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PREVENT OF CORONAVIRUS DISEASES WITH HELP OF FACE MASK DETECTION USING DEEP CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Current scenario of COVID-19 (Corona Virus Disease) pandemic makes almost everyone to wear a mask in order to effectively prevent the spread of the virus. Wearing the face mask is one of the remedial and preventive measures for avoiding the spread of corona virus. Many researchers have introduced and developed traditional and machine learning based face detection model. But still we are lacking in obtain the accurate accuracy of face mask detection. In order to improve the accuracy of face mask detection, we have introduced an automatic face mask detection system using Deep Convolutional Neural Networks (Deep CNN). For evaluating the experimental results, we have used the Real-world Masked Face Recognition Dataset (RMFRD) and the system obtained the 98% of accuracy which outperformed than other classification models.

1. INTRODUCTION

The trend of wearing face masks in public is rising due to the COVID- 19 (Corona Virus Disease) pandemic all over the world. Before Covid-19, People used to wear masks to protect their health from air pollution. While other people are self-conscious about their looks, they hide their emotions from the public by hiding their faces. Scientists proved that wearing face masks works on impeding COVID-19 transmission [1]. COVID- 19 is the latest pandemic virus that hit the human health in the last decade. In 2020, the rapid spreading of COVID-19 has forced the World Health Organization to declare COVID- 19 as a global pandemic. More than five million cases were infected by COVID-19 in less than 6 months across 188 countries. The virus spreads through close contact and in crowded and overcrowded areas. The COVID–19 virus can be spread through contact and contaminated surfaces, therefore, the classical biometric systems based on passwords or finger- prints are not anymore safe. Face recognition are safer without any need to touch any device. Recent studies on coronavirus have proven that wearing a face mask by healthy and infected population reduces considerably the transmission of this virus. However, wearing the mask face causes the following problems:

- Fraudsters and thieves take advantage of the mask, stealing and committing crimes without being identified.
- Community access control and face authentication are become very difficult tasks when a grand part of the face is hidden by a mask.
- Existing face recognition methods are not efficient when wearing a mask which cannot provide the whole face image for description.
- Exposing the nose region is very important in the task of face recognition since it is used for face normalization, pose correction, and face matching.

Due to these problems, face masks have significantly challenged existing face recognition methods [2]. The corona virus pandemic has given rise to an extraordinary degree of worldwide scientific cooperation. Artificial Intelligence (AI) based on Machine learning and Deep Learning can help to fight Covid-19 in many ways. Machine learning allows researchers and clinicians evaluate vast quantities of data to forecast the distribution of COVID-19, to serve as an early warning mechanism for potential pandemics, and to classify vulnerable populations. The provision of healthcare needs funding for emerging technology such as artificial intelligence, Internet of Things, big data and machine learning to tackle and predict new diseases [3]. In order to better understand infection rates and to trace and quickly detect infections, the AI's power is being exploited to address the Covid-19 pandemic. People are forced by laws to wear face masks in public in many countries. These rules and laws were developed as an action to the exponential growth in cases and deaths in many areas. However, the process of monitoring large groups of people is becoming more difficult. The monitoring process involves the detection of anyone who is not wearing a face mask.

Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or

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Volume 13, Issue 1, 2025

decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks. Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics [5].

Deep learning methods aim at learning feature hierarchies with features from higher levels of the hierarchy formed by the composition of lower level features. Automatically learning features at multiple levels of abstraction allow a system to learn complex functions mapping the input to the output directly from data, without depending completely on human-crafted features. Deep learning algorithms seek to exploit the unknown structure in the input distribution in order to discover good representations, often at multiple levels, with higher-level learned features defined in terms of lower-level features [6].

The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones. If we draw a graph showing how these concepts are built on top of each other, the graph is deep, with many layers. For this reason, we call this approach to AI deep learning. Deep learning excels on problem domains where the inputs (and even output) are analog. Meaning, they are not a few quantities in a tabular format but instead are images of pixel data, documents of text data or files of audio data [7]. Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction.

2. RELATED WORKS

Paredes, J. S. et al. [8] proposed a mask detection system for the health care personal inside the operation theatre. As the health care personal need to wear a mask in the operation theatre and the proposed system will alert for any personal not wearing the mask. There are two detection system used for face and medical mask wearing. Their system achieved almost 90% recall and less than 5% of false positive rate. They have worked for the medical mask detection from the images that are taken from 5m distance by cameras. Deore, R. et al. [9] have worked on the masked face detection from the video. The masked person is detected in this presented approach and mainly 4 steps are performed for the detection that are estimation of distance between camera and person, detection of eye line, detection of part of face and detection of eye. They have analyzed their algorithm on various video surveillance systems and achieved a fine accuracy.

Bu, J. et al. [10] developed a model for masked face detection for the security purpose. For this they have presented a special cascade CNN which works on three layers of CNN for the detection of masked face. Also, the authors have worked on the self-created MASKED FACE dataset as the already present masked face dataset is not that much sufficient to evaluate algorithms more precisely. The proposed CNN model worked well and the detection of masked faces is done accurately. Ud Din et al. [11] worked in this field is done for the detection of masked face and after that the detection of the original face. The proposed work has been carried out in two stages, first one is to detect the masks that are covering larger area of face than needed and the secondly to get the face that is not present in the training dataset. They have applied GAN based algorithm and used celebA dataset for training and achieved higher accuracy.

Ejaz and M. R. Islam [12] introduced work related to masks have been done by the authors, they have worked on the face detection from the faces that are covered with the masks. The authors have discovered the images that are covered with masks from the video and then original images are detected from this masked face. For this they have proposed Multi-task Cascaded CNN and SVM for classification. The proposed system is able to detect the masked faces and the original faces of peoples.

Meenpal, A et al. [13] evolved as a very popular problem in Image processing and Computer Vision. Many new algorithms are being devised using convolutional architectures to make the algorithm as accurate as possible. These convolutional architectures have made it possible to extract even the pixel details. We aim to design a binary face classifier which can detect any face present in the frame irrespective of its alignment. We present a method to generate accurate face segmentation masks from any arbitrary size input image. Beginning from the RGB image of any size, the method uses Predefined Training Weights of VGG - 16 Architecture for feature extraction. Training is performed through Fully Convolutional Networks to semantically segment out the faces present in that image. Gradient Descent is used for training while Binomial Cross Entropy is used as a loss function. Further the output image from the FCN is processed to remove the unwanted noise and avoid the false predictions if any and make bounding box around the faces. Furthermore, proposed model has also shown great results in recognizing non-frontal faces. Along with this it is also able to detect multiple facial masks in a single frame. Experiments were performed on Multi Parsing Human Dataset obtaining mean pixel level accuracy of 93.884 % for the segmented face masks

Heydarzadeh, et al. [14] worked on the face detection that is very fast and reliable method presented by Viola. This algorithm uses skin mask for the detection of face which gives result 4 times faster. Here the training is done for modeling the system with 2 eyes or 1 eye and 1 nose for lowering the false detection rate. They got 2.4 percent false negative in place of 10%. Similarly, Bosheng Qin and Dongxiao Li [15] designed a face mask identification method using the SRCNet classification network and achieved an accuracy of 98.7% in classifying the images into three categories namely “correct facemask wearing”, “incorrect facemask wearing” and “no facemask wearing”.

Md. Sabbir Ejaz et al. [16] implemented the Principal Component Analysis (PCA) algorithm for masked and un-masked facial recognition. It was noticed that PCA is efficient in recognizing faces without a mask with an accuracy of 96.25% but its accuracy is decreased to 68.75% in identifying faces with a mask. Park et al. [17] proposed a method for the removal of sunglasses from the human frontal facial image and reconstruction of the removed region using recursive error compensation.

Rodriguez et al**.** [18] introduced a system that detects the presence or absence of the mandatory medical mask in the operating room. The overall objective is to have as few false positive face detections as possible without losing mask detections in order to trigger alarms only for healthcare personnel who do not wear the surgical mask. The medical mask detection is performed with two face detectors; one of them for the face itself, and the other one for the medical mask. Both detectors run color processing in order to enhance the true positives to false positives ratio. The proposed system renders a recall above 95 % with a false positive rate below 5 % for the detection of faces and surgical masks. The system provides real-time image processing, reaching 10 fps on VGA resolution when processing the whole image. The Mixture of Gaussians technique for background subtraction increases the performance up to 20 fps on VGA images. VGA resolution allows for face or mask detection up to 5 m from the camera. Javed et al. [19] developed an interactive model named MRGAN that removes objects like microphones in the facial images and reconstructs the removed region’s using a generative adversarial network.

3. PROPOSED SYSTEM

In this section, we have to implement the real-time face mask detection using the deep learning techniques. The first step is to localize the mask region. To do so, a cropping filter is applied in order to obtain only the informative regions of the masked face (i.e. forehead and eyes). Next, the selected regions are described using a deep learning model. This strategy is more suitable in real-world applications comparing to restoration approaches. Recently, some works have applied supervised learning on the missing region to restore them such as this strategy, however, is a difficult and highly time-consuming process. Despite the recent breakthroughs of deep learning architectures in pattern recognition tasks, they need to estimate millions of parameters in the fully connected layers that require powerful hardware with high processing capacity and memory. Thus an efficient quantization based pooling method for face recognition using the VGG-16 pre-trained model is used. At the last convolutional layer (also called channels) feature maps are represented using Bag-of-Features (BoF) paradigm. The Figure 1 shows the block diagram of the proposed Masked Face detection system.

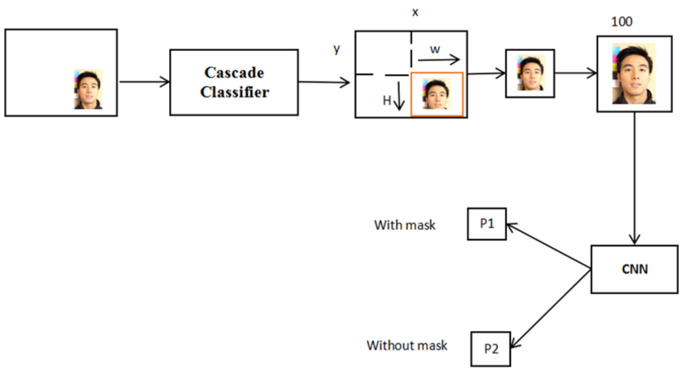

Figure 1 The block diagram of proposed Masked Face detection system

The basic idea of the classical BoF paradigm is to represent images as order less sets of local features. To get these sets, the first step is to extract local features from the training images, each feature represents a region from the image. Next, the whole features are quantized to compute a codebook. Test image features are then assigned to the nearest code in the codebook to be represented by a

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Volume 13, Issue 1, 2025

histogram. In the literature, the BoF paradigm has been largely used only for handcrafted feature quantization to accomplish image classification tasks. But in this work, features from deep learning model is represented using Bof paradigm. The main advantage of using BoF in the trainable convolutional layers is to reduce the number of parameters and makes it possible to classify masked face images. This deep quantization technique presents many advantages. It ensures a lightweight representation that makes the real-world masked face recognition process a feasible task. Moreover, the masked regions vary from one face to another, which leads to informative images of different sizes. The proposed deep quantization allows classifying images from different sizes in order to handle this issue. In addition, the Deep BoF approach uses a differentiable quantization scheme that enables simultaneous training of both the quantizer and the rest of the network, instead of using fixed quantization merely to minimize the model size. The proposed work improves the generalization of the face recognition process in the presence of the mask during the pandemic of coronavirus.

Convolutional Neural Networks (CNN) is neural networks most commonly used to analyze images [20]. A CNN receives an image as an input in the form of a 3D matrix. The first two dimensions corresponds to the width and height of the image in pixels while the third one corresponds to the RGB values of each pixel. As shown in Figure 2, CNNs consist of the following sequential modules (each one may contain more than one layer).

1. Convolution
2. Activation function (Using Relu)
3. Pooling
4. Fully connected layers
5. Output layer

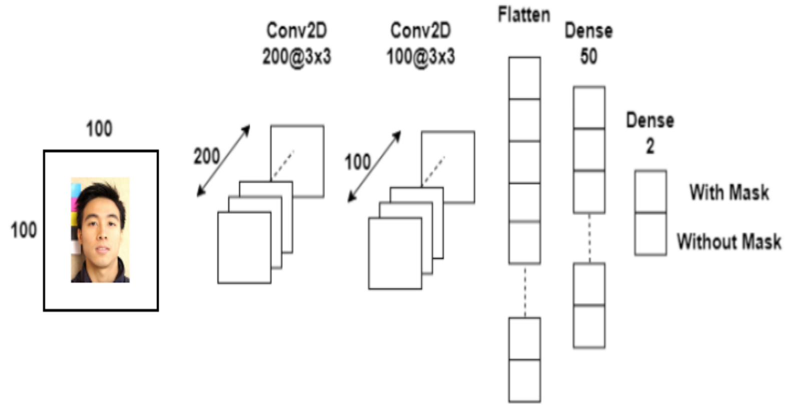

Figure 2 Architecture of Convolution Neural Network

3.2 CONVOLUTION

Convolution operation is an element-wise matrix multiplication operation. Convolutional layers take the three-dimensional input matrix we mentioned before and they pass a filter (also known as convolutional kernel) over the image, applying it to a small window of pixels at a time (i.e 3x3 pixels) and moving this window until the entire image has been scanned. The convolutional operation calculates the dot product of the pixel values in the current filter window along with the weights defined in the filter. The output of this operation is the final convoluted image. The following Figure 3 shows how the sliding of the window is performed over an image gives the
feature map as output.

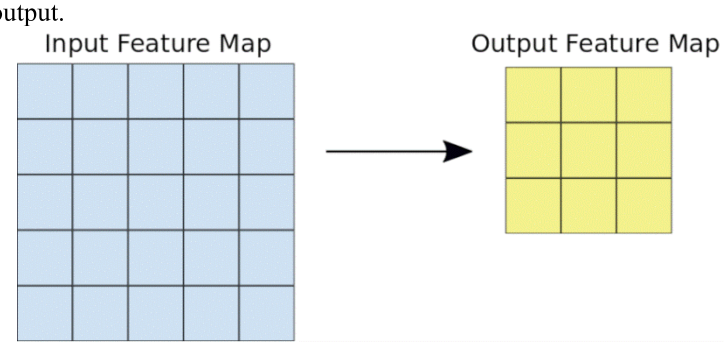

Figure 3 Output of Convolution

International Journal of Information Technology & Computer Engineering
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Volume 13, Issue 1, 2025

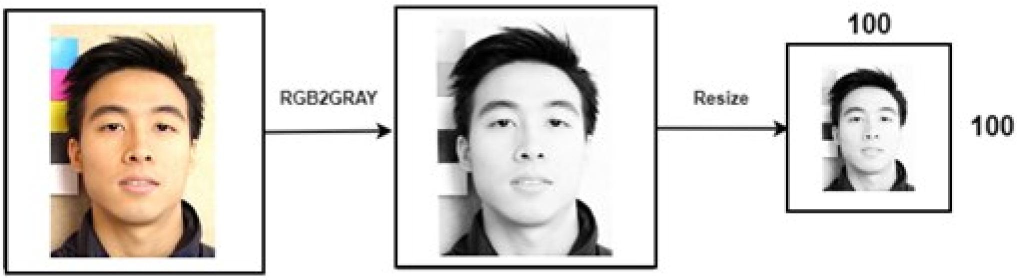

Figure 4 Resizing of the image

For example of the image show Figure 4, The core of image classification CNNs is that as the model trains what it really does is that it learns the values for the filter matrices that enable it to extract important features (shapes, textures, colored areas, etc) in the image. Each convolutional layer applies one new filter to the convoluted image of the previous layer that can extract one more feature. So, as we stack more filters, the more features the CNN can extract from an image. The results are summed up into one number that represents all the pixels the filter observed. This setting enables the network to learn different features while keeping the number of parameters tractable. Mathematically, the output feature map $y_{i,j}{}^{(l)}$ at convolutional layer *l* is calculated as in Equation 3.1.

$$y_{i,j}{}^{(l)} = \sigma^{(l)}\left(\sum_{n=1}^{k}\sum_{m=1}^{k} w_{n,m}{}^{(l)} . x_{i+n,j+m}{}^{l-1} + b^{(l)}\right) \tag{3.1}$$

where, the $w_{n,m}{}^{(l)}$ denoted the convolutional filter with size *k* x *k* at layer *l*, and the $x_{i+n,j+m}{}^{(l)}$ represent the spatial position of the corresponding feature map at the preceding layer *l*-1. The algorithm passes the convolutional filter throughout the input feature map using the dot product (.) between them with an addition of a bias unit $b^{(l)}$. Moreover, a non-linear activation function $\sigma^{(l)}$ at layer *l* is taken outside the dot product to strength the nonlinearity. And the Figure 5 shows Operation between image pixel and filter,

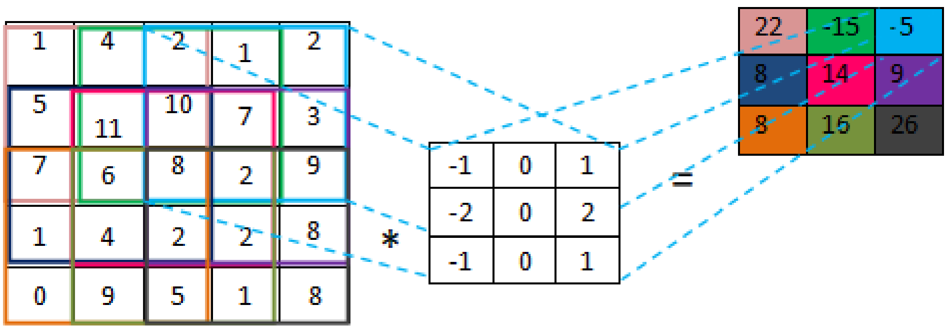

Fig. 5 Convolution Operation between Image Pixel and Filter

3.3 ACTIVATION FUNCTION

Activation functions are really important for learning and making sense of something really complicated and non-linear dynamic functional mapping between inputs and response variable for an Artificial Neural Network. The convolution layer generates a matrix that is much smaller in size than the original image. This matrix is run through an activation function, which introduces non-linearity to allow the network to train itself via back propagation. The most popular types of activation functions are sigmoid, tanh and ReLU.

- Sigmoid

Sigmoid is an activation function of form $f(x) = \frac{1}{1+e^{-x}}$. Its range is between o and 1. It is a S-shaped curve. It is easy to understand and prevent 'jumps' in output. Figure 6 shows the sigmoid activation function.

Figure 6 Sigmoid Activation Function

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 1, 2025

- tanh

tanh is another activation function of form $f(x) = \frac{2}{1+e^{-2x}}$. It is a scaled sigmoid function. This has characteristics similar to sigmoid. Its rage is between -1 to 1. Figure 7 shows the graph of tanh activation function.

- ReLU

ReLU activation function given an output x if x is positive and 0 otherwise. ReLU function is the most widely used activation function in neural networks. One of the greatest advantages ReLU has over other activation functions is that it does not activate all neurons at the same time. In practice, ReLU converges six times faster than tanh and sigmoid activation functions. Figure 8 illustrates the graph of Rectified Linear Unit (ReLU).

3.4 POOLING

The pooling layer can generalize the convolved features through down-sampling and thereby reduce the computational complexity during the training process. A filter is passed over the results of the previous layer and selects one number out of each group of values (typically the maximum, this is called max pooling). This allows the network to train much faster, focusing on the most important information in each feature of the image. Given a pooling/subsampling layer q, the feature output F^q can be derived from the preceding layer $f^{(q-1)}$ through the Equation 3.2.

$$F_{i,j}^{q} = \max(f_{1+p(i-1),1+p(j-1)}^{q-1}, \ldots, f_{pi,1+p(i-1)}^{q-1}, \ldots, f_{1+p(i-1),pj}^{q-1}, \ldots, f_{pi,pj}^{q-1} \quad (3.2)$$

where p x p is the size of the local spatial region, and $1 \le i, j \le (m-n+1)/p$, here m refers to the size of input feature map, while n corresponds to the size of the filter. Then it simply summarizes the input features within local spatial region using the maximum value. On two-dimensional feature maps, pooling is typically applied in 2×2 patches of the feature map with a stride of 1 or 2. Figure 9 demonstrates the max, min and average pooling layer with 2x2 filters of stride 2.

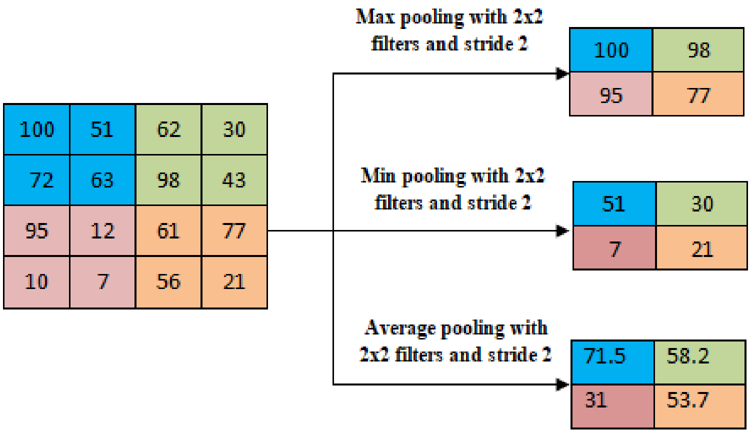

Figure 9 Max, Min and Average Pooling Layer with 2x2 Filters and Stride 2

- ***Max pooling*** is a pooling operation that calculates the maximum, or largest, value in each patch of each feature map.
- ***Min pooling*** is a pooling operation that calculates the minimum or smallest value in each patch of each feature map.
- ***Average pooling*** involves calculating the average for each patch of the feature map. This means that each 2×2 square of the feature map is down sampled to the average value in the square. Once the higher level features are extracted, the output feature maps are flattened into a one-dimensional vector, followed by a fully connected output layer.

3. 5 FULLY CONNECTED LAYERS

After pooling, there is always one or more fully connected layers. These layers perform the classification based on the features extracted from the image by the previously mentioned convolution processes. The last fully connected layer is the output layer which applies a soft-max function to the output of the previous fully connected layer and returns a probability for each class. The general form

ISSN 2347–3657
Volume 13, Issue 1, 2025

of an image classification CNN is the one shown the Figure 10 below:

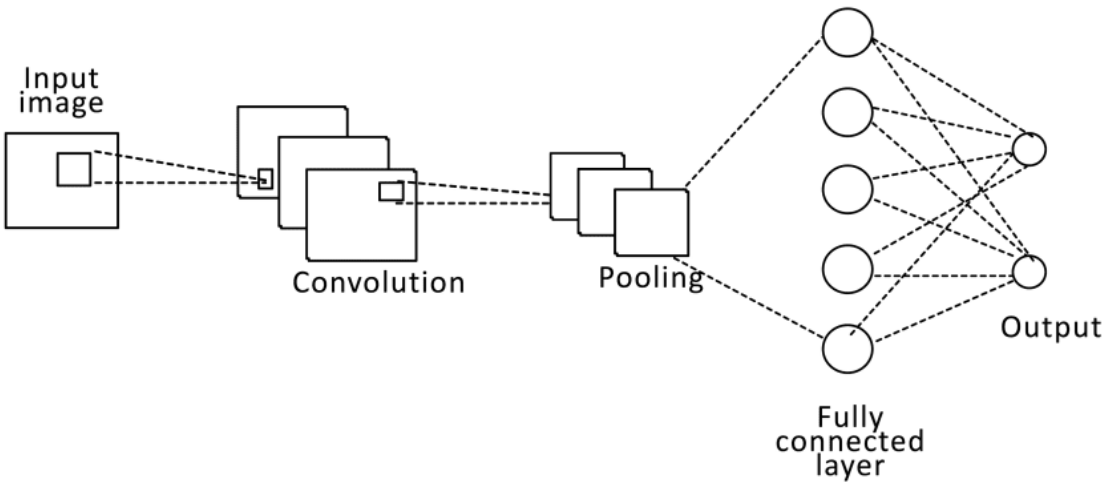

Figure 10 Classification using CNN

3. 6 OUTPUT LAYER

After the fully connected layer it gives the output as shown in Figure 11

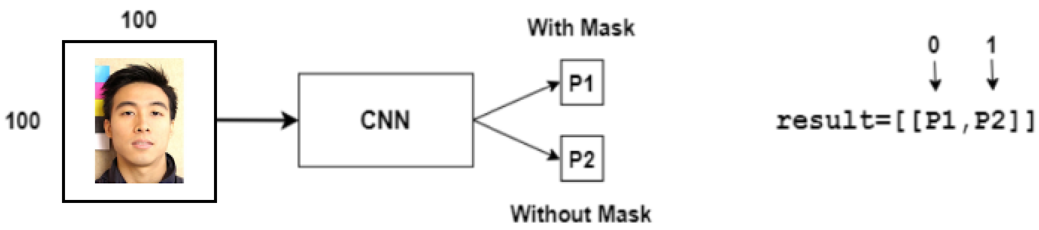

Figure 11 Result of outputs

3.7 DATASET DESCRIPTION

The two face mask classifier models were trained in the dataset. The dataset images for masked and unmasked faces were collected from image datasets available in the public domain, along with some data scraped from the Internet. Masked images were obtained from the Real-world Masked Face Recognition Dataset (RMFRD) and Face Mask Detection dataset by Larxel on Kaggle. RMFRD images were biased towards Asian faces. Thus, masked images from the Larxel were added to the dataset to eliminate this bias. RMFRD contains images for unmasked faces as well. However, as mentioned before, they were heavily biased towards Asian faces.

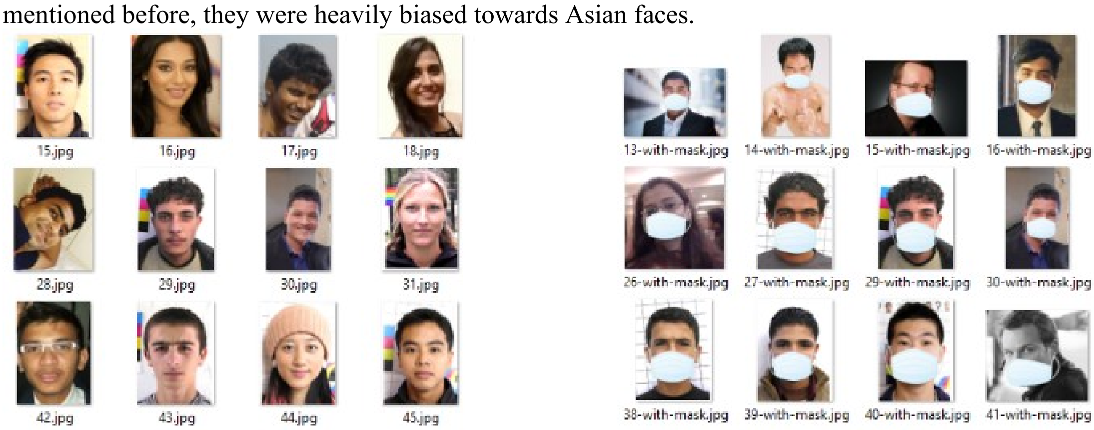

Figure 12 Sample dataset of with out and with masks

The final dataset has 1376images, divided into two classes:

International Journal of Information Technology & Computer Engineering

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Volume 13, Issue 1, 2025

Table 3.1 Datasets

Class name	Description	No. of images
Mask	Faces with masks correctly used	690
Without mask	Faces with no masks or masks incorrectly used	686

3.8 FACE MASK CLASSIFIER MODEL TRAINING:

For the second stage, two CNN classifiers were trained for classifying images as masked or unmasked.

1. The models were trained using the Keras framework.
2. The dataset was split into train and test sets in a ratio of 75:25. That is partition the data into training and testing splits using 75% of the data for training and the remaining 25% for testing.
3. Data augmentation was performed using the Image Data Generator class in Keras.
4. The input image size was set as 224 x 224.
5. To selected an initial learning rate of 0.001. Besides this, the training process included check pointing the weights for best loss, reducing the learning rate on plateau, and early stopping.
6. Each model was trained for 20 epochs and the weights from the epoch with the lowest validation loss were selected. Based on a comparative analysis of performance.

4. EXPERIMENTAL RESULT

In this section, we have conducted experiments using Tensorflow and Keras that classifies the images as with or without mask. The dataset is randomly split the into separate train / test sets. Then call it twice (one for the images that contain a mask and one fot the images that do not) with a train / test split of 80% (80% used for training and 20% for test).

1. The model consists of 10 layers in total.
2. The first 6 layers form 3 sequential Convolution - ReLu - Pooling groups.
3. Then, a flatten layer is applied to reshape the output of the CNN to a single dimension.
4. After the flatten layer, a dropout layer is applied. This layer randomly drops 30% (rate = 0.3) of the tensors in order to avoid overfitting**.**
5. In the end, a fully connected (dense) layer is applied that classifies the images based on the features extracted in the previous layers of the CNN and the final layer outputs the probability of each class label**.**

4.2 TRAINING THE MODEL

Train the model with the following function. First, open 2 training streams ("flows") from the 2 directories of train and test (validation) images. We also save checkpoints during training in separate directories for each checkpoint. Finally, it call the fit_generator function of the model and training begins. During the process, we keep track of training and validation accuracy and loss (we will use the values later to plot learning curves). Then label the outputs of the CNN ans apply colors to the results (red for without mask, green with mask). The OpenCV framework to implement live face detection using the default webcam of the computer. It used the very common Haar Feature-based Cascade Classifiers for detecting the features of the face. This cascade classifier is designed by OpenCV to detect the frontal face by training thousands of images. The learning curves of the model for 50 epochs of training are shown as graph in Figure 13.

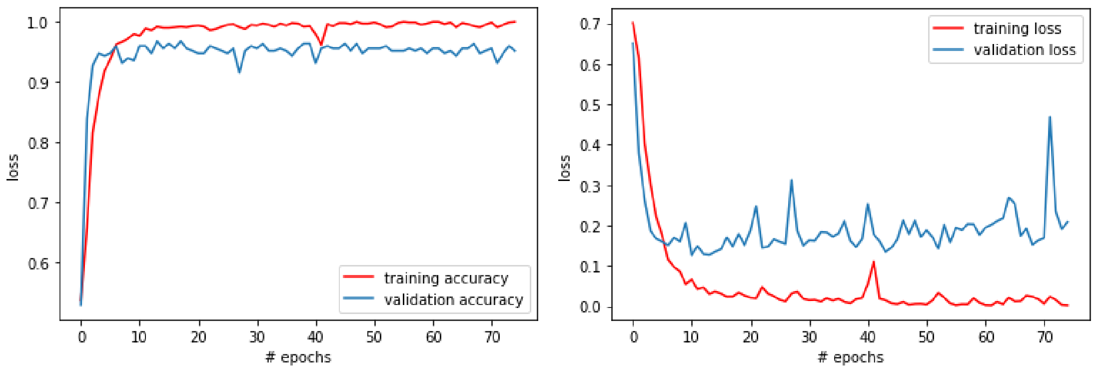


Figure 13 Training and validation accuracy and loss

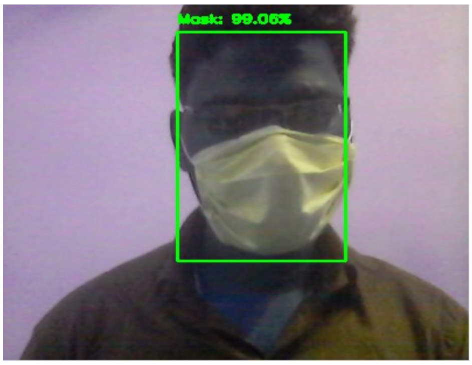
From the Figure 13, it can be seen that the proposed Masked Face detection system performed efficiently with more than 98% accuracy.

4.3 OUTPUT

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 1, 2025



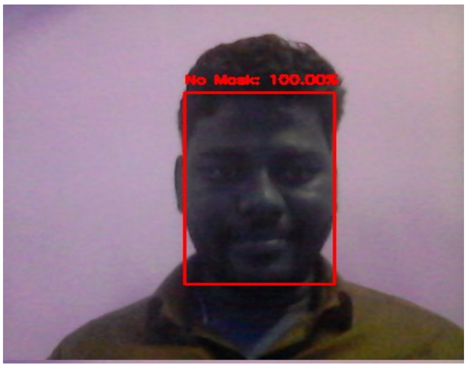


Figure 14 Screenshots of Mask and No Mask Detection with single person using CNN

Figure 15 Screenshots of No Mask, Partial Mask and Full Mask Detection with two persons using CNN

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 1, 2025

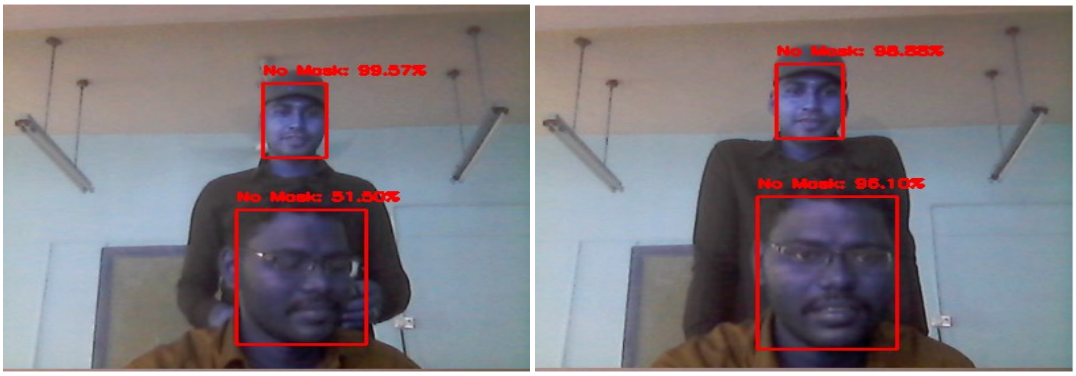


Figure 16 Screenshots of No Mask Detection with Partial Face (turned face) and Full Face using CNN

4.4 EVALUATION METRICS

CONCLUSION AND FUTURE WORK

Face mask wearing is one of the remedial measures for prevention of spreading the coronavirus disease from public sectors. In this research, we attempted to develop an automated face mask detection system using Deep Convolutional Neural Network. For face mask detection, the pretrained VGG-16 Net model is employed. The pretrained model which gaves more accurate results rather than other traditional detection models. In future, we are going to deploy the automated face mask detection system in public sectors like railway station, bus stand, shopping mall, school and colleges.

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