Advances in Artificial Intelligence and Machine Learning; Research 3 (3) 1389-1406 Received 23-06-2023; Accepted 02-09-2023; Published 09-09-2023

A Novel Framework of Face Recognition using Heuristic Development of Ensemble Classifier Model

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Abstract

One of the most difficult and intriguing areas of computer vision is Face Recognition (FR). Due to the low generalization ability, the success rate of FR is affected by illumination, posture shift, and other factors. FR algorithms typically aim to solve the two problems called subject identification and verification. However, such methods have limitations because they frequently call for computer vision specialists to create useful features. Thus, this paper presents the novel framework of FR using an ensemble learning model. Initially, the face images are gathered from the datasets, which is followed by the pre-processing of the images. Once the pre-processed image is obtained, the significant features are extracted by using Local Binary Pattern (LBP) and Discrete Wavelet Transform (DWT). Then, the dimension reduction of the resultant feature is done by utilizing the Principal Component Analysis (PCA). Finally, an Optimal Ensemble Classifier (OEC) is developed that includes Support Vector Machine (SVM), Neural Network (NN), and Adaboost, where the hyperparameters are tuned optimally by Enhanced Hybrid Leader Based Optimization (EHLBO) algorithm. The performance is validated via different parameters and compared over existing approaches. Thus, the findings ensure that it attains impressive results for face recognition.

Keywords: Face recognition, Local binary pattern, Discrete wavelet Transform, Principal component analysis, Enhanced hybrid leader based optimization, Optimal ensemble classifier.

Citation: Santhosh Shivaprakash and Sannangi Viswaradhya Rajashekararadhya. A Novel Framework of Face Recognition using Heuristic Development of Ensemble Classifier Model Advances in Artificial Intelligence and Machine Learning. 2023;3(3):82.

1. INTRODUCTION

FR is a function that helps to match the images of the faces of the very same person. Information security is becoming a very important and challenging issue [1]. At present, security cameras are prevalent in universities, offices, banks, ATMs, and many other places with security systems. A biometric system called FR is used to recognize or authenticate a person from a digital image [2]. Currently, FR technology is utilized in the security systems which have two types. The first is determined by appearance, and the second by features [3]. Holistic traits are applied to the entire face or specific facial regions in the appearance based FR approach [4]. However, eyes, mouth, cheeks, and lips, are used as geometric facial characters in feature based face identification techniques.

FR is an application of the Pattern Recognition (PR) and it is also one of the study of computer vision [5]. Face images are used in FR systems to identify the persons [6]. A face in a picture should be automatically recognized by an FR system. This requires to extract the features before recognizing it, which is a challenging task, regardless of lighting, expression, illumination, ageing, alterations, and stance [7]. FR can identify the representative features when the face images contain illumination, stance, facial expression, or pose problems have occurred. More elements, such as locally aggregated descriptors in place of the joining operations used in the models, can be added to the models [8]. The experiments can make use of additional databases. Other uses for the models include gender recognition and the identification of facial expressions of emotion [9]. Also, this method can be enlarging for other different variables such as partial occlusion, age, or illumination.

FR is the challenge of recognizing and validating individuals in a snapshot based solely on their appearance. Humans can easily complete the task, under different lighting conditions and with faces that have changed with age or are obscured by jewels and facial hair [10]. It is still a difficult computer vision challenge. Deep learning techniques may use very huge face datasets to develop compact and rich indications of faces, which enables contemporary methods to perform FR. Thus, this study focuses on designing a new framework of FR using the heuristic development of an ensemble classifier model.

The main contributions of the recommended method are explained below.

- To design a model of FR using an ensemble classifier model with the heuristic improvement that helps to detect the person identity accurately.
- To extract the features of images with the help LBP and DWT and then the dimension reduction of resultant features are obtained by PCA for improving the performance.
- To develop the EHLBO algorithm for providing the optimal parameters in the OEC model. Such parameters are degree and maximum iteration in SVM, hidden neuron count and learning rate in NN, and estimator in AdaBoost.

The forthcoming sections of this research paper are organized as follows. Section 2 explains the traditional model of FR. Section 3 explains the FR method using an ensemble classifier model. Section 4 elaborates on the EHLBO algorithm for the FR mode using the ensemble classifier model. Section 5 explains the OEC in FR using an ensemble classifier model. Section 6 reviews the outcomes and discussions of the proposed model. Finally, Section 7 summarizes the proposed model.

2. EXISTING WORKS

2.1 Related Works

In 2021, Meng and Cheng [11], have developed a ”simplified multi task FR model and implemented to increase the speed of the performance. Here, among the various tasks correlation function was utilized to enhance the recognition correctness. This multi task methodology could be fast and correct in the small amount of time, which was used in the analysis of the intelligent derived behavior, and the intelligent navigation.

In 2021, Cho *et al.* [12], have implemented a “graph-structured module called Relational Graph Module (RGM)” which retrieved the relational data globally besides common facial features. Relation propagation reduces the dependency of the texture without changing its advantages via RGM from the already trained characters. Moreover, proposed a ”Node Attention Unit (NAU) which performed node wise recalibration to check the more needed nodes they were coming from the relation depend on the propagation.

In 2015, Sharma and Patterh [13], have proposed a new hybrid method utilizing PCA for the “pose invariant face recognition” method. There was three methodologies were mixed to produce a new hybrid method. The initial step was to identify the face and it’s sections. The next step would be to find the every parts of LBP.LBP retrieved characters from the identified faces and it’s sections. The last was to perform PCA on every retrieved characters for the recognition. The correctness of the conventional PCA and the hybrid methodology utilizing PCA were estimated under the circumstances of the changing expression and the poses.

In 2018, Tong *et al.* [14], have explored the performance of the FR. This model was implemented by joining the ”multi-mirror symmetry with LBP, namely multi-mirror LBP. To improve the FR functionality with different interferences, the MMLBP was able to produce the retrieved image character which was very closed to the well controlled circumstances. And also it had the ability to compensate the lighting with the help of different lighting circumstances.

In 2020, Masud *et al.* [15], have developed a tree based on the deep method for automatically recognize the face in the cloud. This method was low cost but it has more correctness. Here, a tree was implemented by its branches which contained height and the factor. Every branch was denoted by a function called residual which was inaugurated with the non linear function, convolution layer, and the batch normalization. This method was estimated with distinct datasets.

Laurens van der Maaten, Geoffrey Hinton [16], presented a new technique called “t-SNE” that visualizes high-dimensional data by giving each datapoint a location in a two or three-dimensional map. The technique is a variation of Stochastic Neighbor Embedding that is much easier to optimize, and produces significantly better visualizations by reducing the tendency to crowd points together in the center of the map. t-SNE is better than existing techniques at creating a single map that reveals structure at many different scales. This is particularly important for high-dimensional data that lie on several different, but related, low-dimensional manifolds, such as images of objects from multiple classes seen from multiple viewpoints. For visualizing the structure of very large data sets, they showed how t-SNE can use random walks on neighborhood graphs to allow the implicit structure of all of the data to influence the way in which a subset of the data is displayed. They have illustrated the performance of t-SNE on a wide variety of data sets and compare it with many other non-parametric visualization techniques, including Sammon mapping, Isomap, and Locally Linear Embedding. The visualizations produced by t-SNE are significantly better than those produced by the other techniques on almost all of the data sets.

Akber Raza, Sharmistha Bardhan et al. [17], Presented the first application of machine learning on per- and polyfluoroalkyl substances (PFAS) for predicting and rationalizing carbon–fluorine (C–F) bond dissociation energies to aid in their efficient treatment and removal. Using a variety of machine learning algorithms (including Random Forest, Least Absolute Shrinkage and Selection Operator Regression, and Feed-forward Neural Networks), they were able to obtain extremely accurate predictions for C–F bond dissociation energies (with deviations less than 0.70 kcal/mol) that are within chemical accuracy of the PFAS reference data. In addition, they show that their machine learning approach is extremely efficient, requiring less than 10 min to train the data and less than a second to predict the C–F bond dissociation energy of a new compound. Most importantly, their approach only needs knowledge of the simple chemical connectivity in a PFAS structure to yield reliable results—without recourse to a computationally expensive quantum mechanical calculation or a three-dimensional structure. Finally, they presented an unsupervised machine learning algorithm that can automatically classify and rationalize chemical trends in PFAS structures that would otherwise have been difficult to humanly visualize or process manually. Collectively, these studies (1) comprise the first application of machine learning techniques for PFAS structures to predict/rationalize C–F bond dissociation energies and (2) show immense promise for assisting experimentalists in the targeted defluorination of specific bonds in PFAS structures (or other unknown environmental contaminants) of increasing complexity.

2.2 Research Gaps and Challenges

FR is a biometric technique which depends on the facial features of the person. Some of the features and challenges in the traditional model are tabulated in TABLE 1. Multi tasking [11], has high efficiency and productivity. It has a low cost. But, it creates more mistakes that degrade the performance and has a limitation of memory. Relation Embedding [12], maintains the control of the object linking. It performs well other deep learning methods. However, it has the problems like data inconsistency and data redundancy. PCA [13], improves the performances of the algorithm. It is largely used in the pattern recognition and the computer vision areas. But, it eliminates the correlated variables. Yet, the principal components are not readable. LBP [14], can design computers utilizing binary logic. It is used for FR training images. Yet, it has high in length, which is very hard to read. It slowdowns the recognition speed. Tree based deep network [15], has high accuracy. It is easy to maintain and find faults. But, it requires large amount of data to train. It is very difficult to configure.

3. ARCHITECTURE OF PROPOSED FACE RECOGNITION USING ENSEMBLE CLASSIFIER MODEL

3.1 Proposed Framework of Face Recognition

FR is a technology to confirm the person's identity by utilizing their face images. There are two types of FR. One is based on the character based and another one is appearance based. The identification

Table 1: Features and challenges of traditional Face recognition models.

Author [citation]	Methodology	Features	Challenges
Meng and Cheng [11]	Multi tasking	• It has high efficiency and productivity. • It has a low cost.	• It creates more mistakes. • It has a limitation of memory.
Cho *et al.* [12]	Relation Embedding	• It maintains the control of the object linking. • It performs well other deep learning methods.	• It has the problems like data inconsistency and data redundancy.
Sharma and Patterh [13]	PCA	• It improves the performances of the algorithm. • It is largely used in the pattern recognition and the computer vision areas.	• It eliminates the correlated variables. • The principal components are not readable.
Tong *et al.* [14]	LBP	• It can design computers utilizing binary logic. • It is used for FR training images.	• It has high in length, which is very hard to read. • It slowdowns the recognition speed.
Masud *et al.* [15]	Tree based deep network	• It has high accuracy. • It is easy to maintain and find faults.	• It requires large amount of data to train. • It is very difficult to configure.

of the face contains three steps. They are face detection, feature extraction, and the face recognition. But the FR method is very faster and convenient than the other biometrics technologies. However, it is vulnerable to detect the face also there is huge storage required. Therefore, a new FR method is implemented using the heuristic development of an ensemble classifier model. The following FIGURE. 1, explains the fundamental architecture of the developed model.

At first, the images of the face are obtained from the datasets, that are pre-processed with the help of median filtering. Once the pre-processed image is gathered, the particular features are retrieved by utilizing the LBP and the DWT. After extracting the features, the dimension of the feature is achieved by using the PCA. Finally, an OEC is implemented which contains the SVM, AdaBoost, and NN where the parameters are tuned optimally by the EHLBO algorithm. The proposed algorithm is analyzed and the results shown that the performance of this method is better than the other conventional algorithms.

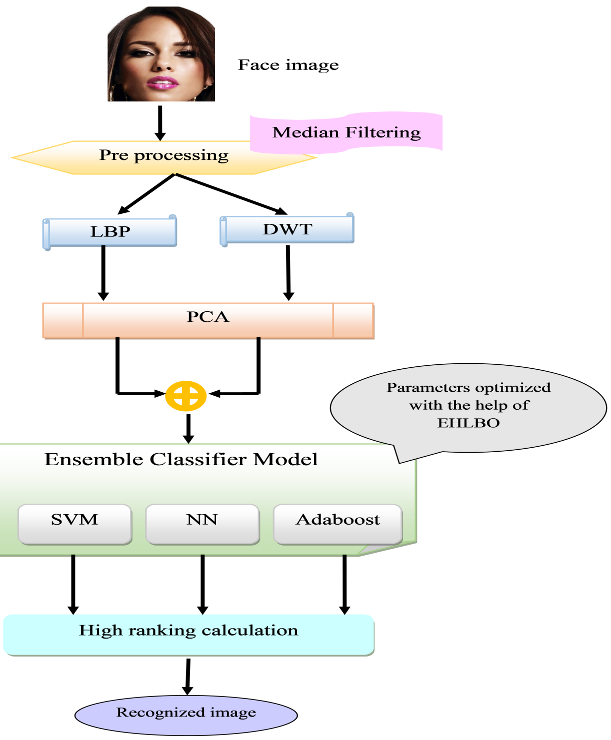


Figure 1: The architectural diagram of face recognition using heuristic development of ensemble classifier model.

3.2 Raw Image Collection

The developed FR framework using the ensemble classifier model utilizes two standard datasets that are described as follows.

Dataset 1 ("Celebrities in Frontal-Profile in the Wild"): The required data is gathered from the link "`http://www.cfpw.io/`": "Access Date: 2023-02-21". This dataset has collected the celebrity images of both frontal to profile face views in the wild. The main goal of this dataset is to separate the pose variation factor regarding extreme poses such as profile.

Dataset 2 ("The Yale Face Database"): The required data is gathered from the link "`http://vision.ucsd.edu/content/yale-face-database`": "Access Date: 2023-02-21".

The following FIGURE. 2, depicts the sample images for the proposed FR model.

From two datasets, the face images are collected and it is indicated as I_g. Where, $g = 1, 2, 3....n$.

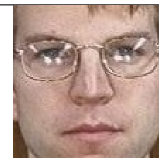
Description	1	2	3
Dataset 1			
Face Images			
Dataset 2			
Face Images			

Figure 2: The sample images for the proposed FR using an ensemble classifier model.

3.3 Image Pre-processing

The images I_g which are gathered from the data sets are executed in the image pre-processing. This method is a development of the image which is utilized to enhance the important image characters for further evaluation. Median filtering [18], is one of the important techniques in the image pre-processing. This median filtering is utilized to remove the noise from the image. The noise value of the image is change by the median value of the neighbor. The neighbor pixels are ordered from their gray levels and the group of the median value is saved to change the noisy value. The output of the median filter is expressed in Eq. (1) below.

$$h(y,z) = med\{g(y-j,z-k)j,k \in X\} \tag{1}$$

Here $g(y,z), h(y,z)$ are the representation of the original image and the output image accordingly. The term X is the two dimensional neighbor. The size of the neighbor is $m \times m$. Here m is basically odd number such as 3×3, 5×5, etc. The shapes of the neighbor might be circle, linear, cross square and etc. The pre-processed image I_g^{pre} is obtained and fed into the further evaluation.

4. FEATURE EXTRACTION AND REDUCTION PROCESS FOR NOVEL FACE RECOGNITION SYSTEM

4.1 Feature Extraction: LBP and DWT

The pre-processed images I_g^{pre} are given as input to this approach to extract the feature of the face. The LBP [19], texturing operator labels the pixels in an image by thresholding the area around each pixel and taking the resulting binary range into consideration. Because of its ability to make distinctions and ease of computation, the LBP texture operator has gained popularity in a number of applications. The computational feature of this method is very simple. Eq. (2) evaluates the number of neighbourhood points on the circle.

$$LBP(Q,S) = \sum_{Q=0}^{Q-1} T(h_q - h_d)2^q \tag{2}$$

Here, Q is the radius and S is the count of neighbourhood points on the circle.

$$T(y) = \begin{cases} 1 \;\; if : y \geq 0 \\ 0, \; otherwise \end{cases} \tag{3}$$

If the binomial factor 2^q for each sign $T(h_q - h_d)$, assigned means Eq. (1) becomes the unique LBP. The extracted image is obtained and represented as F^{LBP}.

The DWT [20], is a well known tool for the image processing. Here also, the face images I_g^{pre} given as the input. The DWT used to split the image into the pixel. The applications of this method are detection, recognition, and compression purpose. It has low computational complexity and high flexibility. It decomposes the image into four sub sections called HH (diagonal), HL (vertical), LH (horizontal), and LL (approximate). The output of this method is obtained for further evaluation. It is used in the character extraction. The extracted image is acquired from this method and denoted as F^{DWT}.

4.2 PCA-based Feature Reduction

The extracted images F^{LBP} and F^{DWT} are given as input to the PCA [21], based feature reduction. PCA detects the correlation between the bands for retrieving the important features of the image. The zero mean image $J = [J_1 J_2 .... J_n]$ is calculated from the matrix of the data E. The mean image vector is denoted as $N = (1/T)\sum_{o=1}^{T} y_m$ and the mean adjusted spectral vector represented as $N = [J_{o1} J_{o2} ...... J_{oG}]^U$. The covariance matrix $D = (1/T)II^U$ is calculated for the Eigen decomposition operation explained in Eq. (4).

$$T = WFW^U \tag{4}$$

Here, W and F indicates the Eigen vectors and Eigen values the respectively. The Eigenvectors called v is taken in the form of $G \times v$ the dimensional matrix x, here $v \leq G$ and mostly $v << G$. Because of this need, the existing method is to line the Eigenvalues from maximum to minimum to taken the top v PCs. The projection matrix Z is evaluated in Eq. (5) below.

$$Z = x^U * J \tag{5}$$

The output of this feature reduction F^{PCA1} and F^{PCA2} are obtained. The final feature set is obtained by the adding of two features and d its is represented as $F_f = \{F^{PCA1}, F^{PCA2}\}$.

5. A HEURISTIC IMPROVEMENT OF ENSEMBLE CLASSIFIER MODEL FOR A NOVEL FACE RECOGNITION SYSTEM

5.1 Enhanced Hybrid Leader Based Optimization

The EHLBO optimization method is utilized for the proposed model which is implemented from the HLBO optimization algorithm. The computation model of the existing approach is explained below.

The HLBO [22], algorithm is used to upgrade the search space in the population. In HLBO a special hybrid leader is used to guide and upgrade every member of the algorithm. Based on the three members, the hybrid leader is implemented. They are, corresponding member, the best member, and one random number. However, the HLBO method utilized r as a random number which lies between $[0, 1]$. So it reduces the accuracy of the model. So, here a new parameter p is implemented to produce the optimal solution. The evaluation of the parameter p is expressed in Eq. (6). The evaluation of the parameter p is shown in Eq. (7)

$$y_{j,k}^{new,q1} = \begin{cases} y_{j,k} + p.(IM_{j,k} + J.y_{j,k}), \; G_{IM_j} < G_j; \\ y_{j,k} + p.(y_{j,k} - IM_{j,k}), \quad else, \end{cases} \tag{6}$$

$$p = ((bestfit + worstfit)/(2 * worstfit)) \tag{7}$$

Here, $y_{j,k}^{new,q1}$ is the new position of j^{th} dimension. I is represented as an integer which is randomly selected. The value of the objective function denoted as G_{IM_j} generated from the hybrid leader.

The local search is helped to enhance the ability of HLBO exploitation which is expressed in Eq. (8) and the newly evaluated position is given in Eq. (8).

$$y_{j,k}^{new,q2} = y_{j,k} + (1 - 2p).P.(1 - \frac{u}{U}).y_{j,k} \tag{8}$$

$$X_j = \begin{cases} y_j^{new,q2}, \; G_j^{new,q2} < G_j; \\ Y_j, \quad else, \end{cases} \tag{9}$$

The term $y_j^{new,q2}$ is the new position of the j^{th} member. $y_{j,k}^{new,q2}$ is its j^{th} dimension. $G_j^{new,q2}$ is the objective function. The constant is denoted as P which is equal to 0.2 and is denoted as iteration counter u and U is represented as the highest number of iterations.

5.2 Ensemble Classifier Model

The ensemble method is the combination of more methods to find the optimal solutions. Here three methods are ensembled. They are, SVM, NN and the Adaboost methods.

SVM [23]: The F_f feature reduced image is given as input to this SVM. It is utilized to predict and train whether the image is negative or positive depends on the extracted characters. It is a supervised learning method. SVM can be used in the classification of the images. The training data are denoted as $y_1 ... y_m$. The calculation of the classifiers is expressed in Eq. (10).

$$g(y) = \sum_{j=1}^{m} \beta_j L(y_j, y) \tag{10}$$

When $g(y) > 0$ can express y as +1 or else y as −1. Here L denotes the Mercer kernel operator and β represents the maximal margin hyperplane in Y. If L satisfies Mercer's condition then we can rewrite Eq. (11) as below in Eq. (12).

$$g(y) = x.\phi(y), where : x = \sum_{j=1}^{m} \beta_j \phi(y_j) \tag{11}$$

The hyperplane of the SVM can be given in Eq. (12) as the set of points which $\vec{z}$ satisfies,

$$\vec{y}.\vec{z} - c = 0 \tag{12}$$

Here, $\vec{y}$ is represented as the normal vector of the hyperplane. The output is obtained.

NN [24]: The F_f feature reduced image is given as input to this NN method. It is helped to pass the data from one place to another in the entire network. Based on the connection capabilities, the activation measures send from one node to another. Every node adds the activation values which is obtained and it modifies the value depends on the transfer function. First, the input layer of the NN initializes the vectors and it is represented as l and the count of input nodes expressed as $y(u)$. In the NN new vector node is trained. The distance of the hidden layer in NN is given in Eq. (13).

$$e_k = \sum_{j=0}^{i-1} (y_j(u) - \theta_{jk}(u))^2, k = 0, 1..., T - 1 \tag{13}$$

Here, $\theta_k = (\theta_{0k}, \theta_{1k}, ..., \theta_{i-1,k})^U$. θ_k is represented as a face pixel character vector and $y(u)$ is denoted as an input vector. The face visual difference character is in pixel level is gained as $M_{k*}, e_{k*} = \min_{0 \le k \le M-1} \{e_k\}$. The output node of the NN is expressed as M_{k*}. The looping classification for the face character is calculated in Eq. (14) below.

$$\theta_{jk}(u+1) = \theta_{jk}(u) + \beta(u)(y_j(u) - \theta_{jk}(u)) \tag{14}$$

Here, $M_k \in F_{k*}(u), 0 \le j \le i - 1, 0 \le \beta(u) \le 1$ is a learning rate of a variable. At last, the sampling model is utilized to function in the batch reading of the facial character data and face character extraction. The output is obtained.

Adaboost [25]: The F_f feature reduced image is given as input to this Adaboost method. It is a face detection methodology and very popular because of its less complexity, solid theoretical basis, and high rate of detection. This model is very speed compared to the other model due to its cascaded classifier structure and Haar like characters. In the pre-processing stage, the integral image F_f is evaluated with the original image I_g^{pre}. Using F_f the pixel intensities of the original image I_g^{pre} is evaluated. After for every member, the image window x is fed into the cascaded classifier $i(x)$ in every position. The $i(x)$ is the addition of a set of character responses called $i_k(x)$. The classifier response $i(x)$ is evaluated in the below Eq. (15).

$$i(x) = \sum_{k=1}^{m_j} i_k(x), i_k(x) = \begin{cases} y_{k1} & g_k(x) < u_k \\ y_{k2} & otherwise \end{cases} \tag{15}$$

Here, $g_k(x)$ is expressed as the character response of the l^{th} Haar character also y_{k1} and y_{k2} are denoted as character weight coefficients. The output of the ensemble classifier model is acquired.

5.3 Optimal Ensemble Classifier Model

The explained ensemble classifier model produces very low optimal solutions. This lacks the existing methodologies accuracy and also the computational difficulty is high. To overcome these problems, a new OEC model implemented with the help of the EHLBO algorithm. The optimization parameters which are used in the OEC model that are a degree in SVM which is limited from 1 to 5, Maximum iteration in SVM that ranges from 50 to 100, hidden neuron count in NN which is ranged from 5 to 255, learning rate in NN that limits from 0.01 to 0.99 and the estimator in AdaBoost limits from 1 to 100. The "Objective Function" is Ob_Fn expressed in Eq. (16).

$$Ob\_Fn = \underset{\{\deg^{svm}, mi^{svm}, hn^{nn}, lr^{nn}, es^{adaboost}\}}{\arg\max} [Acc] \tag{16}$$

The degree of the SVM is denoted as $\deg^{svm}$, the Maximum iteration count in SVM is expressed as mi^{svm}, the hidden neuron count is represented as hn^{nn}, the learning rate in NN indicated as lr^{nn}, and the estimator in AdaBoost given as $es^{adaboost}$. Then, the word Acc explains the accuracy measurement as "How same a given set of calculations are to their true value". It is evaluated in Eq. (17).

$$Acc = \frac{YZ + MO}{YZ + MO + LK + SA} \tag{17}$$

Here, the term SA represented as a false negative LK is denoted as false positive values, and the true negative and the true positive values are expressed as MO and also YZ FIGURE. 3, depicts the OEC model for the developed FR model.

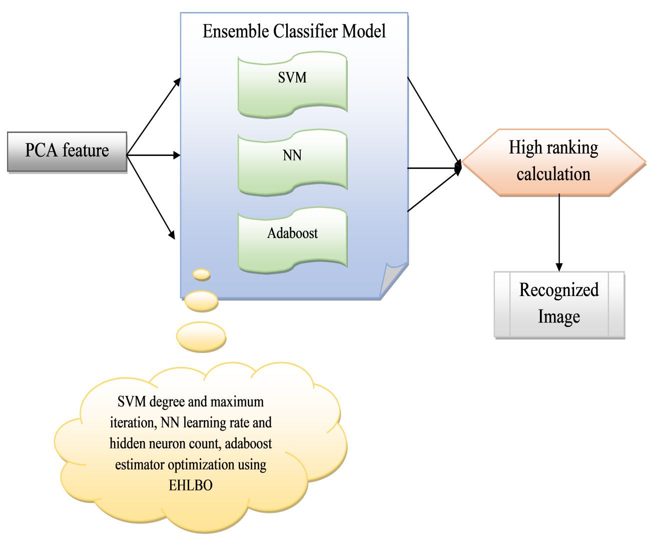


Figure 3: Optimal Ensemble Classifier model for the proposed FR.

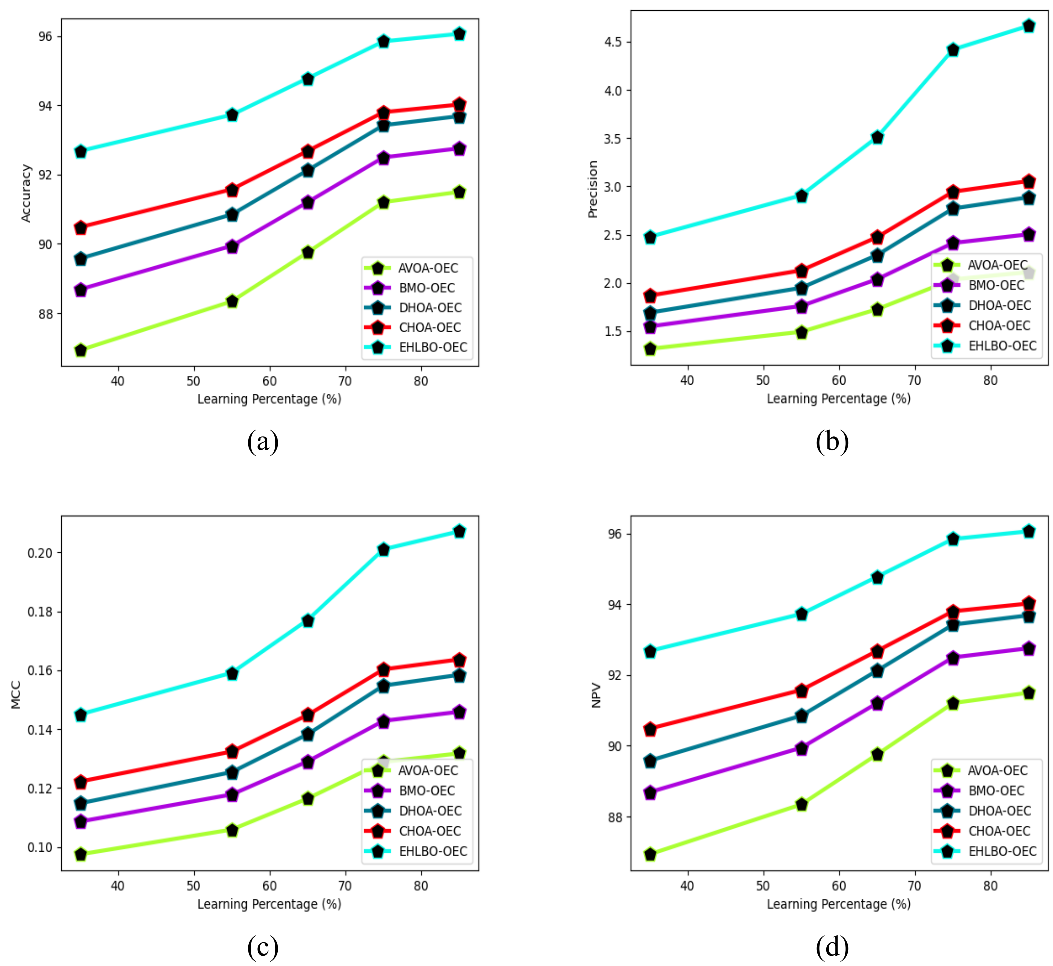


Figure 4: Learning percentage evaluation of developed face recognition method using ensemble classifier model compared with traditional optimization algorithms for dataset 1 concerning "(a) Accuracy, (b) Precision, (c) MCC,(d) and NPV."

6. RESULTS AND DISCUSSION

6.1 Experimental Setup

This developed FR using an ensemble classifier model was executed in the Python platform and the corresponding results were carried out. The proposed algorithm has considered 25 maximum iteration counts and 10 as population size. Different measures were utilized to validate the execution. Thus, the comparison algorithms like respectively. Thus, the comparison algorithms such as "African Vultures Optimization Algorithm (AVOA)" [26], "Barnacles Mating Optimizer (BMO)" [27], "Deer Hunting Optimization Algorithm (DHOA)" [28], and Chimp Optimization Algorithm (CHOA)" [29], were taken. Similarly, the existing classifier models were taken as "Deep

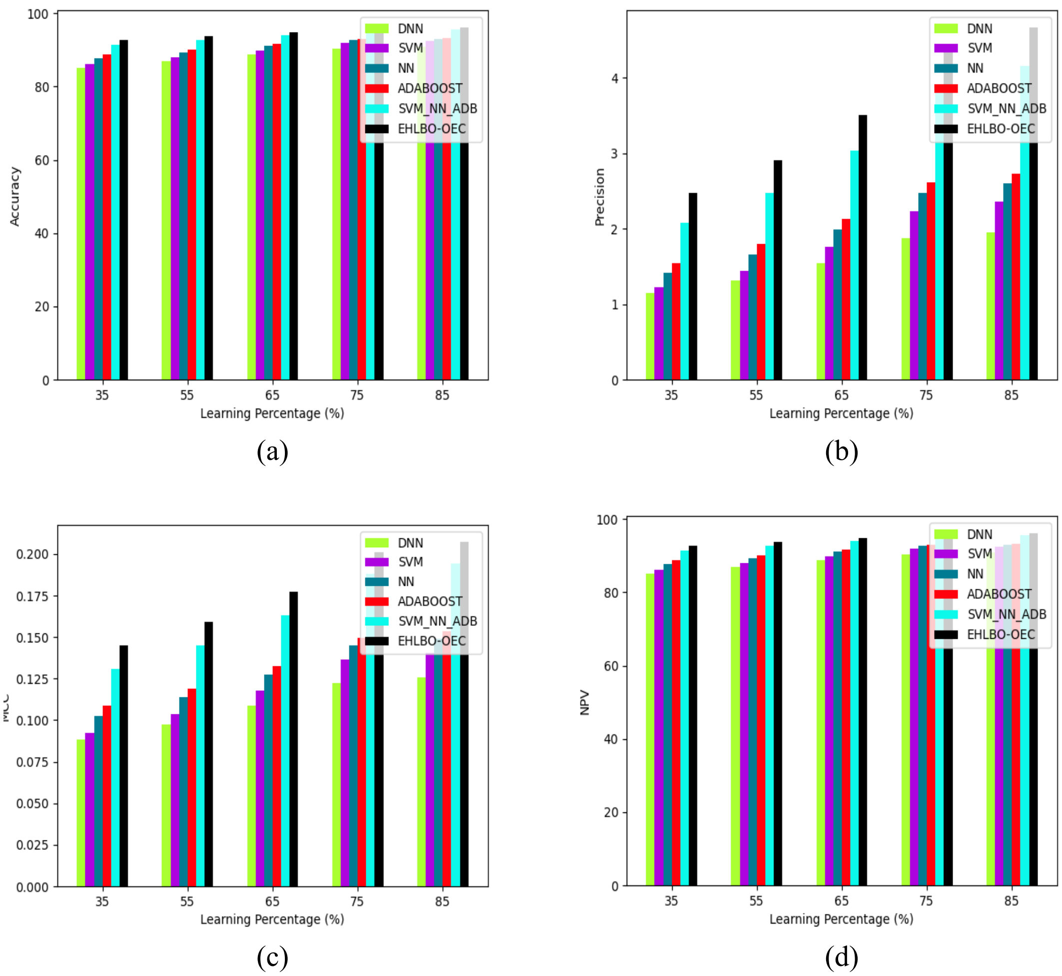
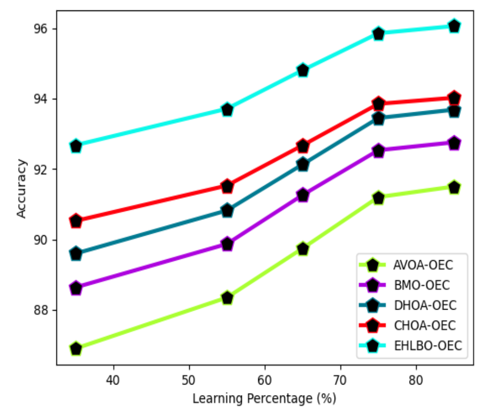


Figure 5: Learning percentage evaluation of developed face recognition method using ensemble classifier model compared with traditional classifier models for dataset 1 concerning "(a) Accuracy, (b) Precision, (c) MCC,(d) and NPV."

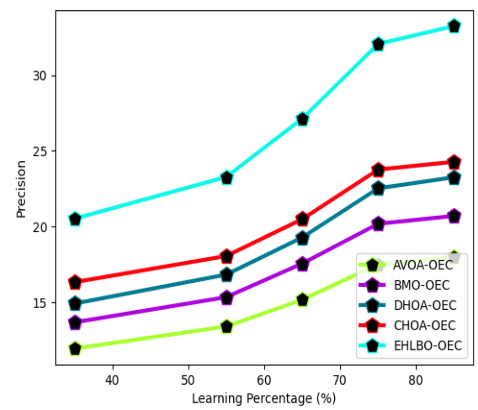
Neural Network (DNN)" [30], SVM [23], NN [24], ADABOOST [25], SVM_NN_ADB [23–25] accordingly.

6.2 Evaluation of Learning Percentage in the Proposed Model for Dataset 1

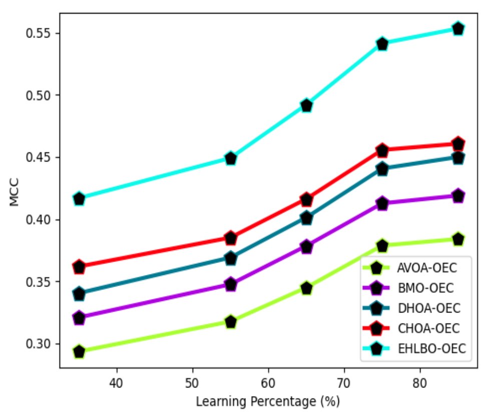
The final estimation of the developed model is contrasted with the conventional methods of different algorithms and distinct classifiers for dataset 1. The EHLBO shows better results than the other traditional methods. FIGURE. 4 displays the performance of the learning percentage compared with distinct algorithms. FIGURE. 4 (a) illustrates the accuracy analysis. When the learning percentage is 55 for the accuracy then the proposed model is improved than 61.81% of AVOA-OEC, 61.09 % of BMO-OEC, 62.90 % of DHOA-OEC, and 64.18% of CHOA-OEC respectively.



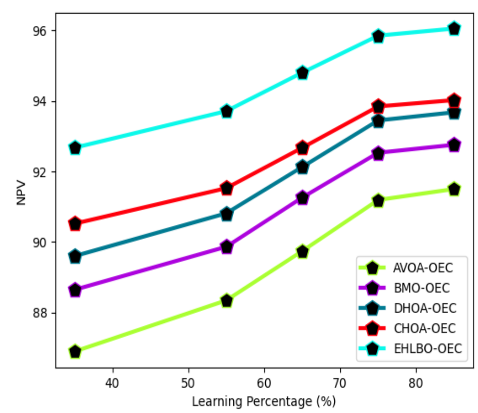
(a)



(b)



(c)



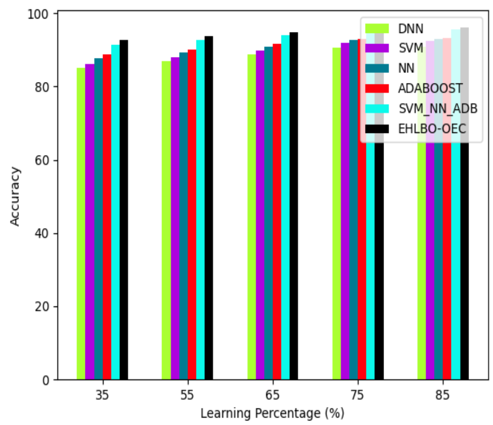
(d)

Figure 6: Learning percentage evaluation of developed face recognition method using ensemble classifier model compared with traditional optimization algorithms for dataset 2 concerning “(a) Accuracy, (b) Precision, (c) MCC,(d) and NPV.”

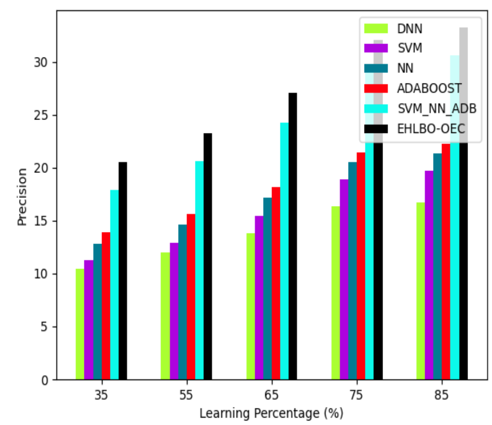
FIGURE. 5 illustrates the performance of learning percentage contrasted with different classifier algorithms. FIGURE. 5(b) shows the precision evaluation. When the learning percentage is 65 then the recommended method is raised by 97.84% of DNN, 97.38% of SVM, 97.07% of NN, 96.76% of AdaBoost, and 95.23% of SVM_NN_ADB accordingly.

6.3 Evaluation of Learning Percentage in the Proposed Model for Dataset 2

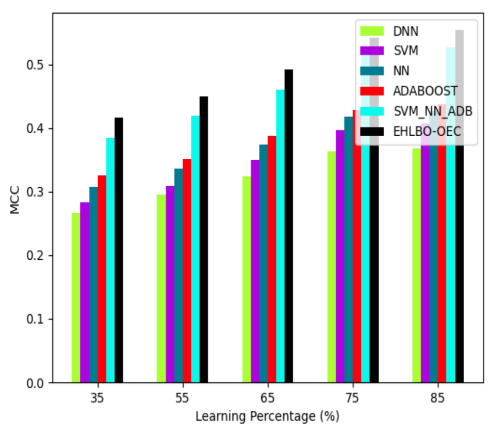
The final estimation of the developed model is contrasted with the conventional methods of different algorithms and distinct classifiers for the dataset 2. The EHLBO shows better results than the other traditional methods.



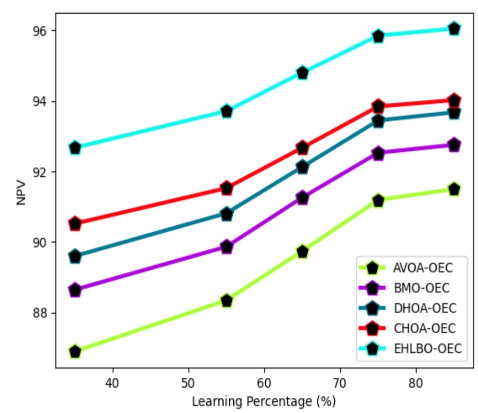
W4726W9560(a)



(b)W4726W9560



W4726W9560(c)



(d)W4726W9560

Figure 7: Learning percentage evaluation of developed face recognition method using ensemble classifier model compared with traditional classifier models for dataset 1 concerning “(a) Accuracy, (b) Precision, (c) MCC,(d) and NPV.”

FIGURE. 6 displays the performance of learning percentage compared with distinct algorithms for data set 2. FIGURE. 6(b) illustrates the precision analysis. When the learning percentage is 35 for the precision then the proposed model is improved than 65.71% of AVOA-OEC, 60 % of BMO-OEC, 57.14 % of DHOA-OEC, and 51.42% of CHOA-OEC respectively.

FIGURE. 7 illustrates the performance of learning percentage contrasted with different classifier algorithms. FIGURE. 7(a) shows the accuracy evaluation. When the learning percentage is 55 then the recommended method is raised by 63.63% of DNN, 65.45% of SVM, 67.27% of NN, 69.09% of AdaBoost, and 70.90% of SVM_NN_ADB accordingly.

7. CONCLUSION

This work has presented the novel framework of FR using an ensemble learning model. At first, the face images were gathered from the datasets, followed by the pre-processing the images. Once the pre-processed image was obtained, the significant features were retrieved by utilizing LBP and the DWT. Then the dimension reduction of retrieved features was obtained by utilizing the PCA. Lastly, the OEC have developed which included SVM, NN, and AdaBoost, where the parameters were tuned optimally with the help of the EHLBO algorithm. The performance was examined through different factors and contrasted over existing approaches. By using dataset 2, the learning percentage was 65 and the accuracy of the developed method improved than 35.84 % of AVOA-OEC, 38 % of BMO-OEC, 40 % of DHOA-OEC, and 41.69% of CHOA-OEC respectively. Thus, the results have showed that it has enhanced the correctness for recognizing the face.

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