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Research paper

Optimization technique to linear discriminant regression for face recognition

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Abstract

To improve the robustness of the linear regression model number of improvements have been made working on the different databases, the main aim of this paper is to show how an optimization algorithms improves the efficiency of linear discriminant regression methods and performance is evaluated, The features are extracted using Active Appearance Model then the classification is done via linear collaborative Discriminant regression classification (LCDRC) model Proposed by Xiaochao Qu. In the LCDRC classifier, the most important evaluation is projection matrix that might get multiplied to the features while classification. In order to select the optimal projection matrix, this paper proposes a improved whale optimization technique, which is the Enhanced form of Whale Optimization Algorithm (WOA). The proposed face recognition model compares its performance over other conventional methods by varying the regularization constant value from0.5 to 2.5 and performance is taken in terms of measures like Accuracy, Specificity, Sensitivity, Precision, Negative Predictive Value (NPV), F1Score and Matthews Correlation Coefficient (MCC), False positive rate (FPR), False negative rate (FNR) and False Discovery Rate (FDR),and the efficiency by varying the regularization constant and the effectiveness of this model is proven.

Keywords: *Face Recognition; Active Appearance Model; Linear Collaborative Discriminant Regression Classification; Whale Optimization*.

1. Introduction

Face recognition is a challenging problem today, finding the exact and correct face is still a tedious task, many algorithms has been proposed which is proved to be the best for the face recognition i.e. PCA and LDA [10] [11] and other related algorithms which is based on regression analysis. The regression analysis algorithm which is focused to improve the accuracy in face recognition [9] has achieved remarkable results. Mostly In face recognition, the matching takes place for the human’s indispensable characteristic to existing data, and the human is traced as per the results. The features of faceare extracted and implemented via different approaches, and that are proficient.

To manifold learning-based dimensionality reduction methods could discover the intrinsic manifold structure of data. Active appreance approach (AAM) [8][34] is a well-known linear manifold learning-based Face recognition approach, which seeks to map the original data in to a subspace where as the neighbourhood relates between samples can be preserved data. As PCA and LDA, over the past few decades researchers have developed many useful dimensionality reduction (DR) techniques for feature extraction. Principle component analysis (PCA) [10], is one of the most well-known methods for feature extraction. PCA aims to transform the original data into a low-dimensional subspace where the variance of the data is preserved as much as possible. PCA is an effective data representation technique, but it may be unsuitable for classification since PCA cannot discover the discriminant structure of the data.

In view to improve the better accuracy regression methods has been effectively used to improve the results, regression method with modular approach is presented [9] but still the LRC and other regression methods do not take between classes in to consideration. Numerous approaches are there for recognizing and detecting the face. Feature extraction approach can be done in which, the extracted features from the face can be processed and compared , for obtaining the better solution the optimization techniques are presented for better and accurate results , here the Enhanced WOA [28] is compared to state of art optimization algorithms like GA [33] ,ABC[32], PSO[31] ,GWO[29].

2. Literature review

2.1. Related works

In 2017, Pu Huang et al.[1] have developed a novel fuzzy linear regression discriminant projection for face recognition and derived a criterion function by maximizing the ratio of with in class reconstruction errors. This paper introduces a novel algorithm called fuzzy linear regression discriminant projection (FLRDP) for face recognition. The proposed algorithm FLRDP seeks efficient subspace for the LRC method could effectively handle variation in facial images.

In 2016, Jing-Wein Wang et al. [2] have developed a new image processing approach namely Adaptive Singular Value Decomposition in the 2D discrete Fourier domain (ASVDF) for recognizing the face under different lighting. The approach could make the clear colour face images, which was more natural and smoother.

This could be achievedeven the face image has undertaken lateral lighting. The model transfers the colour face image to Fourier domain.

In 2015, Xiachou Qu et al [3] have evaluated the performance using the collaborative technique for the linear regression classification. The results show that the accuracy is improved much in the collaborative technique with regression. This method adopts a better between class reconstruction error measurements using class specific representation.

In 2014, Xiachou Qu et al [25] have improved the results by maximizing the between class reconstruction error and minimizing the within class reconstruction error simultaneously. Enhanced LDRC adds a class selection to calculate the construction error from all class except the true class.

In 2013 hang et.al [4] proposed a method which improves the robustness using the linear regression classification. However LRC and RLRC do not take the between class information in to account. simply applying the PCA cannot grantee the better performance. Further the discriminant analysis is presented to robustness of LRC. This proposed method could estimate the optimal projection in such a way that the ration of between class and within class should be maximized.

In 2012 S.-M. Huang et al [5] Proposed a model which solve uncontrollable illumination problem which is a great challenge for face recognition, the improved principal component regression classification (IPCRC) algorithm, which could overcome the problem of multico linearity in linear regression.

In 2011 Ying-Nong Chen et al [6] have propose the Face recognition algorithm often used to solve problems such as facial pose, illumination, and expression (PIE). In this study, a nearest feature space embedding (called NFS embedding) algorithm is proposed for face recognition. The distance between a point and the nearest feature line (NFL) or the NFS is embedded in the transformation through the discriminant analysis. Three factors, including class separability, neighbourhood structure preservation, and NFS measurement, were considered to find the most effective and discriminating transformation in Eigen spaces. The proposed method was evaluated by several benchmark databases and compared with several state-of-the art performances.

In 2010 I.Naseem et al [9] have formulated regression classification based on the fact that pattern in same object lie on same subspace and proposed a modular approach. Further the problem of close occlusion is reduced using distance based evidence fusion. The main advantage is non face portions are rejected dynamically and improves the overall performance.

III. Design representation: Architecture and its subsequent phases

Appearance Model: Basically the AAM [34] model is used to extract the features and for the construction of full model of face image needs both the texture and shape model. Thus, the construction of numerical texture model is the next step, where the texture samples' alignment is needed to a reference texture frame and the appearance is composed of texture information. As the structuring of statistical appearance model is need to warp the colour channels, initially the control points are matched to the mean shape. The piecewise affine warping (i.e., Dividing the convex outlines of the mean shape by triangle sets) is done for matching the texture. The appearance model, $AP(\bar{x})$ is attained by concerning PCA to texture vectors as defined in Eq. (1), where AP_0 denotes the mean appearance vector, δ_i indicates the appearance parameter, and the synthesised appearance vector from affine wrapping is indicated by $AP_i(\bar{x})$.

$$\mathrm{AP}(\bar{x}) = \mathrm{AP}_0(\bar{x}) + \sum_{i=1}^{mm} \delta_i \, \mathrm{AP}_i(\bar{x}) \tag{1}$$

The output of AAM based feature extraction is indicated as F that includes both shape and texture features.

A. Linear Regression Classification (LRC) [9]

Let denote the training face images of the ith class as $X_i \in \partial^{m \times n_i}$. Each column of X_i are n_i training face images, and $1 \le i \ge c$ where c is the total number of classes.

Assume y be the probe face image that can be represented using X_i according to

$$y = X_i \alpha_i, \text{ where } 1 \le i \ge c \tag{2}$$

$\alpha_i \in \partial^{n_i \times 1}$ is the regression parameters; α_i can be calculated using the least-square estimation as,

$$\hat{\alpha}_i = \left(X_i^T X_i\right)^{-1} X_i^T y, \; 1 \le i \ge c \tag{3}$$

The reconstruction of y by each class can be obtained as,

$$\hat{y}_i = X_i \hat{\alpha}_i = X_i \left(X_i^T X_i\right)^{-1} X_i^T y = H_i y, 1 \le i \ge c \tag{4}$$

Where H_i is called hat matrix that maps y into $\hat{y}$ the reconstruction error of each class is calculated as

$$e_i = \|y - \hat{y}_i\|_2^2, \; \ldots. \; 1 \le i \ge c \tag{5}$$

LDRC-based Classification [4]

Let Z belongs to $K^{n \times d}$ denote the projection matrix then within class and between classes can be obtain

$$E_W = \frac{1}{n} \sum_{i=1}^{n} (x_i - x_i^{\mathrm{int}ra})(x_i - x_i^{\mathrm{int}ra})^T$$
$$E_B = \frac{1}{n(c-1)} \sum_{i=1}^{n} \sum_{j=1, j \ne l_i}^{c} (x_i - x_{ij}^{\mathrm{int}er})(x_i - x_{ij}^{\mathrm{int}er})^T \tag{6}$$

$$J(P) = \underset{P}{MAX} \frac{tr(Z^T E_b Z)}{tr[Z^T (E_W + \in I)Z} \tag{7}$$

Where li the label of the sample xi, $x_i^{\mathrm{int}ra}$ the intra class reconstruction error and $x_{ij}^{\mathrm{int}er}$ is the inter class reconstruction vector of xi with respect to jth class, where $\in$ >0, $\in I$ is added to avoid the singularity of the matrix. The optimal projection of the matrix LDRC is composed by Eigen vectors and associated with first d largest values, this can be solving by identifying the largest d Eigen values

$$E_b . a_k = \lambda_k (E_W + \in I) a_k, \; k = 1, 2....d \tag{8}$$

LCDRC-based Classification [3]

Let the training matrix is represented as $X = \left[X_1, \ldots. X_i, \ldots. X_p\right] \in \Re^{p \times q_i}$, where p indicates the dimension of each training face image, q_i refers to the count of training face image from class i. Let the subspace projection matrix that is to be learned is denoted as $P \in \Re^{p \times d}$ and $d < p$. Each x_{ij} can be mapped to learned subspace by $g_{ij} = P^T x_{ij}$, where $1 \le j \le q_i$. The whole training face image matrix is then mapped as $G = P^T X \in \Re^{d \times q}$ and for each class $G_i = P^T X_i \in \Re^{d \times q_i}$. The collaborative between-class reconstruction error (CBCRE) and within-class reconstruction error (WCRE) are defined as in Eq. (9)

$$CBCRE = \frac{1}{q} \sum_{i=1}^{c} \sum_{j=1}^{q_i} || g_{ij} - \hat{g}_{ij}^{\mathrm{int}er} ||_2^2$$
$$WCRE = \frac{1}{q} \sum_{i=1}^{c} \sum_{j=1}^{q_i} || g_{ij} - \hat{g}_{ij}^{\mathrm{int}ra} ||_2^2 \tag{9}$$

Where $\hat{g}_{ij}^{inter} = G_{ij}^{inter}\alpha_{ij}^{inter}$ and $\hat{g}_{ij}^{intra} = G_{ij}^{intra}\alpha_{ij}^{intra} \cdot G_{ij}^{inter}$ is the G with G_i eliminated and G_{ij}^{intra} is the G_i with g_{ij} eliminated. α_{ij}^{inter} and α_{ij}^{intra} is attained by Eq. (10).

$$\hat{\alpha}_i = \left(X_i^T X_i\right)^{-1} X_i^T g, i = 1,2,..c \tag{10}$$

Prior obtaining the P, the value of α in learned subspace is unknown for us. However, the $\hat{\alpha}$ is evaluated in the original space and $\hat{\alpha}$ is used as the approximation of α . From Eq. (9), the difference among CBCRE and BCRE is seen, and CBCRE uses cross-class collaborative representation and BCRE uses class-specific representation. As per the relationship among X and G , CBCRE and WCRE is rewritten as in Eq. (11). This is again rewritten as in Eq. (12).

$$\begin{aligned} CBCRE &= \sum_{i=1}^{c}\sum_{j=1}^{q_i} \| P^T x_{ij} - P^T X_{ij}^{inter}\alpha_{ij}^{intra} \|_2^2 \\ WCRE &= \sum_{i=1}^{c}\sum_{j=1}^{q_i} \| P^T x_{ij} - P^T X_{ij}^{intra}\alpha_{ij}^{intra} \|_2^2 \end{aligned} \tag{11}$$

The Eigen vectors EI_b and EI_w is determined as in Eq. (12).

$$\begin{aligned} EI_b &= \frac{1}{q}\sum_{i=1}^{c}\sum_{j=1}^{q}\left(x_{ij} - X_{ij}^{inter}\alpha_{ij}^{inter}\right)\left(x_{ij} - X_{ij}^{inter}\alpha_{ij}^{inter}\right)^T \\ EI_w &= \frac{1}{q}\sum_{i=1}^{c}\sum_{j=1}^{q_i}\left(x_{ij} - X_{ij}^{intra}\alpha_{ij}^{intra}\right)\left(x_{ij} - X_{ij}^{intra}\alpha_{ij}^{intra}\right)^T \end{aligned} \tag{12}$$

This can be solve by identifying the largest d Eigen values and the according Eigen values as the following Eq. (17), where $\lambda_1 \geq .....\geq \lambda_k....\lambda_d$ and $P = [p_1,....p_k,...,p_d]$. MMC solves the small sample size problem (SSP), where the face image dimensions is greater than the count of training face images.

$$\left(EI_b - EI_w\right)P_k = \lambda_k p_k, k = 1,2....d \tag{13}$$

3. Enhanced proposed algorithm for projection matrix optimization

a) Fitness Function

To evaluate the function at first the error is calculated i.e. $error$ between actual value, act and predicted value, $pred$ is evaluated followed by fitness function. In Eq. (13), λ indicates the regularization and the minimization of overall error along with λ is consider as the major intensive of this proposed work .The analysis is presented in Fig 2 by varying the regularization constant the parameters are calculated for showing the improvement in the optimization technique.

$$error = \left(act - pred\right) \tag{14}$$

$$FT = Min\left(Sum\left(error\right) + \lambda * \sum_{i=1}^{NU}\left(P\right)^2\right) \tag{15}$$

b) Whale Optimization Algorithm[28]

Whale optimization algorithm was proposed by Seyedali Mirjalili and Andrew Lewis in 2016, Different phases are there in WOA algorithm [28], and they are Encircling prey, Spiral bubble-net feeding maneuver, and search for prey. An improvement is made with the conventional WOA to get the optimal P , which is explained below.

Encircling prey: Eq. (16) defines the position update in the direction of the best search agent, where tn indicates the current iteration, $\vec{K}$ and $\vec{L}$ represents the coefficient vectors, p^* indicates the position vector of best solution, position vector is indicated by $\vec{P}$, $|\,|$ is the absolute value, and it denotes the element by element multiplication. Eq. (18) and (19) shows the evaluation of $\vec{K}$ and $\vec{L}$

$$\vec{H} = |\vec{L}.\vec{P}^*(tn) - \vec{P}(tn)) \tag{16}$$

$$\vec{P}(tn+1) = \vec{P}^*(tn) - \vec{K}\cdot\vec{H} \tag{17}$$

$$\vec{K} = 2.\vec{a}.\vec{ru} - \vec{a} \tag{18}$$

$$\vec{L} = 2.\vec{ru} \tag{19}$$

In the exploration and exploitation phase, $\vec{a}$ is linearly reduced from 2 to 0, $\vec{ru}$ denotes the random vector in [0,1].

(i) Exploitation phase: Bubble net attacking model: Two approaches are determined in this phase namely shrinking encircling mechanism and Spiral updating position.

Shrinking encircling approach is achieved by reducing $\vec{a}$ value. Here $\vec{K}$ is a arbitrary value in the range $-\vec{a},\vec{a}$.

Spiral updating position firstly computes the distance between whale that located or positioned at (P,Y) and prey that positioned or located at (P*,Y*).The generation of spiral equation between whale and prey position is happened, which gives the humpback whale's helix shaped movement, and it is defined in Eq. (20). Fig 1 Shows the movement of whale in helix shape and the distance between the P and P* is H'.

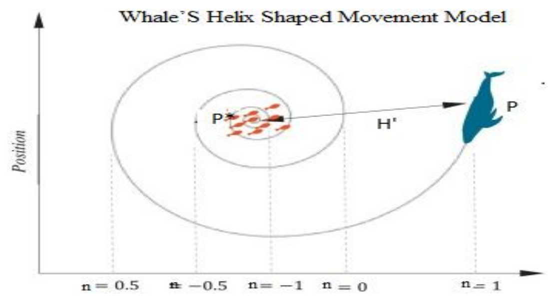


Fig. 1: Helix Shaped Movement of the Whale, Courtesy [28].

$$\vec{P}(tn+1) = \vec{H'}\cdot e^{kn}\cdot\cos(2\pi n) + \vec{P^*}(tn) \tag{20}$$

Where $\vec{H'} = |\vec{P^*}(tn) - \vec{P}(tn)|$, determines the distance of i^{th} whale to prey, k indicates the constant value, n indicates the random number in [-1,1], and $\cdot$ is the element by element multiplication. Eq. (21) gives thel model of whale's position update, where $\tilde{m}$ specifies the random number in [0,1].

$$\vec{P}(tn+1) = \begin{cases} \vec{P^*}(tn+1) - \vec{K}\cdot\vec{H} & if\ \tilde{m} < 0.5 \\ \vec{H''}\cdot e^{kn}\cdot\cos(2\pi n) & if\ \tilde{m} \geq 0.5 \end{cases} \tag{21}$$

c) Conventional Whale Optimization Algorithm[CWOA]

This paper proposes a Conventional WOA algorithm for attaining the optimal projection matrix, P , which is the improvement of conventional WOA algorithm The enhancement is made in case of no improvement in Fitness evaluation. This paper fixes N_{cycle} =3 and finds the best solution as the optimal projection matrix P*.

4. Results and discussions

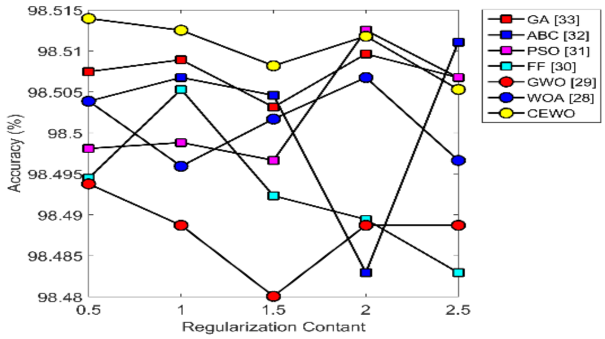
a) Simulation Setup

The proposed method i.e. Conventional enhanced whale optimization technique(CEWO) provide the better and best solution in comparison with other techniques, Simulation results are performed using the image database downloaded from the link shown which is freely available for from URL: http://cswww.essex.ac.uk/mv/allfaces/index.html database and is implemented on MATLAB 2015a to validate the efficiency and other parameters.. The database includes both male and female images with different variations. The proposed method was compared to other conventional methods like conventional Whale Optimization Algorithm (WOA) [28], Grey Wolf Optimization (GWO) [29], FireFly (FF) [30], Particle Swarm Optimization (PSO) [31], Artificial Bee Colony (ABC) [32], and Genetic Algorithm (GA) [33].The performance of proposed model was analyzedin terms ofmeasures like Fig 2(a) shows the Accuracy which shows the accuracy performance over other methods, Fig 2 (b) graph for Specificity shows the its improvement , Fig 2(c) graph which shows that the performance of specificity with respect to regularization constant has improved compared to other conventional methods, Fig 2(d) graph for the improvement in Precision, Fig 2(e) graph shows better FPR in comparison with other methods ,Fig 2(f) graph shows the FNR Performance in comparison with other methods and Fig 2(g) graph for NPV validation in comparison with other methods, Fig 2(h) performance graph for FDR in comparison with other methods, Fig 2(i) graph for F1 Score, Fig 2(j) shows the MCC evaluation in comparison with other models finally the overall analysis for Proposed face recognition model in terms ofefficient parameters are studied.

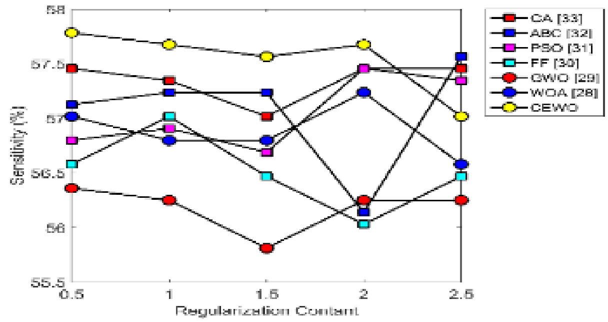
b) Regularization Effect

Fig 2 shows the performance analysis of proposed over conventional models by varying the regulation constant value to 0.5, 1, 1.5, 2 and 2.5. Both the positive and negative measures are analyzed and evident in Fig 2.Here for Regulation constant 0.5, it is proved that the anticipated method is 0.01%, 0.02%, 0.019% and 0.018% better from WOA, GWO, FF, and PSO, respectively. For constant 1, the proposed method is 0.018%, 0.02%, 0.008%, 0.017% and 0.007% better from WOA, GWO, FF, PSO and ABC, respectively. Thus, the overall analysis has proven the capability of proposed work in recognizing face images.

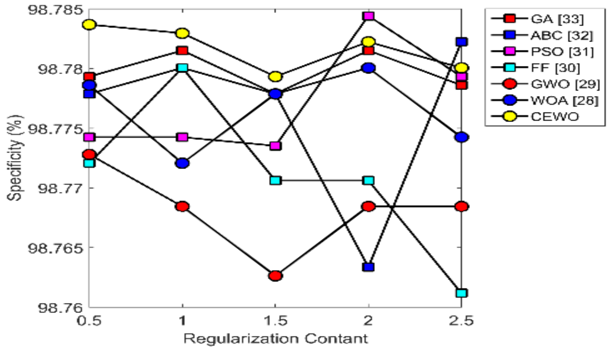
(A)



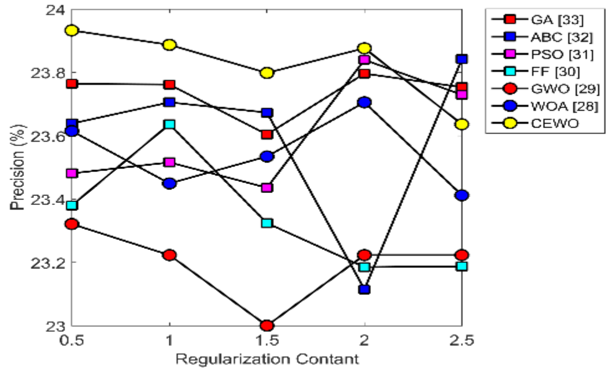
(B)



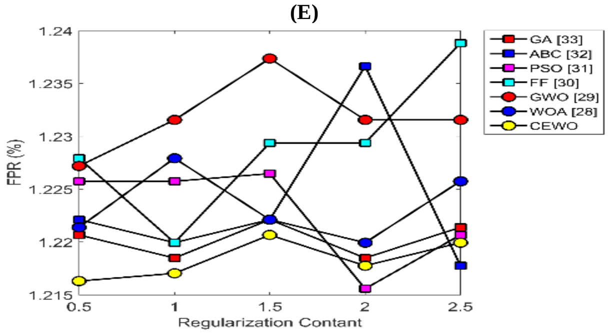
(C)



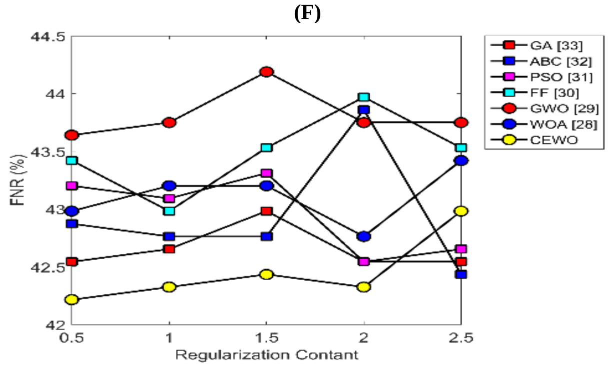
(D)



(E)



(F)



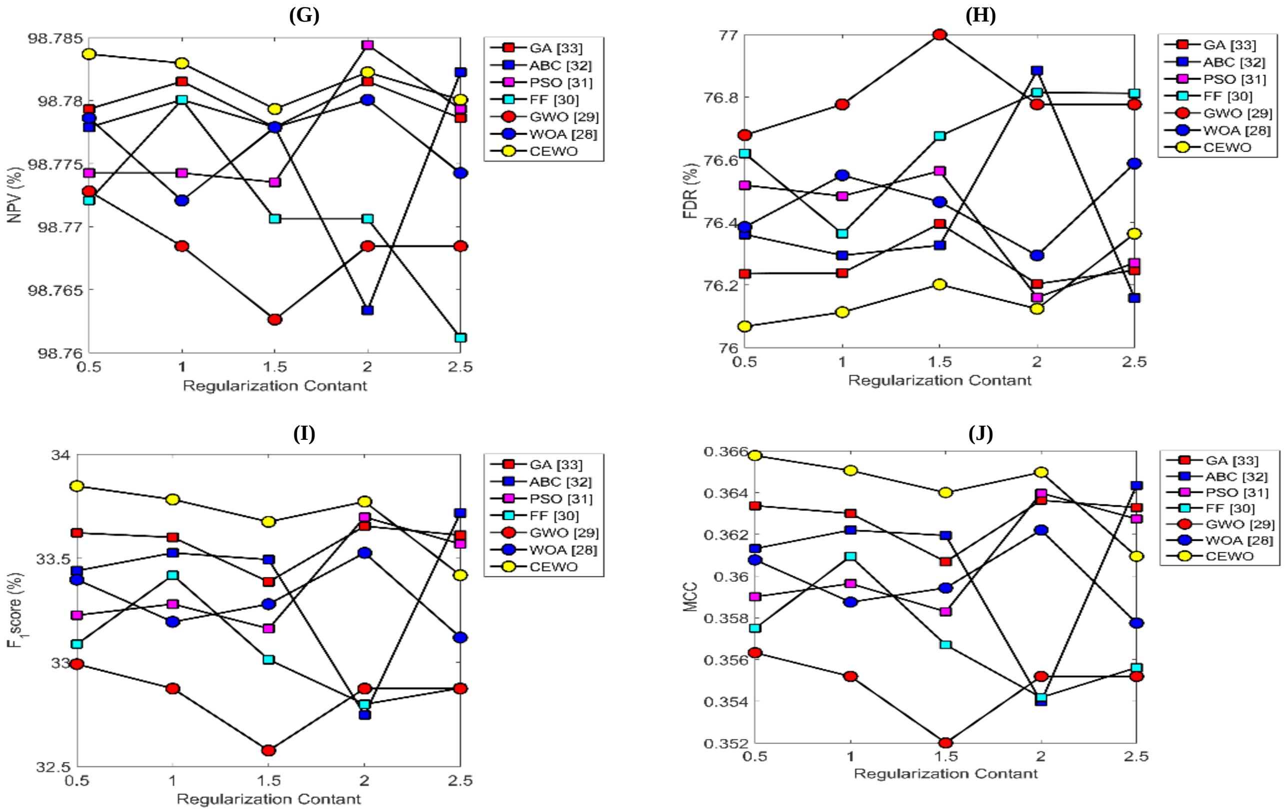


Fig. 2: Regulation Effect on Proposed and Conventional Face Recognition Model A) Accuracy B) Sensitivity C) Specificity D) Precision E)FPR F) FNR G) NPV H) FDR I) F_1Score J) MCC.

5. Conclusion

This paper has developed an efficient face recognition model using the LCDRC classifier the major contribution is choosing the best optimal projection matrix which was fulfilled by Enhanced WOA. The performance of proposed model was studied by varing the regularization Constant value with other conventional methods in terms of various parameters Hence the satisfactory results have shown the better performance of proposed model with high accuracy.

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