PARTIAL FACE RECOGNITION WITH NEW SIMILARITY INDEX Using HYBRID LGWO OPTIMIZATION

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Abstract:

The development of human face image recognition has been fueled by the quick advancement in information technology. Face recognition has recently been effectively used in a number of different fields thanks to computers and information technology. This type of application is crucial to the process of digital forensics investigation because it can identify human face patterns such as eye spacing, nose bridging, lip, ear, and chin contours based on the partial matching of images in 24-bit color image format. The suggested hybrid Lion with Grey Wolf Optimizer (HLGWO) for partial face recognition is presented in this work. The first step is to gather the facial photos from the two public databases FASSEG and ORL. Following that, the Fully Convolutional Network (FCN) and Sparse Representation Classification (SRC) are used to extract the feature vectors from the gathered face photos. This approach is new in that it seeks to optimize the sparse coefficient of Dynamic Feature Matching (DFM), with the goal of minimizing the reconstruction error. Additionally, the structural similarity index metric is presented in this study to determine the similarity scores between a gallery sub-feature map and probing feature map. The dimension of the retrieved features was also reduced or the unnecessary features were rejected using an HLGWO. When compared to the current approaches in an experimental investigation, the suggested methodology performs better.

Keywords: Face recognition, Sparse Representation Classification (SRC), Fully Convolutional Network (FCN), Dynamic Feature Matching (DFM), hybrid Lion with grey wolf optimizer (HLGWO) and facial images

1. INTRODUCTION

Face recognition is one of the biometric techniques that uses a non-intrusive, contactless procedure. Numerous apps presently use the facial recognition technology. Pose and backdrop recognition, occlusion, etc. The design of face recognition systems has a strong emphasis on increasing accuracy and speed [1, 2]. Pre-processing of the input face photos, feature extraction, and classification are the phases that make up the face recognition job in general. Pre-processing is utilized to normalize the data as well as eliminate any noise content, background illumination, etc. Additionally, huge strides have been achieved thanks to the development of artificial intelligence and the fast growth of technology. A growing number of systems are starting to employ a variety of biometric characteristics for recognizing tasks as a result of the development of information technologies and security algorithms. People may be recognized based on their physiological or behavioral traits thanks to these biometric parameters. There are biometric systems that use fixed physiological characteristics like the fingerprint, iris, and palmprint as well as systems that use behavioral traits like the signature, gait, walking pattern, speech pattern, and facial dynamics; the latter are also referred to as soft biometrics [3, 4]. The human face is made up of several structural and phenotypic elements. Identification and verification tasks are both included in face recognition tasks [5].

Face recognition is especially well suited for surveillance applications because, unlike a number of other biometric qualities, it may be carried out inconspicuously and does not always need the person's participation [6]. One of the effective and well explored techniques for extracting the most discriminating facial features from face photos is the local binary pattern. Due to its distinctiveness, immutability, acceptability, simplicity of integration, and cheap cost, face recognition is frequently used for personal verification in military, forensic, and civilian applications. In order to further improve the accuracy, pose- and illumination independence of face recognition systems, the incorporation of shape information is growing in popularity. The use of multimodal biometric solutions has shown that combining the results of recognition algorithms is an effective way to improve accuracy [7, 8]. Approaches for merging both modalities on various algorithmic levels (e.g., face detection, landmark discovery, posture transformation, score fusion) may be employed as 2D and 3D face recognition processes facial information. A face is a 3D object by nature, lighted from various angles by diverse lighting sources, and surrounded by arbitrary backdrop objects. Although face recognition systems have been fairly effective in creating highly secure systems, their accuracy may be limited when frontal face photos are lit normally [10–12].

We may often consider techniques like Convolutional Neural Networks (CNN), Deep Belief Networks (DBN), and Stack Denoising Autoencoders (SDA) while discussing face recognition based on neural networks. Evolutionary techniques, including genetic algorithms, particle swarm optimization, and ant colony optimization, are widely employed to remove unnecessary and inappropriate face traits in the digital age [13]. The convolution process is used by CNNs, a kind of artificial neural network, to extract features from the input data and increase the number of features. The Convolutional Neural Network (CNN), which contains a number of layers for learning a huge number of features, has done well in the biometric identification setting. Recent benchmarks show that the CNN classifier has a major role in the performance of face recognition systems [13]. Filtering methods are used to lessen lighting conditions in photographs of human faces. To extract features, Principal Component Analysis (PCA) is used. Face recognition is carried out using Multiclass-Support Vector Machines (multiclass-SVMs) after the features are extracted using PCA [14]. For a very long time, statistical estimate and pattern recognition have effectively employed K-nearest neighborhood. KNN is also a highly efficient face recognition method in terms of computing. However, the initialization of the parameter K causes it to suffer.

PSO is one of the population-based optimization techniques that is often used to improve parameters in pattern recognition software since it doesn't have the issue with local minima. Consequently, it is crucial to evaluate current face recognition algorithms using challenging instances including sibling face identification. If the models can successfully handle difficult scenarios, they will be able to successfully handle straightforward ones as well [15].

Main contribution of the research is,

- The suggested face recognition framework creates a model for identifying faces in a noisy and heavily obscured environment.
- For face recognition, a well-optimized Sparse Representation Classification and Fully Convolutional Network (SRC-FCN) classifier is created, in which the newly created hybrid Lion with Grey Wolf Optimizer (HLGWO) algorithm chooses the activation functions for the training.
- The most accurate objective model is established in order to choose the best feature set from the dynamic feature matching.
- Different noise circumstances are added to the experiment, and the outcomes are compared with various state-of-the-art techniques.

The organization of the research is as follows: in section 2, the existing research related to the proposed malicious node detection with the energy-efficient routing is explained; in section 3, the proposed research methodology has been explained; in section 4, the results and discussion of the proposed approach are explained; and in section 5, the paper is concluded with future enhancement.

2. RELATED WORK

In response to the interest in this field of study, experimental work for the intended partial facial recognition has been growing over time and is now underway. In writing, certain methods for feature matching and feature identification based on face photographs have been suggested. In this part, not many research methodologies are covered.

A genetic algorithm-based face recognition has been described by Zhi, Hui, et al. [16]. Principal component analysis, genetic algorithms, and support vector machines are used to create an efficient face recognition model in which principal component analysis is used to reduce feature dimension, genetic algorithms are used to optimize search strategy, and support vector machines are used to realize classification.

Through the NVIDIA Jetson Nano, Sati, Vishwani, et al. [17] have shown face detection, identification, and emotion recognition. For improved accuracy than the previously created models, face detection is accomplished using OpenCV's deep learning-based DNN face detector, backed by a ResNet architecture. With the assistance of the aforementioned hardware, the

OpenCV framework libraries' calculated results showed consistent accuracy despite changes in illumination and viewing angle.

Real-time face recognition based on DLib has been presented by Xu, Min, Daijiang Chen, et al. [18]. That is, using the convolution neural network method (CNN) and the deep residual network (ResNet) for in-the-moment face recognition, and then using the GPU to speed up the face feature extraction network's operation while distributing the CPU load to increase the system's overall operating effectiveness.

A recent advancement in face recognition has been given by Jayaraman et al. [19]. A face recognition system has significant difficulties in terms of position, lighting, and expression due to the high degree of flexibility in head movement and human emotion. Aging also causes permanent changes to the human face. These elements make facial recognition difficult and not a simple procedure.

A hybrid meta-heuristic method based deep neural network for face recognition has been reported by Soni, Neha, et al. [20]. In order to increase efficiency, it was important to discover the best features using deep learning from the occluded and noisy face picture. The suggested solution solved this issue. The Viola Jones method preprocessed the face photos from the obscured and noisy database to identify the face component, and the identified images were then subjected to cascaded feature extraction.

3. PROPOSED HYBRID OPTIMIZATION FOR PARTIAL FACE RECOGNITION SYSTEM

The technique of confirming or locating the facial expressions of human faces from a video frame, video source, digital picture, or still image is known as partial face recognition (PFR). These systems use a variety of techniques to compare the attributes of chosen face photographs with the photos in the database. In order to address the problems with partial face recognition, this study seeks to develop a brand-new PFR technique called DFM that combines Sparse Representation Classification (SRC) with FCN. This proposal's main contribution is its attempt to optimize the tuning of the DFM's sparse coefficient such that the reconstruction error is kept to a minimum. Additionally, this proposal provides the Jaccard Similarity Index metric to determine how similar the gallery sub feature map and probe feature map are to one another. This study uses a hybrid HLGWO method for optimization. The block diagram for the recommended method is shown in Figure 1.

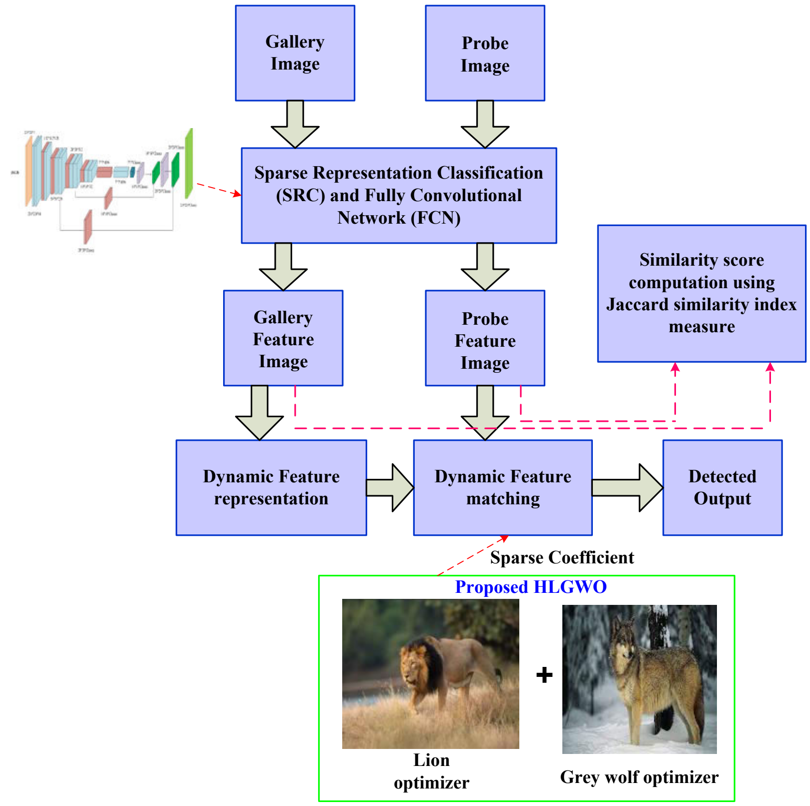

Figure 1: Block diagram for the proposed research methodology

3.1. Feature Extraction using Sparse Representation Classification and Fully Convolutional Network (SRC-FCN)

The feature extraction strategy utilized in this research is further explained in this section. Implementing an offline face recognition system with an enhanced and reliable feature extraction approach employing optimization methods is one of the study's goals. Common recognition networks generate non-spatial outputs from inputs of a defined size. In classification and retrieval tasks, fully-connected layers construct fixed-dimensional feature representation without taking into account spatial coordinates. In a deep neural network, the recurrent connections cannot be changed, but the feedback connections may. Convolution, pooling, and ReLU layers are present in the FCN. Spatial feature representation is produced by the FCN's final pooling layer; these results are referred to as feature maps [21]. The pool5 layer's outputs become more discriminative thanks to the empirical softmax log-loss connection. On the CASIA-WebFace database, the changed FCN (from VGGFace) is adjusted. The output of the softmax log-loss is dictated by the subjects in the training set, and Sparse Representation Classification (SRC) is utilized for optimization. In the training phase, all pictures of the same size (224 × 224 in our tests) are used to train the FCN.

The softmax log-loss layer is discarded when training is completed, and the pre-trained FCN is used in extracting spatial feature maps from arbitrary-sized face images. For example, 7×7×512 and 5×6×512 spatial feature maps can be extracted by FCN from 224 × 224 × 3 and 160 × 200 × 3 face images, respectively. This approach avoids the demand of fixed input size by using FCN and the computed dense spatial feature maps are beneficial for subsequent processes. Suppose with $h(l)$ input, $p(l)$ output, the number of softmax log-loss layer and undertake neurons are τ, the weight of input layer to softmax log-loss layer is τ_1, the weight of undertake layer to softmax log-loss layer is τ_2, the weight of softmax log-loss layer to output layer is τ_3; $u(k-1)$ is the input of neural network, $h(l)$ is the output of softmax log-loss layer, $t(l)$ is the output of pool5 layer, and $p(l)$ is the output of neural network; then,

$$h(l) = f(\tau_2 \zeta_i + \tau_1(e_t)) \tag{1}$$

$$t(l) = h(l-1) \tag{2}$$

Where, f denotes the activation function which is based on swish activation which is derived as follows,

$$f = e_t . sg_d(e_t) \tag{3}$$

Here, $sg_d(e_t)$ specifies the sigmoid function of the input value. The output layer function $p(l)$ is given as follows,

$$p(l) = f(\tau_3 h(l)) \tag{4}$$

The final error of the process is derived as follows,

$$l_s = \sum (g(l) - p(l))^2 \tag{5}$$

Where, l_s indicates the error function and $g(l)$ specifies the target output value.

3.2. Dynamic Feature Matching

It is difficult to identify the appropriate location of the gallery face to match since the probe face's position in relation to the holistic face is unknown beforehand. In most cases, moving the window in each gallery feature map will provide the sub-feature maps that are the closest in similarity. It is ineffective, nonetheless, since the spatial linkages between nearby sub-feature maps are disregarded [22]. As a result, the matching issue is changed into a problem of sparse reconstruction. The dynamic gallery dictionary's G features may be linearly superimposed to depict the probing feature P. In order to get the sparse coefficients q of P with regard to the gallery dictionary G, we must solve. The reconstruction error may be minimized to do this. It is possible to express the sparse reconstruction issue as,

$$\underset{q}{Min}\|P - Fq\|_2^2 + \alpha\|q\|_1 \tag{6}$$

where $q \in \Omega^{M\times 1}$ is the term for the sparse constraint $\alpha\|q\|_1$. α is a constant that strikes a compromise between the reconstruction error and the sparsity restriction. Equation (5) may be solved to get the ideal sparse coefficient q. Euclidean distance is used to calculate the similarity scores between each gallery sub-feature map g_x and the probing feature map P, where $G = \{g_1, g_2.g_3,...g_K\}$ the similarity of P and g_x is shown as,

$$D_x = \|P - g_x\|_2 \tag{7}$$

As a result, there $-D$ is a positive correlation between the sparse coefficient q. Equation (6) may be rewritten as follows:

$$\underset{q}{Min}\|P - Fq\|_2^2 + \mu D^R q + \alpha\|q\|_1 \tag{8}$$

Where μ is a constant that limits how strict the similarity restriction is applied. Even though the reconstruction term is subject to both the sparse constraint $\|q\|_1$ and the feature selection constraint $D^R q$, their effects q are distinct $\|P - Fq\|_2^2$. While feature maps selection constraints are used to choose comparable gallery sub-feature maps in order to complete probe reconstruction, the sparse reconstruction term addresses reducing the reconstruction error based on the whole collection of gallery sub-feature maps [23]. To find the best q, we use the feature-sign search method.

We use the following matching technique to ascertain the identification of the probing picture after acquiring the sparse coding q:

$$\underset{f}{Min}\, r_f(P) = \|P - G_f\phi_f(q)\|_2 + \mu D_f^R \phi_f(q) \tag{9}$$

where $\phi_f(.)$ is the formula used to choose the sparse coefficient that corresponds to focus f. G_f and D_f are the associated sub-dictionary and similarity score vector corresponding to subject f. The identity of the probing picture is determined by Equation (8) by returning the result with the least amount of error after adding up the reconstruction error and weighted matching score. The flowchart for dynamic feature matching is shown in figure 3.

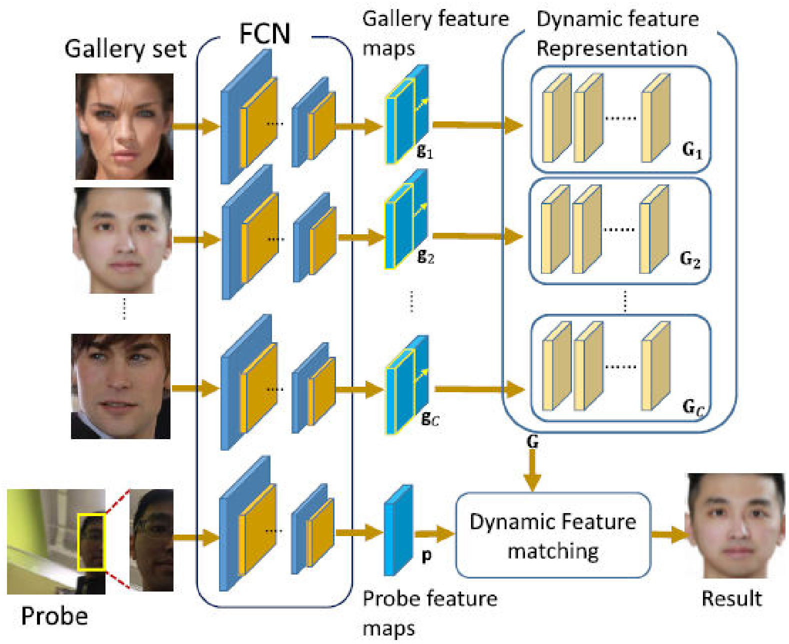

Figure.2: The flowchart of dynamic feature matching

The algorithm flow of DFM

Input: 1. A probe face image and gallery images of F subjects

2. The parameters of feature selection constraint μ and sparsity strength α

Output: Identify f of the probe face image

Begin

Extract feature maps for subject x in the gallery: G_x by FCN and construct feature dictionary X of subjects $G = \{g_1, g_2.g_3,...g_K\}$

Extract feature maps of the probe patch **P;**

Construct dynamic gallery dictionary X of subjects $G = \{g_1, g_2.g_3,...g_K\}$

Solve the equation (6) to obtain the sparse coefficient q

Return f

End

Partial Face Verification: Spatial feature maps g and p are recovered by FCN from a pair of face photos, one of which is a whole face and the other is a partial face. x a sub-feature maps dictionary here $G = \{g_1, g_2.g_3,...g_x\}$. Using equation (6) in this situation. In light of the specified threshold, the reconstruction error $f(P.G)$ may be utilized for face verification.

3.3. Dimensionality Reduction and Feature Selection using hybrid Lion with grey wolf optimizer (HLGWO)

The binary singleton expansion function is applied as an element-wise operator given the training data's calculated mean face. The single value decomposition function is used to breakdown the resulting picture in order to lower the coefficient that was previously used to describe it. The primary component is created by computing the cumulative sum of the squares of the diagonal matrix and choosing the component's first k eigenvalues. Using a hybrid lion with grey wolf optimizer (HLGWO), the dynamic feature matching is chosen from the created partial face verification in this case. Based on the lions' social behavior, which is to be the strongest in every generation, the lion optimization algorithm was created. It looks for the best solution based on two distinctive lion behaviors, territorial defense and territorial conquest. The territorial takeover occurs between the old resident male and the new adult resident male, and territorial defense occurs between the inhabitant males and migratory males [24]. However, it has a local optimum issue for complicated data, which might make its already subpar searching much worse. This study approach uses the grey wolf optimization procedure to change the location in order to address that issue. The suggested approach offers a rapid convergence rate global search. The suggested approach offers a dynamic GWO capability that increases the classifier of the face recognition and a high LOA search efficiency. Each extract features are referred to as the lions in this instance. The lion optimization algorithm's initial step is to produce a population at random across the problem space. It is said that each solution is represented by:

$$I_p = \{e_1, e_2, ..., e_n\} \tag{10}$$

where the dimensional space is specified by e_n. The proportion of nomad lions $\%n$ is determined at random, whereas resident lions make up the majority of the population. The fitness is then assessed for the planned study using a process that takes throughput (t_p) and the maximum quantity of leftover energy (r_e) into account. The following (F_t) is a mathematical definition of the fitness function:

$$F_t = \max(r_e, t_p) \tag{11}$$

The hunters are then randomly split into three smaller groups. The group with the largest total members' penalties is regarded as the center, while the other two groups are regarded as the two wings. The center wing is comprised of the top six prides, with the remaining prides being shared between the other two wings. In the following equation, a fake prey is positioned in the middle of the hunters:

$$D_p = \frac{\sum_{i=1}^{n} O_i}{N(O_i)} \tag{12}$$

Where D_p represents fictitious prey, $N(O_i)$ and represents all face images. When hunting, D_p a hunter sharpens his or her own skills, the hunter will flee and D_p^{new} a new position will be attained with the aid of the energy valley optimization's updating technique, which is stated as follows:

$$D_p^{new} = D_p + (\eta_d \times VV_s - \eta_d \times VV_{ng}) \tag{13}$$

where, η_d represents the random value, which ranges from 0 to 1, VV_{ng} is the position vector of the neighboring particle, VV_s is the position vector of the particle with the greatest degree of stability, and D_p is the current location. The following is how the new places of hunters, who belong to both the left and right wings, are generated:

$$P(O_i)^{new} = \begin{cases} \eta_d((2*D_p - P(O_i)), D_p), & (2*D_p - P(O_i)) < D_p \\ \eta_d(D_p, (2*D_p - P(O_i))), & (2*D_p - P(O_i)) > D_p \end{cases} \tag{14}$$

Following the presentation of the prey location in the center of the wings, the new position of the hunters is determined as follows:

$$P(O_i)^{new} = \begin{cases} \eta_d(P(O_i), D_p), & P(O_i) < D_p \\ \eta_d(D_p, P(O_i)), & P(O_i) > D_p \end{cases} \tag{15}$$

Since each pride's territory consists of the individual members' best current locations, it aids the Lion Optimization Algorithm (LOA) in saving the best results so far throughout the duration of each iteration and may be utilized as dependable and important data to enhance GWO solutions. As a result, the following might be the new position for a female lion:

$$FL' = [FL]^{GWO} + [2G \times \eta_d \{S_1\}]^{GWO} + w(-1,1) \times \tan(\theta) \times [G \times \{S_2\}]^{GWO} \tag{16}$$

Whereas FL' is a vector whose start point is the previous location of the female lion FL, whose direction is toward the selected position, and $\{S_1\}$ is perpendicular to $\{S_1\}$, and G shows the distance between the female lion's position $\{S_1\}$ and the selected point chosen by tournament selection among the pride's territory.

General working of GWO

The social leadership and hunting techniques of grey wolves in nature served as the basis for the grey wolf optimizer (GWO) algorithm. In order to guide the remaining wolves called wolves into potential locations and discover the overall solution, the GWO algorithm selects three leader wolves named λ, η, and μ as the best choices. Encircling, hunting, and attacking the target are the three primary components of wolf hunting [25]. Thus, each wolf's updated location is dependent on the positions of λ, η, and μ.

$$\Delta_1 = \Delta^t_\lambda - \omega_1 * \psi_\lambda \tag{17}$$

$$\Delta_2 = \Delta^t_\eta - \omega_2 * \psi_\eta \tag{18}$$

$$\Delta_3 = \Delta^t_\mu - \omega_3 * \psi_\mu \tag{19}$$

Where,

$$\omega_1 = 2 * a * \gamma'_1 - a, \quad \omega_2 = 2 * a * \gamma'_2 - a, \quad \omega_3 = 2 * a * \gamma'_3 - a$$
$$\psi_\lambda = \left|C_1 \times \Delta^t_\lambda - \Delta^t\right| \quad \psi_\eta = \left|C_2 \times \Delta^t_\eta - \Delta^t\right| \quad \psi_\mu = \left|C_3 \times \Delta^t_\mu - \Delta^t\right|$$
$$C_1 = 2 \times \gamma''_1, \; C_2 = 2 \times \gamma''_2, \; C_3 = 2 \times \gamma''_3$$
$$\Delta^{(t+1)} = \frac{\Delta_1 + \Delta_2 + \Delta_3}{3}$$

Here, Δ^t is the solution in the tth iteration, and $\Delta^t_\lambda, \Delta^t_\eta$ and Δ^t_μ are the locations of λ, η, and μ wolf at tth iteration. $\gamma'_1, \gamma'_2, \gamma'_3, \gamma''_1, \gamma''_2$ and γ''_3 are undetermined vectors with [0, 1] ranged components. and C_1, C_2 and C_3 are two random vectors with a [0, 2] range. Then, the prey is also being hunted by the nomad lions. The following is how the nomad lions are created:

$$N_d\left(O_{ij}\right) = \begin{cases} O_{ij} & if \;\; (\eta_d)_j > (p_b)_i \\ (\eta_d)_j & otherwise \end{cases} \tag{20}$$

Where, j is the dimension, $(\eta_d)_j$ is a uniform random integer between [0, 1], $N_d\left(O_{ij}\right)$ is the current location of i^{th} the nomad lion, and $(p_b)_i$ is an independently determined probability for each nomad lion. The mating procedure is then completed. It is crucial for lions to reproduce in order to ensure their existence and to allow for communication among the pride members. The mating operator combines the parents in a linear fashion to create two new offspring. Two offspring processes are formed from the mating process and are as follows:

$$og_j^1 = \tau * FL_j + \sum \frac{1-\tau}{\sum Z_i} * ML_j * Z_i \tag{21}$$

$$og_j^2 = (1-\tau) * FL_j + \sum \frac{\tau}{\sum Z_i} * ML_j * Z_i \tag{22}$$

where τ is a randomly generated integer with a normal distribution and a mean value of 0.5 and j a standard deviation of 0.1, ML_j indicating the male lion when it Z_i equals 1 if Lions are chosen for mating and equals 0 otherwise.

Algorithm 2: Pseudocode for HLGWO

Input: Obtained feature map
Output: To reduce the dimension of the extracted features

Begin

Initialize population, fitness, iteration and maximum iteration
Compute fitness
Set iteration $I = 1$
While $(I_t \le x_{ma})$ **do**

While $(Itr \le \max)$ **do**

Update the new position by, $D_p^{new} = D_p + (\eta_d \times VV_s - \eta_d \times VV_{ng})$

Update the position of hunter by left and right side

If $(2 * D_p - P(O_i)) < D_p$ {

$$P(O_i)^{new} = \eta_d((2 * D_p - P(O_i)), D_p)$$

} **else** {

$$P(O_i)^{new} = \eta_d(D_p, (2 * D_p - P(O_i)))$$

} **end if**

Update the position by centre wing

Calculate fitness

$$FL' = [FL]^{GWO} + [2G \times \eta_d \{S_1\}]^{GWO} + w(-1,1) \times \tan(\theta) \times [G \times \{S_2\}]^{GWO}$$

Set $I = I + 1$

End while

Return facial images

End

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4. RESULT AND DISCUSSION

This result section focuses at the evaluation of the proposed research. The proposed research methodology is implemented using the MATLAB workbench. Additionally, comparisons between additional optimization techniques will be covered utilizing the same datasets and three other classifiers.

4.1 Evaluation metrics

Performance metrics are used to collect, display, and analyze data on a team's or an individual's performance. The accuracy, F-Measure, precision, recall, and Jaccard similarity coefficient (JSC) of partial face recognition using the proposed FCNHLGWO are compared with those of the existing Deep Learning Neural Network (DLNN) with Honey Badger firefly (HBFF) algorithm, Deep Neural Network (DNN), and Support Vector Machine (SVM). The mathematical formulae for precision, accuracy, recall, F-measure, and Jaccard similarity coefficient (JSC), respectively, are given in equations (23), (24) and (25).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{23}$$

$$\text{Recall} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{24}$$

$$\text{Precision} = \frac{1}{Q} * [(TP) \cdot (TP + FP)] \tag{25}$$

$$\text{F - Measure} = \frac{(\alpha^2 + 1) P \times R}{\alpha^2 (P + R)} \tag{26}$$

$$\Psi_{JI} = \left|\frac{R \cap S}{R \cup S}\right| \tag{27}$$

Where Q describes the class count, α is set to 1 to make it an F1-score, P and R the values of accuracy and recall are TP-True Positive, FP-False Positive, TN-True Negative, and FN-False Negative. The S ground truth displays, R the segmented volume generated by the suggested approach. Upgrade best practices should now be more precise.

4.2. Experiments on FASSEG dataset

The FASSEG dataset is used in this part to assess the effectiveness of the suggested effort. The FASSEG dataset is divided into four subsets, each of which contains a number of face pictures (multipose01, frontal03, frontal02, and frontal01). FASSEG dataset is particularly helpful for training and evaluating the automated algorithms in face segmentation. 200 face photos with ground-truth masks for the six classes (background, mouth, eyes, nose, skin, and hair) make up the subset (multipose01). The frontal01 and frontal02 subsets each include 70 RGB pictures together with tagged ground truth masks [26]. Finally, the frontal03 subgroup includes 150 face masks that were photographed in a variety of lighting, orientations, and facial expressions. Figure 3 shows the sample of face photographs from the FASSEG dataset that were obtained.

Fig.3: Face images of FASSEG Database

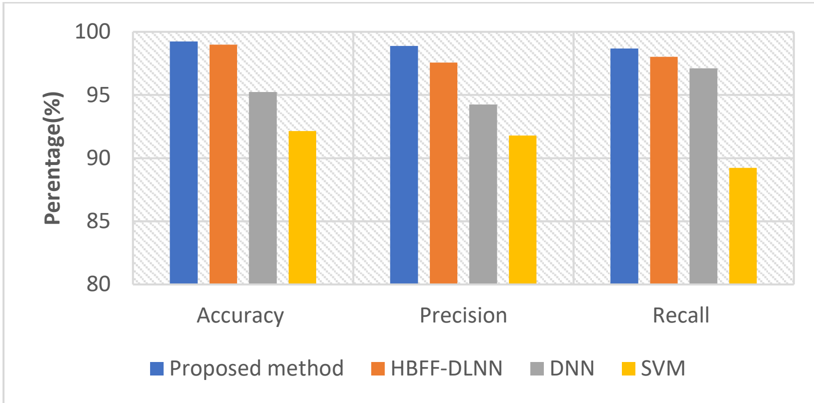

Fig.4: Comparative analysis of Accuracy, Precision and Recall on FASSEG

The suggested FCN- HLGWO based route selection's accuracy and F-measure analysis is contrasted with the current HBFF-DLNN, DNN, and SVM techniques with regard to the accuracy and F-Measure metrics. Here, the suggested methodology's accuracy is more than 99.24%, compared to other two approaches' accuracy of 98.98% for HBFF-DLNN, 95.24% for DNN, and 92.15% for the SVM approach. Figure 5 illustrates the evaluation of the comparative study of F-Score and JSC on the FASSEG dataset. This proves that the suggested method-based facial recognition achieves superior results than the current research methodologies.

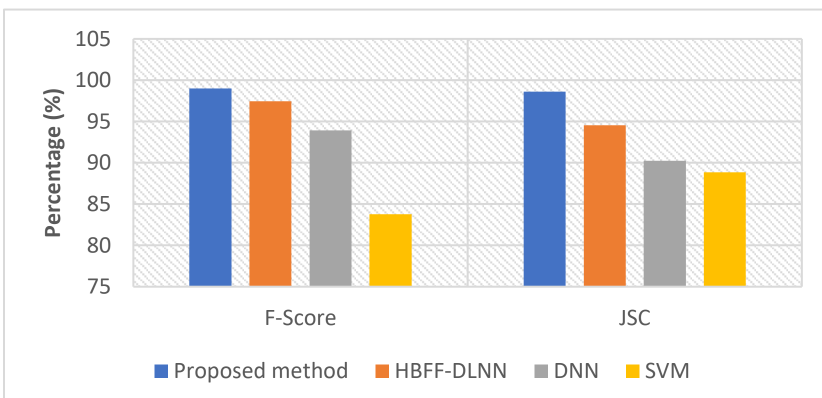

Fig.5: Comparative analysis of F-Score and JSC on FASSEG dataset

4.3. Experiments on ORL dataset

For each of 40 different persons, there are 10 different face pictures in the ORL face dataset [27], which is in PGM format. The facial features (no glasses/glasses), lighting, and facial emotions (closed/open eyes, not smiling/smiling) of the collected face photos in this collection differ. Three people's face picture samples from this dataset are shown in Fig. 6.

Figure 6: Some samples of face images from the ORL face dataset

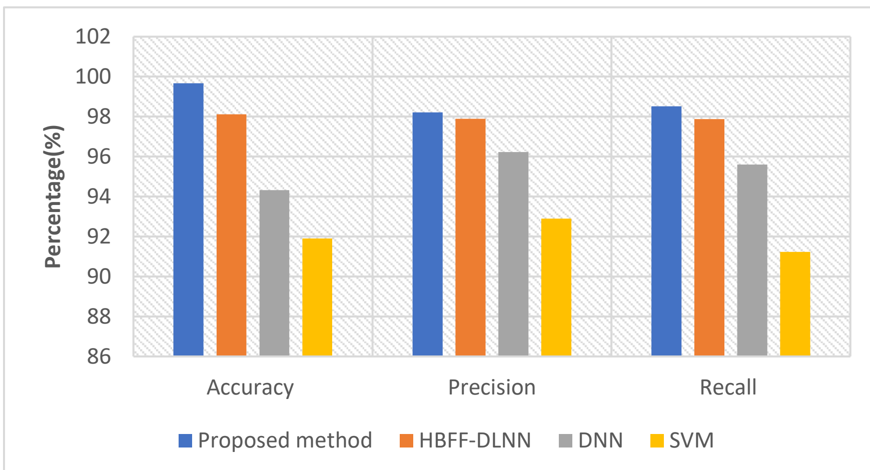

Fig.7: Comparative analysis of Accuracy, Precision and Recall on ORL dataset

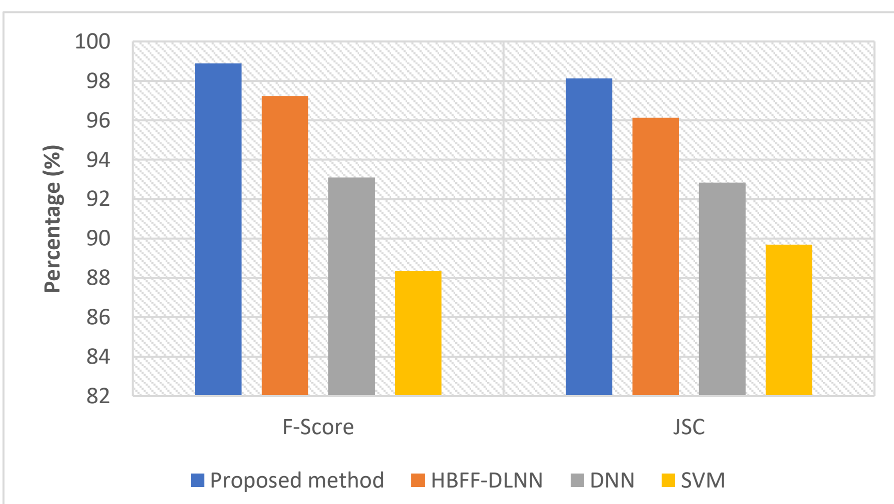

Fig.8: Comparative analysis of F-Score and JSC on ORL dataset

The suggested methodology-based face recognition process system with the current methodologies is shown graphically in Figures 7 and 8. The analysis of the F-score, Recall, Accuracy, Precision, and JSC metrics is shown in Figure. When compared to other comparable algorithms, such as HBFF-DLNN, DNN, and SVM, with accuracy rates of 98.12%, 94.32%, and 91.9%, respectively, proposed FCN-HLGWO prediction has the best accuracy with 99.67%. The suggested methodology's accuracy also produces superior results. Considering that the suggested technique has greater activation function. The suggested strategy's JSC value is 98.63%, whereas the present approach is somewhat less effective. The suggested method also performs better than the current research methodologies based on the accuracy, recall, and F-score metrics.

Table 1: Comparative analysis of recognition rate in various datasets

Datasets	**Recognition rate (%)**			
	Proposed Method	**HBFF-DLNN**	**DNN**	**SVM**
FASSEG	98.42	97.83	94.3	91.27
ORL	98.78	96.23	92.74	88.45

Table 2: Comparative study of proposed and existing work

Methodology	**Datasets**	**Accuracy (%)**
IKLDA+PNN [28]	ORL	93.3
KNN [29]	ORL	72.3
	FASSEG	74.8
SVM	ORL	95.24
	FASSEG	91.9
DNN	ORL	92.15
	FASSEG	94.32
HBFF-DLNN	ORL	98.24
	FASSEG	98.98
Proposed method	ORL	99.12
	FASSEG	99.67

Table 1 demonstrates the evaluation of the comparative study of recognition rate across multiple datasets. The datasets and accuracy of different approaches have been established in table 2 reports. Here, improved kernel linear discriminant analysis (IKLDA) and probabilistic neural networks (PNNs) have accuracy values based on the ORL dataset of 93.3%, 72.3%, 95.24, 92.15%, and 98.24 respectively. As can be shown, the suggested FCN-HLGWO produces the greatest results with a 99.12% accuracy rate. Similar to other research techniques, the suggested

FCN-HLGWO achieves greater performance based on the FASSEG dataset, with a proposed FCN-HLGWO of 99.67% outperforming HBFF-DLNN of 98.98%, DNN method of 94.32%, SVM method of 91.92%, and KNN method of 74.8%.

5. CONCLUSION

This research proposed a new approach called Dynamic Feature Matching (DFM) to deal with partial face recognition. A Fully Convolutional Network (FCN) is used to generate spatial features in the partition computation independent of any size input. A dictionary of dynamic features appropriate to the size of the study is created. With respect to feature matching, the feature selection constraint imposed on the SRC provides orientation-free matching while improving partial face recognition performance. Here Hybrid Lion Enhanced with Gray Wolf Optimizer (HLGWO) was used to eliminate irrelevant features or reduce the dimensionality of extracted features. In an experimental assessment, the proposed strategy to be compared with currently applied research methods. In this study, the proposed FCN-HLGWO is evaluated against existing RNNs and ANNs for accuracy, recall, and accuracy using F-measure metrics. Recommended search performs well on all metrics. Also, the proposed technique achieves better results based on different performance analysis of different steps. Also, SRC tries to build a training dictionary that vaguely states the test image; in other words, the performance of SRC is also affected by the size of the dataset. For future work, the performance of the proposed system will be evaluated using a larger dataset.

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