Deep Learning Model Based on Mobile-Net with Haar-like Algorithm for Masked Face Recognition at Nuclear Facilities

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Abstract: ***During the spread of the COVID-I9 pandemic in early 2020, the WHO organization advised all people in the world to wear face-mask to limit the spread of COVID-19. Many facilities required that their employees wear face-mask. For the safety of the facility, it was mandatory to recognize the identity of the individual wearing the mask. Hence, face recognition of the masked individuals was required. In this research, a novel technique is proposed based on a mobile-net and Haar-like algorithm for detecting and recognizing the masked face. Firstly, recognize the authorized person that enters the nuclear facility in case of wearing the masked-face using mobile-net. Secondly, applying Haar-like features to detect the retina of the person to extract the boundary box around the retina compares this with the dataset of the person without the mask for recognition. The results of the proposed modal, which was tested on a dataset from Kaggle, yielded 0.99 accuracies, a loss of 0.08, F1.score 0.98.***

Keywords: ***COVID-19, Deep learning, Mobile-Net, and Haar-Like.***

I. INTRODUCTION

In the computer vision field and due to COVID-19, masked-face recognition has a great interest of most researchers[1]. Therefore, the individuals in the authority must wear a mask to limit the spread of COVID-19. The tools to identify features of masked-face are ineffective in numerous circumstances, like Face access control at the authority's gate attendance. [2]Consequently, it is very critical to develop an efficient frame-work recognition on the masked faces. The effort related to face features detection recognized many variants in scale, location, in-plane rotation, pose, facial appearance, camera lighting environments, etc.

The mobile-Nets classifier uses deep intelligent separable convolution is an enhancement of Convolutional neural network (CNN) due to the limitation of the CNN in face recognition where features extracted from an image like an eye, eyebrow, mouth, and nose are more shrinking in size as a result of pooling and filtering and also, The non-linearity inside the narrow level is removed. Most researchers use pre-train models of CNN to enhance biometrics recognition. Therefore, the motivation of this paper to use a Mobile-Nets classifier to improve feature extraction of masked-face best identification and authentication to introduce a better algorithm that can attain face features information. In [3] introduced how to implement a Haar-like algorithm to detect faces with superior performance in multi-condition. In this research. We propose a framework recognition of masked-face using a Mobile-Nets network. The reset or research is organized as follows, sec. one related work, and sec. two the proposed method of the work used in detect and recognize the masked-face, finally sec. three the simulating results and conclusion.

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II. RELATED WORKS

In [4] introduced an algorithm to detect face features for mobile applications for objects wearing a mask. [5] proposed the capability of dissimilar structures of the mask with and without operational Micro-Ventilator. [6] proposed Cascade-Classifier to concentrate the individual, the Convolutional Neural Network models to recognize the individual and non-individual image, and the Kalman filter technique to track individual motion with an accuracy range of 77.7%. [7] introduced deep-learning (DL) perceptions relevant to face appearance examination and face-recognition, and delivers a survey of readings on exact face recognition difficulties. [8] proposed a method using CNN by restricted training ratio, considerable progress in face-recognition amount. [9] introduced clustering on the sizes of bounding boxes to get a good image and speed up the divergence speed of the network using the YOLO algorithm.[10] suggested a face detection prototype to detect the faces and their consistent facial milestones current in the video frame using the Mobile-Net-V2 construction. [11] showed a non-masked-face recognition and also relate in the masked-face recognition method. Principal-Component-Analysis (PCA) got a more operative and popular numerical technique and generally used. [12] suggested by what means to form mobile semantic separation models concluded a reduced form of Deep-Labv3 which called Mobile Deep-Labv3.[13] showed a deep Meta Caps-net Equivariant Embedding Modal with three different innovations. [14] the proposed algorithm improves the face recognition accuracy from 50% - 95% without providing data on their starting point. [15] suggested a model called the Face-Net trained which is used for improving masked- face gratitude.

[16] proposed a Multilayer-Perceptron (MLP) for the classification process and showed that that the middling size of the code-book (RBF neurons) provided a greater recognition-rate associating with the code-book of size 70.

[17] showed that the Viola-Jones algorithm gave the efficiency 12% on average. [18] suggested a deep-cascaded multi-task to detect the face. [19] suggested a modal called the anchor-free category and showed that it realized real-time speed and great correctness with a minor model-size.

[20] introduced precise face-segmentation masks from any arbitrary size input object using VGG-16 with malicious pixel-level accuracy of 93.884 % for the face-segmentation masks.[21] proposed a CNN prototype to be used in ensemble technique for detection.[22] used CNN models to progress the accuracy in face detection.[23] introduced Neural Networks for matching symmetrical structures of the social face.[24] used only one feature for each fragile classifier Specified the same amount of features, this technique diminishes the error by 37% and 2.6 times as fast as Viola-Jones' face-detector.[25] suggested an algorithm for real-time human-robot communication uses, the modal was clever for detection, recognition, and tracking faces up to 24 frames per second.[26] illustrated global-dynamic global Haar-like features in which it was is faster than that of the customary method.

[27] suggested a four new Haar-Like feature in which it got improved consequences compared with other customary face detection classifiers like Haar-Like.[28] proposed a novel usual of ±26.565 ° haar-like features which can be designed rapidly to characterize the features of rotated faces.

III. THE PROPOSED METHOD

3.1 Masked face Data set

This paper used a large dataset associated with face patterns, which were images of faces wearing masks and without-mask. The images were collecting from Kaggle datasets. This dataset consists of 3835 images belonging to two classes:

- With mask: 1916 images (refer with: Figure.1),
- Without mask: 1916 images in (refer with: Figure.1).

Figure.1 Dataset with-mask

Figure.2 Dataset without-mask

3.2 Data-Augmentation

In the next stage, to succeed the training and propose an efficient modal we must enlarge and develop the data-set to get a greater number of patterns for training by rotate, casual crop, and flip each image in the data-set in which, data-augmentation avoid over-fitting or training patterns. A purpose image data generation is generated for image-augmentation, which profits test and train collections of data-set. After that, this dataset splitting to 80% for training and 20%for test as shown in (refer with: Figure.1).

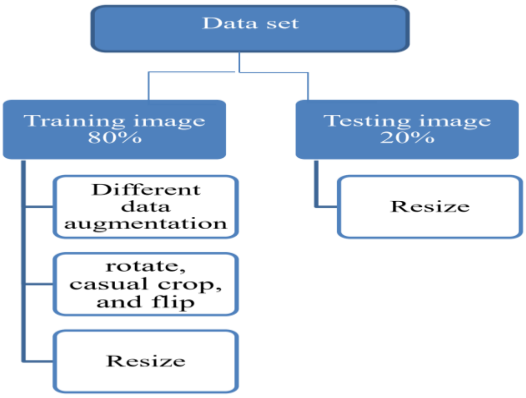

Figure.3 Block diagram of used data- augmentation.

3.3 Mobile-Net in use

Mobile-Net stayed practical as a detection network to detect the people-wearing mask or people without the mask, which was an inconsequential CNN and accomplished very high accuracy in image-classification. The highest structures of mobile-Net were residual blocks to the training of deep network and depth-wise to separable convolution (refer with: Figure.1), In this step, we use Conv2D, Batch Normalization, ReLU, expanded_conv_depthwise (Depthw), blocks expand, flatten, dense, dropout to build the proposed modal to improve the accuracy.

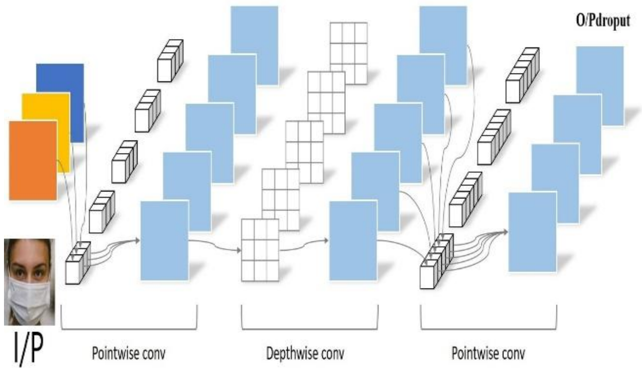

Figure.4 Blocks of Mobile-Net.

As shown in (refer with: Figure.1), illustrate the block diagram of the proposed modal, in this step will appear the motivation of our work and how to recognize the authorized person that enters the nuclear facility in case of wearing the masked-face. After pre-trained the dataset on mobile-net we detect if a person wears a mask or not, by applying the steps of planned algorithms illustrate in Table1 step by step from Image data generator to increase the dataset for training until reach to training the modal on Mobile-net to detect the masked-face and evaluate the performance of modal by accuracy/accuracy-validation,

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loss/loss-validation, and precision/recall/F.score. The interesting step after that applying Haar-like features to detect the retina of the person to extract the boundary box around the retina compare this with the dataset of the person without the mask for recognition.

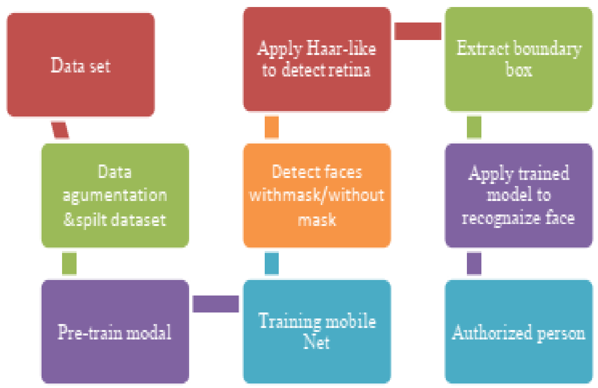

Figure.5 the block diagram of the proposed modal

(Refer with: Table 1) there are the following steps of our proposed algorithm:

1. Apply data augmentation method to increase the dataset.
2. Pre-processing method on the image (rescale).
3. Dataset splitting to 80% for training and 20%.

Table1. The algorithm of the planned modal

Algorithm 1 proposed model		
Input	:	Face mask dataset
Output	:	Face recognition
Initialization	:	
1	:	Import numpy, pandas, sklearn, matplotlib, Os, keras and tensorflow_gpu libraries
2	:	Set INIT_LR=1e-4, EPOCHS=20, BS=32 aug=ImageDataGenerator(rotation_range=20, zoom_range=0.15, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.15, horizontal_flip=True, fill_mode="nearest")
3	:	Test_datagen=keras.preprocessing.image.ImageDataGenerator(rescale=1./255)
4	:	Training_set = Train_datagen.flow_from_directory('training_folder', target_size=(image_width,image_high), batch_size= BS, class_mode='categorical')
5	:	test_set = test_datagen.flow_from_directory('test_folder', target_size=(image_width,image_high), batch_size= Batch_size, class_mode='categorical')
6	:	Training_Model
7	:	Training_Model.compile(loss='categorical_crossentropy',optimizer=Adam(lr= INIT_LR, decay=INIT_LR / EPOCHS) , metrics = ['categorical_accuracy'])

8	:	Training_Model. fit(aug.flow(trainX,trainY,batch_size=BS),
		steps_per_epoch=len(trainX)//BS,
		validation_data=(testX,testY),
		validation_steps=len(testX)//BS,

3.4 Haar-like proposed algorithms for training

Technology in the extent of computer vision for support and distinctive objects in an image.

Individuals recognize a commonality of objects in images with brief attempts, spite the circumstance that the image of the objects may modify something in separate survey appoint [19], in many separate dimension and scales, or even when they are transfer or rotated.

Objects can recognize when they are partly retard from view.

This task is still a challenge for computer vision systems [1, 29]. Many approximate to the work has been accomplished over multiple decades.

So, Haar-like is used in object-recognition.

The important advantage of a Haar-like feature above maximum other features is its calculation rapidity[1, 17]. Owing to the use of a summed-area table, a Haar-like of any size can calculate in constant time.

A Haar-like is characterizing by taking a boundary box of an image and separating that box into several parts [30].

They are visualizing as black and white adjacent boxes [31].

In the limited access area as it is within a designated zone comprising a nuclear facility to which access is limited and controlled for physical protection purposes.

At this zone, the masked-face recognition to limit the spread of COVID-19 applies to all individuals that enter the facility.

In this interesting step of work, after we training the Mobile-Net to our data set and detect which person wears a mask, and he takes permission to enter the facility to limit the spread of COVID-19, it must recognize if this person in our data set.

(Refer with: Table 2), by applying the proposed modal for Haar-like detection and recognition algorithm as illustrated next, First, we determine the interesting features to detect in our case it is the retina and determines the (x,y,w,h) dimensions to extract the boundary box from the object which it is Region of interest to recognize the person by using Haar cascaded detect function.

After that, each object assigns a label and saves it with this label for comparison with the dataset without the mask according to the following steps:

1. Extract feature using haar-cascaded function.
2. Labeling each object using people.index(person) function.
3. Determine the boundary box of right and left eyes.
4. Use face recognition function.

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Table 2. Algorithm of retina detection modal

```
Algorithm 2 proposed model
Input          : Face mask dataset
Output         : Retina detection
Initialization : Initialize DIR, people //DIR directory of face mask data set, and people
1              : Import numpy, pandas, sklearn, matplotlib, Os, keras and tensorflow_gpu librar
2              : haar_cascade=cv.CascadeClassifier('harrcascade_righteye.xml')
                 features=[]
                 labels=[]
3              : def create_train():
                   for person in people do
                     path=os.path.join(DIR,person)
                     label=people.index(person)

                     for img in os.listdir(path) do
                       img_path=os.path.join(path,img)

                       img_array=cv.imread(img_path)
                       gray=cv.cvtColor(img_array,cv.COLOR_BGR2GRAY)

                       faces_rect=haar_cascade.detectMultiScale(gray,scaleFactor=1.1,
                                          minNeighbors=3)

                       for (x,y,w,h) in faces_rect do
                         faces_roi=gray[y:y+h,x:x+w]
                         features.append(faces_roi)
                         labels.append(label)

4              : create_train()
5              : features=np.array(features,dtype='object')
                 labels=np.array(labels)
6              : face_recognizer=cv.face.LBPHFaceRecognizer_create()
7              : face_recognizer=cv.face.LBPHFaceRecognizer_create()
8              : np.save('features.npy',features)
```

3.5 *Haar-like proposed algorithms for recognition*

(Refer with: Figure.6 the proposed structure of face recognition classifier. After applying the retina detection algorithm and determine the boundary box of the right eye and left eye by using Haar-cascaded classifier the features were saving and labeling. So, in the final step applying the face recognition algorithm as illustrated in Table 3, by comparing the boundary box of the labeled object with the dataset of objects without the mask for recognition to take the permission to the person to access and enter the facility after following the next steps of the algorithm of face recognition:

1. Using haar-cascaded classifier function.
2. Apply face.LBPHF face recognition function.
3. Training the masked-images.
4. Put label using a put text function.
5. Finally, using imshow function to review the detected face.

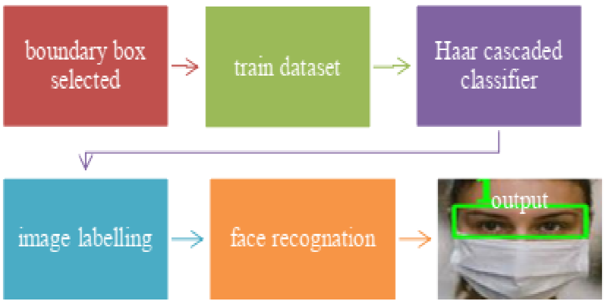

Figure.6 the proposed structure of face recognition classifier

Table 3. Algorithm of face recognition

```
Algorithm 3 proposed model
Input          : Face mask dataset
Output         : Face recognation
Initializatio  :
n
1              : Import numpy, pandas, sklearn, matplotlib, Os, keras and tensorflow_gpu libraries
2              : haar_cascade=cv.CascadeClassifier('harrcascade_righteye.xml')
3              : face_recognizer=cv.face.LBPHFaceRecognizer_create()
                 face_recognizer.read('maskedface_trained.yml')
4              : gray=cv.cvtColor(img,cv.COLOR_BGR2GRAY)
5              : faces_rect=haar_cascade.detectMultiScale(gray,scaleFactor=1.1,minNeighbors=7)
6              : for (x,y,w,h) in faces_rect do
                   faces_roi=gray[y:y+h,x:x+w]
7              : cv.putText(img,str(people[label]),(20,20),cv.FONT_HERSHEY_COMPLEX,1.0,(0,2
                 55,0), thickness=2)
8              :   cv.rectangle(img,(x-10,y),(x+2*w+20,y+h),(0,255,0),thickness=2)
                 cv.imshow('Detected Face',img)
```

(Refer with: Fig.7), shows the recognized output person after applying the proposed algorithm for face recognition which indicates the label of the person with the mask.

Figure.7 the recognized output person

3.6 *Experimental Result.*

The proposed methods are applied to employ a laptop background (Intel(R) Core (MT) i7-7700 HQ CPU @ 2.80 GHz, win10 64-bit operating method, RAM 16 GB, 256 GB SSD, NVIDIA GTX 1060 graphics card, and implemented in python 3.6 contains a deep learning library. The assessment metrics engaged here are accurate, (refer to Fig.8, Fig9, Fig.10) precision, recall, and F1.score. accuracy in, accuracy – validation, loss, loss- validation.

(Refer with: Eq. (1), Eq. (2), Eq. (3), Eq. (4))

The evaluation metrics of the proposed modal is illustrating as follow:

1. Accuracy $= \frac{Tp+Tn}{Tp+Fp+Fn+Tn}$ Eq. (1),
2. Precision $= \frac{Tp}{Tp+Fn}$ Eq. (2),
3. Recall $= \frac{Tp}{Tp+Fn}$ Eq. (3),
4. F1 score $= 2 * \frac{Recall * precision}{Recall+precision}$ Eq. (4),

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(Tp True positive, TN true negative),(Fp False positive, FN False negative)

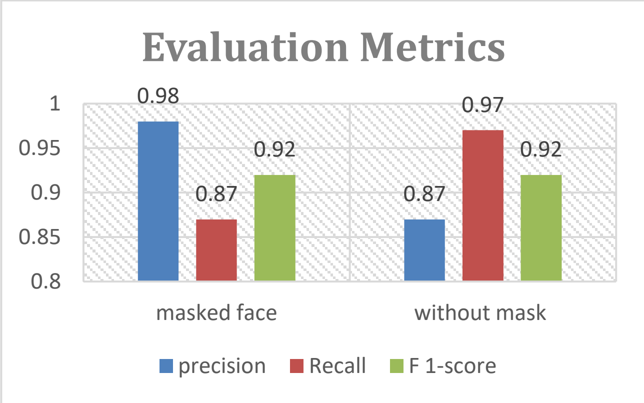

Figure.8 Evaluation metrics for the proposed modal

Table 4 Evaluation metrics for the proposed modal

	precision	Recall	F1-score
Masked face	0.98	0.87	0.92
Without mask	0.87	0.97	0.92

(Refer with: Fig. 9) indicates that the Mobile-netv2 is faster for accuracy across the spectrum. Also, Mobile-netv2 is the most effective in feature-extraction.

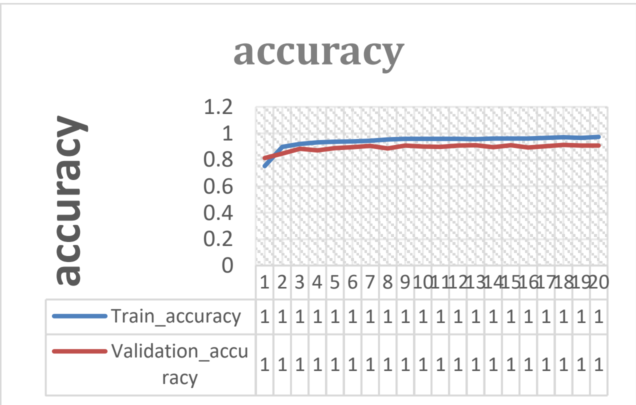

Figure.9 Accuracy/Accuracy-validation

Table 5. Accuracy/Accuracy-validation

	Accuracy	Accuracy-validation
1	0.7518	0.8125
2	0.8975	0.8468
3	0.9188	0.8831
4	0.9315	0.871
5	0.9368	0.8891
6	0.94	0.8962
7	0.9445	0.9063
8	0.9533	0.8861
9	0.9583	0.9073
10	0.9583	0.8992
11	0.9583	0.8982
12	0.9583	0.9073
13	0.9565	0.9093
14	0.9608	0.8952
15	0.9598	0.9093
16	0.96	0.8921
17	0.9653	0.9022
18	0.971	0.9123
19	0.9653	0.9073
20	0.9718	0.9073

(Refer with: Fig. 10), we only iterated 20 epoch, the data improved and accelerate the training.

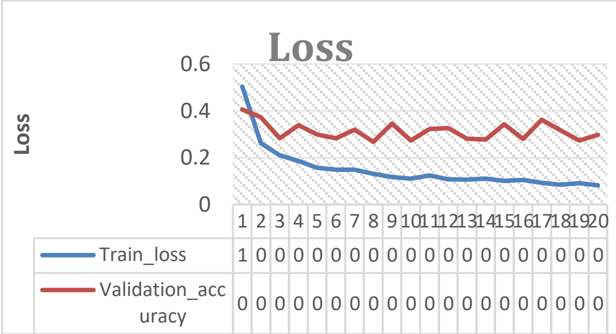

Figure.10 Loss/Loss-validation

Table 6. Loss/Loss-validation

	Loss	Loss-validation
1	0.5051	0.4059
2	0.2628	0.3733
3	0.2102	0.2834
4	0.1856	0.3395
5	0.1575	0.2992
6	0.1489	0.2823
7	0.1482	0.3193
8	0.1312	0.2674
9	0.1176	0.3453
10	0.1104	0.2729
11	0.1248	0.3233
12	0.1082	0.3268
13	0.106	0.2822
14	0.1102	0.2775
15	0.1015	0.3426
16	0.1049	0.2807
17	0.093	0.3624
18	0.0843	0.3175
19	0.0918	0.2737
20	0.0816	0.2981

(Refer to Table 7), which illustrates the Related research used different techniques CNN, Mobile-Net, Hyperface-ResNet, and cross-class object removal algorithm used in face detection and recognition with our proposed modal.

Table 7. Related research used different techniques

Authors/year	Technique	Performance
(Nagrath et al., 2021)	Single Shot Multi-box Detector as a face detector and MobilenetV2	Accuracy the score of 0.9264 and an F1 score of 0.93.
(Rahman, Manik, Islam, Mahmud, & Kim, 2020)	CNN	Accuracy is 98.7%
(Jiang & Fan, 2020)	cross-class object removal algorithm	2.3% and 1.5% the face and mask detection precision
(Pathak, 2020)	mobileNets	2.3% and 1.5% the face and mask detection precision
(Ranjan, Patel, & Chellappa, 2019)	HyperFace-ResNet	
Our proposal model	Mobile-Nets and Haar-like	An accuracy the score of 0.99 and an F1 score of 0.98.

IV. CONCLUSION

In our proposed modal, a novel face detection and recognition framework is implementing using mobile-net and haar-like algorithms applying in the dataset contain images with-mask and image without -mask in which, data augmentation is applying and after that, the data set is splitting into 80%for training and 20% for testing. The proposed techniques and algorithms give an excessive accuracy, the results of the proposed modal was tested on a dataset from Kaggle, yielded 0.99 accuracies, a loss of 0.08, F1.score 0.98 and it would be supportive to the facility to detect and recognize masked –faces in this great pandemic.

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