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# Improved Face Recognition Using Optimized Linear Collaborative Discriminant Regression Classification With Hybrid Algorithm

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***Abstract***
*This paper addresses the persisting issues in face recognition, like aging, partial occlusion, and facial expressions, despite advancements in automatic facial recognition. The proposed innovative framework comprises three crucial phases: Pre-Processing, Feature Extraction using Active Appearance Models (AAM), and Classification employing an optimized Linear Collaborative Regression Classification method. A key focus is placed on enhancing recognition accuracy through the optimization of the projection matrix in the Linear Collaborative Regression Classification. To achieve this optimization, a novel Combined Whale Lion Model (CWLM) is introduced, which hybridizes the concepts of Lion Algorithm (LA) and Whale Optimization Algorithm (WOA). The proposed model's performance is evaluated against other methods, including LCDRC, LCDRC-WOA, and LCDRC-CEWO, demonstrating significant improvements in recognition accuracy on FACE94, ORL, and YALE datasets. The experimental results indicate a maximum recognition accuracy of 98.67%, 91.24%, and 94.33% on FACE94, ORL, and YALE datasets, respectively, showcasing notable enhancements over existing benchmark models.*

***Keywords—****Face Recognition; Active Appearance Model;LCDRC based classification;Whale Optimization Algorithm;Lion Algorithm.*

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## I. INTRODUCTION

Latterly, biometric-based techniques have emerged as a promising solution for individual recognition, offering an alternative to traditional methods like passwords, PINs, smart cards, and tokens. Instead of relying on easily forgotten or sealable credentials, these techniques focus on examining individuals' physiological and/or behavioural characteristics, which remain relatively constant. Unlike passwords or PINs, an individual's inherent traits, such as facial features, cannot be easily misplaced, forgotten, stolen, or counterfeited. Face recognition, in particular, has become a compelling and essential area of research in biometric recognition. Given its applicability in various security domains, including airports, criminal detection, face tracking, and forensics, researchers have shown significant interest in advancing the capabilities of face recognition technology.

Face recognition involves identifying a previously encountered face as familiar or unfamiliar. It is important to distinguish this from face detection, where the focus is on locating faces within an image. The process of face recognition determines whether a detected face belongs to a known or unknown individual by comparing it with a database of known faces [12] [13] [14] [15].

Two predominant approaches are commonly employed to address the face recognition problem: photometric (view-based) and geometric (feature-based). In the geometric recognition approach, the facial features like eyes, nose, and mouth are initially identified. Subsequently, faces are categorized based on various geometrical distances and angles between these features [16] [17] [18] [22]. On the other hand, photometric stereo involves recovering the shape of an object from multiple images captured under different lighting conditions [23] [24] [25]. These approaches contribute to the diverse methodologies employed in the face recognition field.

The existing face recognition system with PCA is the simplest and easily implementable approach. But, isn’t sensitive to illumination circumstances. On the other hand, LDA is a renowned linear projection approach that is good in mapping higher-dimensional data into lower-dimensional space. [21] [19] [20]. When the samples' dimensionality is low, the main disadvantage of LDA occurs with small sample sizes. Furthermore, SVM is superior in terms of false and detection rates. Other than this, SVM does not allow for the minimization of error rate. As a result, real time face identification techniques must be used to create an automated emotion detection system.

Below is a representation of this research's main contribution:

I. A face recognition framework is developed and here the classification is accomplished using the optimized LCDRC classifier.

II. A hybrid algorithm dubbed CWLM, which conceptually combines LA and WOA, optimizes the vector representation of LCDRC.

III. The proposed LCDRC-CWLM Linear Collaborative Discriminant Regression Classification -Combined Whale Lion Model is analysed by determining Accuracy, FPR and FDR over other compared methods like: only LCDRC, Linear Collaborative Discriminant Regression Classification Based Whale Optimization Algorithm (LCDRC-WOA), and Linear Collaborative Discriminant Regression Classification with Cyclic Exploration Based Whale Optimization Model (LCDRC- CEWO) respectively.

The paper is structured as follows: Section II initiates a discussion on recent noteworthy research projects. Section III delves into the domain of face recognition, elucidating its archetype and providing an explanation. Section IV provides a succinct overview of feature extraction through Active Appearance Models (AAM) and the refined Linear Collaborative Regression Classification (LCDRC) method. Additionally, Section V details the hybrid optimization approach used to optimize the projection matrix, encompassing elements such as the objective function and solution encoding. Progressing further, Section VI briefly examines the outcomes derived from the presented works. Finally, Section VII encapsulates a comprehensive conclusion for this study project.

## II. LITERATURE REVIEW

***Related works***

In their work, Ran He et al. [1] devised a high-resolution heterogeneity face synthesis model, combining a texture-in-painting element and a posture adjustment element within an end-to-end deep network through a warping method. Visual quality improvement is achieved using a wavelet and a fine-grained discriminator. To ensure synthesis outcomes, the authors imposed unique 3-dimensional posture correction reduction, two adversarial reductions, and an image failure. Feng Liu et al. [2] introduced a combined face alignment and 3-dimensional face regeneration approach for 2-dimensional face photos, addressing random positions and expressions simultaneously. Based on a summation theory of three-dimensional face shapes and cascaded regression in two-dimensional and three-dimensional face shape spaces, this technique uses two cascaded regressors alternatively, one for upgrading two-dimensional landmarks and another for three-dimensional face shape.

Chaoyou Fu et al. [3] presented a Heterogeneous Face Recognition (HFR) system using a unique Dual Variation Generation framework, treating it as a twofold generation issue. They use a complex dual variation generator to obtain the joint probability distribution of matched heterogeneous pictures. To overcome the limitation of small-scale coupled heterogeneous training data, the proposed method incorporates a wealth of identifying information from large-scale observable evidence into the joint distribution.

Mandi Luo et al. [4] introduced a Face Augmentation Generative Adversarial Network (GAN) to mitigate the impact of uneven deformable feature patterns. The authors utilized a hierarchical disassociation module to isolate features from the identification model. Additionally, Graph Convolutional Networks (GCN) were employed to recover spatial information by analyzing relationships among local areas, ensuring the preservation of identifiers in face data augmentation.

The new GDCNN ensemble method incorporates two key features: GDCNN building and GDCNN groups. Each GDCNN is constructed to specialize in a particular Gabor face expression. In the work by Hao Yang and Xiaofeng Han [8], they developed a real-time facial recognition system utilizing graphics processing. The primary objectives of the paper are to address challenges related to the face recognition truancy rate in real-time video computation, the system's consistency in video clip processing, its accuracy in actual visits, and the device's connection configurations for real-time video refining.

Zhou et al. [56] presented a face recognition approach that combines Principal Component Analysis (PCA) with logistic regression. To extract pertinent characteristics from face photos and minimize the number of dimensions in the input data, PCA is used. For face recognition, the authors presented a logistic regression classifier. Experiments carried out on difficult face databases proved the efficacy of their approach. However, the performance of PCA was found to be affected by the number of samples per individual in the training dataset, affecting the recognition rate, particularly when sample numbers were limited.

Gao et al. [57] presented a approach addressing data representation and occlusion-induced errors in images at the same time. Their Robust-Discriminative Low-Rank Representation (R-DLRR) optimizes low-rank representations for classification while minimizing deviation from an ideal-code regularization term. This method proved effective in scenarios with substantial occlusions in face images.

Li et al. [58] introduced a perspective on face recognition, emphasizing the need to obtain discriminant information from unique individuals by taking into account the dynamic subspace of images. The distinctive qualities of discriminative components are represented by this data. When compared to current popular methods, the results on public databases, including AR, Extended Yale B, and ORL, showed remarkable identification rates. The research acknowledges the challenges posed by both inter-personal and intra-personal variations in face images, including factors like facial expressions and facial hair.

Jian Zhao et al. [5] developed a deep Age-Invariant Model (AIM) for face identification with three unique features. AIM introduces a unified deep learning model to conduct cross-age face synthesizing and recognition simultaneously. It avoids the need for coupled data and actual test samples, achieving continual face aging with realistic and identity-similar qualities. The end-to-end training of the whole deep architecture using effective and unique training procedures produces age-invariant facial models disentangled from aging variability.

Jin Chen et al. [6] suggested an Identity-Aware Facial Mega Network to retrieve personal data from low-resolution faces. They decomposed the magnitude and direction of characteristics projecting identity features into a more space into two opposing components, aiming to successfully acquire identity-aware traits.[7] developed a revolutionary GDCNN approach for successfully applying various and numerous Gabor facial models as data during the learning phase of a DCNN for FR purposes.

**TABLE I. Features and Challenges of Existing Face Recognition Approach**

| Author [citation] | Methodology | Features | Challenges |
|---|---|---|---|
| **He *et al*. [1]** | WCNN | ➢ Reduces the error rate<br>➢ Reduce the modality difference | × Prone to over-fitting on small-scale datasets |
| **Deng *et al*. [2]** | APA | ➢ Reduce facial geometric variations<br>➢ Reducing information loss | × Requires improvement in recognition accuracy.<br>× Require more time to train the network |
| **Mocanu*et al*. [3]** | Deep-See Face | ➢ Minimize the required computational resources<br>➢ Training process is quite efficient | × Low accuracy.<br>× Extensive Computational time |
| Mandi Luo***et al*. [4]** | Face Augmentation Generative Adversarial Network (FA-GAN) | ➢ Geometric information is recovered by Graph Convolutional Networks (GCNs) by examining the relationships between nearby regions | × FA-GAN need to make simpler. |
| **Zhou *et al*. [5]** | Deep Age-Invariant Mode | ➢ Cross-Age Face Recognition (CAFR) benchmark dataset to to support current initiatives. | × Classification accuracy with other datasets. |

***Review***

Facial recognition can even be done by the humans, but, their limitation of memory does not assist them in all the circumstances. In spite of rapid progress in the area of automatic facial recognition, it still faces obstacles like as Aging, Partial Occlusion, and Facial Expressions etc. The most significant research projects carried out in this area are covered in the literature, and Table I presents a concise summary of their embedded characteristics. Among them, WCNN in [1] is good in enhancing the Verification rate even under lower false acceptance rate. However, this method calls for a lot of parameters, and those parameters are vulnerable to over fitting. Further, APA in [2] enhances the recognition performance. In this approach, when the training data is smaller, the network convergence is lower. Moreover, DEEP-SEE FACE in [3] is transportable, wearable and gainful. But, the computational time is extensive.

Further, a hybrid angularly discriminative feature [4] greatly improves the strength of feature categorization. The training accuracy is lower, since the number of resources is low and hence, it is complex to enhance the deep CNN architecture. EDA in [5] is good in mining forceful and differentiate features beneath unrestrained illumination situation. This technique could be much better if the performance of lighting pre-processing and feature extraction is improved. The face recognition efficiency, computation rate, and recognition rate are all increased by the WT-LLE-LSSVM in [6]. Further, here the total reconstruction error can be reduced.

Moreover, the 2D–MTLBP-F in [8] achieves the uppermost identification rates in dissimilar illumination circumstances as well as in unrestrained surroundings. This technique isn't specific for illumination problem.In the realm of medical image processing, MRI image segmentation, as explored by MyatThetNyo et al. [54], stands as a formidable challenge. This challenge is compounded by the inherent low contrast of MRI scans. The central objective of medical image segmentation, rooted in specific input features or expert insights, is to isolate and characterize anatomical components. However, the segmentation of brain tumours within MRI images proves even more intricate due to the intricate nature of brain structures. A widely recognized technique in image segmentation is Otsu's thresholding method. This investigation [55] delves into the analysis of class or bin selection within Otsu's thresholding for the segmentation of brain tumours in MRI images. In a pre-processing phase, 2D MRI images are transformed into greyscale and resized uniformly. Subsequently, a median filter is employed to remove noise from the MRI images.

To successfully distinguish brain tumors from the MRI data, different classes or bins within Otsu's thresholding are used in the MRI image segmentation procedure. A morphological operation is then applied to ensure accuracy in delineating tumour regions. All experimental procedures are conducted on the 2015 BRATS dataset. Segmentation quality is gauged using metrics such as the Jaccard similarity index, sensitivity (true positive rate), specificity (true negative rate), and accuracy, serving as validation against ground truth. In an independent study, Xiaochao Qu et al. [59] introduce an enhanced discriminant linear regression classification (EDLRC) algorithm aimed at amplifying the discriminative potency of LDRC. This augmentation entails selective consideration of classes with minimal reconstruction errors. By increasing the reconstruction error between the true class and its analogous counterparts, EDLRC enhances the discriminative power of LDRC. Experimental data validate that the projection matrix created in EDLRC is more efficient than that in LDRC, particularly when the ratio of within-class reconstruction error to between-class reconstruction error is raised. It is inferred that as dimensionality increases, EDLRC and LDRC converge to comparable recognition accuracy levels. The experimental results underscore the proficiency of EDLRC in comparison to LRC and LDRC when applied to the ORL and AR databases. The detailed comparison is shown in Table II .

**TABLE II. Review on Various Methods on Face Recognition Along with Its Performance**

| REFERENCE | YEAR | FEATURE SELECTION | MODEL | DATASET, PERFORMANCE |
|---|---|---|---|---|
| Jiang et al [40] | 2013 | LPQ | AdaBst | f1-0.66,Acc-0.947 |
| Tong et al [39] | 2010 | Gabor | AdaBst-DBN | CK ,tpr-0.88,fpr-0.05 |
| Zhu et al[43] | 2011 | AAM,SVM | AdaBst | RU-FACS , auc -0.74 |
| Seenachal et al[44] | 2016 | AAM | AdaBst | GEMP,f1-0.62 |
| Wu et al[45] | 2011 | GABOR | AdaBst | GEMP,f1-0.58 |
| FERA Base Lin[46] | 2019 | PCA | SVM | GEMP,f1-0.45 |
| Valstar&pantic[47] | 2012 | SVM,HMM | GnstAdbst | CK ,f1-0.61,cr-0.92 |
| Shih-Wei Lin et. al [ 48] | 2009 | LDA | PSOLDA | Acc -84.5% |
| Imran Naseem et al [49] | 2010 | PCA | LRC | AT&T -Acc -0.93 |
| Huang et al [50] | 2013 | PCA | LRC | AR -Acc -0.90 |
| Xiaochao Qu, et al [25] | 2015 | PCA | Collaborative Regression | Acc-0.9421 |
| Sailaja et al [51 ] | 2018 | PCA | Deep learning | Acc-0.95 |
| SHosgurmath et al [53] | 2019 | PCA | GWO-Optimization | ORL-Acc-0.98 |
| SHosgurmath et al [52] | 2022 | PCA | CNN | ORL-Acc-0.96 |
| Sailaja et al [37 ] | 2017 | PCA | PSO -optimization | ORL-Acc-0.831 |
| Yang et al[36] | 2009 | FS -ADABst | AdaBst | CK ,Accy-0.77 |
| Tong et al [38] | 2007 | Gabor | AdaBst | CK ,tpr-0.87,fpr-0.06,cr-0.93 |
| Simon et al [42] | 2010 | AAM,SVM | AdaBst | RU-FACS , acu -0.85,f1-0.52 |
| Kolestra et al [41] | 2018 | Gnt+bst | AdaBst | CK ,f1-0.73,cr-0.93 |

CK-Comprehensive database for facial expression analysis, fpr-false positive rate, tpr-true positive rate, Acc-Accuracy,

Cr-classification rate, f1-F1Measure,auc-area under curve, GEMP-Geneva multimodal expression corpus for experimental research on emotion perception.

## III. FACE RECOGNITION: ARCHITYPE AND ITS DESCRIPTION

Here, a unique face recognition method is created by going through the following three stages: **Preprocessing, Feature Extraction and Classification.** Fig. 1 shows a diagrammatic depiction of the suggested facial recognition method. The following list of stages describes how face recognition works:

**Step 1:** Pre-processing is first applied to the obtained face picture. In the pre-processing stage, the RGB to gray scale conversion and contrast enhancement is undergone.

**Step 2:** The pre-processed image is $\mathrm{Im}_{pre}$, from which the features are extracted using AAM.

**Step 3:** Subsequently, these extracted features $F$ are classified using LCDRC model.

**Step 4:**The projection matrix, which is multiplied with the characteristics throughout the classification process, is the LCDRC classifier's most crucial assessment.

**Step 5:** To enhance the recognition accuracy, the projection matrix must be improved. A unique hybrid algorithm called CWLM, which is an extension of the conventional LA and WOA, is presented.

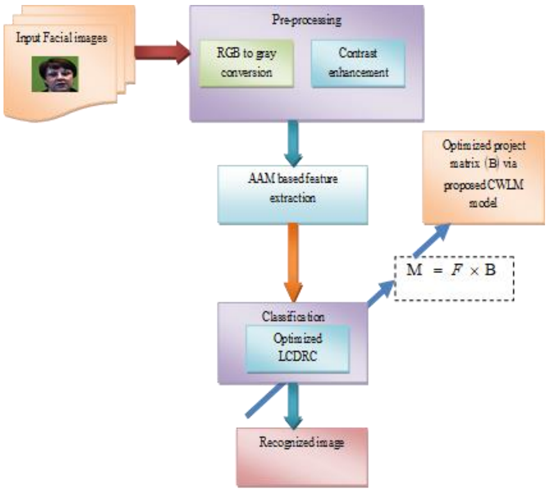


**Fig. 1 Diagrammatic depiction of the suggested facial recognition method**

There are two main methods for image processing:Greyscale conversion from RGB with contrast boosting. Initially, all collected input facial image $\mathrm{Im}_{in}$ is read using the function $read()$.This image is transformed into a grey scale image using RGB to grey scale conversion.

**RGB to Grey Level Conversion [30]:** Typically, aRGB image makes use of no color map and it is represented on the basis of three colour components: red, green, and blue. Such that, converting RGB to Greyscale for Greyscale Image Pre-processing is crucial. Here, the grayscale image's luminance is matched with the llluminance of the color image. The gamma expansion is initially used to encode. The gamma expansion is defined mathematically by Eq. (1).

$$E_{linear} = \begin{cases} \dfrac{E_{RGB}}{12.92} & E_{rgb} \leq 0.04045 \\ \dfrac{(E_{RGB} + 0.065)}{1.065} & E_{rgb} > 0.04045 \end{cases} \quad (1)$$

In which, $E_{RGB}$ → RGB primitives in [0, 1] and $E_{linear}$ →linear-intensity valuein [0, 1]. Further, the weighted sum of the three linear intensity values is used to obtain the output brightness. The transformation mechanism of RGB to grey $\left(\mathrm{Im}_{gray}\right)$is obtained using Eq. (2).

$$\mathrm{Im}_{gray} = f\left(\mathrm{Im}_{in}\right) \quad (2)$$

The function $f\left(\mathrm{Im}_{gray}\right)$achieves this conversion on the basis of the intensity of the three primary colours. This is mathematically expressed in Eq. (3).

$$f\left(\mathrm{Im}_{gray}\right) = 0.2989 * R + 0.5870 * G + 0.1140 * B \quad (3)$$

The resultant grey image $\mathrm{Im}_{gray}$is passed to the contrast enhancement phase for enriching the transparency and the visibility of the image.

**Contrast enhancement** $\left(\mathrm{Im}_C\right)$**:** The image values of $\mathrm{Im}_{gray}$are low contrast, such that the contrast enhancement [29]aids in stretching the intensity of the pixels Adopting $R$'s relative brightness and darkness, as stated in Eq. (4), greatly increases the contrast.

$$\mathrm{Im}_C \to c = \begin{pmatrix} \left(\left(\left(R - low\_in\right)/\left(high\_in - low\_in\right)\right) \wedge gamma\right) \\ * \left(high\_out - low\_out\right) \end{pmatrix} + low\_out \quad (4)$$

Here, $c \rightarrow$contrast enhancement of $R$, $low\_in$ and $high\_in$ $\rightarrow$bounds of the supplied image's contrast and $low\_out$ and $high\_out$ $\rightarrow$boundaries of the generated image's contrast.
From the acquired contrast enhanced pixel $\mathrm{Im}_C$, the AAM features are extracted.

## IV. Aam Based Faeture Extraction And Optimized Lcdrc Based Classifiaction: A Brief Overview

***Feature Extraction with AAM***

Here, the form and look of face characteristics are extracted using the computer vision algorithm AAM [31].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. (6), 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. (5).

$$Y = (Y_1, Z_1, Y_2, Z_2, ......_z Y_n, Z_n)^T \qquad (5)$$

In order 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).

$$\overline{Y}_k = \frac{1}{N} \sum_{j=1}^{j=N} Y_j \qquad (6)$$

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 varianceof 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 given in Eq (7). Here, $\overline{Y}$ is the mean shape vector and $\phi_j$ are the shape parameters. The shape features extracted are denoted as $f_{shape}$.

$$Y_j = \overline{Y} + \sum_{j=1}^{t} \phi_j b_j \qquad (7)$$

**Appearance Model:** The construction of the appearance is based on the intensities of the pixels crosswisethe target image modeled entity. The colour 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. (8).

$$A(Y) = A_0(Y) + \sum_{j=1}^{m} \delta_j A_j(Y) \qquad (8)$$

Here, $A_0$ $\rightarrow$mean appearance vectors
$\delta$ $\rightarrow$Appearance parameters
$A_j(Y)$ $\rightarrow$Affine warping-derived synthetic appearance vectors

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

***Linear CollaborativeDiscriminant Regression Classification method (LCDRC)-optimized :***

Features $(F)$ is the extracted feature which are subjected to classification via optimized LCDRC classifier, in which the facial images are recognized from the training images proposed by Xiaochao Qu [25]. The training matrix of the facial image is expressed in matrix form as $F = [F_1, .....F_2, .....F_c] \in \Re^{p \times q_i}$ .In which $F_j = [F_{j1}, .....F_{j2}, .....F_{jq_j}] \in \Re^{p \times q_i}$ . Further, in each of the training faces, the dimensions are defined as $p$ and the training face image count is indicated as $jq_j$ (from class $j$ ), and $q = \sum_{j=1}^{j=c} q_j$ . $\mathrm{B} \in \Re^{p \times d}$ 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 $g_{ji} = \mathrm{B}^T f_{ji}$, in which $1 \le i \le q_j$.

The overall facial training image is mapped as $G = \mathrm{B}^T F \in \Re^{d \times q}$ and for every class $G_j = \mathrm{B}^T F_j \in \Re^{d \times q_j}$ .The CBCRE and WCRE are defined as in Eq. (9).

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

Where $\hat{g}_{ji}^{\mathrm{int}er} = G_{ji}^{\mathrm{int}er}\alpha_{ji}^{\mathrm{int}er}$ and $\hat{g}_{ji}^{\mathrm{int}ra} = G_{ji}^{\mathrm{int}ra}\alpha_{ji}^{\mathrm{int}ra} \cdot G_{ji}^{\mathrm{int}er}$ is $G$ with $G_i$ eliminated and $G_{ji}^{\mathrm{int}ra}$ is $G_j$ with $g_{ji}$ eliminated. $\alpha_{ji}^{\mathrm{int}er}$ and $\alpha_{ji}^{\mathrm{int}ra}$ is attained by Eq. (10).

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

The value of $\alpha$ is unknown before obtaining $\mathrm{B}$ in the learned subspace However, in the original space the value of $\hat{\alpha}$ is evaluated and $\hat{\alpha}$ is used as the approximation of $\alpha$. The difference between CBCRE and BCRE, as per the CBCRE notion presented in Eq. (9), is that CBCRE uses collaborative cross-class representation, whereas BCRE uses class-specific representation. Further, the relation existing in $F$ and $G$, the WCRE and CBCRE can be written as per Eq. (11)

$$CBCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j} \| \mathrm{B}^T f_{ji} - \mathrm{B}^T F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{intra}} \|_2^2$$
$$WCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_i} \| \mathrm{B}^T f_{ji} - \mathrm{B}^T F_{ji}^{\mathrm{intra}}\alpha_{ji}^{\mathrm{intra}} \|_2^2 \tag{11}$$

This is again rewritten as in Eq. (12).

$$CBCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j}\left(f_{ji} - F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{inter}}\right)^T \mathrm{B}\mathrm{B}^T\left(f_{ji} - F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{inter}}\right)$$
$$WCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j}\left(f_{ji} - F_{ji}^{\mathrm{int}ra}\alpha_{ji}^{\mathrm{intra}}\right)^T \mathrm{B}\mathrm{B}^T\left(f_{ji} - F_{ji}^{\mathrm{int}ra}\alpha_{ji}^{\mathrm{int}ra}\right) \tag{12}$$

In the above tow cases (CBCRE and WCRE), the factor $\frac{1}{q}$ 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. (13) is used to represent the CBCRE and WCRE [26].

$$CBCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j} tr\left(\mathrm{B}^T\left(f_{ji} - F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{inter}}\right)\left(f_{ji} - F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{inter}}\right)^T \mathrm{B}\right)$$
$$WCRE = \sum_{j=1}^{c}\sum_{i=1}^{q_j} tr\left(\mathrm{B}^T\left(f_{ji} - F_{iji}^{\mathrm{intra}}\alpha_{ji}^{\mathrm{intra}}\right)\left(f_{ji} - F_{ji}^{\mathrm{intra}}\alpha_{ji}^{\mathrm{intra}}\right)^T \mathrm{B}\right) \tag{13}$$

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

The eigen vectors $J_b$ and $J_w$ is denoted as in Eq. (14). Eventually, the CBCRE and WCRE are rewritten as in Eq. (15).

$$J_b = \frac{1}{q}\sum_{j=1}^{c}\sum_{i=1}^{q_j}\left(f_{ji} - F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{inter}}\right)\left(f_{ji} - F_{ji}^{\mathrm{inter}}\alpha_{ji}^{\mathrm{inter}}\right)^T$$
$$J_w = \frac{1}{q}\sum_{j=1}^{c}\sum_{i=1}^{q_j}\left(f_{ji} - F_{ji}^{\mathrm{int}ra}\alpha_{ji}^{\mathrm{intra}}\right)\left(f_{ji} - F_{ji}^{\mathrm{intra}}\alpha_{ji}^{\mathrm{intra}}\right)^T \tag{14}$$

$$CBCRE = tr\left(\mathrm{B}^T J_b \mathrm{B}\right)$$
$$WCRE = tr\left(\mathrm{B}^T J_w \mathrm{B}\right) \tag{15}$$

The MMC is deployed to simultaneously maximize CBCRE and minimize WCRE. This is expressed as per Eq. (16).

$$\max_{\mathrm{B}} S(\mathrm{B}) = \max_{\mathrm{B}}(CBCRE - WCRE) = \max_{\mathrm{B}}\left(tr\left(\mathrm{B}^T (J_b - J_w)\mathrm{B}\right)\right) \quad (16)$$

The mathematical expression given in Eq. (16) is solved by means of determining the largest $d$ eigen values and the associated eigenvalues according to Eq (17).

$$(J_b - J_w)b_k = \lambda_k b_k,\ k = 1,2....d \quad (17)$$

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

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

1. A unit $l_2$ norm is acquired by normalizing all the training as well as testing face images.
2. The projection matrix $\mathrm{B}$ is found for the given training facial image $F$. Further, $F$ is projected into the discriminant subspace in order to acquire $G = \mathrm{B}^T.F$ .
3. For every class $j = 1,2,..,c$ , the hat Matrix $H_j$ is computed.
4. Then, for the specified test face image $f$ , convert $f$ into discriminant subspace by using Eq. (18). Then, for $j^{th}$ class, the reconstruction is computed as per Eq. (19).

$$g = \mathrm{B}^T.f \quad (18)$$

$$\hat{g} = H_j.g_j;\ j = 1,2,..,c \quad (19)$$

5. 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. (20).To improve the recognition accuracy, an unique optimization approach called CWLM is used to optimize the project matrix.

$$\mathrm{M} = F \times \mathrm{B} \quad (20)$$

## V. Hybrid Optimization Algorithm For Projection Matrix Optimization : Objective Function And Solution Encoding

***Objective Function and Solution Encoding***

For the best tuning, the suggested model is given the project matrix as input. Fig. 2 provides an illustration of the solution encoding.

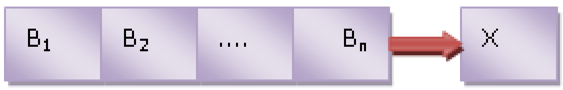


**Fig 2. Solution Encoding**

The major intention 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. (21) and the fitness function is expressed in Eq. (22).

$$error = (act - pred) \quad (21)$$

$$FT = Min\left(Sum(error) + \lambda * \sum_{j=1}^{B_N} (\mathrm{B})^2\right) \quad (22)$$

Here, $\lambda$ →regularization constant

***Proposed Combined Whale Lion Model(CWLM) Model:***

A new improved version of the method is provided in this work to improve the performance of the conventional WOA [27] algorithm and LA [32] [33] [34] [35] algorithm with regard to convergence rate and speed. According to reports, hybrid optimization methods [26] show promise for a number of 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. (23).

$$\vec{X}_{(t+1)} = \left|\vec{X}_{rand} - \vec{V}.\vec{U}\right| \quad (23)$$

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 expressedin Eq. (24) and Eq. (25), respectively.

$$.\vec{U} = \left|\vec{C}.\vec{X}_{p(t)} - \vec{X}_{(t)}\right| \quad (24)$$

$$\vec{X}_{(t+1)} = \vec{X}_{p(t)} - \vec{V}..\vec{U} \quad (25)$$

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

**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. (26)provides a mathematical formulation for this

$$X_{(t+1)} = \vec{U}'e^{bl}.Cos(2\pi l) + \vec{X}_{p(t)} \quad (26)$$

The mathematical formula for $\vec{U}'$ is depicted in Eq. (27). 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 $[-1,1]$

$$\vec{D}' = \left|\vec{X}_{p(t)} - \vec{X}_{(t)}\right| \quad (27)$$

**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 (28) and (29), is applied to the remaining solutions.

$$x_l^{Fe+} = \min\left[x_u^{\max}, \max(x_u^{\min}, \nabla_u)\right] \quad (28)$$

$$\nabla_u = \left\lfloor x_u^{Fe} + (0.1r_2 - 0.05)(x_u^{Ma} - r_1 x_u^{Fe})\right\rfloor \quad (29)$$

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 expressions for $x_l^{Fe+}$ and $x_u^{Fe+}$, which correspond to the $l^{th}$ and $u^{th}$ vector elements, are found in Equations (28) and (29), in that order. The female pdate function $(\nabla)$ is expressed in Eq. (29). Here, $r_2$ and $r_1$ are integers.

**Step 8:** Subsequently, $Fit(i) = value(least\ fitness)$ is checked. Among the overall population, the position of least four fitness is evaluated. If these four fitness values lie within the aforementioned conditions (Step 3 – step 7), then the solution gets updated using Eq. (30). Here, $X^{\min}$ and $X^{\max}$ are the minimal and maximal boundaries of the output. In addition, $ran$ is a random number.

$$X = X^{\min} + X^{\max} - X^{\min} * ran \quad (30)$$

**Step 9:** Terminate

Fig. 3. (a) illustrates the suggested model's flowchart Algorithm 1 contains the suggested CWLM approach's pseudo code.

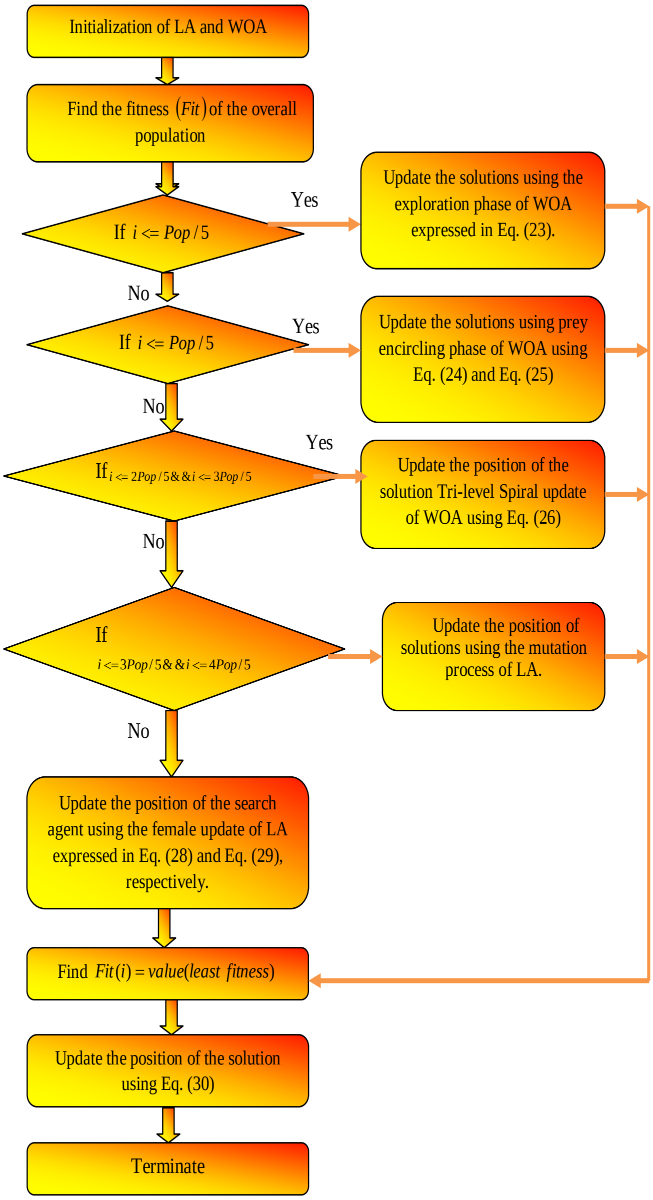


**Fig 3.(a) Flow chart of proposed CWLM approach**

| | |
|---|---|
| **Algorithm 1: Pseudo code of proposed CWLM approach** | |
| **Initialization of LA and WOA population** | |
| **Find the fitness** $(Fit)$ **of the overall solutions** | |
| **If 1** $i <= Pop/5$ | |
| | Update the solutions using the exploration phase of WOA expressed in Eq. (23). |
| **Else if 2** $i <= Pop/5$ | |
| | Update the solutions using prey encircling phase of WOA using Eq. (24) and Eq. (25) |
| **Else If3** $i <= 2Pop/5 \,\&\&\, i <= 3Pop/5$ | |
| | Update the position of the solution Tri-level Spiral updatee of WOA using Eq. (26) |
| **Else If 4** $i <= 3Pop/5 \,\&\&\, i <= 4Pop/5$ | |
| | Utilizing LA's mutation process, update the positions of the solutions. |
| **Else** | |
| | The female update of LA indicated in equations (28) and (29), respectively, should be used to update the search agent's location. |
| **Find** $Fit(i) = value(least\ fitness)$ | |

| |
|---|
| **Update the position of the solution using Eq. (30)**<br>**End if 1** |
| **End if else 2** |
| **End if else 3** |
| **End if else 4** |
| **Terminate** |
| |

**Fig 3.(b) Pseudo code of proposed CWLM (Combined Whale Lion Model) approach**

The execution process is explained systematically in the Fig 3. (b) Which gives the systematic approach of the procedure.

## VI. Results And Discussions

***Simulation procedure***

In this case, MATLAB (2019a) program with Windows 10 operating system, 128 GB RAM, 4 TB hard drive, and Intel Core i7 processor is used to simulate the suggested LCDRC -CLWM algorithm. The ORL face dataset, Yale face dataset, and Face 94 dataset are three common databases from which the evaluation's dataset was compiled. The database encompasses both male and female images. Figure 4 displays the example picture that was gathered for analysis. Thesuggested work is compared to other conventional methods like, LCDRC [25], LCDRC-WOA [27] and LCDRC-CEWO [28] in terms of accuracy, specificity, Precision,

FDR, F1score, MCC. By changing the regularization constant and learning percentage, this evaluation is conducted. Equations(31),(32),(33),(34)(35)(36)and(37) respectively, are the mathematical formulas for accuracy, Specificity, Precision,FDR,F1score,MCC, and FDR.

Accuracy = Correct prediction s / Total prediction s

$$= \frac{TrP + TrN}{TrP + TrN + FrP + FrN} \quad (31)$$

$$\text{Specificity} = \frac{TrP}{Trp + FrP} \quad (32)$$

Specificity=TrN/(TrN+TrP) (33)

$$\text{Precision} = \frac{TrP}{Trp + FrP} \quad (34)$$

$$\text{F1score} = 2 * \frac{precision * recall}{precision + recall} \quad (35)$$

$$MCC = \frac{TrP * TrN - FrP * FrN}{\sqrt{(TrP + FrP)(TrP + FrN)(TrN + FrN)(TrN + FrN)}} \quad (36)$$

$$\text{FDR} = \frac{FrP}{FrP + TrP} \quad (37)$$

Here, TrP→True Positive
TrN→ True Negative
FrP→ False Positive
FrN→ False Negative

## VII. Conclusion

This model outlines aninnovative face recognition system achieved through a systematic three-step process: Pre-Processing, Feature Extraction, and Classification. During the Pre-Processing phase, Contrast Enhancement and RGB to Grey Level Conversion were applied to enhance the quality of facial images. The subsequent Feature Extraction employed Active Appearance Models (AAM) to characterize facial texture. The Classification stage utilized an optimized LCDRC model, where the assessment of the projection matrix played a pivotal role in the classification process. Recognizing the importance of accuracy, the article introduced a novel hybrid method, CWLM, which fused concepts from the Whale Optimization Algorithm (WOA) and Lion Algorithm (LA) to enhance the projection matrix. Performance analysis, comparing the suggested model with alternative methods including LCDRC, LCDRC-WOA, and LCDRC-CEWO, involved metrics such as Accuracy, Sensitivity,

Specificity, Precision, False Discovery Rate (FDR), F1 score, and FDR. Notably, the presented model demonstrated accuracy closely aligned with LCDRC-CEWO within the LP (parameter) range of 40-80. At 80, the proposed model surpassed LCDRC, LCDRC-WOA, and LCDRC-CEWO by 1.5%, 1.02%, and 1.32%, respectively. Particularly noteworthy was the increased accuracy observed for Face 94 when alterations were made to training images. The provided model, boasting an accuracy of 98.82%, outperformed LCDRC, LCDRC-WOA, and LCDRC-CEWO under the condition where tr-sampleis 2. Finally, the developed face recognition system, incorporating innovative pre-processing techniques, feature extraction with AAM, and the novel CWLM method for improving the projection matrix, exhibited superior accuracy and performance compared to existing methods. The results underscore the effectiveness of the proposed approach in achieving robust and precise face recognition outcomes.

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