An Efficient method for Recognition of Occluded Faces from Images

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Abstract:

The detection of masked face is becoming an essential part of health care safetydue to the pandemic caused by the coronavirus and the surveillance systems. One of the most challenging problems in face recognition systems is the accurate identification of faces in the presence of occlusion like wearing of glasses and masks. The current study proposes a novel convolutional neural network(CNN)-based model for accurate detection of faces in the presence of mask and glasses.The novel architecture of the model was developed using ten convolutional layers, five max-pooling layers, and a dropout layer. The Adam optimizer was used for optimization of the performance our model. Early stopping criteria in conjunction with the ReduceLROnPlateau class was employed to avoid the overfitting problem. Our proposed model could achieve the accuracy of 99.71% on the test dataset suggesting its superiorityto its existing counterparts. Based on the results, the suitability of the proposed model for face detection in the presence of occlution in real-life application has been recommended.

Keywords: *Deep learning, convolutional neural network, facial recognition, image processing , Occluded Faces with Mask, Occluded Faces with Glasses*

DOI Number: 10.14704/nq.2022.20.13.NQ88264 Neuro Quantology 2022; 20(13):2115-2124

I. INTRODUCTION

Wearing a mask is extremely important during this pandemic since it has a high chance of preserving people from disease transmission[1]. Governments all over the world are taking the required steps to monitor and regulate persons who wear face masks. However, the traditional approach may struggle to monitor billions of people over time; in this case, technology can help society by upgrading the system by employing advanced facedetection algorithms[2].The process of matching a human face from an image or a video source against a database of faces is accomplished by a face detection system by identifying and quantifying facial characteristics from inside a given image. This process is known as "facial fingerprinting"[3]. Regardless of the fact that most humans are able to recognize faces with little to no effort at all, face recognition is a difficult pattern recognition issue in the field of computation. Face recognition systems aim to recognize a three-dimensional human face from a two-dimensional snapshot by analyzing how the face responds to different lighting conditions and how it expresses different emotions[4]. In order to solve this computational issue, facial recognition algorithms proceed sequentially through four phases[5]. In the first phase, the face is first extracted from the image backdrop. In the second phase, the picture of the segmented face is aligned to take into account factors such as the face's attitude, the size of the image, and photography qualities such as lighting and grayscale. In the third step, which is known as the extraction of facial features, the purpose of the alignment technique is to ensure that correct facial feature localization is possible. In order to portray the face, several characteristics inside the picture, such as the eyes, the nose, and the mouth, are found and measured. In the fourth stage, the extracted features of the face are compared against a

database containing images of other people's faces.

II. LITERATURE REVIEW

In the recent years, deep learning-based face detection methods have received the special attention of researchers[6].Sun *et al.*(2015)observed that the features learned by DeepID2+ (a highly accurate deep learning algorithm) demonstrate a good degree of tolerance against image contamination in the face verification test[7]. The robustness was further improved by combining the characteristics derived from 25 different face patches using DeepID2+. A long short term memory (LSTM)-Autoencoder was presented by Cheng *et al.*(2017) to reconstruct occluded facial regions in the wild[8]. They then carried out identification on the restored face pictures using the LSTM-Autoencoder. However, there was no assurance that the recovered section actually corresponds to the identities of the people who were to be identified, particularly in the case when the openset was considered. Daniel *et al.*(2018) addressed the occlusion challenge by supplementing the training data with synthesized occluded faces[9]. These occluded faces encompassed just the parts of the face from which a convolutional neural network (CNN) derived the most distinguishing information. This allowed for the extraction of characteristics to occur more uniformly and locally. It was proposed by Wan *et al.*(2017) to add a MaskNet branch to the intermediate layer of CNN models[10]. This branch was anticipated to award lower weights to hidden units that are triggered by occluded face regions. However, the intermediate convolution layer does not have sufficient detection accuracy, and the MaskNet branch does not have sufficient extra supervision information to guarantee the functioning. To put it another way, the discriminative capabilities of conventional low-level feature-based approaches are restricted, and the current deep learning-based approaches do not have a knowledge of how partial occlusions genuinely affect CNN models[11]. It has not been thoroughly examined yet whether or not there would be inconsistency between the characteristics of two faces that have been obscured in various ways. The goal of the study was to develop a novel feature engineering algorithm for producing superior features and building a highly suitable model for recognizing different types of occlusionsinvolved with the images like wearing of mask and glasses. Further, fine-tuning of the various parameters of the deep learning model were attempted to make the algorithmhighly accurate.

III. METHODOLOGY

The current study proposes an effective and simple method of monitoring persons who wear masks by detecting occluded faces. The capability of the proposed method for efficient face mask detection in real-life applications has been verified using its ability to correctly identify face occlusions due to other factors like wearing glasses and discriminating it from the mask. The development of deep learning models to detect people with and without masks can be an ideal way of monitoring and managing avastdata set of people. The methodology for designing a system to recognize faces with or without masks involves feature engineering the images to extract more detailed characteristics about the image, followed by data fragmentation to generate training and testing images for further processing. Adeep learning architecture has been developed and trained using the generated data, and the model has then been fine-tuned by utilizing generalization methods to attain higher accuracy (Figure 1). Finally, numerous performance measures have been calculated to analyze the performance of the model,allowing the model to be improved in the future.

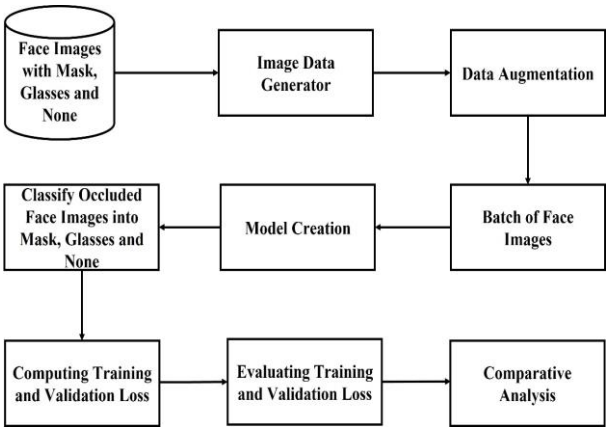

Figure 1: Block diagram representation of the proposed methodology for face occlusion detection

a. Dataset &Preprocessing:

The image dataset used in our study comprises 3866 images of human faces with no occlusion, 2000 occluded images of human faces wearing glasses [12],and 2000 images with face occlusion caused by the wearing of the mask[13].The sample images of each type have been shown in Figure 2. Tensorflowwas used to import the images. The pre-processing of the images through operations like rescaling, rotation, and zooming was performed with the help of Kerasto establish their suitability for use in the deep learning architecture proposed in this study.

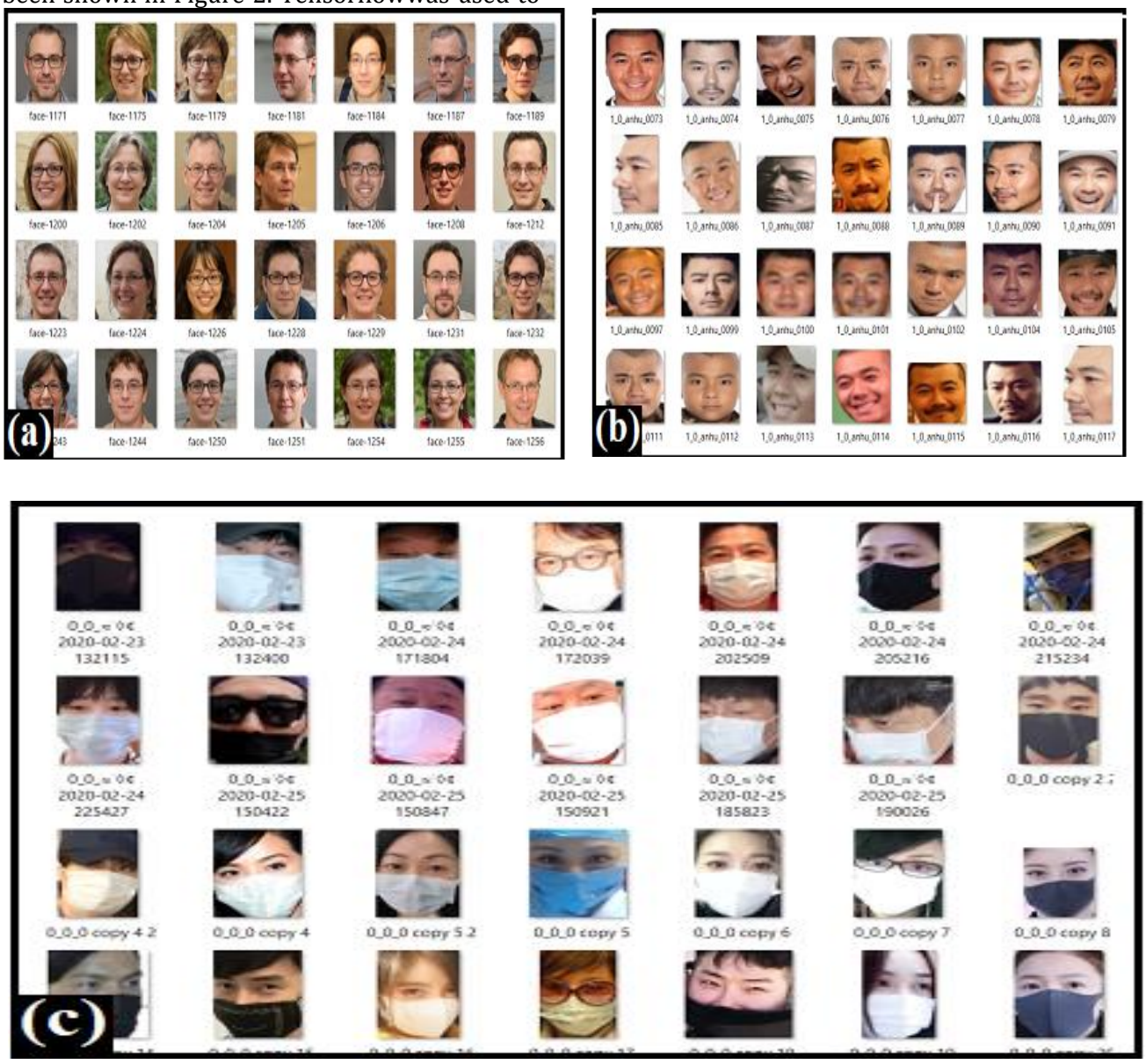

Figure 2: Sample images present in dataset (a) faces with glasses (b) faces without any occlusion (c) faces with the mask

b. Feature Engineering:

The act of choosing and transforming raw data into relevant parameters that may be utilized in supervised learning is regarded as feature engineering[14].One of the primary focuses of this study lies in developing a better feature engineering method for the facial recognition of people with and without occlusion. An algorithm was built to check the entering images along with the number of channels present. The input imageswere fragmented, i.e., divided into arbitrarily formed homogeneous sections called pieces. Fragment

sizes varied depending on the level of detail in different image sections, and their borders were aligned with image edges.The factors regulating the fragmentationprocess in our study included rotation range, zoom range, brightness range, vertical and horizontal flip, and so on.The fragmented images were then used to generate the images usingthe Image Generator algorithm. The Image Generator is an image pre-processing feature that allows the production of fake images from genuine photographs[15]. The Image Generator's primary goal is to generate more augmented image outputs, which will improve the deep learning model's training and testing accuracy.

c. Deep Learning Architecture:

The training and testdatawere passed into the deep learning model algorithm after the completion of the feature engineering process which included the image fragmentation and generation. The deep learning algorithm learns specific features using various mathematical models present in the algorithm[16]. Deep learning, more defined by multilayerperceptrons, has been regularised into CNNs[17].In most cases, multilayer perceptrons take the form of fully connected networks, where every neuron of a layer is connected to all of the neurons in the layer that comes after it. Given the fact that all of their nodes are linked to one another, these networks are susceptible to data overfitting. There are a number of ways with the help of which regularisation (also known as the prevention of overfitting) may be achieved. Two of these ways are: (i) by limiting connectivity and (ii) penalizing parameters while training, like weight loss (skipped connections, dropout, etc.) [18]. The CNNs consider an alternative approach to regularisation in that they make use of the hierarchical pattern that is present in the data and make use of small and simple patterns embedded in its filters in order to create patterns of greater complexity. As a direct consequence of this, the CNNs are located towards the bottom of the scale that measures connectivity and complexity. The convolutional layer is the most important component that goes into the construction of a CNN [19]. It is comprised of a group of filters (or kernels), the parameters of which are required to be learned in the span of the training procedure. In most cases, the size of the filter will be smaller than the original image. By integrating itself with the picture, each filter generates an activation map of some kind. The convolutional layer is responsible for picking the crucial features to be used in the neural network's learning and classification processes. It does this by playing the role of the feature selection layer. Equation 1 [19] may be used to provide the feature map that was generated by the convolutional layer.The CNN model developed in this research comprised a total of 10 convolutional layers.

$$G[m,n]=(f*h)[m,n]=\sum_{j}\sum_{k}h[j,k]f[m-j,n-k] \quad (1)$$

where m and n are the height and width of the feature matrix

The max-pooling layer is one of the critical layers associated with CNN.It is possible to describe this layer as the one in which the kernel obtains the highest value from the region that it convolves, and this explanation may be given. The CNN is told, in essence, by max pooling that the information will be carried forward in the CNN architecture only if it is the biggest information available in terms of amplitude. This is the only criterion for the information to be carried forward.The output from the max-pooling layer can be determined using Equation 2. In our study, five max-pooling layers were used in the development of the novel CNN architecture.

$$\left[\frac{I_x - P}{S}\right]+1 \quad (2)$$

where S is stride, P is padding, and I_x is the input

Batch normalization is anothercrucial step in the development of a CNN model. It can be more explained as an approach that speeds up and stabilizes the training of the deep neural networks (DNN).It involves normalizing activation vectors from hidden layers using the current batch's first and second statistical moments (mean and variance). The nonlinear function is applied before (or after) this normalization step.The batch normalization comprisesthree steps: transformation, backpropagation, and inferences. Theprocedure of each step can be mathematically described as given in Equations 3-6. In the current research,

batch normalization was performed after two convolutional layers.

$$y^{(k)}{}_i = \gamma^{(k)} \hat{x}_i^{(k)} + \beta^{(k)} \quad (3)$$

$$\frac{\partial l}{\partial x^{(k)}{}_i} = \frac{\partial l}{\partial \hat{x}_i^{(k)}} \frac{1}{\sqrt{(\sigma^{(k)2}{}_B + \varepsilon)}} + \frac{\partial l}{\partial \sigma^{(k)^2}{}_B} \frac{2(x^{(k)}{}_i - \mu^{(k)}{}_B)}{m} + \frac{\partial l}{\partial \mu^{(k)}{}_B} \frac{1}{m} \quad (4)$$

$$y^{(k)} = BN^{\inf}{}_{\gamma(k)\beta^{(k)}}(x^{(k)}) \quad (5)$$

where BN denotes batch normalization inference

Dropout is one of the regularization methods which prevents the model from getting overfitted with the learning algorithm[20].In addition to this, it has the potential to enhance the performance of the model as it is being trained. During the training process, the dropout layer will arbitrarily set all of the input units to zero using a rate at each phase. Inputs which are not set to 0 are multiplied by a factor of 1/ (1 - rate) in order to keep the overall amount from changing.In this study, one dropout layer was employed and the rate was fixed at 0.2. The model summary represented in figure 3.

DNN Algorithm: Occluded Face Recognition In Images

While (Face Images! =0)

{start:

Step1: Let a collection of images V which contains a set of K Images

$$V = \{K_1, K_2, K_3, \ldots\ldots, \mathrm{K}_n\}$$

$$V = \sum_{i=0}^{n} K_n \quad (6)$$

Step2: Each Image K_n, having a pixel's map of P which is

$$P = \sum_{i=0}^{i} P^n = \{\mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3, \ldots\ldots, \mathrm{P}_n\}$$

Now, first the colour and pixel dominancy as distribution determined:

Let the total possible colours can be present in "n", total possible colour combination = ${}^{n}C_r$, using discrete equation algorithm

$$2\hat{Y}\sum \hat{Y}_i P_j = \bar{Y}_i^{+} \hat{Y}_j, i = 1, 2, \ldots\ldots N$$

Step3: After the analysis, it is passes into deconvolution for data correction,

$$\hat{Y} = \frac{1}{\left|A(\phi)^2\right| + \left|\alpha^2\right|} \hat{Y} \quad (7)$$

Where, ϕ is a conjugate image gradient (ϕ = ϕ + β P)

Step4: After the data correction is done, now the recognition of occlusions areperfomedusing following equation

$$\hat{Z} = \int \hat{Y} \frac{1}{\left|A(\beta)^3\right| + {}^{n}C_r + \hat{Y}_i \hat{P}_i} dX \quad (8)$$

Step5: Finally, Recognition of Occluded Faces from Images are performed

$$\left|\hat{Z}_i\right| \left|\hat{D}_i\right| = \varphi\left[\hat{Y}\right] dX$$

[where $\left|\hat{D}_i\right|$, stands for delta vector, $\left|\hat{D}_i\right|^2 = (\left|D_x\right|^2 + \left|D_y\right|^2)$

: Stop}

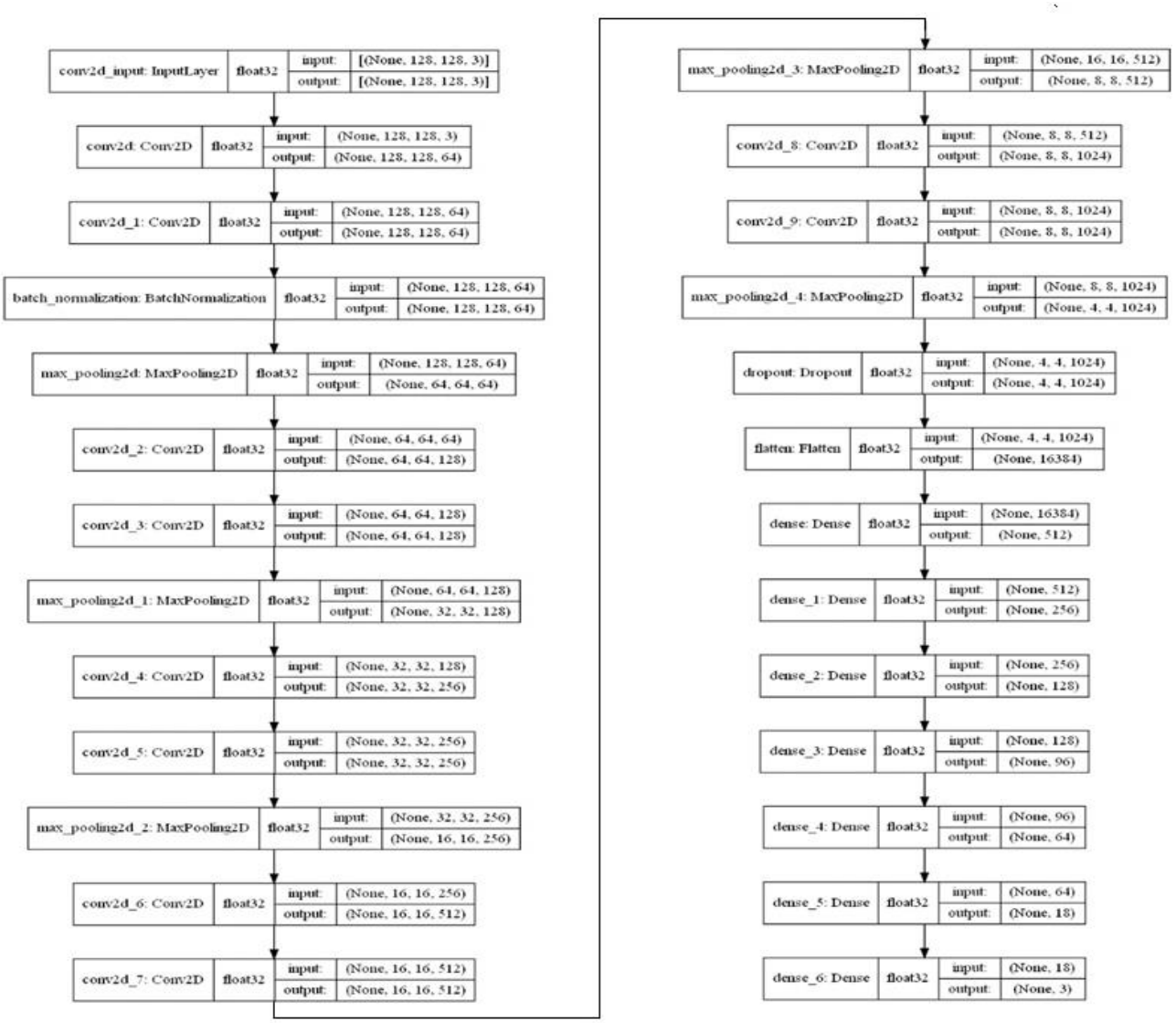

Figure 3. The architectureof the proposed CNN model

d. Optimization and Regularization:

The CNN model can be made more accurate and suitable for the given data after the involvement of optimization and regularization techniques. An optimization approach will identify the parameters of the model (weights) that will result in the least amount of error when the inputs are translated into outputs. These optimization strategies, also known as optimizers, have a significant impact on the degree to which the CNN model is accurate. Additionally, they have an effect on the speed at which the model is trained. Within the scope of this investigation, Adam served in the capacity of optimizer. A gradient descent optimization approach is utilized in the implementation of the algorithm for adaptive moment estimation. This strategy is highly effective for dealing with massive situations that include a significant amount of data or parameters. It doesn't take up much memory and works quickly. It's a cross between the gradient descent, momentum, and RMSP algorithms all combined into one. By taking into account the exponentially weighted average of the gradients, this strategy is utilized to hasten the process of the gradient descent method.

The regularization methods involved in developing the proposed model were Early stopping and the ReduceLROnPlateau class. When training a learner with an iterative approach such as gradient descent, early stopping is a sort of regularization that is utilized to prevent overfitting [21]. Early stopping may also be characterized as a type of regularization that is employed to avoid

underfitting. These kinds of tactics improve the learning algorithm with each subsequent repeat, making it more adept at conforming to the training data. To a certain extent, the learner's performance on information not related to the training is improved as a result of this. To improve the learner's fit to the training data beyond that point, however, comes at the expense of an increase in the generalization error. Early stopping criteria define the maximum number of iterations that a learner may complete before reaching an unhealthy level of fitness. Early stopping criteria with varied degrees of theoretical basis have been utilized in a number of diverse machine learning systems throughout the years. The learning rate is slowed down when a statistic stops showing any signs of improvement. When there is no further progress in learning, it is generally beneficial for models to reduce the rate of learning by a factor of 2-10. This call-back monitors a quantity and slows down the learning rate if there is no discernible progress after a predetermined amount of epochs have passed.

III. RESULTS AND DISCUSSION

The research on facial recognition of people with or without occlusionhas been gaining momentum in recent years. In this study, the major occlusions focused on werethe glassesand the mask on the face.The deep learning model was trained to classify the three classes, namely,face with and without mask and face with glasses. The training data set comprised of 6291 images, the validation data set consisted of 1572 images and the testing data set contained 1055 images in our study. The model was trained with the afore-mentioned image data dataset at a learning rate of 0.01 and with the epoch of 50. For the development of the proposed novel CNN model, the number of trainable parameters were 27 x 878 x 443 and 128 parameters were non-trainable. The “Adam” optimizer was used to optimize each epoch while training. During the training stage the loss was inversely proportional to the accuracy of the model. Although the number of epochs was set to 50, the training process was stopped after the 39thepoch due to the early stopping regularization method. ReduceLROnPlateau reduced the learning rate to 1.18 x 10^{-7} from the earlier value of 0.01. The reduction in the training and validation losses with the increase in the number of epochs can be observed from Figure 4.

Figure 4: Variation of training and validation losses with epochs

With these model parameters, the proposed CNN architecture could achieve an accuracy of 99.71%for the test data. The term accuracy plays aimportant role in the development of a deep learning model by which the model performance over the given data can be estimated. Accuracy is a statistic that summarizes how far a model fits across all classes. It is helpful when all courses are on an equal footing in terms of importance. In order to calculate it, we take the ratio of the number of accurate estimates to the total number of predictions.The proper organization of the convolutional filters and the kernel size of each layer can be attributed to produce accuracy of 99.71% for the test data.

The various performance metrics of the proposed CNN model such as confusion matrix, precision, F1 Score, recall, and support were also calculated.A table structure that offers representation of the effectiveness of an algorithm for supervised learning is called a confusion matrix. This structure is sometimes referred to as the error matrix. In the field of unsupervised learning, this concept is typically referred to as a matching matrix. The origin of this phrase derives from the fact that it is simple to determine whether or not the system is mixing together two different groups. Each case in an actual class is represented by a row in the confusion matrix, whereas each instance in a predicted class or vice versa is represented by a column. Both of these differences are described in the scholarly research that was conducted (i.e., commonly mislabelling one as another).The confusion matrix for our proposed CNN model

has been shown in Figure 5. In the confusion matrix, A = faces with glasses,B = faces without any occlusion andC = faces with the mask.

Predicted Class	True Class		
A	768	1	0
B	1	150	0
C	0	1	134

Figure 5: Confusion Matrix of the proposed CNN model

One metric of a deep learning model's success is its level of precision, which refers to the reliability of a positive prediction that the model has produced. The term "precision" refers to the ratio of the number of actual positive results to the overall number of successful forecasts.The recall is determined by finding the ratio of total of positive samples that were accurately identified as positive to the total number of positive samples. This ratio is then multiplied by 100. The model's capacity to recognise positive samples is evaluated using the recall metric. The greater the recall, the greater the number of positive samples found.The F1-score is a statistic that is determined by measuring the harmonic mean of the accuracy and recall values of a classifier and combining them into a single value. Its primary purpose is to evaluate the relative effectiveness of two different classifiers. Assume for the sake of argument that classifier A has a greater recall, whereas classifier B has a better precision. In this scenario, the F1-scores for both these classifiers may be compared to each other to see which one generates superior results.The number of observations of the true response which fall into each category of goal values is known as support. The respective precision, F1 Score, recall, and support values our proposed CNN model have been shown in Table 1. Figure 6 shows the comparison of accuracy obtained from various CNN models. From figure 6 it shows that proposed model outperforms compare to other CNN models in terms of accuracy.

Table 1: Performance Parameters of Model

Models	Classes	Precision	Recall	F1 Score
Baseline CNNModel	Glasses	0.95	0.93	0.94
	None	0.96	0.94	0.94
	Masked	0.85	0.83	0.84
Simple CNN	Glasses	0.90	0.87	0.88
	None	0.88	0.91	0.89
	Masked	0.87	0.89	0.87
DenseNet	Glasses	0.90	0.87	0.88
	None	0.93	0.91	0.91
	Masked	0.88	0.86	0.86
Proposed Model	Glasses	1.00	1.00	1.00
	None	0.99	0.99	0.99
	Masked	1.00	1.00	0.99

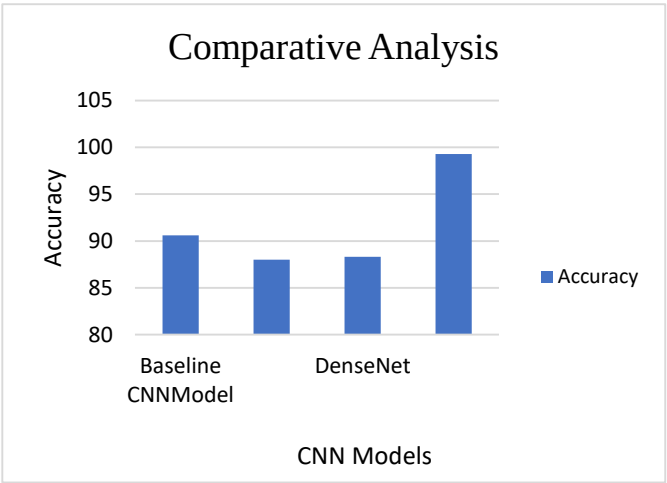

Figure 6: Comparative Analysis of different CNN Models

V. CONCLUSION

Utilizing an individual's face as the primary means of identification or verification of that individual's identity is what is referred to as face detection. Face recognition has been utilized for a variety of purposes including surveillance of restricted access areas (such as intrusion detection and prevention and public acknowledgment of celebrities), auto-control

attendance control schemes, and largely in mask detection after the onset of Covid19 pandemic. However, the most significant obstacle in its real-time use in society is the correct identification of face in cases where there is occlusion in the face, such as when someone is wearing glasses or a mask. In this study, an unique CNN architecture has been suggested for the identification of faces that are occluded. The wearing of a mask and spectacles are both considered to be examples of facial occlusions for the purposes of our research. The suggested CNN model included batch normalization as one of its components, as well as ten convolutional layers, five max-pooling layers, and a dropout layer. The goal of the model was to deliver superior performance to the models that were already in use. Adam optimizer was responsible for achieving the optimization. The overfitting problem was solved by making use of and early stopping, in conjunction with the ReduceLROnPlateau class. The fact that the suggested CNN model was able to deliver an accuracy of 99.71% on the test dataset indicates that it is superior to the current models that have been described in the literature. As a result, the model that we have suggested is applicable to real-world applications such as the identification of masks by governmental agencies.

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