Face Recognition under Illumination based on Optimized Neural Network

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***Abstract*—Face recognition is a significant area of pattern recognition and computer vision research. Illumination in face recognition is obvious yet challenging task in pattern matching. Recent researchers introduced machine learning algorithms to solve illumination problems in both indoor and outdoor scenarios. The major challenge in machine learning is the lack of classification accuracy. Thus, the novel Optimized Neural Network Algorithm (ONNA) is used to solve the aforementioned drawback. First, we propose a novel Weight Transfer Ideal Filter (WTIF) which is employed for pre-processing to remove the dark spots and shadows in an image by normalizing low frequency and high frequency of illumination. Secondly, Robust Principal Component Analysis (RPCA) is employed to perform efficient extraction of features based on image area representation. These features are given as input to ONNA which classifies the given input image under illumination. Thus we achieve the recognition of the face under various illumination conditions. Our approach is analyzed and compared with existing approaches such as Support Vector Machine (SVM) and Random Forest (RF). ONNA is better in terms of high accuracy and low error rate.**

Keywords*—Face recognition; illumination; neural network; robust principal component analysis

I. Introduction

Face recognition is an interesting research area in computer science and information technology since 1990 [1] with several applications such as biometrics, law enforcement and surveillance video systems. Various face recognition methods have been developed during the previous two decades, and significant progress has been reached. Consequently, the efficiency of facial recognition systems under controlled conditions has already achieved a sufficient level. Unfortunately, the recognition rate of the existing FR system needs to be enhanced, also in real-world conditions like noise, illumination changes, pose and disguise. Because the accuracy of a face recognition technique varies a lot depending on the type of illumination and lighting used, illumination is one of the major aspects to consider when creating a human face recognition system. Due to the 3D geometry of human faces, it is noted that variations in illumination conditions form various shading and shadows on the face. This may make some facial characteristics appear weaker, or it may cause bright or dark areas in face images.

Face recognition accuracy is now quite high under perfect illumination; however, there are still issues to be solved under varying illumination [2, 3]. Several approaches have been developed in recent decades to improve the accuracy of facial recognition in different illumination conditions, which can be divided into three groups: illumination modeling, illumination extraction of invariant features, and face image normalization [4]. The Retinex illumination model [5] describes the apparent illumination at every spot on the face in terms of that point's inherent reflectance, as well as the amount and angle of incident illumination. According to this concept, the low spatial frequency elements of the face image convey information on illumination, but the components with a high spatial frequency indicate inherent sensitivity of the face that ought to be retrieved for recognition.

As a result, self-quotient imaging [6] is used to estimate the illumination on a smoother version of the image of the face that reduced the logarithmic of the actual face image to produce an unchangeable representation. Similar filtering can be done in the frequency to normalize the low-frequency illumination and high-frequency illumination components using a logarithmic Gaussian Band Pass Bilateral Filter [7]. As previously established, the way faces are represented in the actual world is always flawed, as well as the images contain significant flaws. As a result of its extreme sensitivity to the flaws and inability to cope with information that is lacking, the traditional PCA estimation may be distant from the underlying real distribution of the facial image.

To address this issue, a significant sparse learning framework named Robust Principal Component Analysis (RPCA) is used to extract the features [8] [9]. Some modern technologies take advantage of the similarities that every human face possesses. To find the most matching area at each face location, the area representation is achieved using a 2D Fourier magnitude spectrum [10].

In this research, we propose a Weight Transfer Ideal Filter (WTIF) for face recognition that is robust to illumination variation. It is employed to remove dark spots, shadows and reflections in an image. Further, Robust Principal Component Analysis (RPCA) is used to extract features based on image area representation. The proposed WTIF method is used to recognize the face accurately based on a position-based voting scheme by increasing the features matching. The Optimized Neural Network Algorithm (ONNA) improves the classification accuracy under illumination and the proposed method is analyzed and compared with existing methods such as Support Vector Machine (SVM) and Random Forest (RF). Consequently, ONNA is better in terms of Accuracy, Equal Error Rate.

II. Related Work

Kim et al. [11] presented a method in which ground truth image could be employed to train the Illumination Normalization (IN) method using a convolutional neural network to convert the illumination variant face image into a feature map. The result showed that the IN-Net achieved better Face Recognition (FR) accuracy. Wu et al. [12] discussed the face recognition method across the posture and illumination issue, given a modest collection of training samples and one sample per gallery. The different illumination samples and deep neural network capacity to perform nonlinear transformations make multitask deep neural network ideal for posture and illumination normalization. Results show that this algorithm achieved better results on MultiPIE dataset less training data and also verified the effectiveness of introduced method.

Xiangpo Wei et al. [13] developed a face recognition approach based on a convolutional neural network (CNN) and a local binary pattern feature extraction method (LBP) that overcomes the impacts of illumination, posture, and expression. Local Binary Pattern (LBP) represents the local texture features of an image. CNN is capable of extracting image features and reducing their dimensionality. The experimental result demonstrated that the method could significantly increase the rate of accuracy and also has better robustness of illumination and posture.

Khan et al. [14] presented Particle Swarm Optimization (PSO) to optimize textural and wavelet features. The Discrete Wavelet Transform had the benefit of isolating significant characteristics, which reduced processing time and improved recognition accuracy. The results showed that the suggested technique is superior and resistant to illumination and has good accuracy rate. Han et al. [15] discussed the Accelerated Proximal Gradient (APG) technique and illumination regression filtering that was applied to remove the illumination effect. The results showed the introduced technique was robust to illumination.

Liang et al. [16] presented a method where Wavelet transform images of the Low Frequency Sub-Band (LFSB) and High Frequency Sub-Band (HFSB) were boosted and denoised, which frequently resulted in a loss of information due to less attention of HFSB. Furthermore, the Particle Swarm Optimization-Neural Network (PSO-NN) was used to classify the data. The suggested network can effectively create a robust visual impact under varied illumination and greatly increase recognition performance, according to experimental results.

Zhang et al. [17] presented the Expected Patch Log Likelihood (EPLL) algorithm that extracted illumination weight and used Neighboring Radiance Ratio algorithm (NRR) which optimized the initial vector of the Gaussian mixture model that utilized redundant data in image. Dewantara et al. [18] presented a novel optimized fuzzy based illumination constant approach that overcomes the influence of illumination for photometric based face recognition. It efficiently eliminates the impact of illumination on facial images and has a high level of robustness. Output proved that the introduced algorithm improved computational time and also that improve the face detection performance.

Baradarani et al. [19] presented the multi resolution analysis and sub band filtering the Double-Density Dual-Tree Complex Wavelet Transform (DD-DTCWT) was helpful and easy for illumination invariant face recognition. Principal Component Analysis (PCA) was employed for feature extraction and the Extreme Learning Machine (ELM) was used for faster classification. The result proved that the introduced method has high recognition rate and computational complexity.

Vidya et al. [20] used Discrete Wavelet Transform (DWT) that aided in the efficient extraction of features and the introduced Selective Illumination Enhancement Technique (SIET) which has high incidence of recognition. The result showed that the introduced method has average recognition rate for Color FERET database. Yang et al. [21] presented Nuclear Norm based Matrix Regression (NMR) for face recognition and categorization. Result showed that the NMR was more reliable for recognition with illumination changes.

III. Proposed Methodology

Face recognition consists of three sections such as preprocessing, feature extraction, and classification. Fig. 1 explains the proposed methodology. Optimized Neural Network Algorithm (ONNA) is used to improve the classification accuracy under illumination conditions and also recognizes the face accurately. The scheme comprises preprocessing using the proposed method Weight Transfer Ideal Filter, to find the most matching area at each face location using a 2-D Fourier magnitude spectrum. Robust Principal Component Analysis (RPCA) is used for feature extraction. ONNA along RPCA gave better results in terms of high accuracy and low error rate.

A. Weight Transfer Ideal Filter

The main purpose of pre-processing is to improve image quality so that it can be processed further by removing or minimising unrelated and surplus components in the illumination images. Weight Transfer Ideal Filter (WTIF) is employed to remove dark spots, shadows and reflection and also it reduces low frequency illumination and high frequency illumination. WTIF technique is used to recognize the face accurately based on a position-based voting scheme by increasing the features matching. A Weight Transfer Ideal Filter is a complete filter that combines spatial domain and range domain filtering to remove noise while preserving edge characteristics using (1) and (2).

$$\mu = \frac{1}{ab}\sum_{n_1 n_2} m(n_1, n_2) \tag{1}$$

$$Z_i = \sum_{k=0}^{i} P_{i,j}.Q_{i,j}.\, y_i \tag{2}$$

In Weight Transfer Ideal Filter, weights of the pixel decay as a function of distance from the filter's center, as provided by,

$$G_\sigma(\mathrm{a, b}) = \frac{1}{2\pi\sigma^2}\, e^{-\frac{(a^2+b^2)}{2\sigma^2}} \tag{3}$$

$$I_F(\mathrm{B}) = \frac{1}{W}\sum_{q\in S} G_{\sigma_s}(\|P-Q\|)G_{\sigma_r}(|I(P)-I(Q)|)I\,(Q) \tag{4}$$

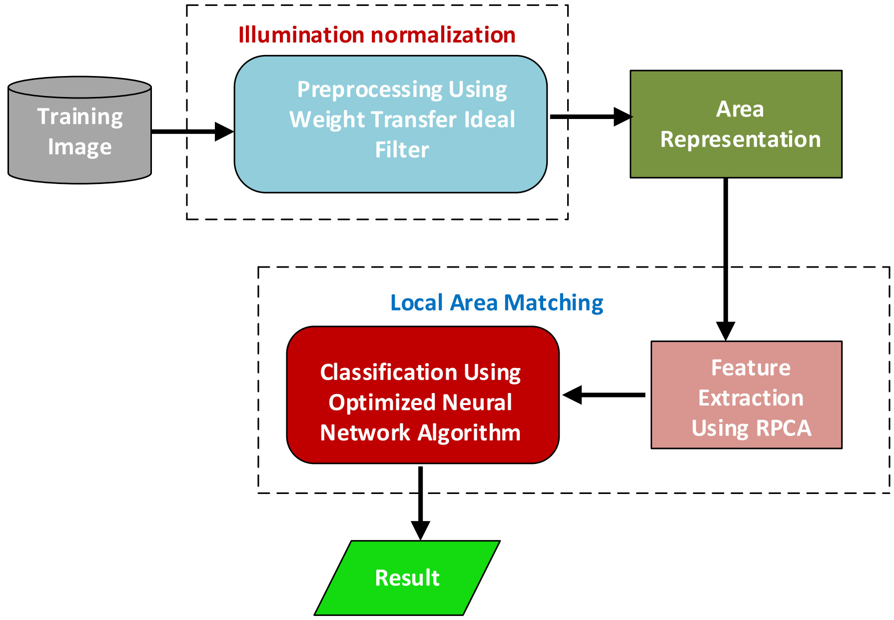

Fig. 1. Proposed Methodology.

The Weight Transfer Ideal Filter is used for smoothing nonresponsive noise from two-dimensional signals while maintaining image quality. As a result, it's particularly well-suited to improve the illumination of the face image. The pre-processing technique is utilized in illumination improvement, artifact removal, and alignment. The pre-processing technique involved, creates masks for pixels with the greatest amount of effort to reduce dark spots and reflection and Fourier Magnitude Spectra as Image Area Representation Features.

Due to slight changes in a person's facial features and head position, even with properly matched face images, matching local pixel areas on the faces may not correlate to the same spatial structure. We employ a 2-D Fourier magnitude spectrum as the feature to describe each local image area to limit the outcome of modest mismatch errors in recognition [23]. We use the shift-invariance of the Fourier magnitude representation to enhance the ability to withstand minor mismatch errors and variations in face expression by taking the magnitude spectrum instead of the phase spectrum. When the 2-D Fourier transform is applied to an area in a Nonlinear Active Band pass Filter testing image, the magnitude spectrum of the resulting testing image may be represented as

$$\left|\tilde{I}_{\delta(a,b)}(m,n)\right| \cong \beta_{\delta(a,b)}\left|\widetilde{R_{\delta(a,b)}}(m,n)\right| + \delta(m,n)\widetilde{\alpha_{\delta(a,b)}} \qquad (5)$$

Where $\left|\tilde{I}_{\delta(a,b)}(m,n)\right|$ and $\left|\widetilde{R_{\delta(a,b)}}(m,n)\right|$ indicate the spectral magnitudes of the Gaussian band pass bilateral filter pixel value and intrinsic reflectivity of the area, $\widetilde{\alpha_{\delta(a,b)}}$ indicate the residual constant illumination background and the $\delta(m,n)$ is the Kronecker delta function.

B. *Feature Extraction using Robust Principal Component Analysis*

The output of the matching area representation is given as the input to the feature extraction. The Robust Principal Component Analysis (RPCA) method is used to extract textural features accurately by reducing the sparse error. Consider a huge data matrix $H \in \mathbb{R}^{m \times n}$ has a reduced layout I but is contaminated by sparse errors element M, i.e., H=I+M. The goal is to reclaim a low-rank element I from the substantially corrupted matrix H in a reliable manner. Unlike in conventional PCA, the noise is small, the entries in M might have any magnitude and their support is believed to be simple but uncertain. The following is the original concept of Robust Principal Component Analysis (RPCA) [24]:

$$\min\ (\text{rank}\ (I) + \gamma\|M\|_0), \quad \text{s.t. } H=I+M \qquad (6)$$

Where ‖M‖0 represents the matrix $\ell_0$norm that is collecting nonzero components in the matrix H. Due to the rank measure's non-smoothness and non-convexity as well as the zero-norm penalty, (1) is hard to solve. Principal Component Pursuit (PCP) is solved in the relaxed form using tractable convex optimization:

$$\min\ (\|I\|_* + \gamma\|M\|_1), \text{ s.t. } H=I+M \qquad (7)$$

Where the rank procedure in (6) is nuclear matrix has taken its place$\|.\|_*$, the matrix ℓ_1 −norm estimates the matrix ℓ_0-norm and γ is regulation variable for balance and has been fixed to $1/\sqrt{\max(m,n)}$. It has been demonstrated both mathematically and practically that the resolution of (7) properly retrieves the low-rank and sparse elements under very weak conditions, as provided as the rank of I is not too great and the errors M is sparsely maintained [22].

C. *Optimized Neural Network (ONNA)*

An Optimized neural network is used to improve the classification accuracy under illumination. Firstly, search space algorithm is used to extract the features of the image. A search in a search space method is an example of a possible solution to the problem of determining the relevance of each characteristic. Suppose there are n search k dimensional space, then the position of search i can be represented as X_i= ($x_{i,1}$,

$x_{i,2}$,....,$x_{i,k}$)(i= 0,1,2,...,n). The velocity and position of each search are updated as follows:

$$V_i(t+1) = \omega V_i(t) + C_1 r_1[pbest(t) - x_i(t)] + C_2 r_2[gbest(t) - x_i(t)] \quad (8)$$

$$x_i(t+1) = x_i(t) + V_i(t+1) \quad (9)$$

Where C_1 is the cognitive coefficient and C_2 is the social coefficient and matching values r_1 and r_2 are two independently generated random numbers and ω is the inertia weight. The maximum generations or the better position of the object in the cluster is no more included in the search algorithm, which cannot be improved even after a many number of generations. Therefore, the proposed searching algorithm has proved its efficiency and robustness in overcoming complex optimization challenges.

The range of C_1 *and* C_2 are $C_1 \in$ (2.75, 1.25) and $C_2 \in$ (0.5, 2.25) respectively. The learning factor function expression of linear change is described as given below using (10) and (11).

$$\Delta Pbest = g_1 * rand(0,1) * (Pbest_{i,j} - x_{i,j}) \quad (10)$$

$$\Delta Gbest = g_2 * rand(0,1) * (Gbest_{i,j} - x_{i,j}) \quad (11)$$

Where C_1 and C_2 are learning factors; rand is a positive random number between 0 and 1 distributed normally. This search algorithm is mainly used to learn the features. Given the face images q_1, q_2,..., q_m, the average face of these given face images is defined by (12).

$$\varphi = \frac{1}{S}\sum_{i=1}^{S} q_i \quad (12)$$

The difference between each input face and the average face is calculated as follows

$$\Psi_i = q_i - \varphi \quad (13)$$

The covariance matrix CM can then be computed using

$$\text{CM} = \sum_{i=1}^{N} \Psi_i \, \Psi_i^T = AA^T \quad (14)$$

The component effective method is used to train the learned sample. Finally, the error-reduced training sample is sent to the classification phase; here the neural network is issued to classify the training sample. It classifies the face accurately and finalizes feature matching and recognition. Finally, the feature matrices that correlate to numerous facial images are sent to the neural network as training data. The neural network driven feature learning framework, consists of 3 layers i.e., input layers, an output layer, and a hidden layer. For the Facial illumination Recognition problem, the right multiplication projection matrices in the hidden layer are also employed to get more discriminative characteristics among the high-level characteristics.

Let G_i = $\{G_{i,j}^t j = 1, \dots, E_l\}$ (t = 1,... , P_t) indicate the t^{th} multi-channel projection matrix set consisting of C_l channels of projection matrices, where $G_{i,j}^{(t)}$ denote the j th channel matrix of G_i , P_i indicate the number of multi-channel projection matrix sets, and E_t indicate the number of channel matrices in G_i . The hidden layer can therefore be represented in the following way:

$$C_i = \sum_{j=1}^{E_t} G_{i,j}^{(t)} Q_j, \text{ (i=1, 2, ... ,} P_t) \quad (15)$$

Where C_i indicates the matrix in t^{th} channel of the output and Q_j is the jth channel of the input matrices. If the input layer performs proper multiplication,

$$C_i = \sum_{j=1}^{E_a} Q_j \, G_{i,j}^{(a)}, \; (t = 1,2,...,P_a) \quad (16)$$

Then each row of the input matrix is projected onto a different feature area, resulting in a dimension reduction result at the same time. The resulting error by the given mode or result, i.e., the weight of the present related edge in the network is computed by combining the hidden layer and output layer results. The error of the hidden neuron is also calculated using the correlation weight and the error of the next layer's neuron. The network weight is updated with each neuron's error computed. Finally, the optimized neural network algorithm classifies the images. Fig. 2 shows the steps in ONNA.

Algorithm steps

Input: Dataset, image size P, inertia feature ω, cognitive coefficient $c1$, social coefficient $c2$, and matching value

Step 1: Initialize the parameters x_i, pbest, and gbest

Step 2: Determine the best face feature value selection

Step 3: Determine and pbest and gbest value

Step 4: Update x_i for each feature using (17)

$$V_i(\text{t+1}) = \omega V_i(\text{t}) + C_1 r_1[pbest\,(\text{t}) - x_i(\text{t})] + C_2 r_2[gbest\,(\text{t}) - x_i(\text{t})] \quad (17)$$

$$x_i(\text{t+1}) = x_i(\text{t}) + V_i(\text{t+1}) \quad (18)$$

Step 5: If the matching value is not met, go to step 2

Step 6: Steps 5 and 6 should be repeated until the set minimal error or the matching value is reached.

Step 7: Take the global best value of the training process.

Step 8: Set the learning rate, maximum iterations, number of hidden layer neurons, features and thresholds between the input and hidden layers, between the hidden and output layers, and the algorithm termination minimal allowable error.

Step 9: The training samples should be normalized.

Step 10: Start the training process by dividing the images into sub-images to match with the corrupted images and enhance the classification decision.

Step 11: Validate the original data by the trained process, and restores the output data to the original order of image.

Step 12: Testing Process

Step 13: Hybrid Weight Transfer Ideal Filter is used to recognize the face under illumination and matches the features. After that, the neural network is used to classify the image and implement the Optimized Neural Network Algorithm (ONNA) techniques to improve the classification.

Step14: In this manner, a deep neural network classifier based on a position-based voting scheme is used to recognize the face accurately.

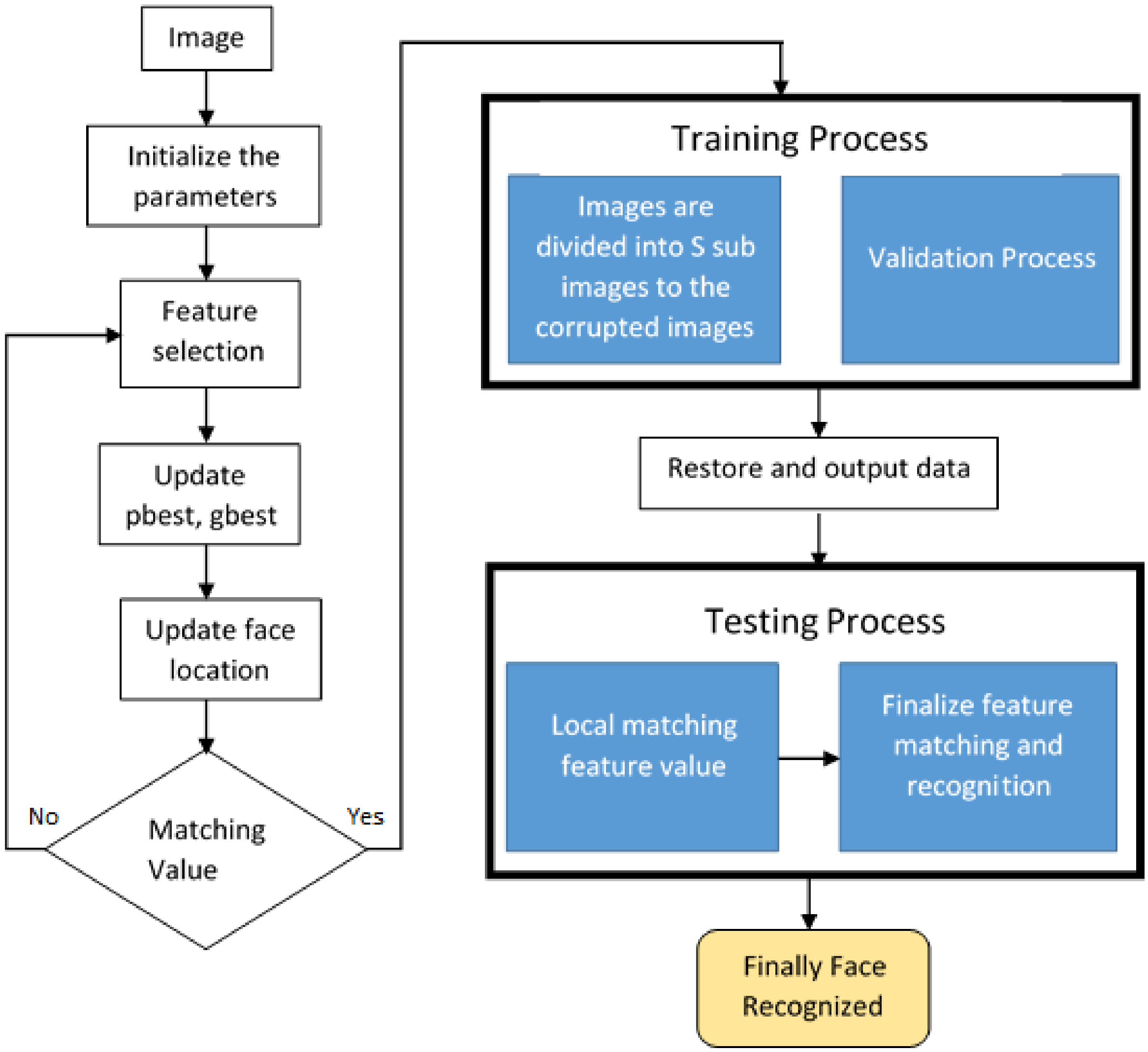

Fig. 2. Steps in Optimized Neural Network Algorithm.

IV. Results and Discussions

All the experiments are performed in the Extended Yale-B dataset [25] and CMU Multi-PIE dataset [26]. Extended Yale-B database consists of 16128 images of 28 people under 64 different illumination conditions. CMU Multi-PIE database consists of 750,000 images of 337 people taken under 19 different illumination conditions. The Optimized neural network is introduced in this paper. Compared with SVM and RF the proposed method achieves high accuracy and low error rate.

The first column in Fig. 3 shows the input images full of dark spots. The proposed Weight Transfer Ideal Filter method enhances the low frequency images by removing the dark spots as shown in column 2. Column 3 images show the most matching area at each face location and the area representation is achieved using a 2-D Fourier magnitude spectrum. RPCA algorithm is applied to the images in column 3 to extract the features. Then the extracted features are given as an input to the Optimized Neural Network Algorithm which improves the classification accuracy and by increasing local area matching, this method recognizes the face under illumination conditions. The recognized faces are shown in column 5.

The proposed method is compared with the existing classification methods such as support vector machine (SVM) and Random Forest (RF) in terms of accuracy and Error Rate as shown in Table 1 and Table 2. The accuracy of the proposed method is high compared to the existing classification methods because of the optimized neural network. Table 1 shows the results of face recognition under varied illumination on the Extended Yale-B database and Table 2 shows the results face recognition under varied illumination on the CMU-PIE database.

To prove the success rate of the introduced technique, it is essential to compare the Optimized Neural Network Algorithm with SVM and RF method, and the results are shown in Fig. 4.

Fig. 3. Dark Spot Removal and their Result.

TABLE I. PERFORMANCE ANALYSIS OF FACE ILLUMINATION IMAGE FOR OPTIMIZED NEURAL NETWORK ALGORITHM AND EXISTING METHOD ON EXTENDED YALE –B DATABASE

S.No	Performance analysis	SVM	RF	Proposed method
1	Accuracy	0.92	0.88	0.95
2	Error rate	0.037	0.074	0.03

TABLE II. PERFORMANCE ANALYSIS OF FACE ILLUMINATION IMAGE FOR OPTIMIZED NEURAL NETWORK ALGORITHM AND EXISTING METHOD ON CMU-PIE DATABASE

S.No	Performance analysis	SVM	RF	Proposed method
1	Accuracy	0.935	0.902	0.97
2	Error Rate	0.035	0.063	0.028

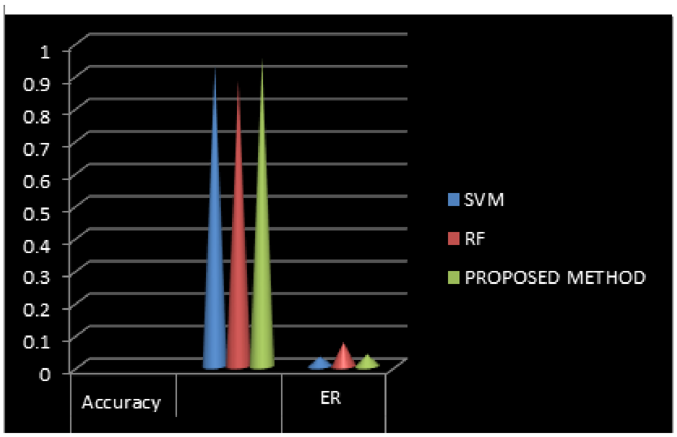

Fig. 4. Graphical Analysis of Optimized Neural Network Algorithm and Existing Classifier on Extended Yale-B Database.

Finally, the results showed that the performance of the proposed system is high in comparison to the existing methods.

V. CONCLUSION AND FUTURE WORK

In the presence of varied illumination conditions, recognizing a face with good accuracy is the main challenge. In this paper, the Optimized Neural Network Algorithm (ONNA) is proposed to improve classification accuracy in varied illumination. Firstly, a pre-processing technique Weight Transfer Ideal Filter is proposed to reduce the dark spots, shadows, and reflection in the input image. Secondly, Robust Principal Component Analysis (RPCA) is applied to extract efficient features based on image area representation and the output of the RPCA is given as an input to the optimized neural network algorithm (ONNA) which improves the classification accuracy under illumination. Experiments are conducted on Extended Yale B and CMU-PIE datasets. According to the findings of the experiments, the ONNA outperforms the existing method such as SVM and RF in recognizing the faces under varied illumination in terms of high accuracy and low error rate. The future work is to use deep neural architectures such as Siamese Neural Network to improve the recognition rate.

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