Hybrid Model for Face Recognition Using Optimized Linear Collaborative Discriminant Regression Classification

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Article Info
Page Number: 10916 - 10924
Publication Issue:
Vol 71 No. 4 (2022)

Article History
Article Received: *15 September 2022*
Revised: *25 October 2022*
Accepted: *14 November 2022*
Publication: *21 December 2022*

Abstract

Humans can easily solve the difficulty of facial recognition; nevertheless, the fundamental issue is limited memory. The field of automatic facial recognition has advanced quickly, thus far it still confronts challenges like "Ageing, Partial Occlusion, and Facial Expressions," etc. Considering this, the three main stages of pre-processing, feature extraction, and classification are used in this article to design a novel face recognition framework. The contrast enhancement and RGB to Grey Level Conversion are first carried out in the pre-processing stage. The pre-processed facial image is used to extract the features in the form of shape and texture using AAM. The categorization is then carried out using an improved LCDRC model. The projection matrix is the most important evaluation in the LCDRC. Therefore, it is necessary to optimize the projection matrix to improve recognition precision. The notion of WOA and LA are combined to create the revolutionary hybrid algorithm known as the Combined Whale Lion Model (CWLM), which is used to improve the projection matrix. Recognition rate, False Positive Rate (FPR), and False Discovery Rate (FDR) comparisons with other compared approaches such as LCDRC-WOA, LCDRC-CEWO, and just LCDRC are used to assess the overall performance of the proposed model.

Keywords—Face Recognition; AAM based feature extraction; Linear Collaborative Discriminant Regression Classification based classification; Lion Algorithm; Whale optimization Algorithm.

I. INTRODUCTION

Over the past two decades, the Biometric-based techniques are emerging as a promising solution for individual recognition. Instead of confirming people's identity and permitting them to entrance to physical and virtual domain based on "passwords, PINs, smart cards, plastic cards, tokens, keys" and so, it is good to examine the individual's "physiological and/or behavioural characteristics" that do not change. The password or pin-based approaches are complex to memorize, and they can be stolen easily. However, an individual's natal personality can never be misplaced, elapsed, stolen or faked Thus, the face recognition is one of the interesting as well as important research in the field of biometric recognition. Due to the presence of human activity across a range of security applications, it has attracted significant interest from researchers like "airport, criminal detection, face tracking, forensic" etc.

The importance of face recognition has increased recently with the expansion of security-oriented applications. Increased. Face recognition (FR) is still a topic of current research. Pattern recognition is a hot button issue in the computer vision community. Compared to methods for biometric identification like Recognition of iris and fingerprints. several algorithms been put forth in the literature for facial recognition. The renowned Principal Component Analysis (PCA) is a technique [1]. LDA [2] (Linear Discriminant Analysis), etc.

Recently, Linear Regression Classification (LRC) [3] has been employed to boost facial recognition accuracy. LRC categorises face images based on the presumption that the images belong to a particular subspace. S.M. Huang and J.F. Yang [4] presented Discriminant factor in LRC as an LDRC algorithm for face recognition to overcome these problems.

II. LITERATURE REVIEW

A. *Related works*

Xiaochao Qu et al. [5] suggested an improved discriminant linear regression classification technique. In this paper, only the classes with small reconstruction errors are considered. Their EDLRC increased the discriminatory power of the LDRC by raising the construction error of the genuine class's related classes. Through extensive investigation, it was determined that the acquired projection matrix in EDLRC was more effective than the projection matrix in LDRC after increasing the ratio of BCRE and WCRE. It is determined that enhanced method and LDRC will seam to the same recognition accuracy as the number of dimensions increases. The experiment's findings showed that for ORL and AR databases, EDLRC performed better than LRC, LDRC.

Xiaochao Qu et al [6] has presented a Linear Collaborative Discriminant Regression Classification (LCDRC) to achieve face recognition. Additionally, collaborative representation—which is regarded as the upper bound of all class-specific BCRE—was addressed in this paper as a better BCRE measurement that could be achieved. Therefore, the rise in the collaborative BCRE emphasises the modest class-specific BCRE and enhances each class's between-class reconstruction, both of which are beneficial for the future LRC. This method's primary flaw was the use of a single linear regression model, which only had one predictor and produced inaccurate results.

P. Huang et al. [7] By paying close attention to the various contributions of the training samples. To differentiate the various contributions of the training samples, ALDRC used a variety of weights. The BCRE and WCRE were then measured using this weighting information. Then ALDRC looks for the best projection matrix possible to raise the ratio of BCRE to WCRE. An extensive study conducted on the AR, FERET, and ORL face databases demonstrated the effectiveness of ALDRC.

Seyedali Mirjalili and Andrew Lewis [8] proposed a novel optimization model called Whale Optimization Algorithm (WOA), which is suggested in this study, is a revolutionary nature-inspired algorithm with meta-heuristic optimization procedure that imitates the social behaviour of humpback whales. The bubble-net searching tactic served as the basis for the algorithm. Which solves many mathematical optimization problems and structural design challenges are used to test WOA. According to optimization results, the WOA algorithm outperforms both traditional techniques and cutting-edge meta-heuristic algorithms.

T.S Akheel et al [9] proposed a model which embeds optimization with regression methods , However, the research has not yet reached the level of human brain recognition. This method tends to present a fresh face recognition pattern with a notion of feature extraction and classification, enhancing the intelligence in face recognition with high accuracy rate. The Active Appearance Model is used to extract the features (AAM). The classification is then carried LCDRC model.

Rajakumar Boothalingam [10] proposed a model called Lion algorithm (LA) which is defined as an innovative, nature-inspired optimization algorithm. It is one of the cutting-edge, naturally inspired algorithms that was developed in the twenty-first century. The territorial defense and territorial takeover update procedures are two unique updating methods used in LA. These mechanisms play a significant part in the pursuit of the global optimal solution and the avoidance of the local optimal solution. Important steps including nomad coalition, survival fight, cub growth, and mating promote the processes. The technique has been demonstrated to be superior at resolving optimization issues with a variety of characteristics, including multimodal optimization issues, problems with enormous search spaces, etc. LA has been used to address the tough and difficult system identification problem.

III. AAM BASED FEATURE EXTRACTION AND OPTIMIZED LCDRC BASED CLASSIFICATION: A BRIEF OVERVIEW

A. *Feature Extraction with AAM*

Here, the form and look of face characteristics are extracted using the computer vision algorithm AAM [11]. Finding the landmark points is usually how the form and look of the face features are extracted. That define the "form and the texture" of things that are statistically modelled in the face picture automatically.

Shape Model: It is a consistent geometric form of data that applies to the whole image class. The shape model is logically specified by Eq. (2), where the nk vector represents the shape given by n landmark points in k dimensions of space. In 2D images, n landmarks $\{(Y_j, Z_j): j = 1,2,....n\}$ define $2n$ vector $(k = 2)$ as in Eq. (1).

$$Y = (Y_1, Z_1, Y_2, Z_2, ..., Y_n, Z_n)^T \qquad (1)$$

To achieve the statistical validity, it is essential to have all the shape of the in the equivalent referential space. Further to localize all the shapes in a common frame, the GPA is performed after neglecting the location, scale and rotation effects. The aligning sequential pairs corresponding to the shape are extracted with the mean shape. This mechanism is accomplished till there occurs no significant modifications in the iterations. The re-computation of the aligned shape in GPA is expressed mathematically as per Eq. (6).

$$\bar{Y}_k = \frac{1}{N} \sum_{j=1}^{j=N} Y_j \qquad (2)$$

The PCA is then deployed on the extracted shape features in order to lessen the data dimensions. This is accomplished by means of exploring the data direction with highest variance of data and putting the information on the direction. Further, each point Y_j of the data is computed as "the sum of the mean and orthogonal linear transformation". Here, $\bar{Y}$ is the mean shape vector and ϕ_j are the shape parameters. The shape features extracted are denoted as f_{shape}.

$$Y_j = \bar{Y} + \sum_{j=1}^{t} \phi_j b_j \qquad (3)$$

Appearance Model: The construction of the appearance is based on the intensities of the pixels crosswise the target image modeled entity. The color channels must be wrapped in the statistical appearance model's design, and the "control points are linked to the mean shape. For the purpose of matching the texture, the piecewise affine warping is finished. Further, by means of employing the PCA to texture features, the appearance model $A(Y)$ is acquired. This is expressed mathematically in Eq. (4).

$$A(Y) = A_0(Y) + \sum_{j=1}^{m} \delta_j A_j(Y) \qquad (4)$$

Here, A_0 →mean appearance vectors

δ →appearance parameters

$A_j(Y)$ → affine warping-derived synthetic appearance vectors

A extracted appearance parameter is denoted as $f_{apperance}$. The extracted shape and texture features are together represented as $F = f_{apperance} + f_{shape}$.

B. Optimized LCDRC based Classification

(F) is the extracted feature which are subjected to classification via optimized LCDRC classifier Proposed by Xiaochao Qu, et al. , in which the facial images are recognized from the training images. The training matrix o the facial image is expressed in matrix form as $F = [F_1,....F_2,....F_c] \in \Re^{p \times q_i}$ .In this feature can be represented as $F_j = \left[F_{j1},....F_{j2},....F_{jq_j}\right] \in \Re^{p \times q_i}$. Further, in each of the training faces, the dimensions are defined as p and the count of the training face image is denoted as jq_j (from class j), and $q = \sum_{j=1}^{j=c} q_j$. $B \in \Re^{p \times d}$ and $d < p$ represent the subspace projection matrix that has to be learned. The mapping of each of f_{ji} on to the learned subspace is denoted as $g_{ji} = B^T f_{ji}$, in which $1 \le i \le q_j$.

The overall facial training image is mapped as $G = B^T F \in \Re^{d \times q}$ and for every class $G_j = B^T F_j \in \Re^{d \times q_j}$ .The CBCRE and WCRE are defined as in Eq. (5).

$$
\begin{aligned}
CBCRE &= \frac{1}{q}\sum_{j=1}^{c}\sum_{i=1}^{q_j} \| g_{ji} - \hat{g}_{ji}^{\text{inter}} \|_2^2 \\
WCRE &= \frac{1}{q}\sum_{j=1}^{c}\sum_{i=1}^{q_j} \| g_{ji} - \hat{g}_{ji}^{\text{intra}} \|_2^2
\end{aligned}
\qquad (5)
$$

Where $\hat{g}_{ji}^{\text{inter}} = G_{ji}^{\text{inter}} \alpha_{ji}^{\text{inter}}$ and $\hat{g}_{ji}^{\text{intra}} = G_{ji}^{\text{intra}} \alpha_{ji}^{\text{intra}} \cdot G_{ji}^{\text{inter}}$ is G with G_i eliminated and G_{ji}^{intra} is G_j with g_{ji} eliminated. $\alpha_{ji}^{\text{inter}}$ and $\alpha_{ji}^{\text{intra}}$ is attained by Eq. (6).

$$
\hat{\alpha}_i = \left(F_j^T F_j\right)^{-1} F_j^T g,\ j = 1,2,..g \qquad (6)
$$

The value of α is unknown before obtaining B in the learned subspace [22]. However, in the original space the value of $\hat{\alpha}$ is evaluated and $\hat{\alpha}$ is used as the approximation of α . According to the CBCRE concept given in Eq. (9), CBCRE and BCRE differ in that CBCRE employs "cross-class collaborative representation" while BCRE employs "class-specific representation. Further, the relation existing in F and G , the WCRE and CBCRE can be written as per Eq. (7)

$$
\begin{aligned}
CBCRE &= \sum_{j=1}^{c}\sum_{i=1}^{q_j} \| B^T f_{ji} - B^T F_{ji}^{\text{inter}} \alpha_{ji}^{\text{intra}} \|_2^2 \\
WCRE &= \sum_{j=1}^{c}\sum_{i=1}^{q_i} \| B^T f_{ji} - B^T F_{ji}^{\text{intra}} \alpha_{ji}^{\text{intra}} \|_2^2
\end{aligned}
\qquad (7)
$$

This is again rewritten as in Eq. (8).

$$
\begin{aligned}
CBCRE &= \sum_{j=1}^{c}\sum_{i=1}^{q_j} \left(f_{ji} - F_{ji}^{\text{inter}} \alpha_{ji}^{\text{inter}}\right)^T BB^T \left(f_{ji} - F_{ji}^{\text{inter}} \alpha_{ji}^{\text{inter}}\right) \\
WCRE &= \sum_{j=1}^{c}\sum_{i=1}^{q_j} \left(f_{ji} - F_{ji}^{\text{intra}} \alpha_{ji}^{\text{intra}}\right)^T BB^T \left(f_{ji} - F_{ji}^{\text{intra}} \alpha_{ji}^{\text{intra}}\right)
\end{aligned}
\qquad (8)
$$

In the above two cases (CBCRE and WCRE), the factor 1/q is common, and so it can be eradicated in a safer manner. The relative worth of CBCRE versus WCRE is not impacted by this safer eradication. As a result, Eq. (9) is used to represent the CBCRE and WCRE [10].

$$CBCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j} tr\left(\mathrm{B}^T\left(f_{ji} - F_{ji}^{\text{inter}}\alpha_{ji}^{\text{inter}}\right)\left(f_{ji} - F_{ji}^{\text{inter}}\alpha_{ji}^{\text{inter}}\right)^T \mathrm{B}\right)$$
$$WCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j} tr\left(\mathrm{B}^T\left(f_{ji} - F_{iji}^{\text{intra}}\alpha_{ji}^{\text{intra}}\right)\left(f_{ji} - F_{ji}^{\text{intra}}\alpha_{ji}^{\text{intra}}\right)^T \mathrm{B}\right) \quad (9)$$

Here, $tr(\cdot) \rightarrow$ trace operator

The eigen vectors J_b and J_w is denoted as in Eq. (10). Eventually, the CBCRE and WCRE are rewritten as in Eq.(11).

$$J_b = \frac{1}{q}\sum_{j=1}^{c}\sum_{i=1}^{q_j}\left(f_{ji} - F_{ji}^{\text{inter}}\alpha_{ji}^{\text{inter}}\right)\left(f_{ji} - F_{ji}^{\text{inter}}\alpha_{ji}^{\text{inter}}\right)^T$$
$$J_w = \frac{1}{q}\sum_{j=1}^{c}\sum_{i=1}^{q_j}\left(f_{ji} - F_{ji}^{\text{intra}}\alpha_{ji}^{\text{intra}}\right)\left(f_{ji} - F_{ji}^{\text{intra}}\alpha_{ji}^{\text{intra}}\right)^T \quad (10)$$

$$CBCRE = tr\left(\mathrm{B}^T J_b \mathrm{B}\right)$$
$$WCRE = tr\left(\mathrm{B}^T J_w \mathrm{B}\right) \quad (11)$$

The MMC is deployed to simultaneously “maximize CBCRE and minimize WCRE”. This is expressed as per Eq. (12).

$$\max_{\mathrm{B}} S(\mathrm{B}) = \max_{\mathrm{B}}\left(CBCRE - WCRE\right)$$
$$= \max_{\mathrm{B}}\left(tr\left(\mathrm{B}^T\left(J_b - J_w\right)\mathrm{B}\right)\right) \quad (12)$$

The mathematical expression given in Eq. (12) is solved by means of determining the largest d eigen values and the associated eigenvalues according to Eq (13).

$$\left(J_b - J_w\right)b_k = \lambda_k b_k,\ k = 1,2\ldots d \quad (13)$$

Here, $\lambda_1 \geq \ldots\ldots \geq \lambda_k \ldots\ldots \lambda_d$ and $\mathrm{B} = \left[b_1,\ldots b_k,\ldots,b_d\right]$.The the SSSP, in which the face image dimension is larger than the training face images can be solved by MNC.

The comprehensive algorithm of LCDRC is summarized in the subsequent section:

1. For every class $j = 1,2,..,c$, the hat Matrix H_j is computed.

2. Then, for the specified test face image f , convert f into discriminant subspace by using Eq. (14). Then, for j^{th} class, the reconstruction is computed as per Eq. (15).

$$g = \mathrm{B}^T . f \quad (14)$$

$$\hat{g} = H_j . g_j\ ;\ j = 1,2,..,c \quad (15)$$

3. Evaluate RC from j^{th} class: $e_j = \| g - \hat{g}_j$, $j = 1,2,..c$. The class with the lowest RC is assigned to the test face picture g .

This is a step in the LCDRC classification strategy where the retrieved features are multiplied by the project matrix according to Eq. (16). To improve the recognition accuracy, a unique optimization approach called CWLM is used to optimize the project matrix.

$$\mathrm{M} = F \times \mathrm{B} \quad (16)$$

IV. Hybrid Optimization Algorithm For Projection Matrix OPTIMIZATION: Objective Function and Solution Encoding

A. *Objective Function and Solution Encoding*

For the best tuning, the suggested model is given the project matrix as input. Fig. 1 provides an illustration of the solution encoding.

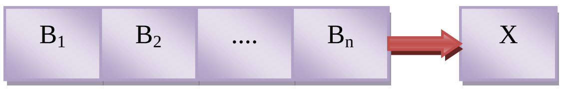

Fig. 1. Solution Encoding

The major objective of the recommended facial recognition model is to minimize estimation error and predicted outcomes of the classifier. The objective method is mathematically expressed in Eq. (17) and the fitness function is expressed in Eq. (18).

$$error = (act - pred) \qquad (17)$$

$$FT = Min\left(Sum(error) + \lambda * \sum_{j=1}^{B_N} (\mathrm{B})^2\right) \qquad (18)$$

Here, $\lambda \rightarrow$ regularization constant,

B. *Proposed CWLM (combined whale lion Model)*

A new improved version of the method is provided in this work to improve the performance of the conventional WOA [8] algorithm and LA [10] algorithm about convergence rate and speed. According to reports, hybrid optimization methods show promise for several search issues. The mathematical model of the CWLM algorithm is discussed here.

Step 1: Overall population (Pop) of solutions is initialized (WOA and LA).

Step 2: Find the fitness (Fit) of the overall population

Step 3: If $i <= Pop/5$, then update the solutions using the exploration phase of WOA expressed in Eq. (19).

$$\vec{X}_{(t+1)} = \left|\vec{X}_{rand} - \vec{V}.\vec{U}\right| \qquad (19)$$

Here, the random position vector selected is denoted as $X_{(rand)}$. Further, $\vec{V}$ is a random value in the interval $[-v, v]$, in which v decreasing from 0 to 2.

Step 4: Else If $i <= Pop/5 \,\&\&\, i <= 2Pop/5$, then update the solutions using prey encircling phase of WOA. This is mathematically expressed in Eq. (20) and Eq. (21), respectively.

$$.\vec{U} = \left|\vec{C}.\vec{X}_{p(t)} - \vec{X}_{(t)}\right| \qquad (20)$$

$$\vec{X}_{(t+1)} = \vec{X}_{p(t)} - \vec{V}.\vec{U} \qquad (21)$$

In which, $\vec{V}$ and $.\vec{U}$ are the coefficient vectors. The letter t stands for the current iteration. Additionally, $\vec{X}_p$ and $\vec{X}$ is the best location of the best outcome acquired and position vector, respectively.

Step 5: Else If $i <= 2Pop/5 \,\&\&\, i <= 3Pop/5$, then modify the solution's tri-level spiral evaluation position under the bubble net attack plan. Eq. (22) provides a mathematical formulation for this

$$X_{(t+1)} = \vec{U}' e^{bl}.Cos(2\pi l) + \vec{X}_{p(t)} \qquad (22)$$

The mathematical formula for $\vec{U}'$ is expressed in Eq. (23). Here, $\vec{U}'$ is the distance of i^{th} whale to prey and b is a constant that defines logarithm helical form. In addition, random number l is in between the range $[-1,1]$

$$\vec{D}' = \left| \vec{X}_{p(t)} - \vec{X}_{(t)} \right| \qquad (23)$$

Step 6: Else if $i <= 3Pop/5 \,\&\&\, i <= 4Pop/5$. Then update the position of solutions using the mutation process of LA.

Step 7: The female version of LA, as described in Equations (24) and (25), is applied to the remaining solutions.

$$x_l^{Fe+} = \min\left[x_u^{\max}, \max(x_u^{\min}, \nabla_u)\right] \qquad (24)$$

$$\nabla_u = \left\lfloor x_u^{Fe} + (0.1r_2 - 0.05)(x_u^{Ma} - r_1 x_u^{Fe}) \right\rfloor \qquad (25)$$

On the other hand, when $Se_r > Se_r^{\max}$, the lioness X^{Fe} undergoes update X^{Fe+}. This process continues until gen_c (female generation count) reaches $gen_c^{\max}$. The mathematical formula for x_l^{Fe+} and x_u^{Fe+} corresponding to l^{th} and u^{th} vector element are denoted are expressed in Eq. (24) and Eq. (25), respectively. The female update function (∇) is expressed in Eq. (25). Here, r_2 and r_1 are integers.

Step 8: Subsequently, the $Fit(i) = value(least\ fitness)$ is checked. Among the overall population, the position of least four fitness is evaluated. If these four fitness values lie within the conditions of steps from (Step 3 – step 7), then the solution gets updated using Eq. (26). Here, $X^{\min}$ and $X^{\max}$ are the minimal and maximal boundaries of the output. In addition, ran is a random number.

$$X = X^{\min} + X^{\max} - X^{\min} * ran \qquad (26)$$

Step 9: Terminate

V. RESULTS AND DISCUSSIONS

A. *Simulation procedure*

The suggested facial recognition method with optimization method was put into practice in MATLAB, and the outcome is documented. The proposed face recognition model was implemented in MATLAB 2018a. The image database was downloaded from authenticated cite which is given in URL: http://cswww.essex.ac.uk/mv/allfaces/index.html. The database includes both male and female images.

B. *Performance Evaluation: Varying Regularization* Constant:

The performance assessment of the work given in Figure 2 was obtained by adjusting the RC . The regularization constant is varied from 0.5 to 2.5. Fig.2(a)demonstrates the Recognition Rate of the presented work which is almost stable above the range 98.6. At RC=2.5 in Fig. 2(a), the recognition rate of the presented work is better than the conventional methods, LCDRC [6], LCDRC-WOA [8] and LCDRC-CEWO[9] respectively by 1.15%, 0.15%, and 0.14%. Correspondingly. Additionally, the given study records the lowest value for FPR shown in Fig.2(b) when compared to the existing models. Also, at Fig.2(c) the novel model having less FNR compared to the traditional models like

LCDRC [6], LCDRC-WOA[8] and LCDRC-CEWO[9] Particularly, at RC=2, the developed model LCDRC-CWLM reaches 31.25 of FNR which is 26.92% and 26.16% superior than LCDRC [6], LCDRC-WOA[8] and LCDRC-CEWO[9] Moreover the FDR of the proposed works is the lowest among all the traditional works and hence verified to be efficient. The following results shows the proposed and existing method performance in terms of regularization constant.

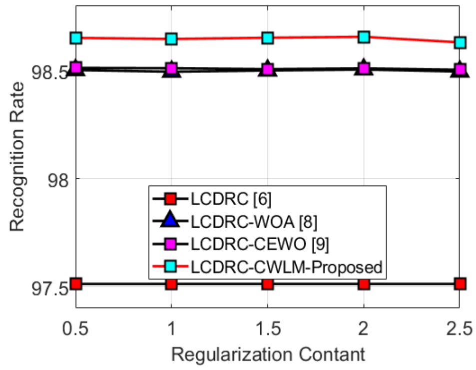

Fig 2(a) Regularization Constant Vs Recognition Rate

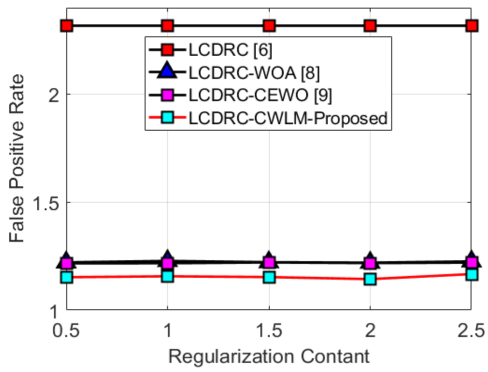

Fig 2(b) Regularization Constant Vs False Positive Rate

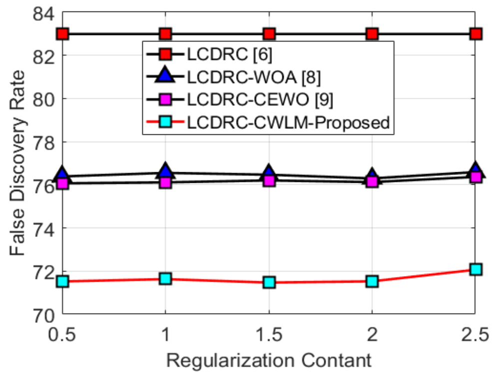

Fig 2(c) Regularization Constant Vs False Discovery Rate

Fig 2. Performance evaluation of the presented work (LCDRC- CWLM) over the traditional approaches by means of varying the regularization constant in terms of (a) Recognition Rate (b) FPR (c) FDR.

VI. CONCLUSION

Pre-Processing, Feature Extraction, and Classification are the three main steps this article used to construct a revolutionary face recognition system. In the pre-processing phase, the Contrast enhancement and RGB to Grey Level Conversion were performed. The pre-processed facial picture is used to extract the characteristics in the manner of texture using AAM. Subsequently, the classification was accomplished via optimized LCDRC model. The projection matrix was the LCDRC classifier's most crucial assessment, and it was multiplying with the characteristics throughout the classification process. To improve the recognition accuracy, the projection matrix was improved. As a novelty, to improve the projection matrix, a novel hybrid method known as CWLM was developed by fusing the WOA and LA concepts. The performance of the suggested model is analysed by determining Accuracy, FPR and FDR over other compared methods like only LCDRC, LCDRC-WOA, and LCDRC- CEWO, respectively.

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