Masked Face Recognition Using Convolutional Neural Networks

Saja Mohsen Abbas
Department of Computer Science, Faculty of Education, University of Kufa,
ALNajaf, Iraq
sajaalthebhaweiy@gmail.com
https://orcid.org/0009-0007-5004-1432

Mohammed Hasan Abdulameer
Department of Computer Science, College of Education for Girls, University of Kufa,
ALNajaf, Iraq
mohammed.almayali@uokufa.edu.iq

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***Abstract*— *Since the COVID-19 epidemic's rise in 2020, Cover face recognize achieve advanced significantly in the range of computer vision. Face cover is important to stop or limit the COVID-19 disease's spread due to the global outbreak. Face recognize is among of the most commonly used biometric recognition approach, because it can be utilized for monitoring systems, identity management, security verifying, and a lot of applications. The majority features of faces were hidden by mask, leaving just a quite some, including eyes plus head-region, that's utilized for recognize. This challenge may reduce the recognition percentage because of the limited area to extract features. Due to the popularity of deep learning to extract and recognize deep features in many research areas especially computer vision,In this work, a covered face recognize system is introduced. utilizing Convolutional neural network (CNN), one of the most widely common deep learning algorithms. The final layer in the CNN architecture, the softmax activation function, was utilized to identify the facial characteristics after they had been extracted using CNN from the masked face's eyes, forehead, and brow regions. In the Study employ the "Extended Yale B database," which has issues with changes in placement and lighting. additionally, they covered faces in Dataset with medical masks. In comparison to other approaches to solving this problem, our strategy showed to be successful and promising with a recognition accuracy for "Extended Yale B" of 95%.*

Keywords— COVID-19, CNN, Face Recognition, Masked Face

I. INTRODUCTION

Since the corona infection expansion quickly, it presented a significant danger to daily life for individuals[1].The World Health Organization (WHO) has recommended the mask-wearing correctly in general areas with keeping secure distance effficient ways to stop the transmission of the virus and cross-infection[2]. In order to stop the COVID-19 outbreak from spreading, people were forced to wear masks[3]. Facial recognition algorithms may be more adaptive in reality with the aid of masked face recognition. Furthermore, the numerous mask forms used in this technique made it impossible for standard facial recognition systems to perform correctly, pushing the researchers to think of alternative solutions[4]. The Covid-19 outbreak has seen a long-standing legacy of mask wear. As a result, successfully and effectively resolving this issue has grown challenging[2].A subset of occlusion face recognition systems known as "masked face recognition" is thought to be different from normal occluded face recognition [3]. Masked face recognition faces two major obstacles: Firstly, the vast majority of face recognition systems are designed particularly to work with all or most of the available facial characteristics. Secondly, the mouth and nose features are obscured, which significantly reduces the effective features. To deal with the problems mentioned above and find solutions, deep learning model CNN is used[5]. The expected systems for masked facial recognition could be practically implemented focuses upon examining features that can derived through parts of the face that are not covered via mask, like, eyes, brows, and head-region [6] . Several recent studies have used a variety of algorithms and methodologies to create systems for masked facial identification. We mention a group of studies for contributors and researchers who are building and developing a masked face recognition system.

They suggested a new method for auto removing masks from faces, and they used a GAN-based network with couple of properties, first for discover the generic facial structure and second property concentrate on learn the deep lacking area. On the basis of realistic images obtained from Internet,the evaluation was made. Both qualitatively and quantitatively, the model outperforms other representative modern strategies [7].

The suggested method consists of detecting the face region, whilst obscured face detection challenge was strategy using a Multi-Task Cascaded Convolutional Neural Network (MTCNN). The Google FaceNet embedding model is utilized to obtain facial features. Lastly, Support Vector Machine(SVM) was used to accomplish the classifier. Findings demonstrate that the mentioned methods performs excellently on masked face recognition. On the "AR face database," our strategy has an accuracy of 90.40%[8].

During the pandemic COVID-19 virus, the vast majority of face recognition technologies in use performed poorly. A new Identity-Aware Mask GAN with segmentation-driven multi-level identities and a domain-constrained ranking loss was developed by the authors of [9]. The trial results upon that MFSR dataset demonstrate that the recommended methods work well, as measured by their accuracy of 86.5%.

A technique for recognizing masked faces based on person re-identification associations was introduced in 2020 by the authors[10]. By using this technique, the difficulty of recognizing disguised faces is changed to the difficulty of detecting relations between the cover face and the visible faces of the same individual. The approach of re-identification uses attributes rather than just a person's looks. Comparative tests demonstrating the accuracy (64.23%) of modern disguise face recognition systems show its advantage.

Convolutional Block Attention Module (CBAM) was released in 2021 by researchers[5] to address the masked face issue. Large-scale Empirical data-sets illustrate the proposed approach can efficiently masked face recognition performance. Achieves an general accuracy rate of 82.8648%.

The researchers in[11] proposed a framework using the ResNet-50 architecture to address the challenge of identifying people with masked faces; accuracy of 47% was obtained for covered face identification on the RMFRD dataset.

Lastly, the researchers in[12] showed how ineffective traditional facial recognition methods are in identifying people wearing masks. They then used a hybrid approach PCA and CNN to analyze the unobscured section of the face in order to reconstruct the hidden portion of the facial image. The accuracy of hybrid techniques PCA and CNN ranges from 85 to 95 percent, and for CNN it is between 70 and 80 percent.

Its manuscript is stated as following for this remaining portions: Contributions are discussed in segment 2, the study's problem statement is offered in segment 3, the CNN is displayed in segment 4, the suggested approach defined in segment 5, The study findings have been shown in segment 6, and conclusion has been stated in segment 7.

II. CONTRIBUTIONS

These are the three main achievements of this significant work:

1. Construct a convolution neural network model with the best performance for mask face identification.
2. Use the new MaxPooling window size of 1*2 to reduce the dimension of the face image.
3. Build programming code to add masks to faces to generate masked face datasets.
4. Build a masked face recognition model to identify masked faces that have issues with changes in illumination and positioning

III. PROBLEM STATEMENT

Computer vision models have a difficult problem recognizing persons with masked faces since a medical mask will typically hide the mouth and nose to prevent the expansion of illness. The most significant facial features are the mouth and nose. Masks can conceal a significant amount of the face, including the lips and nose, making it difficult to extract numerous features, which could have a significant impact on how well the facial recognition method works. The most challenging facial occlusion problem today is face masking, yet researchers still trying to use deep CNN to solve it . The biggest problem and challenge when we train the model with full seen faces and test it using masked faces which we investigate in this study.

IV. CONVOLUTIONAL NEURAL NETWORK

A subcategory of methods for deep learning is CNN. that has gained prominence in a variety of tasks in computer vision and is generating attention in a variety of programs. It is comprised of several layers, including fully-connected layers, max pooling, and convolution layers, and it is intended to automatically and able to adapt discover spatial hierarchies of information.[13]. Fig.1 demonstrates CNN's overall structure.

1. Convolutional Layer can execute convolutional filters among the input images or outcome of Max Pooling Layer to feature extraction.
2. Following the Convolutional Layer, the Max Pooling Layer is typically utilized to decrease the size of the feature.
3. In the Fully Connected Layer, There is no connection between neurons in the same layer, whilst every neuron is connected to every other neuron in the layer below and above it[14][15].

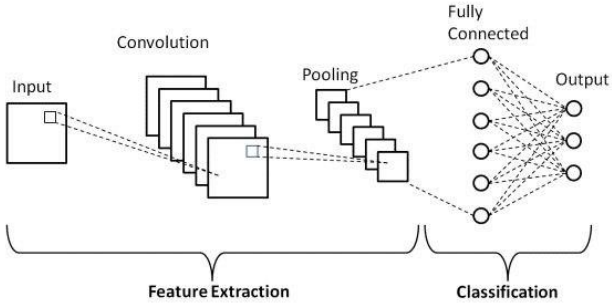

Fig. 1. demonstrates CNN's overall structure[16].

V. The suggested method of masked face recognition

As illustrated in Fig.2, Three main steps constitute the suggested method: preprocessing, feature extraction using CNN, and classification with Softmax.

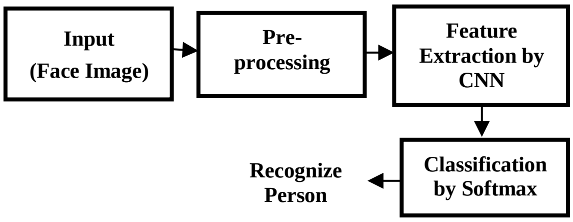

Fig.2. The Approaching Masked Face Identification

A. Pre-processing phase

Various steps were carried out on the source images, and they can be summed as:

1. Begin with face detection
2. Crop the face that was detected.
3. Resize the image that was cropped
4. Image grayscale conversion
5. Normalization
6. Images of faces, a mask has been added.

B. Feature Extraction and Classification

The convolutional neural network described in the paper contains nine layers, comprising three convolution layers, three max-pooling layers, one fully connected layer, one dropout layer, and finally the output layer. The steps for the study are as follows:

1. The input image is a grayscale facial image with a size of 200*200 pixels.
2. In convolution layers kernel size is 3*3, whereas the MaxPooling layers window size is 1*2 with a stride of 2.
3. Convolution is applied as the first layer, and the activation function rectifier linear unit (LeakyReLU) is used after each convolution layer. The image's size remains at 200* 200 pixels, Followed The MaxPooling layer is applied to minimize the size of the feature image, and the outcome is 100*100 pixels.
4. The third layer, also convolution layer and the output's size is unchanged. followed by MaxPooling layer, the output size is 50*50.
5. The fifth layer is still a convolution layer, and the resulting image's size is 50 *50 ,next by the max-pooling layer. The output of the MaxPooling layer is 25*25.
6. The seventh layer is the image passes through a fully connected layer.
7. The eighth layer is dropout carried out to avoid overfitting.
8. The last layer is the softmax layer, Members are recognised utilising Softmax classifier, which is typically used for numerous classification tasks. This layer is always altered to accept more classes. It is utilized at the top-level network layer which have superior non-linear classifying capabilities.

VI. Experimental Results

A. Platform

Python 3 is freely available through Google Colab, and an Nvidia Tesla K80 12 GB processor with 12 GB of RAM was used to build the system. Utilizing Spyder Python (2.7), face was also detected and cropped .Using the "Extended Yale B" dataset. In terms of accuracy and loss function, the proposed method is then assessed overall.

B. Experiments on Faces database

The "Extended Yale B database" contains 38 participants and 2414 frontal-face images with a resolution of 1920x168. 64 image on averaged for every class were originally extension ".pgm",type prior to its being transformed into ".png" type. The images were acquired within different bright conditions and a variety of emotions [17]. From a 200*200 pixel grey level, characteristics should be obtained, we used 1254 images from the "Extended Yale B". We split it into 25% for testing and 75% for training, using the same individual's information for both. Mask added on face for used in testing stage, and to prove how wearing a mask during the testing procedure influences the face recognition system.

C. Evaluation Metrics

This study evaluates the suggested technique using accuracy and loss function.

1. Accuracy

which accuracy is described by equation 1[18]

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2. Loss function

For multiclass categorizing problems, cross-entropy is the standard loss function. It is intended for multiple -class classification, with objective values for each category provided a unique integer value spanning from 0-1, 3,..., n. Cross-entropy will generate a score for each class in the challenge that represents the typical variation among the true and calculated probabilistic.When value of the cross-entropy is zero , the score decreases. When building the model, provide "categorical cross entropy" to recognize cross-entropy as the Keras loss function[19] .

D. Evaluation of the Proposed Method Using Accuracy, Loss Function

In "Extended Yale B"[19], 921 images of face were used for training, and 333 obscured face images have been used for testing. The network has been trained with Keras, a well-known deep learning framework, utilizing the Softmax function as the classification function. The testing model's best accuracy rate after numerous training iterations was 95%, and the loss function was 0.2426, and the number of kernels in the convolution were sequentially 32, 64, and 64, with a filter size of 3*3 in all convolution layers and a window size of 1*2 with a stride of 2 in all MaxPooling. The optimal size of the proposed construction of CNN is determined. After some tribally it was decided to create the suggested network based on its high accuracy. Gradually altering the max pooling, then the count of kernals, and the count of convolutions. Tables 1, show samples of tries for build model until get best performance model performed on "Extended Yale B".

	Conv2D_1	Conv2D_2	Conv2D_3	Max_pooling2d (1,2,3)layers	No.of hidden layers	Activation Function	Accuracy	Loss function
Try1								
No. & size of filters	256,(3*3)	64,(3*3)	32,(3*3)	2*2	512	relu	77	1.4726
Try2								
No. & size of filters	16,(5*5)	32,(5*5)	64,(3*3)	2*2	256	relu	46	38
Try3								
No. & size of filters	32,(3*3)	64,(3*3)	64,(3*3)	2*2	256	relu	79	1.3554
Try4								
No. & size of filters	64,(3*3)	32,(3*3)	64,(3*3)	3*3	256	Leaky_relu	50	4.9936
Try5								
No. & size of filters	**32,(3*3)**	**64,(3*3)**	**64,(3*3)**	**1*2 ,stride=2**	**256**	**Leaky_relu**	**95**	**0.2426**

TABLE 1: Samples of tries for build model until get best performance model performed on "Extended Yale B"

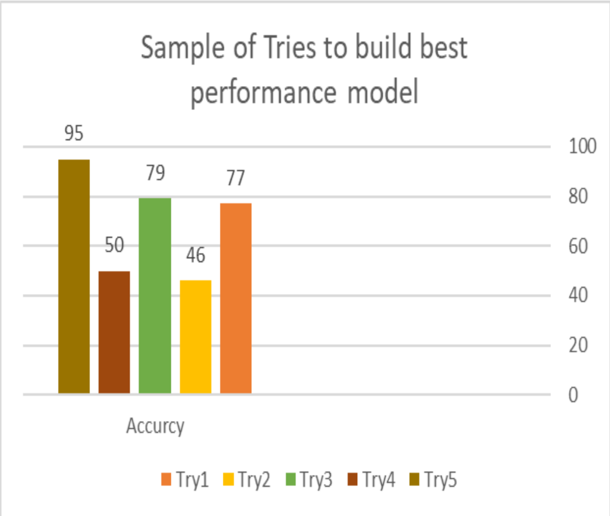

Fig.3. represent performance of model in each try in accuracy scale

The association between samples of tries to construct a model with a result in the accuracy, Loss Function scale, is depicted in Figs. 3, 4. It should be mentioned that the best outcome was attained in the fifth attempt. The fifth experiment's architecture will be used as the proposed architecture, as stated in the Table1 above.

Fig.4. represent performance of model in each try in Loss Function scale

Reference	algorithm	Findings	Data
[10]	ResNet-50	47%	RMFRD
[11]	CNN	70-80%	Essex,COMASK20
Our suggested	**CNN**	**95%**	**Extended Yale B**

E. A comparison of the suggested method and relevant fields

Our suggested framework illustrate superior when evaluated it against alternative strategies, and the comparative procedure proved the suggested technique was preferable to several other ways especially our solution for identification of individuals wearing masks as opposed to locating the mask itself. The comparative procedure is illustrated in Table 2.

Table 2.Comparing the proposed technique with related works

VII. Conclusion

A convolutional neural network was implemented in this experiment to enhance face recognize while a medical mask was being utilized. Our strategy was examined based on the model being tested with a disguised face after training it with an visible face, which proved to be difficult task,

Added difficulty has been examined, we dealt with different challenges such as illumination variation and pose changes along simultaneously with a mask over their face. This procedure has been utilized on the following datasets "Extended Yale B dataset", Practical research is done using the to assess the model and a score of accuracy is used to evaluate it. The evaluation's findings illustrate that the presented algorithm performs far better than many covered face recognize systems, where we achieved 95% accuracy using the "Extended Yale B" database. To establish our model unique and general, the suggested model will be enhanced in the future to take into account another sort of facial occlusions. Also, the classical feature extraction method can be combined with CNN model to increase performance.

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