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A face recognition system using convolutional feature extraction with linear collaborative discriminant regression classification

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ABSTRACT

Face recognition is one of the important biometric authentication research areas for security purposes in many fields such as pattern recognition and image processing. However, the human face recognitions have the major problem in machine learning and deep learning techniques, since input images vary with poses of people, different lighting conditions, various expressions, ages as well as illumination conditions and it makes the face recognition process poor in accuracy. In the present research, the resolution of the image patches is reduced by the max pooling layer in convolutional neural network (CNN) and also used to make the model robust than other traditional feature extraction technique called local multiple pattern (LMP). The extracted features are fed into the linear collaborative discriminant regression classification (LCDRC) for final face recognition. Due to optimization using CNN in LCDRC, the distance ratio between the classes has maximized and the distance of the features inside the class reduces. The results stated that the CNN-LCDRC achieved 93.10% and 87.60% of mean recognition accuracy, where traditional LCDRC achieved 83.35% and 77.70% of mean recognition accuracy on ORL and YALE databases respectively for the training number 8 (i.e. 80% of training and 20% of testing data).

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1. INTRODUCTION

Biometric face recognition is now an evolving area of work in the field of image processing [1]. The primary aim of biometry is to distinguish people from many visible characteristics such as their face, fingerprints, voice, and andiris [2]. These traits are ideal for biometric identification, but more protection for individual authentication is offered by the human face [3], [4]. Face recognition is an effective biometric authentication technique, because face recognition is highly used in the number of applications, including social networking, access control, video monitoring, and law enforcement [5], [6]. There are two types of face recognition systems, the appearance-based [7], and feature-based [8]. For successful face recognition, the feature-based framework has been introduced in this research study. The variations in occlusion and illumination cause critical degradation of the image [9], [10]. The common issues in face recognition are illumination variations, frontal vs profile, expression variations, aging and occlusions [11]. For tackling the above-stated problems, an effective convolutional neural network-linear collaborative discriminant regression classification (CNN-LCDRC) model is proposed in this research. The researchers developed five major methods for face recognition, where the methods include geometrical characterization method, the subspace analysis method, the elastic graph matching method, the hidden Markov model method [12], and the neural network method [13]. Mostly, the first four approaches are known as shallow learning because they can only take advantage of certain simple image features, and all rely on artificial intelligence to obtain sample features. Neural network-based methods are considered to be a profound learning since they could extract more complicated features such as corner point and plane features [14], [15]. The researchers developed the popular deep-learning approaches CNN, the deep belief network (DBN) [16], and the stacked denoising autoencoder (SDAE) [17]. In this analysis, CNN is used to extract facial characteristics as it takes images as the direct input, and resilient to image deformation rotation, translation, and scaling. Additionally, it is relatively difficult to manually acquire facial features from the face images, whereas CNN may automatically extract successful facial features. Thus, the proposed CNN-LCDRC combined model increases the recognition accuracy. The experiments are conducted on two datasets such as ORL and YALE in terms of mean accuracy and maximum accuracy. The scientific contributions of the proposed face recognition method in real-time are: i) provides security to devices; ii) to investigate criminals; iii) protects law of enforcement; iv) protects from the threats in business fields; v) gives control access to sensitive area; and vi) facilitates secure transactions.

This research paper is organized as follows: section 2 presents the study of existing techniques that are related to face recognition. The proposed method is explained in section 3, where the validation of CNN-LCDRC on two datasets with comparative study is described in section 4. Finally, the conclusion of the study is drawn in section 5.

2. LITERATURE REVIEW

In this section, a study of various existing techniques that are used to recognize the face are presented. In addition, the key benefits of existing techniques with its limitations are also described. Yang *et al.* [18] recognized the face and extracted the features by using an local multiple pattern (LMP) feature descriptor on Weber's law. The changing directions were described by generating multiple feature maps using a modified ratio of Weber's law. In the feature maps for image representation, the non-overlapping regions' histogram were concatenated by LMP. However, the improved LMP was only computationally efficient using integral images. Ouyang *et al.* [19] recognized the input face by implementing the hybrid approach that combined the improved kernel linear discriminant analysis (IKLD) and probabilistic neural network (PNN). At first, the relevant data were obtained by removing the sample features and recognition problems were solved by PNN. The computation time of the IKLD with PNN was higher than existing KLD with PNN, when the number of training was high.

Bhattacharya *et al.* [20] developed a local force pattern (LFP) based on local-appearance for recognizing the face effectively. Compared to the traditional pattern technique, a discriminating code was produced by encoding the textures' directional information using LFP. The Van der Waal’s force between pixel pairs were computed the micro-pattern structure, which was used to extract the information and encoded that directional information by a two-dimensional vector. The LFP method has high computation time, when the training samples had imbalance data. Nikan and Ahmadi [21] identified the input face images by implementing improved face recognition algorithms with degrading conditions. The optimum distinctive features were obtained by the combination of discriminative feature extractor with pre-processing techniques that were used for classification. The facial images were pre-processed by using enhanced complex wavelet transforms and multi scale Weber pre-processing techniques. In order to improve the recognition rate, different feature extraction techniques, namely block-based local phase quantization, Gabor filters with principal component analysis used in this study. However, the algorithm had peak signal-to-noise ratio (PSNR), when the recognition rate was 0.8.

Peng *et al.* [22] solved the issues of cross-modality face recognition by developing a Sparse graphical representation based discriminant analysis (SGR-DA). The adaptive sparse vectors were generated by constructing the Markov network model, which was used to represent the face images from various modalities. The discriminability was improved and complex facial structure was handled by SGR-DA and also refined the adaptive sparse vectors for facial matching. In the thermal infrared image recognition experiments, the SGR-DA provided poor performance, because the infrared images contained less facial structure and more detailed information.The major problem faced by the existing feature extraction techniques includes high computation time for extracting huge amounts of data as well training for classification. To address these issues, the research study developed the CNN as feature extraction techniques and classifies using LCDRC classifier.

3. PROPOSED METHOD

In this research, the proposed CNN-LCDRC model comprises of four phases; data collection, feature extraction, classification, and performance analysis, which is shown in Figure 1.

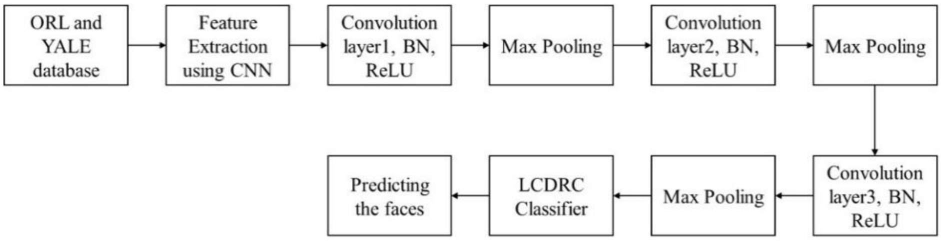

Figure 1. Working flow of the proposed CNN-LCDRC technique

3.1. Collection of dataset

In this research study, two online datasets namely YALE and ORL are used for image collection. In ORL database, 40 classes of ten facial images are collected for each and every individual, therefore 400 facial images are presented in this database. In the research, large number of images from ORL database is taken and YALE is taken from different angles for consideration. 40 images are considered for feature extraction but not for classification. Figure 2 shows the sample images of ORL database, where some individual's facial images are collected under different lighting variations, different facial expressions include eye open/closed, smiling and without smiling, facial details include with glass and without glass. Moreover, 165 grayscale images are presented in the YALE datasets, which are collected from 15 individuals. Figure 3 describes the sample images of YALE dataset, where 11 facial images are collected from each subject. Each image is taken with various facial expressions like normal, sleepy, wink, happy, with/without glasses, center-light, surprised and sad [23].

Figure 2. Sample images of ORL dataset

Figure 3. Sample images of YALE dataset

3.2. Feature extraction

CNN, which has the convolution and pooling layer, is used as a feature extraction technique in this study. In CNN, the raw images are taken as input, which prevents complicated feature extraction and massive data by using a conventional recognition algorithm. The complexity of the CNN method can be reduced by using weight sharing approach and also by reducing the count of the parameters used or measured. The process in which the entire image is filtered, which is defined as in (1) and (2):

$$y_j^l = f\left(\sum_{i \in M} x_i^{l-1} * k_{ij}^l + b_j^l\right) \tag{1}$$

$$f(x) = max(0, x) \tag{2}$$

where $x_i^{l-1}$is the i^{th} input feature map at the $l-1^{th}$ layer, y_j^l is the j^{th}output feature map at the l layer, M is the set of feature maps at the $l-1^{th}$ layer. k_{ij}^l is the convolution kernel between the i^{th}input map at the layer $l-1^{th}$ and the j^{th} Output map at the layer l, b_j^l is the bias of the j^{th} output map at the l^{th} layer. $f(x)$ is Rectified Linear Unit's function.

In this paper, the CNN adopts the max pooling. In (3) the maximum pool formula used in this research study is explained mathematically in (3):

$$y_{j(m,n)}^{l+1} =_{0 \le r,k<}^{Max} \left\{x_{(m.x+r,n.s+k)}^l\right\} \tag{3}$$

where $m \geq 0, n \geq 0, s \geq 0$ and $y_{j(m,n)}^{l+1}$is the value of the neuron unit (m, n) that in the j^{th} output feature map y_j^{l+1} at the $l+1$ layers, $(m.s + r, n.s + k)$ is neuron unit in the i^{th} input map x_i^l at the $l+1$ layers, whose corresponding value is $x_{(m.s+r,n.s+k)}^l$, $y_{j(m,n)}^{l+1}$ is obtained by computing the big value over an $s \times s$ non-overlapping local region in the input map x_i^l. The CNN structure has nine layers as shown in the Figure 4, where the layers includes batch normalization (BN)-3, convolution layers-3 and pool layers-3.

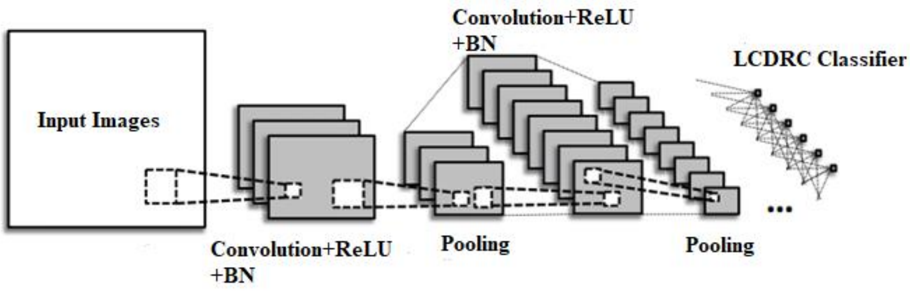

Figure 4. Structure of proposed CNN model

The layers C1, C2, and C3 are convolution layers and consist of 30, 60, and 80 feature maps that extract and combine those features, respectively. Layers S1, S2, and S3 are layers of sub-sampling whose number of feature maps are equal to the number of maps of their previous layers of convolution. The output layer must identify all the input images based on the exact functions. Two optimization methods are used to design the convolutional neural network. First, using the $f(x)$ function of the rectified linear units that describes the neural signal activation well in the convolutionary layers to replace the sigmoid feature. Second, BN is the core design block of CNN structure, where the typical CNN model has a vast amount of BN layers in their deep architecture. During training, the mean and variance calculations over each mini-batch are required by the BN.

3.3. Classification using linear collaborative discriminant regression classification

Using linear collaborative discriminant regression classification (LCDRC), classification is carried out after extracting the 2048 features of the facial images. It is a method for extraction of features which employs discriminating analysis for adequate discrimination in the classification of linear regression. It uses the labeled training data to create a more robust subspace on which to perform an efficient discriminant regression classification. Effectively learn a subspace using discriminant analysis where data samples from different classes are far away from each other while samples from the same class are similar to each other. Therefore, LDRC calculates an optimal projection in such a way that by maximizing the linear regression classification, the ratio of the reconstruction error between classes over the reconstruction error within class achieves. Due to optimization using CNN in LCDRC, the distance ratio between the classes has been highly maximized and the distance of the features inside the class greatly reduces. The proposed CNN algorithm selects, therefore, the best weight value in LCDRC to reduce the reconstruction error. Consequently, the proposed approach seeks a discriminating subspace by maximizing the ratio of reconstruction error between classes and minimizing reconstruction error inside the class.

4. RESULTS AND DISCUSSION

In this section, the validation of proposed CNN-LCDRC is conducted on two datasets namely ORL and YALE in terms of mean recognition accuracy (average accuracy) and maximum recognition accuracy. The simulation of the algorithm is implemented in the computer with Pentium IV processor of 1.8 GHz using MATLAB Version 18.a. Recognition accuracy is the parameter that is used to identify the efficiency of proposed CNN-LCDRC. The mathematical expression for recognition accuracy is shown in (4).

$$RecognitionAccuracy = \frac{TP+TN}{FN+TP+TN+FP} \times 100 \tag{4}$$

Where, true positive is described as TP, false positive is represented as FP, true negative is defined as TN and false negative is illustrated as FN.

4.1. Analysis of proposed CNN-LCDRC on ORL database

The performance of proposed CNN-LCDRC is compared with traditional LCDRC for different training datasets. In the upcoming tables, Training number represents the ratio of training and testing data for input facial images. Table 1 presents the validated results of the proposed method in terms of mean accuracy and Figure 5 illustrates the graphical representation of CNN-LCDRC.

For instance, the ratio of 40% training and 60% testing data i.e. training number 4, the proposed CNN-LCDRC method achieved 92.78% of mean accuracy, where LCDRC method achieved only 83.20% of mean accuracy. The reason for achieving better performance than LCDRC is the usage of CNN as feature extraction technique in this research study. Table 2 provides the comparative study of both LCDRC and proposed CNN-LCDRC in terms of maximum recognition accuracy and Figure 6 presents graphical presentation of CNN-LCDRC.

Table 1. Performance of proposed method on ORL database in terms of mean recognition accuracy (%)

Method	Training Number						
	2	3	4	5	6	7	8
LCDRC	74.47	80.18	83.20	84.33	84.27	83.88	83.35
Proposed CNN-LCDRC	83.65	90.27	92.78	93.20	93.60	93.24	93.10

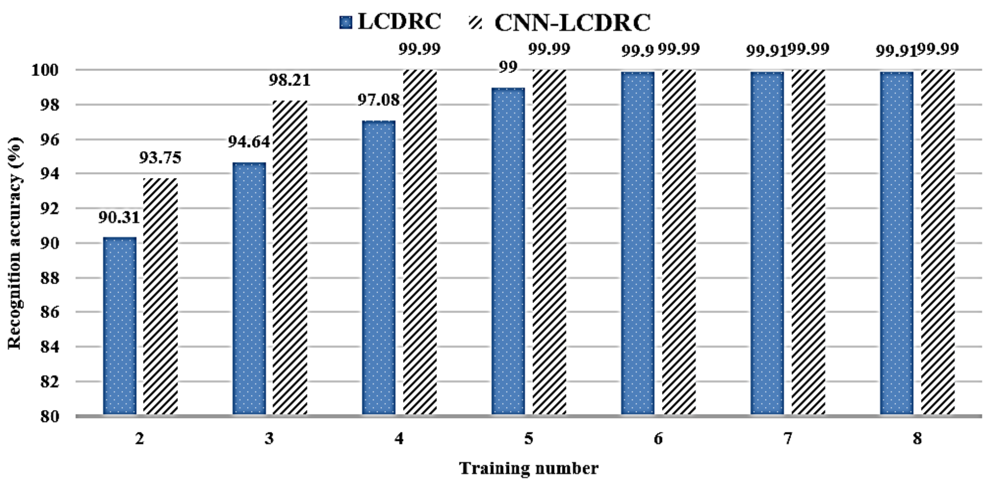

Figure 5. Graphical illustration of proposed CNN-LCDRC in terms of maximum recognition accuracy

Table 2. Performance of proposed method on ORL database in terms of maximum recognition accuracy (%)

Method	Training Number						
	2	3	4	5	6	7	8
LCDRC	90.31	94.64	97.08	99.00	99.90	99.91	99.91
Proposed CNN-LCDRC	93.75	98.21	99.99	99.99	99.99	99.99	99.99

From the Table 2, it is clearly stated that the proposed CNN-LCDRC achieved higher maximum recognition accuracy than LCDRC. The proposed CNN-LCDRC achieved highest maximum recognition accuracy (i.e. 99.99%) because of 50 iterations and 300 dimensions leads to saturate the performance of CNN-LCDRC. The results proved that CNN effectively extracts the input features from the facial ORL images. The next section will explain the performance analysis of proposed CNN-LCDRC on YALE dataset.

4.2. Analysis of proposed CNN-LCDRC on yale database

In this section, the performance of CNN-LCDRC and traditional LCDRC technique in YALE database is experimented. The validated results are presented in Table 3 and graphical representation is illustrated in Figure 6 on the basis of mean recognition accuracy. For instance, CNN-LCDRC achieved only 82.18% of mean accuracy of YALE database, where the same method achieved 92.78% of mean accuracy of the ORL database in the ratio of 40% training with 60% testing data (training number 4). Table 3 and Figure 7 describes the experimental results of CNN-LDCRC with traditional LCDRC by means of maximum recognition accuracy on YALE dataset. From the above experiments, it is clearly stated that the proposed CNN-

LCDRC achieved better performance on YALE database on the basis of maximum recognition accuracy. The ratio of 70% training and 30% testing data (training number 7) has achieved nearly 98% of maximum recognition accuracy for the proposed CNN-LCDRC method, where traditional LCDRC achieved only 95% of accuracy. The reason behind the high performance is due to the effective use of CNN as feature extraction with the least number of layers.

Table 3. Performance of proposed method on YALE database in terms of mean recognition accuracy (%) and maximum recognition accuracy (%)

Method	Training Number						
	2	3	4	5	6	7	8
LCDRC (Mean)	57.03	67.39	72.50	75.04	75.51	76.65	77.70
LCDRC (Maximum)	68.89	80.00	87.62	90.00	92.00	95.00	97.78
Proposed CNN-LCDRC (Mean)	67.50	76.95	82.18	85.61	86.30	86.83	87.60
Proposed CNN-LCDRC (Maximum)	77.04	85.00	93.33	95.56	97.33	98.33	99.99

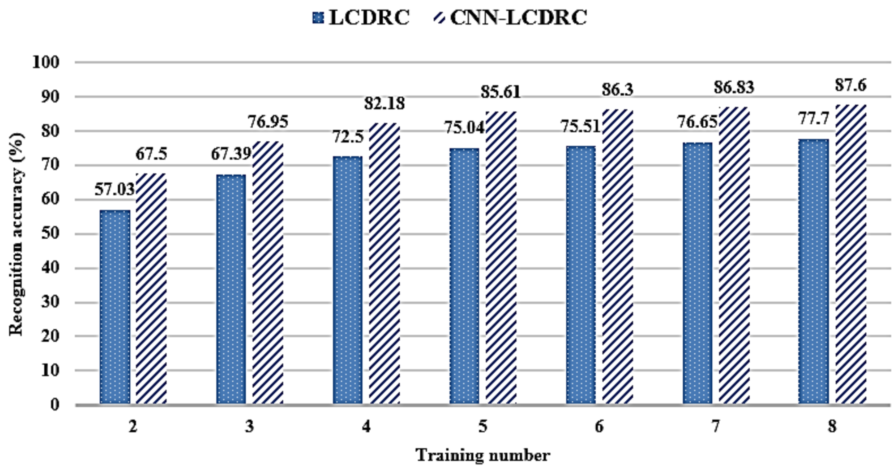

Figure 6. Graphical representation of proposed CNN-LCDRC in terms of mean recognition accuracy on YALE database

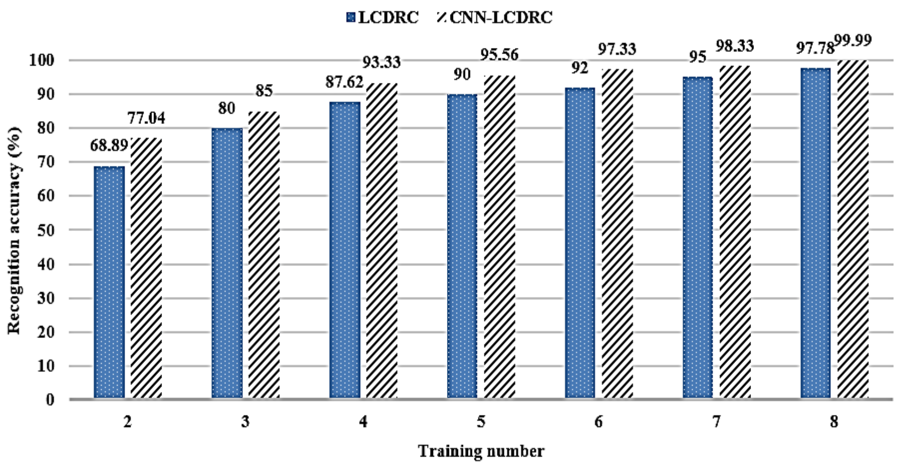

Figure 7. Graphical illustration of CNN-LCDRC in terms of maximum recognition accuracy (%) on YALE dataset

4.3. Comparative study

In this section, the performance of CNN-LCDRC is compared with other existing techniques such as sparse multiple maximum scatter difference (SMMSD) [24], multiple maximum scatter difference (MMSD) [25]. Maximum scatter difference (MSD) discriminant condition presents the binary discriminant condition for the classification of pattern which utilizes the general scatter difference not general Rayleigh quotient for the measure of class separability which avoids the problem of singularity by addressing smaller sample sized issues. The comparison of proposed CNN-LCDRC with existing methods in terms of MSD is shown in Table 4. The error value of SMMSD [24] was 0.1907 and for MMSD [25] the error value was 0.0395. The comparison graph of CNN-LCDRC with existing method in terms of MSD is shown in Figure 8. The existing IKLD with PNN provides poor performance on YALE database [26], but the proposed CNN-LCDRC provides better performance (i.e. 87.60% mean recognition accuracy), when the training number increases.

Table 4. Comparison of proposed CNN-LCDRC with existing methods in terms of MSD

Authors	Methods	Maximum Scatter Difference
Yu *et al.* [24]	SMMSD	0.1907
Song [25]	MMSD	0.0395
Proposed method	CNN-LCDRC	0.0302

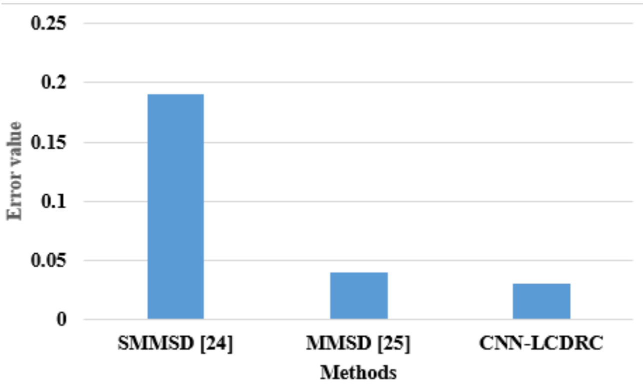

Figure 8. Comaparison graph of CNN-LCDRC with existing methods in terms of error valuefor MSD

5. CONCLUSION

The main challenging area in the field of biometrics is the recognition of the face due to various difficulties such as occlusions, variations of emotions and aging factors. In order to solve the issues, the research study implemented a novel algorithm called CNN with LCDRC classifier. In this study, the results stated that the proposed CNN-LCDRC technique achieved 99.99% of maximum recognition accuracy on both YALE and ORL databases in the ratio of 80% training and 20% testing data (training number 8). The LCDRC technique achieved only 97% to 99.90% of maximum recognition accuracy on both YALE and ORL databases. The proposed CNN-LCDRC achieved highest maximum recognition accuracy (i.e. 99.99%) because of 50 iterations and 300 dimensions leads to saturate the performance of CNN-LCDRC. The efficiency of the CNN is high, because it reduces the number of parameters. In future work, the meta-heuristic algorithms are developed to recognize the input facial images effectively.

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