Face Recognition Using Improved Short-Long-Term Memory Neural Network by the Whale Optimization Algorithm

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***Abstract*—Recognizing the identity of people through their unique characteristics is one of the searches that has received much attention in recent years, and is used in many legal and security cases. Considering that, facial image-based identification methods have complex processes, it is necessary to provide an algorithm that is useful in facilitating the identification process with high accuracy. One of the problems of facial recognition systems is identifying face. Face recognition in different views and poses is related to the limitation of the poses used in the face recognition algorithm in the system. In this research, the identification of the identity using the face is discussed. In order to identify people, feature extraction is done using principal component analysis algorithm and 9 features with high resolution are selected and after the normalization of the selected features using the improved short-long-term memory neural network with the Whale Optimization Algorithm, identity recognition is performed based on the face and the results have been compared with the convolutional neural network and the k-nearest neighbor classifier. Improved short-long-term memory neural network with the Whale Optimization Algorithm performs face-based identity recognition with 0.25 mean square error and 99% accuracy.**

Keywords— face recognition, short-long-term memory neural network, the Whale Optimization Algorithm.

I. INTRODUCTION

With the rapid development of computer and network technology, information security is of unprecedented importance. Identification is an essential prerequisite to ensure system security. Accurate identification is required in the fields of finance, national security, justice, e-commerce, etc., and biological characteristics are inherent human characteristics. Uniqueness and features that are not easy to replicate provide the necessary prerequisites for recognition. Therefore, the personal identification system based on biometric recognition technology is receiving more attention for security, reliability and validity and has started to enter all areas of our lives. Common biometric methods include: fingerprint detection, palm print detection, ECG detection, iris detection, DNA detection, etc. [1]

Among many biometrics, face recognition has become the main direction of biometric research due to the convenience of collecting facial images, carrying a large number of personal information features, high detection and uniqueness [2]. Face recognition is a practical issue that in recent years, with the rapid progress of various fields, face recognition technology has made significant progress and its field of application has gradually expanded. At this stage, it is mainly used in security system, public security system, payment system, etc [3].

Face-based identity recognition includes the steps during which distinguishing features are extracted from face images and by which a learning algorithm is trained to learn to recognize different people [4]. In this article, the focus is on the use of deep neural network in facial recognition and we intend to use the improved short-long-term memory neural network using the Whale Optimization Algorithm to identify the identity based on the face.

II. LITERATURE REVIEW

Hangaragi et al. used the face network under varying conditions of light reflection and background for face recognition. The corresponding model received images of men and women of different ages and races and fed them into the deep neural network. The obtained accuracy was reported as 94.23%. [5]

Alshabi et al used deep convolutional neural learning network to recognize faces of masked women. In the set of MTCNN images, the accuracy was 18.5%, Mobile net images were 21.9% accurate, and in the images of veiled women, they were 59.1% accurate. [6]

Bah et al used the local binary pattern algorithm in combination with advanced image processing techniques such as sharpness adjustment and abundance graph equalization for face recognition in reflective and noisy environments. They were able to reach a higher accuracy of 99.0% compared to the compared methods. [7]

Udawant et al. used deep convolutional networks to recognize images in a collection of 4000 images. The results of their work showed superiority with 97.5% accuracy compared to advanced compared methods [8].

III. PROPOSED METHOD

The facial recognition system includes the following steps:

1) Preparation of images

2) Feature extraction with principal component analysis algorithm

3) Using improved short-long-term memory neural network with the Whale Optimization Algorithm for face recognition

4) Using convolutional neural network and k-nearest neighbor classifier for face Recognition.

A. *Preparation of images*

In this article, the ORL database is used, which includes 100 image samples with dimensions of 70x80 from 10 different people. In this research, 8 images of each person are included in the training set and two images are included in the test set. Therefore, there are 80 image samples in the training set and 20 image samples in the test set. First, the images are read and entered into the memory, thus each image is stored in a 70x80 matrix. Then each image is converted into a column Vector and training set is created with 5600 rows and 80 columns, each column is an image of a person. Then the average feature in each line is calculated and the value of the feature in that line is reduced, thus the average feature in each line becomes zero. In the same way, test images are also read and entered into the memory then, in order to create a test set, each image is converted into a column vector and placed in the test set. As a result, the test set is finally created with 5600 rows and 20 columns; each column corresponds to the image of each person. The average of each row and its difference with the average is calculated until the average of the data in each row is equal to zero. This process simplifies the calculation of the covariance matrix. To determine the output of the educational goal, a vector 80*1 has been used, where the identification number of each person is displayed in decimal form, and since the number of educational samples is equal to 80 samples, therefore, the output set of the educational goal is 80*1. In the same way, a 20*1 matrix was used to create the target output of the test, and the identification number of each person was displayed in decimal form, and since there are 20 samples, then the target output set is 1*20. Also, 80% of the data is used for training the neural network and 20% of the data is used for testing the model. Table 1 shows the information about the training and testing data.

TABLE 1. THE NUMBER OF TRAINING AND TEST SAMPLES

	Training database	***Test database***	***Database***
The dimensions of the samples	5600*80	5600*20	5600*100

B. *Feature extraction with principal component analysis algorithm*

In the phase of feature extraction, feature extraction is performed from the principal component analysis algorithm. In this step, first, the average of the features in each row is calculated and the value of the feature in the image is reduced from the average of that feature, thus the average of the features in the images becomes zero, which makes the calculation of the covariance matrix simple because in this matrix the average value is zero. Then the covariance matrix is calculated using the images of the training set. The covariance matrix is analyzed and its eigenvalues and eigenvectors are determined. In this way, the eigenvalues represent the variance of each feature in the mapped space. Then, the eigenvalues (the variance of each feature in the new space) are sorted in descending order (because the greater the variance, the resolution increases) and then the eigenvectors are sorted based on the sorted order of the eigenvalues and from the product of eigenvectors in the image matrix, mapping happens and the data is mapped to the new space. In this situation, features are selected based on eigenvalues and by trial and error, and their training and testing errors are checked until it is determined that the lowest error value corresponds to the state where the number of features is equal to 9. Therefore, the number of the first 9 features is selected from the eigenvectors that have the highest eigenvalues, the dimension reduction process also takes place, and by multiplying the training data matrix, a new training set with reduced dimensions is determined and extracted. It should be noted that these 9 features are separate from each other and the mapping resulting from the multiplication of the eigenvector in the image matrix creates a linear combination in the new space, which causes the face's nature to disappear in the mapped space. To extract eigenvectors of the test set, eigenvectors and eigenvalues related to training data are used. In the matrix related to the experimental data, first the average of each feature is calculated and each feature of the image is subtracted from the average of that feature, in this way the features of the images have a zero average. Then, the special vectors determined for the training data are used and by multiplying it with the test data matrix, the feature extraction is done for the test data. Table 2 shows the results of using the number of different features for training and testing data.

TABLE 2. RESULTS OF USING DIFFERENT FEATURES NUMBERS

The number of features	***Error per training data***	***Error per test Data***
5	0.0041	0.0097
10	0.0036	0.0078
15	0.0094	0.0064

One of the basic challenges in the short-term memory neural network is determining the following parameters that are determined by the user, and the optimal values may not be selected by the user, and the accuracy of identifying the identity based on the face will decrease.

1. The type of training algorithm: it is an algorithm that is considered for training the neural network of short-long-term memory and can include one of the values of adam, rmsprop and sgdm.

2. Initial value of learning rate: this parameter is used to update the weights, and it is the initial value of the learning rate, which can be determined in the range of [0.001, 0.02].

3. Learning factor reduction rate: this parameter is used to reduce the learning factor rate and its optimal value can be determined in the range of [0.07, 0.2].

4. Learning factor reduction rate reduction period: this parameter is used for the learning factor reduction rate reduction period and its optimal value is determined in the interval {3, 4, …, 10}

5. Maximum number of training repetitions: it represents the number of times the training algorithm is repeated for the short-long-term memory neural network, and the optimal value can be determined in the interval {20, 21, … , 30}.

Therefore, in this research, the parameters mentioned in the short-long-term memory neural network are defined as decision variables, and the mean squared error is defined as the objective function, and the optimal values of the parameters are determined by the Whale Optimization Algorithm in order to perform face-based identity recognition with high accuracy. The Whale Optimization Algorithm includes two stages: initial preparation and iteration stage.

C. Using improved short-long-term memory neural network with the Whale Optimization Algorithm for face recognition

1) Surrounding the hunt

Humpback whales can detect the location of prey and surround them. Since the optimal point in the search space is unknown at first, the Whale Optimization Algorithm considers the current best solution as hunting the target or close to optimal.

After the position of the best agent (hunting) is determined, then other agents change their new position using the position of the best agent (hunting) according to equation (2) [9].

$$\vec{D} = |\vec{C}.\vec{X}^*(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}.\vec{D} \quad (2)$$

Where t represents the current iteration, A ⃗ and C ⃗ are coefficient vectors and X* is the best solution vector, X ⃗ is the position vector, | | the absolute value and. It means multiplying member by member. It should be noted that if there is a better solution, X* should be updated at the end of each iteration [9]. Vectors A ⃗ and C ⃗ are updated using relations (3) and (4).

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (3)$$
$$\vec{C} = 2.\vec{r} \quad (4)$$

Where a ⃗ decreases linearly from 2 to 0 in different iterations (exploitation search is performed by it) and r ⃗ is a random vector in the interval [0, 1].

2) Bubble attack method (exploitation phase)

Based on the mathematical model of the bubble behaviour of humpback whales, the following two plans are proposed:

a) Blockage reduction mechanism: This behaviour is obtained by reducing the value in relation (2). Note that the swing range A ⃗ is also reduced by a ⃗. In other words, A is a random value in the interval [-a, a], where a decrease from 2 to 0 during repetition. Setting random values for A in [-1, 1], a new position of the search agent can be defined at any point between the original position of the agent and the position of the current best agent.

b) Spiral position synchronization: This approach first calculates the distance between the whale located at (X, Y) and the prey located at (X*, Y*). A spiral equation is created between the position of the whale and the prey to imitate the spiral movements of humpback whales in the form of equation (5).

$$\vec{X}(t+1) = \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) \quad (5)$$

That D ⃗^'=|X ⃗^* (t)-X ⃗ (t)| and represents the distance of the i-th whale from the prey (the best solution), b is a constant to define the logarithmic spiral shape, l is a random number in the interval [-1, 1] and. It indicates the multiplication of member by member [9].

Note that humpback whales swim around prey in a small circle along a spiral path simultaneously. For modelling the behavior, 50% probability between the encirclement reduction mechanism and the spiral model is considered to update the position of the whales during the optimization process. Mathematical modelling is shown according to equation (6) [9].

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & if\ p < 0.5 \\ \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) & if\ p \geq 0.5 \end{cases} \quad (6)$$

Where p is a random number in the interval [0, 1]. In addition to the bubble method, humpback whales search randomly for prey. The mathematical model of the search is as follows.

3) Search for hunting (search phase)

A similar method based on the variation of the vector A ⃗ can be used for hunting (exploration). In fact, humpback whales search randomly according to each other's position. Therefore, A ⃗ with random values larger than 1 or smaller than -1 is used to move the search agent closer or further away from the reference whale. Unlike the exploitation phase, the position of a search agent in the exploration phase is determined by using a randomly selected search agent. In fact, the random factor replaces the best solution in the exploration phase to determine the new position of the factor. This mechanism A ⃗ >1 emphasizes the search (exploration) and allows the Whale Optimization Algorithm to search globally. The mechanism is modelled according to equation (8) [19].

$$\vec{D} = |\vec{C}.\vec{X}_{rand} - \vec{X}| \quad (7)$$
$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \quad (8)$$

Where X ⃗_rand is a random position vector (random whale) selected from the current population.

4) Steps of the Whale Optimization Algorithm

The Whale Optimization Algorithm starts with a set of random solutions. In each repetition, the positions of the search agents are updated with the random search agent or the best solution. The parameter a is reduced from 2 to 0 to create search and exploit.

A random search agent is selected when A ⃗>1 and when A ⃗<1 is the best solution for updating the search agents. Depending on the value of p, the Whale Optimization Algorithm is able to switch between spiral and ring motion. Finally, the Whale Optimization Algorithm ends when the termination conditions are met. Figure 1 shows the pseudo code of the Whale Optimization Algorithm.

Based on theoretical points, the Whale Optimization Algorithm can be considered as a global optimizer because it has the ability to search (explore) and exploit. In addition, the presented mechanism defines the hypercube search space within the range of the best solution and allows search agents to exploit the best solution within that range.

The diversity of the search vector A allows the Whale Optimization Algorithm to transition equally between exploration and exploitation (as A decreases, some iterations are dedicated to exploration (| A | ≥ 1) and the rest are dedicated to exploitation (| A | < 1)). The Whale Optimization Algorithm has only two parameters A and C that need to be adjusted.

Although mutation and other evolutionary operators are included in the formulation of the Whale Optimization Algorithm to fully reproduce the behaviour of humpback whales, the goal of the Whale Optimization Algorithm is to reduce internal and adjustable parameters [9].

```
Initialize the whales population Xi (i = 1, 2, ..., n)
Calculate the fitness of each search agent
X*=the best search agent
while (t < maximum number of iterations)
   for each search agent
   Update a, A, C, l, and p
      if1 (p<0.5)
         if2 (|A| < 1)
            Update the position of the current search agent by the Eq. (1)
         else if2 (|A| ≥ 1)
            Select a random search agent (X_rand)
            Update the position of the current search agent by the Eq. (8)
         end if2
      else if1 (p≥0.5)
            Update the position of the current search by the Eq. (5)
      end if1
   end for
   Check if any search agent goes beyond the search space and amend it
   Calculate the fitness of each search agent
   Update X* if there is a better solution
   t=t+1
end while
return X*
```

Fig. 1. The pseudo code of the Whale Optimization Algorithm [9]

In the initial preparation stage, a population of whales is created and distributed randomly in the response space. The position of each whale includes the parameters of the training algorithm type, the initial value of the learning rate, the learning factor reduction rate, the learning factor reduction rate reduction period, and the maximum number of training repetitions in the short-long-term memory neural network. Figure 2 shows the position of the whale, Then the parameters in the position of the whale are placed in the short-term memory neural network and the training inputs are applied to the neural network and the training outputs are calculated and the mean squared error is obtained based on the ideal outputs and the outputs of the neural network and is considered as the fitness value of the whale. The above process is performed to calculate the position and fitness value for each whale.

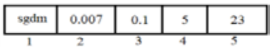

Fig. 2. The position of the whale in the Whale Optimization Algorithm

The following occurs in the repetition section.

Parameter setting: In this step, parameters A and C are randomly set.

Updating the whale's position; In this step, based on the best position of the whale and the current position of it, the new position of the whale is determined using a spiral movement. Figure 3 shows how the spiral moves and produces the new position of the whale.

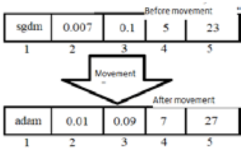

Fig. 3. The new position of the whale before and after moving in the Whale Optimization Algorithm

Evaluating the new position of the whale: In this step, the new position of the whale after production is evaluated by the objective function. That is, based on the new position of the whale, the new values of the parameters are placed in the short-long-term memory neural network and its training is done and the training inputs are applied to it and the mean squared error is calculated and considered as the fitness of the whale.

Synchronization of parameter A: In this step, parameter A is linearly synchronized.

The operations are repeated from the repetition stage until the termination conditions are met. The output of the Whale Optimization Algorithm is a member of the population whose mean square error is lower than the rest of the population, so the best parameters of the training algorithm type, the initial value of the learning rate, the learning factor reduction rate The period of reduction of the rate of reduction of the learning factor and the maximum number of repetitions of training in the neural network of short-long-term memory.

D. Using convolutional neural network and k-nearest neighbor classifier for face recognition

Feature extraction was done using principal component analysis algorithm and convolutional neural network is used for face recognition. Table 3 shows the level of accuracy and types of errors for training, testing and total data.

TABLE 3. THE RESULTS OF USING CONVOLUTIONAL NEURAL NETWORK IN FACE RECOGNITION

	MSE	*RMSE*	*MAE*	*SSE*	*Accuracy*
Train Data	0.3125	0.559	0.0625	25	98.75
Test Data	2.5	1.581	0.5	50	90
All Data	0.75	0.866	0.15	75	97

According to table (3), convolutional neural network has mean square error of 0.3125, 2.5 and 0.75 and accuracy of 98.75%, 90% and 97% for training data, test data and total data respectively.

After feature extraction by principal component analysis, k-nearest neighbor classifier was used for face recognition. Table 4 shows the level of accuracy and types of errors for training, testing and total data.

TABLE 4. THE RESULTS OF USING THE K-NEAREST NEIGHBOR CLASSIFIER IN FACE RECOGNITION

	MSE	*RMSE*	*MAE*	*SSE*	*Accuracy*
Train Data	0.625	0.791	0.125	50	97.5
Test Data	2.5	1.581	0.5	50	90
All Data	1	1	0.2	100	96

IV. EVALUATION OF THE PROPOSED ALGORITHM

According to table 5, short-long-term memory neural network improved with the Whale Optimization Algorithm, convolutional neural network and k-nearest neighbor classifier perform face recognition based on face recognition with mean square error of 0.25, 0.75 and 1 respectively and accuracy of 99%, 97% and 96% for all images and the best performance belongs to the improved short-long-term memory neural network with the Whale Optimization Algorithm.

TABLE 5. THE RESULTS OF USING DIFFERENT ALGORITHMS IN FACE RECOGNITION WITH ALL THE IMAGES

	MSE	*RMSE*	*MAE*	*SSE*	*Accuracy*
LSTM+WOA	0.25	0.5	0.05	25	99
CNN	0.75	0.866	0.15	75	97
KNN	1	1	0.2	100	96

V. CONCLUSION

The development of the proposed model was done and the problem of face-based identity recognition was done by collecting images from the image database and applying the principal component analysis feature extraction algorithm, and in the feature extraction, 9 features with the highest variance values were selected. In the next step, 80% of the images are used for training and 20% of the images are used for testing and the improved short-long-term memory neural network was improved with the Whale Optimization Algorithm. The results show that the improved short-long-term memory neural network with the Whale Optimization Algorithm performs face-based identity recognition with a mean square error of 0.25 and 99% accuracy, and performs better than the compared methods.

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