International Journal on "Technical and Physical Problems of Engineering" (IJTPE)
Published by International Organization of IOTPE
ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com
December 2023 | Issue 57 | Volume 15 | Number 4 | Pages 11-18

COMBINING FEATURE DESCRIPTOR TECHNIQUES WITH CONVOLUTIONAL NEURAL NETWORK FOR MASKED FACIAL RECOGNITION

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Abstract- As a more reliable technique of efficiently identifying or validating a person than other traditional methods, such as a PIN, password, fingerprint, etc., facial recognition is commonly used in biometric technology. Due to numerous occlusions or medical masks, especially in the era of Corona virus infections, the traditional approaches, nevertheless fail to identify the necessary traits accurately. This made the use of powerful techniques that can extract deep features, like deep convolutional neural networks, necessary. Our objective in this effort is to develop a method that can identify someone without requiring them to take off their mask. In this paper, two distinct approaches based on fusing conventional feature extraction techniques with convolutional neural networks are put forth. Local Binary Pattern (LBP) and CNN are integrated in the first technique, while Local Derivative Pattern (LDP) and CNN are merged in the second. We created a feature map for each technique using a different feature descriptor technique, fed it into the CNN, trained the network, and then used the SoftMax activation function to identify the features. Medical masks were added to two datasets, the "AR Face Database" and the "Extended Yale B Database," which both had problems with illumination and position changes. In order to determine which strategy performed more accurately, a comparison between the two is conducted at the end. The results show that the combination of LBP and CNN achieves the best results, where the recognition accuracy for "Extended Yale B" was 99%, compared to 96% for the "AR Faces database." Our studies have shown that the rate of masked face recognition can be greatly increased by combining conventional techniques with the CNN model.

Keywords: Face Recognition, Covid-19, Convolutional Neural Network, Local Binary Pattern, Local Derivative Pattern.

1. INTRODUCTION

The COVID-19 global epidemic, which began in the year 2019, has had an influence on a number of industries, including flight, teaching, medical care, tourism, and luxury retail, and more. It has also caused a global health crisis. The daily lives of individuals were also significantly impacted. One of the finest preventative steps one can take to prevent the transmission of ailment and keep lives, as stated by the "World Health Organization (WHO)", is masking one's face [1]. Password-based or fingerprint-based unlocking techniques should be avoided since the COVID-19 infection can propagate via touch. Face identification makes it much safer without touching. However, current facial recognition technology is inaccurate when wearing a mask. As a result of wearing a facial mask, vital facial characteristics like the lips and nose are hidden, which lowers the rate of detection in conventional face recognition systems [2].

Existing face recognition technologies, which are mainly based on all points of facial features, need to be upgraded in order to address the problems caused by missing features or partially obscured areas. So that identity identification is still accurate when only a portion of the face is shown [3, 4]. We need an alternate solution by combining deep feature extraction techniques like CNN with the traditional approaches in order to address the challenges that the conventional methods face due to concealed areas of faces and recognize persons without removing the face mask. In this paper, we offered two approaches that combine traditional techniques with the CNN model. Combining LBP and CNN in the first technique, LDP and CNN in the second technique, and the following are the main contributions to this paper:

1) To construct a novel LBP and CNN-based method for masked face identification.
2) To develop a separate new strategy based on fusing LDP and CNN.
3) Recognize people with masked faces using only the most basic attributes that were gleaned from viewed face areas throughout the training phase.
4) A thorough assessment and comparison of the two suggested strategies to determine which is better.

The manuscript is stated as follows for these remaining portions: Related work is displayed in Segment 2, the study's problem statement is offered in Segment 3, in segment 4 the proposed methodologies are discussed, Classification stage for the proposed methodologies have been shown in segment 5, experimental results are discussed at segment 6 and conclusion has been stated in segment 7.

2. RELATED WORK

Recent studies have looked at many different methods for masked face recognition. In [5], they released a method for masked face classification based on person re-identification association, which transforms the issue of association between the mask and the visible faces of the same person into an issue with covered face recognition. The approach to re-identification for individuals is based on their traits rather than only their facial appearances, where it reaches an accuracy of 64.23 percent. The majority of current facial recognition algorithms, according to [6], perform poorly in this masked face scenario. They therefore proposed a new approach called Identity Aware Mask GAN (IAMGAN), which incorporates a domain-constrained ranking (DCR) loss and segmentation-guided multi-level identity. Their experiments on the MFSR dataset showed that these methods were effective; they have an accuracy of 86.5%.

In order to assess the accuracy of masked facial identification, a well-known conventional approach (PCA) was employed in [7]. A mask-covered face has a low rate of recognition in PCA, as has been shown. 72% of the experimental outcomes are in the ORL Face database. But nevertheless, due to the problems and difficulties posed by masked faces, most conventional procedures were unable to produce superior results. Several researchers have recently looked at deep learning to address these kinds of issues. In order to overcome the issue of detecting people with covered faces, the study in [8] employed the ResNet-50 architecture in conjunction with transfer learning to alter a pre-trained ResNet-50 model on their images of individuals without face masks. For their RMFRD dataset, a pre-trained ResNet-50 model was fine-tuned to achieve accuracy of 89%, while a ResNet-50-based architecture's hyperparameters were developed and fine-tuned to achieve accuracy of 47%.

In a different study, the researcher [9] presents a solid solution to the issue of the Face's mask recognition procedure relies on obstacle elimination and utilizing deep learning based on traits. The mask's placement on the face must be removed first. Three already-trained CNNs, namely VGG16, AlexNet, and ResNet50, are then applied to the resulting regions in order to get deep features (mostly from the eyes and forehead areas). According to experimental results on the RWMF Dataset, 91.3% accuracy represents a great recognition performance when compared to other cutting-edge techniques. As stated in [1], the majority of important facial features are hidden by the face mask, rendering Classical face recognition that are employed for safety purposes are ineffective. This makes it hard to recognize the individual. A novel approach to facial recognition with masks was presented by [10] to deal with the limitation of missing features. It included using the Convolutional Block Attention Module (CBAM) and cropping method. Several experimental datasets appear that the suggested strategy can significantly improve covered face identification performance. In all categories, it has an accuracy rate of 82.8648% on MFR.

Using a cropping-based deep learning architecture, the authors of [11] propose a remarkable method for solving the challenge of covered face identification. Using a hybrid VGG-16-Random Fourier deep learning model that disallows masks for recognition, the top portion of the face is used to extract enhanced features. Even with these limits, they still got better results. The experiment on Robotics Lab showed that accuracy was 97.460. In order to reconstruct the occluded component of the facial image, the authors in [12] claim that the non-occluded part of the face may be evaluated using CNN or a hybrid method combining CNN and PCA. In trials, CNN's accuracy is between 70% and 80%, while PCA and CNN hybrid techniques reach accuracy between 85 and 95%, respectively, on the Essex and CoMASK20 datasets. All of the aforementioned methods, though, continue to face a variety of problems, including the use of small datasets, complexity, or other issues like pose variation or lighting. So that, deep investigations should be taken into account in order to leave opportunity for improvement.

3. PROBLEM STATEMENT

Any face recognition algorithm finds it challenging to identify masked faces since the traits needed to correctly predict a person's identity are reduced to just the eye and occasionally the forehead, rather than the complete face. The use of masks increases fundamental doubts related to the precision of current face recognition algorithms because they hide the majority of facial features. A large area of the face, including the lips and nose, can be hidden by a mask, making it difficult to retrieve many facial traits from them. The facial recognition system's efficacy could be significantly hampered by this. Another problem arises if the position of the covered face changes further, as the facial recognition technology may be less effective as a result. If the position of the covered face changes further, there is a new problem. All of these issues, especially when using traditional techniques, might result in unsatisfactory face recognition findings. The objective of this study is to handle the problem of identifying a person wearing a facemask by combining the advantages of traditional techniques and convolutional neural network models.

4. THE PROPOSED METHODOLOGIES

The primary objective of this study is to identify a person wearing a mask by training our models on faces without masks and putting them to the test in real-world scenarios. The masked face has fewer features than the unmasked face, and there isn't a uniform feature mapping; therefore, it was considered that the occlusion on the face presents a challenge to our model. Two new methodologies are suggested to address this problem: the first one combines the LBP technique and CNN, and the second one combines the LDP approach and CNN. The LBP and LDP descriptors accept images of size m*n and describe the local texture features for them. The output is a feature map that is two-dimensional with identical dimensions to those presented as input, which is presented as input to CNN, which successfully extracts the spatial features and reduces the dimension of the features [13]. The CNN output is approximately half or a quart of the original size .The three main stages of each methodology are pre-processing, feature extraction, and classification, as shown in Figure 1.

4.1. Pre-processing Stages for the Proposed Methodologies

Several methods are applied to datasets, as seen in Algorithm1. In the first step, faces are detected using the Harr Cascade approach, and in the second, faces are cropped. Third, because deep learning models learn more quickly from small training sets of photos, the dataset's images are resized. Fourth, to lessen computing needs, transform color images to grayscale. finally, using masking add-ons, another method for producing masked faces for model testing was used to test images. Algorithm 1 illustrates the preprocessing processes.

Algorithm 1. Pre-processing stages

Input: Face Image Output: Processed Face Image Begin Step1: Face Detection Step2: Crop Face Image Step3: Resize Face Step4: Convert to grey Step5: Masking add-ons, for producing masked face End

4.2.1. The First Methodology: Combined LBP and CNN Model

There are numerous ways to extract the most helpful features from (preprocessed) face images. The first methodology is built on the combination of LBP features and CNN. Initially, LBP is used as a feature descriptor, and after collecting a feature map, the CNN can successfully extract spatial features of images and reduce feature dimensions [14]. LBP accepts images with a size of 200×200 on "Extended Yale B" and 129×165 on the "AR Face Database." From these images, LBP extracts local information by calculating the local changes in intensity between the value of the pixel of center and its surrounding neighboring pixels [15]. The output is a feature map that is two-dimensional with identical dimensions to those presented as input. And served as input for CNN, which extracted features and decreased the size of images. Where the size output of CNN for "Extended Yale B" is 25×25 and the size for "AR Face Database" is 16×20. Using CNN, which has improved the LBP results, can guarantee, this combination can improve performance. The following Equations (1) and (2) are ways to express operators to obtain the value of the LBP approach [16]:

$$LBP(P_c,Q_c)=\sum_{n=0}^{n=i-1} M(g_n-g_c)2^n \tag{1}$$

where, g_n stands for the intensity grey values of n evenly spaced pixels on an R-radius circle, gc stands for the center pixel's gray value (P_c; Q_c), the neighborhood's pixel number is represented by n, and the function M is as follows [16]:

$$M(x)=\begin{cases}1\ , & i\ge 0\\ 0\ , & i<0\end{cases} \tag{2}$$

Algorithm 2 provides a detailed explanation of the hybrid LBP-CNN procedure.

Algorithm 2. Hybrid LBP and CNN Feature Extraction Steps

Input: Processed Face Image Output: Vector Features Begin Step 1: With a 3×3 mask, LBP operation is carried out on images with a size of 200×200 on "Extended Yale B" and 129×165 on the "AR Face Database." Step 2: Utilizing the value of the central pixel as a threshold, this operator operates with a pixel's eight neighbors. Step 3: Comparing the threshold with the neighboring pixel a one is given to a pixel if it has a neighboring pixel with a gray value that is higher than the center pixel (or the same gray value); otherwise, a zero. Step 4: Once the eight ones or zeros have been concatenated into a binary code in a clockwise orientation, the LBP code for the center pixel is created. Step 5: After that, the binary numbers are transformed into decimal values. Step 6: The result is a feature map that is two-dimensional with identical size to those presented as input, which is used as input for CNN. Step 7: The input layer of CNN is set up primarily to accept LBP feature map. Step 8: The next layer utilized in the suggested model is the convolution layer, where the number of layers employed changes based on the datasets used. The "Extended Yale B" model employs three convolutional layers. There were 32, 64, and 64 kernels respectively, with a dimension of 3. While the "AR Face Database" model employs three layers, 256, 64, and 64 filters, respectively, with a 3-filter size Step 9: The pooling layer, which is the maximum pooling layer, is applied after each convolution layer; it reduces the spatial dimensions of the information derived from the feature maps. The "Extended Yale B" model has a 1×2 window size and a 2 stride. And the window size for the "AR Face Database" is 2×2. Output of CNN for "Extended Yale B" is 25×25 and the size for "AR Face Database" is 16×20. Step 10: fully connected layers, the feature maps produced by the final convolution or pooling layer are flattened or converted into a one-dimensional array of integers. These arrays are then linked to one or more dense layers, on "Extended Yale B ", Number node used 512, while on "AR Face Database" is 256 neurons. End

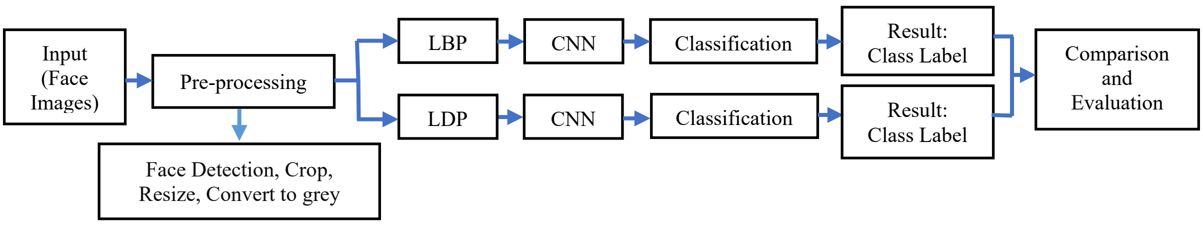

Figure1. The structure of the suggested methods

4.2.2. The Second Methodology: Combined LDP and CNN Model

LBP extracts information from across all orientations, making it a first-order non-directional pattern operator, whereas LDP extracts higher-order information with more meaningful features [17]. Local derivative pattern, which combines directional high-order local derivative pattern with LBP, can be seen as an extension of LBP [18]. The transition output is concatenated as a 32-bit binary code by LDP, which finds local features in the following four orientations: 0°, 45°, 90°, and 135° [19]. Based on local derivative variety, LDP serves as a broad foundation for representing derivative pattern features and producing binary numbers, it enables particular information to be extracted from the incoming data and has been demonstrated to be one of the most efficient techniques for extracting two-dimensional features, notably in computer vision applications. LDP receives images with a size of 200×200 on both the "Extended Yale B" and the "AR Face Database." Local features are extracted from these images by LDP. The output is a feature map that is two-dimensional with identical dimensions to those presented as input, and is provided as input for CNN, which extracts features and lowers the size of images. Where the size of the CNN output is 25×25 for both datasets. The following equation describes the three steps that LDP takes to calculate a feature map [16]:

1) Calculate the first order derivative in four directions according to Equation (3).

$$I'_a = I(L_0) - I(L_i) \tag{3}$$

where, a is (0, 45, 90, 145) direction. L_0 specifies the 3×3 mask's central pixel and pixels and L_i refers to L_1 to L_8 the neighbors' pixels clockwise.

2) Second-order derivatives are calculated by multiplying first-order derivatives by the center pixel, as shown in Equation (4):

$$\begin{aligned} &LDP_\alpha^2(L_0) = \\ &= \left\{ f(I'_\alpha(L_0), I'_\alpha(L_1)), f(I'_\alpha(L_0), I'_\alpha(L_2)), \ldots, f(I'_\alpha(L_0), I'_\alpha(L_8)) \right\} \end{aligned} \tag{4}$$

Using the LDP operator, two adjacent pixels' derivative directions are compared, and the results of the 0°, 45°, 90°, and 135° directions are combined. The step of comparison is displayed in Equation (5):

$$f(I'_\alpha(L_0), I'_\alpha(L_i)) = \begin{cases} 0 \text{ , if } (I'_\alpha(L_0).I'_\alpha(L_i) \geq 0 \\ 1 \text{ , otherwise} \end{cases} \tag{5}$$

The hybrid LDP and CNN are outlined in detail in Algorithm 3.

Algorithm 3. Hybrid LDP and CNN Feature Extraction Steps

Input: Processed Face Image
Output: Vector Features
Begin
Step 1: On the facial image with a size of 200 x 200 on both the "Extended Yale B" and the "AR Face Database", LDP operator of size 3*3 was used.
Step 2: Calculate the referenced pixel's first-order derivatives in the following directions: 0°, 45°, 90°, and 135°.
Step 3: Second order derivative is calculated for output of first order derivative, by multiplying the value of the pixel's central and one of its neighbors
Step 4: Comparing the outcome of multiplication Pixel, value is zero if the result is larger than zero, else it is 1.
Step 5: Results from the 0°, 45°, 90°, and 135° directions are combined. Consequently, a 32-bit binary code for LDP is produced.
Step 6: Feature vectors are created by converting binary to decimal.
Step 7: all previous steps performed on regions of images. The results are a feature map that is two-dimensional with identical size to those served as input, and it is provided as input for CNN.
Step 8: LDP feature Map is accepted as input-by-input layer.
Step 9: The convolution layer is the next layer used in the suggested model.
Respectively "Extended Yale B" and "AR Face Database" use three layers of convolution in an order of 256, 64, and 64 filters, with a size of 3.
Step 10: After each convolution layer, the pooling layer, which is the maximum pooling layer, is applied. It lowers the information's spatial size that were derived from the feature maps. On both datasets, the maximum pooling had a window size of 1×2 and a stride of 2, and the size of the CNN output is 25×25.
Step 11: fully connected layers, the feature maps produced by the final convolution or pooling layer are flattened or converted into a one-dimensional array of integers. These arrays are then linked to one or more dense layers; on "Extended Yale B", 256 nodes in dense layer are utilized, while on "AR Face Database," 512 neurons are used.
End

5. CLASSIFICATION STAGE FOR THE PROPOSED METHODOLOGIES

The suggested masked face recognition methods can solve the issue of face recognition using deep feature extraction. To do this, during the initial training phase, the system is given a set of images of recognizable individuals without masks. A new, mask-covered face is given to the system for recognition during testing. Individuals are recognized using the SoftMax classifier, which is often used for multiclass classification. It is mostly utilized in the field of mathematics, particularly in fields associated with probability theory. With regard to handling N-dimensional vectors, the SoftMax classifier offers a distinct advantage for classifying extraction vectors in deep learning. After calculating the extracted vector's probability, it will be classified. It indicates that all vectors' cumulative probabilities are 1, given the same set of data [20]. According to the changes made to this layer, more categories are now supported. It is used at the network's bottom layer and has strong non-linear classification capabilities.

6. EXPERIMENTAL RESULTS

The Google Colab platform, which provides Python 3 in a cost-free environment, along with a GPU Nvidia Tesla K80 12GB processor with 12GB of Memory, served as the implementation platform for the suggested techniques. The "Extended Yale B" dataset and the "AR" dataset are two distinct datasets utilized in the research. After that, the overall effectiveness of the presented approaches is assessed in terms of accuracy, F1-score, recall, and precision.

6.1. Experiments on "Extended Yale B Database"

There are an average of 64 frontal-face images per subject in the (.pgm) format in the "Extended Yale B" collection, which has 2414 frontal-face pictures of 38 persons at a resolution of 192×168 pixels. The pictures were captured with varied face expressions and under varying lighting conditions [21]. To extract features from an image that was 200×200 pixels in size and produced a grayscale image, we used 1254 images from the "Extended Yale B", we separated it into two sections: training (75%), and testing (25%), with the same person's data utilized in both. In addition, testing data is masked add-ons.

6.2. Experiments on “AR Face Database”

"Aleix Martinez and Robert Benavente" created the face database, which consists of over 4,000 images of individual's faces (70 men and 56 women). Images depict faces in frontal view with a range of occlusions (scarf and sunglasses), lighting effects, and facial expressions [22]. To extract characteristics from a grayscale image with a dimension of 129×165 pixels, we utilized 1299 images from the “AR Face Database”. Both the training and testing stages utilized the same individual's dataset, which were separated into 75% and 25%, respectively. The test images are handled by adding masks for the faces.

6.3. Evaluation Metrics

This paper employs various measures such as Accuracy, F1-score, Precision and Recall to assess the proposed techniques.

1. Accuracy is among the most popular evaluation metrics for issue recognition and classification. It shows the number of predictions that were true to all sample [23]. It has the following definition by Equation (6) [24]:

$$ACC = \frac{(T_{Pos} + T_{Neg})}{(T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg})} \tag{6}$$

where,

- True positives (T_{Pos}) refer to the count of correctly recognized masked faces.
- True Negative (T_{Neg}) refers to the count of masked faces that were negatively categorized.
- False Positive (F_{Pos}) refers to the count of masked face that were wrongly identified.
- False Negatives (F_{Neg}) indicate the count of masked faces that are recognizing as misclassified.

2. Precision: The proportion of successfully categorize positive forecasts to the predicted count of positive specimens [25]. which is characterized as follows by Equation (7):

$$Pre = \frac{T_{Pos}}{(T_{Pos} + F_{pos})} \tag{7}$$

Recall is that measures the count of correct positive forecasts created for all potential positive forecasts [26]. which is defined as follows by Equation (8):

$$Rec = \frac{T_{Pos}}{(T_{Pos} + F_{Neg})} \tag{8}$$

The F1-score is the harmonic median of precision and recall, and the F1-score can be obtained by utilizing the formula in Equation (9) [23]:

$$F1 - score = \frac{2(Pre \times Rec)}{(Pre + Rec)} \tag{9}$$

6.4. Evaluation of the Hybrid Models via Accuracy, Precision, Recall and F1-Score

The facial images were used in the experiments are divided into 947 training images and 352 testing masked face images in the “AR Face Database”, and 921 training images and 333 testing masked face images in the “Extended Yale B”. Feature maps are produced by applying feature descriptors (LBP, LDP) to faces. Following that, the network is trained using the well-known deep learning system Keras. The classifying function is defined as the Softmax function, and the weights of every convolution layer are determined using ReLU. Tables 1 and 2 display the proposed methods' best outcomes.

Table 1. Result of proposed models on "Extended Yale B"

Proposed Method	Accuracy	Precision	Recall	F1 score
LDP+CNN	99	99	99	99
LBP+CNN	99	99	98	99

Table 2. Result of proposed methods on "AR Faces database"

Proposed Method	Accuracy	Precision	Recall	F1 score
LDP+CNN	88	88	87	88
LBP+CNN	96	96	95	95

Tables 1 and 2 display the Results on both datasets to compare the performance of various techniques. LBP and CNN's proposed hybrid technique performs best on the "Extended Yale B" and "AR Faces database," respectively. The hybrid LBP and CNN architecture is shown in Tables 3, 4 for both datasets.

Table 3. An Overview of the Suggested Hybrid, the LBP-CNN Model Structure for "Extended Yale B"

Type of layer	Size of kernel	Num. of kernel	Shape of Input	Shape of output	Num of params
Conv2D-1	3×3	32	200,200,1	200, 200,32	320
MaxPooling-1	1×2	-	200,200,32	100,100,32	0
Conv2D-2	3×3	64	100,100,32	100,100,64	18496
MaxPooling-2	1×2	-	100,100,64	50,50,64	0
Conv2D-3	3×3	64	50,50,64	50,50,64	36928
MaxPooling-3	1×2	-	50,50,64	25,25,64	0
Flatten	-	-	-	40000	0
Dense1	-	-	-	512	20480512
Dropout	-	-	-	512	0
Dense2	-	-	-	37	18981
Total params: 20,555,237 Trainable params: 20,555,237 Non-trainable params: 0					

Table 4. An Overview of the Suggested Hybrid, the LBP-CNN Model Structure for "AR Face database

Type of layer	Size of kernel	Num. of kernel	Shape of input	Shape of output	Num of parameter
Conv2D-1	3×3	256	129,165,1	129,165,256	2560
MaxPooling-1	2×2	-	129,165,256	64,82,256	0
Conv2D-2	3×3	6	64,82,256	64,82,64	147520
MaxPooling-2	2×2	-	64,82,64	32,41,64	0
Conv2D-3	3×3	64	32,41,64	32,41,64	36928
MaxPooling3	2×2	-	32,41,64	16,20,64	0
Flatten	-	-	-	20480	0
Dense1				256	5243136
Dropout				256	0
Dense2				87	22359
Total parameters: 5,452,503 Trainable parameters: 5,452,503 Non trainable parameters: 0					

Furthermore, Figures 2 and 3 demonstrated the relation between the accuracy of the presented approach and the number of epochs for each dataset individually.

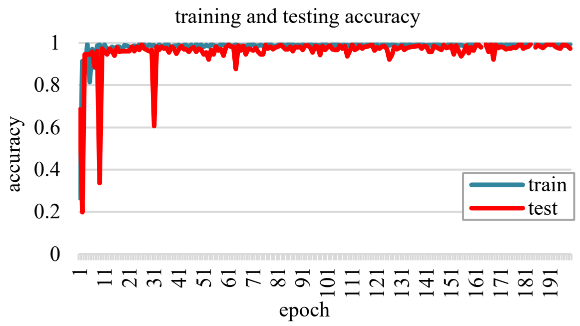

Figure 2. The accuracy of the suggested approach for "Extended Yale B"

The Figure 2 depicts the relation between training and testing accuracy and the number of epochs in the "Extended Yale B" database. Training accuracy grows gradually and demonstrates stability at epoch 25. The test's accuracy starts off rising gradually and quickly, then it varies up and down at epoch 25, and it continues to fluctuate until it demonstrates stability by rising at epoch 175 in terms of accuracy.

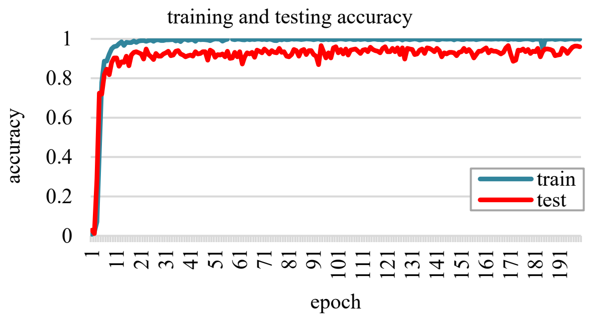

Figure 3. The accuracy of the suggested approach for "AR Face Database"

The Figure 3 depicts the relation between training and testing accuracy and the number of epochs in the "AR Face database". Training accuracy grows gradually and demonstrates stability at epoch 25. The test's accuracy starts off rising gradually and quickly, then it demonstrates stability at epoch 50 in terms of accuracy.

6.5. Comparison of the Proposed Hybrid Models and Relevant Works

Table 5 compares the proposed hybrid models to earlier relevant works in order to prove the efficiency of our models against earlier research. The comparison technique shown that the proposed approach outperformed a variety of alternative approaches, particularly our suggestion to identify people wearing masks rather than aiming at the mask itself. Our proposed strategy outperforms existing methodologies in terms of results.

Table 5. Comparisons of the proposed hybrid models and relevant

Ref.	Method	Result	Dataset
[5]	Identification Association	64.23%	Pedestrian
[6]	IAMGAN, segmentation driven multi-level identity and a (DCR)	86.5%	MFSR
[7]	PCA	72%	ORL face
[8]	ResNet50	47%	RMFRD
[9]	VGG 16, AlexNet, and ResNet50	91.3%	RWMF
[1]	deep metric learning and FaceMaskNet-21	88.92%	RMFRD
[10]	Cropping, and CBAM	82.8648%	MFR
[11]	VGG16-Random Fourier model	97.460%	robotics lab
[12]	Hybrid PCA and CNN	85-95%	Essex, COMASK20
The proposed LBP-CNN	Hybrid LBP and CNN	99%,96%	Extended Yale B, AR
The proposed LDP-CNN	Hybrid LDP and CNN	99%,88%	Extended Yale B, AR

7. CONCLUSION

Two hybrid techniques, namely LBP-CNN and LDP-CNN, were proposed in this study that are based on feature descriptors and convolutional neural networks. Using a face mask, they used to be able to identify human faces. It became clear that the task was challenging once the model was trained on a whole face and tested with a masked face. Further difficulties were examined in the handling of problems including simultaneous changes in facial expression and variations in illumination, in addition to the individual with a mask concealing their face. This process has been applied to the necessary datasets. For practical study, the "AR Face database" and "Extended Yale B" are employed. The model is assessed using accuracy, precision, recall, and F1-score scores. Findings from the evaluation show that the suggested hybrid LBP-CNN model works better than a variety of occluded face recognition systems. Which LDP is less resistant to changes in illumination since it depends on the size and direction of local derivative changes, both of which can be impacted by illumination changes .LBP simply takes into account local binary patterns, making it more resistant to variations in illumination. We were able to attain 99% accuracy on the "Extended Yale B" and 96% accuracy on the "AR Face Database". Additional improvements to the recommended model will be made to account for more types of facial occlusions in order to make our model distinctive and complete. Another common feature extraction technique may be coupled with a CNN model to improve performance.

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