neural Network(CNN) architecture:

For classification and image processing, CNN is used. CNN consists of one or more convolution layers. CNN aims to find features that are effective inside an image rather than working with an entire image. There are several secret layers in CNN, as well as an input layer and an output layer. In this research, we have applied deep CNN with 3 convolution layers. Convolution helps to get a new function by combining two mathematical functions. Max pooling is a discretization method dependent on samples. The aim is to reduce the complexity of an input representation, enabling decisions to be made regarding features found in the binned sub-regions. Our CNN model's working process with Max pooling is depicted in Fig. 3.

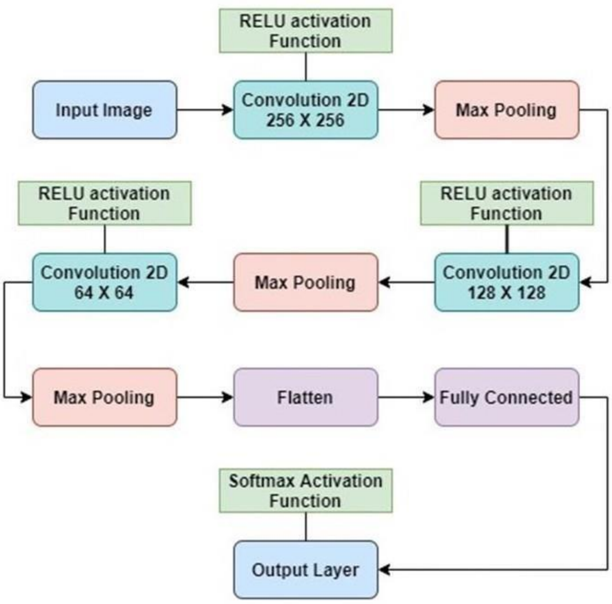

Fig. 3. Three Convolution Layer with Max pooling operation.

This time, the same architecture is used for function mapping, but with an average pooling process. The model's activity is shown in Fig. 4. Average pooling takes the average of all values within the picture matrix's area of interest, while Max pooling takes the largest amount within that region. Our CNN model initiates with Keras. Models. sequential (). In the first hidden layer, the Relu activation feature is used, preceded by the Max pooling process. Max pooling helps to gather significant information and reduces the size of the images. After that, the data is passed to the second convolution layer. Maximum pooling is used once more to obtain the most notable information. The obtained image matrix is then flattened and trained. After that, the image matrix is flattened and trained. Instead of using the Max pooling operation to observe the model's performance, we used the Average pooling operation. For more accurate training, Adam stochastic gradient descent algorithms were used. We use 80% of our dataset's images for training.

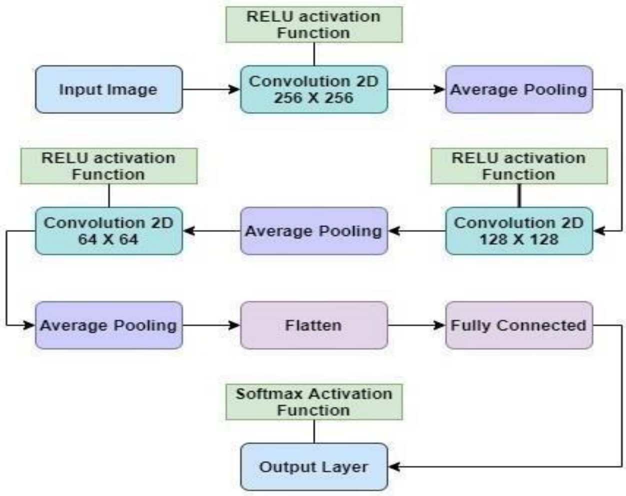

Fig. 4. Three Convolution Layer with Average pooling operation.

D. MobileNetV2 Architecture:

MobileNetV2 is a powerful image classification tool. TensorFlow provides the image weights in MobileNetV2, a lightweight CNN-based deep learning model. First, the MobileNetV2 base layer is removed, and a new trainable layer is added. The model analyzes the data and extracts the most relevant features from our images. There are 19 bottleneck layers in MobileNetV2 [30]. In the base model, we used OpenCV, which is based on the ResNet-10 architecture [30]. To detect the face and mask from an image and a video stream, OpenCV's Caffemodel is used. The mask detecting classifier receives the output face detected image. It allows for fasterand more accurate detection of masks in video streaming. In machine learning, overfitting is a major problem. The Dropout layer was used to ignore our model being overfitted with the dataset. Using MobileNetV2 (include top=False), we were able to get rid of the base layer. The pictures have been resized. The average pooling operation is used with a pool size of 128 hidden layers in our trainable model (7,7). In the secret layer, the Relu activation function is used, and in the entire linked layer, the SoftMax activation function is used. For better accuracy, we set a learning rate of 0.01. The Adam stochastic gradient descent algorithm aids in the model's comprehension of picture characteristics. MobileNetV2 working layer depicted in Fig. 5.

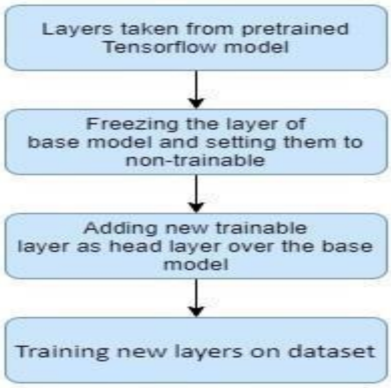

Fig. 5. MobileNetV2 Architecture.

E. Evaluating performance using performance matrix:

We measured the performance of two models using precision, recall, f1-score, and accuracy after completing the training and testing phase. The formulas that we used are as follows:

[illegible] (1)

[illegible] (2)

[illegible] (3)

[illegible] 1- [illegible] (4)

III. Experiment Result Analysis

We used two datasets to detect masks from images: 1845 images from various sources and 120 co-author's photos taken with a webcam and a mobile phone camera. The training and validation accuracy after using the Deep CNN [31] model with Max Pooling to reduce the dimension of our image feature map is shown in Table I. The highest accuracy is 96.49% in training data and 98.67% in validation data set.

TABLE I. Outcomes for Deep CNN after applying Max Pooling of different epochs

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	42.13%	89.76%	12.32%	90.73%
2	10.01%	91.87%	8.43%	94.34%
3	8.45%	93.97%	7.33%	96.10%
4	8.21%	94.53%	7.25%	96.25%
5	7.04%	94.98%	7.10%	97.03%
6	6.90%	95.12%	6.35%	97.23%
7	6.83%	95.24%	6.12%	97.54%
8	6.56%	95.65%	6.01%	97.71%
9	5.99%	95.89%	4.88%	97.92%
10	5.83%	96.07%	4.76%	98.12%
11	5.72%	96.45%	4.65%	98.36%
12	5.12%	96.48%	4.23%	98.43%
13	5.05%	96.49%	4.12%	98.67%

The training accuracy and validation accuracy graphs are shown in Fig. 6. Later on, the same CNN architecture is applied later where Average Pooling is used to reduce the dimensions of the feature map. Compared to the previous one, the expected outcome is less accurate. The estimated outcomes as seen in Table II, with a maximum training accuracy of 95.19% and a training loss of 5.92%, and a validation accuracy of 96.23%.

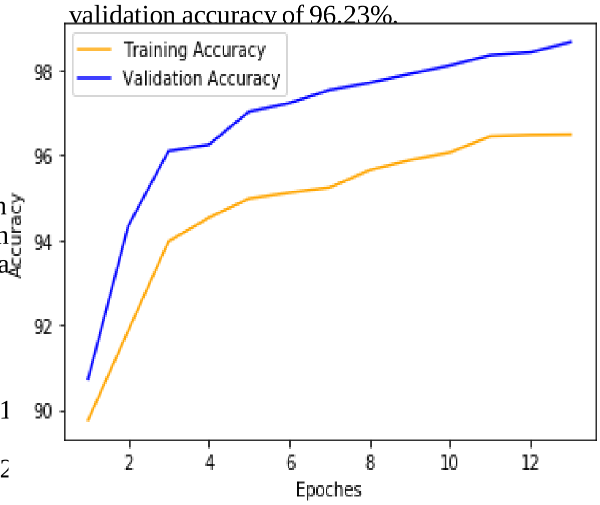

Fig. 6.Test Accuracy and Training Accuracy for CNN with Max Pooling Layer

TABLE II. Outcomes for Deep CNN after applying Average Pooling of different epochs

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	43.54%	88.92%	13.32%	89.95%
2	11.80%	90.21%	9.43%	90.12%
3	10.99%	90.85%	9.33%	91.01%
4	9.82%	91.06%	8.25%	91.52%
5	9.21%	91.24%	8.10%	93.25%
6	8.95%	92.37%	8.35%	93.54%
7	8.71%	92.69%	7.12%	94.21%
8	8.12%	94.01%	7.01%	94.39%
9	7.10%	94.29%	7.88%	95.11%
10	6.75%	94.65%	6.76%	95.15%
11	6.62%	94.82%	6.65%	95.20%
12	6.32%	95.12%	6.23%	96.12%
13	5.92%	95.19%	5.12%	96.23%

For each epoch, Fig. 7 depicts a graph of relative validation and training accuracy.

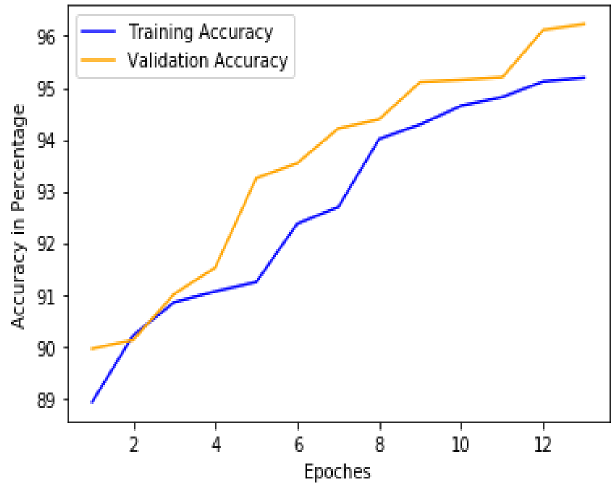

Fig. 7.Test Accuracy and Training Accuracy for CNN with Average Pooling Layer.

The accuracy improved significantly by using the MobileNetV2 architecture. For each epoch, Table III shows the validation and test accuracy.

TABLE III. DIFFERENT OUTCOMES AFTER APPLYING MOBILENETV2 ARCHITECTURE.

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	4.43%	98.67%	4.21%	98.71%
2	4.32%	98.72%	4.12%	98.81%
3	4.21%	98.81%	4.09%	98.92%
4	4.12%	98.92%	3.89%	99.10%
5	3.90%	98.99%	3.72%	99.13%
6	3.82%	99.01%	3.61%	99.25%
7	3.78%	99.13%	3.56%	99.32%
8	3.65%	99.24%	3.41%	99.37%
9	3.61%	99.32%	3.23%	99.47%
10	3.54%	99.51%	3.20%	99.65%
11	3.46%	99.63%	3.18%	99.82%
12	3.42%	99.72%	3.18%	99.82%
13	3.42%	99.72%	3.18%	99.82%

The best precision is 99.72% for training data and 99.82 percent for validity data, according to Table III. Just 3.18% of data lost during the validation process. Fig. 5 shows the detailed comparison of test accuracy and validation accuracy of MobilenetV2 which is a CNN-based architecture. After using the MobilenetV2 architecture, we measured the confusion matrix. The confusion matrix is correctly depicted in Fig. 8.

```
              precision    recall  f1-score

   with_mask       1.00      0.97      0.98
without_mask       0.97      1.00      0.98

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

Fig. 8.Confusion Matrix after applying MobilenetV2.

The MobilenetV2 design outperformed many of the other models included in this study. This model is capable of recognizing the mask in a picture. In Fig.9, 10, and 11 showing the detection result of MobileNetV2.

Fig. 9.Detection of No Mask from an image.

Fig. 10.Detection of Mask from an image.

MobilenetV2 can successfully identify the mask from video streams with proper accuracy.

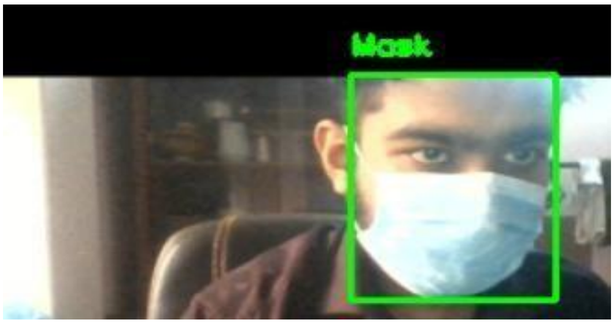

Fig. 11. Detection of the mask from video streams using MobilenetV2.

The Max pooling achieved 96.49% training accuracy and validation accuracy is 98.67%. Besides, the Average pooling achieved 95.19% training accuracy and validation accuracy is 96.23%. MobileNetV2 architecture gained the highest accuracy 99.72% for training and 99.82% for validation. A short explanation is added in Table IV.

TABLE IV. COMPARISON WITHIN THE CNN TECHNIQUES

	Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
Max Pooling	13	5.05%	96.49%	4.12%	98.67%
Average Pooling	13	5.92%	95.19%	5.12%	96.23%
MobileNetV2	13	3.42%	99.72%	3.18%	99.82%

IV. CONCLUSION AND FUTURE WORK

We used two deep CNN architectures and one CNN-based MobilenetV2 architecture in this study. Our primary objective was to propose a compatible model with high accuracy such that mask identification will be simple throughout the pandemic. In order to assess performance with a wider dataset, we can attempt to add further models to compare with Mobilenetv2 and tried to integrate this model with IoT [32-35] to detect humans without masks automatically.

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