OPTIMIZING FEATURE SELECTION ACCURACY OF A FACE RECOGNITION SYSTEM USING AN IMPROVED CHICKEN SWARM OPTIMIZATION ALGORITHM

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Abstract: *The process of selecting the best solution for a given problem from a large number of alternatives is known as optimization. For the face recognition system, an Improved Chicken Swarm Optimization (ICSO) algorithm was presented. Chicken Swarm Optimization is a swarm intelligence-based approach that maintains a fair balance between exploration and exploitation. Nevertheless, Standard CSO still suffers from the ease of slipping into local optimum and sluggish convergence speed when solving high dimensional issues. To better combine the global and local search, the rooster and hen position update procedure now includes a Chaotic gauss map and tent map. This is done to avoid the rooster and hens slipping into local optimum which could lead to premature convergence. For feature extraction, Local Binary Pattern (LBP) was employed, and for feature selection, the Improved Chicken Swarm Optimization (ICSO) was applied. When LBP and CSO were combined, the accuracy of the facial images was measured. When LBP and ICSO were combined, the accuracy of the facial images was measured. According to the results of the trials, LBP-CSO had a classification accuracy of 91.67%, whereas LBP-ICSO had a classification accuracy of 96.25%.*

1. INTRODUCTION

Feature dimensionality reduction has been used successfully in a variety of machine learning applications, including data classification. The process of classifying incoming data into one of a set of categories is known as classification [1]. Classification approaches based on feature selection have been researched in recent research to improve classification performance [2]. Currently, finding one of the most drastic ways to tackle the classification problem is to discover a set of informative features with minimal size and high accuracy [2]. As a result, machine learning algorithms use the feature selection process to pick high-quality feature sets by removing irrelevant and redundant features [2].

Feature selection intends to select a relevant feature that is necessary and sufficient to describe the target concept, by reducing the irrelevant and redundant features and improving the general performance of a classification algorithm [3]. The two major problems of this process are the feature interaction and the large search space. Nature-inspired algorithms are stochastic approaches for solving these kinds of optimization problems. They commonly combine deterministic and randomized techniques and then iteratively compare a number of solutions until one is identified that is satisfactory [4]. The performance of Evolutionary Algorithms is largely influenced by maintaining a balance between exploration and exploitation of search space [5]. As a result, academics have developed hundreds of swarm intelligence algorithms to strike this balance and provide improved answers for existing optimization issues [4]. Some of well-known swarm intelligence algorithms are cat swarm optimization (CSO) [4]. particle swarm optimization (PSO) [6][7][8], Genetic algorithms (GO) [9][10], Bee Swarm Optimization (BSO) [11][12][13], Grey Wolf Optimization (GWO) [14], and Chicken Swarm Optimization (CSO) [15].

Many studies have been done on Local Binary Pattern and Chicken Swarm Optimization approaches, however they either use the algorithm for feature extraction or feature selection to evaluate face recognition accuracy. Standard CSO have a slow convergence speed, and can quickly fall into local optimal when dealing with high-dimensional problems. The standard CSO was improved in this study by incorporating the chaos theory map function: gauss map, and tent map into the Rooster and chicks update equation of the chicken swarm optimization method, which was then used for feature selection. LBP was used for feature extraction. The comparison of the combination of LBP-CSO and LBP-ICSO was done and used as a yardstick to evaluate experimental results and determine the accuracy of the new technique.

Chicken Swarm Optimization (CSO), is a swarm intelligence-based approach [15]. CSO successfully exploits the chicken swarm's hierarchical order as well as the food-seeking behavior. The division of the population into three categories, rooster, hen, and chick, is CSO's distinguishing feature or difference from other algorithms. The utilization rate of the population is increased by dividing the population into three groups. Furthermore, when compared to other algorithms, CSO maintains a fair balance between exploration and exploitation. [5].

Local Binary Pattern (LBP) is an operator used to describe the local characteristics of the image. The local binary pattern (LBP) is to compare the size of the surrounding pixels and the central pixel to binarize the pixel values in the neighborhood [16]. Its expression is:

$$LBP\ p,\ r\ (x_c,\ y_c) = \sum_{p=1}^{8} 2p_s(i_C - i_p)2^C \quad \text{with} \quad s(x)=\begin{cases}1 & x \geq 0\\ 0 & x < 0\end{cases} \qquad (1)$$

where i_C and ip are the intensity value of the center pixel and neighborhood pixels, respectively.

The principle of the LBP algorithm is to take the pixel value of each point in the image as the central threshold and take out the area around this pixel. Comparing the two pixels is worth producing a relative binary value. Take the resulting binary number as the center LBP eigenvalue [16].

Related Works

The process of feature selection can be divided into four approaches viz Filters, wrappers, embedding, and hybrid techniques. Wrapper models compute the accuracy attained with a given classifier to drive the search for the most discriminating feature subset, whereas filter models use statistical measures to evaluate features or subsets of features [1]. The advantages of both filters and wrappers are combined in the hybrid technique. A wrapper is utilized to select the best candidate subset, while the filter technique is used to reduce the feature space dimension space [17]. We used a filter strategy to address the problem of feature selection in the face recognition system. The basic Steps of Feature Selection Process is showed in the figure 1.

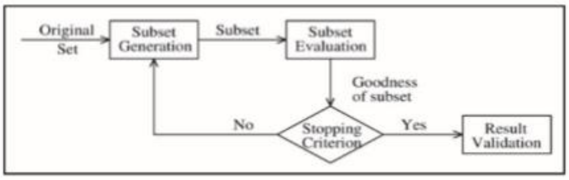

Fig. 1. Basic Steps of Feature Selection Process source: [18].

Filter Approach

Regardless of the data modelling algorithm used, filter approaches choose features based on a performance metric. Modelling algorithms can only employ the best features once they have been determined [19], filter approaches do not rely on any learning process and use feature set statistical analysis, and they are usually very rapid [20]. The filter method is further broken down into two parts: univariate and multivariate. Multivariate feature filters analyse a complete feature subset, whereas univariate feature filters evaluate a single feature. [21].

The improvement of the chicken swarm optimization method has been demonstrated to be effective in a variety of computer and engineering applications as shown in the literature reviewed below:

i. To improve CSO, the researcher applies four components of chicken swarm optimization: cock position update mode, hen position update mode, chick position update mode, and population update method, abbreviated as ICSO-RHC. The impact of the number of retained elite individuals and control parameters on the algorithm's convergence speed is examined based on algorithm improvement. In addition, 30 test functions and CEC 2005 benchmark functions were chosen to verify the performance of ICSO-RHC. The study was deemed a success [21].

ii. The fuzzy system is used to change the number of chickens and random parameters in the CSO algorithm. The position update of roosters was computed using the cosine function, which was integrated into the FCSO. A nonparametric statistical Friedman test was also used to verify the FSCO method. The FCSO outperforms the other Swarm Intelligence Optimization (SIO) technique in both convergence time and optimization accuracy, according to the experimental results on the 30 black-box optimizations benchmarking (BBoB) function [22].

iii. To ensure the optimal solution, the effectiveness and convergence of the solution of a chicken swarm optimization (CSO) and a genetic algorithm (GA) were used for text summarization. The suggested methods are evaluated using the CNN / Daily Mail standard dataset, which is measured using the Recall-Oriented Understudy for Gisting Evaluation (ROUGE). On the ROUGE-1, ROUGE-2, and ROUGE-L, the results demonstrated that the novel method hybrid (CSOGA) has the best performance on text summarization quality, capable of creating a higher accuracy than previous algorithms. When compared to the largest improvement in accuracy of the suggested approach, ROUGE-1 had a 4.4 percent increase, ROUGE-2 had a 12.01 percent increase, and ROUGE-L had a 9.8 percent increase [23].

Chicken Swarm Optimization (CSO)

According to [24]. CSO algorithm has, three kinds of roles, roosters, hens, and chicks, each having different behaviour specifications. The following assumptions were given for the basic CSO algorithm: (i) CSO algorithm divides a chicken swarm into a few groups, each of which has one rooster, several hens, and a small number of chicks. (ii) identities of roosters, hens, and chicks are determined by their fitness values, the best fitness is selected as roosters, the worst fitness is the chicks, and other individuals are the hens. Each hen randomly chooses one rooster as her mate and becomes a member of his group, and each chick also randomly selects one hen as its mother. (iii) In the whole population, the individual identities, the spouse relationships, and the mother-children relationships remain unchanged for G generations (G is the iterative cycle), and the identities, the spouse relationships, and the mother-children's relationships will be updated after G generations. (iv) In each group of the whole population, hens follow their spouse rooster to find foods, and they will randomly compete for foods with other individuals within a group. Let RN, HN, CN, and MN represent the number of roosters, hens, chicks, and mother hens, respectively, and $x^t_{i,j}$ is the position of the ith chicken in the jth dimensional space on the tth iteration, where i ∈ { } 1, . . . , N, j ∈ { } 1, . . . , D , and t ∈ { } 1, . . . , T and, D, and T represent the total number of chickens, the dimension number, and the maximum iteration times, respectively parentster, a hen, and a chick have their specific position update formulas.

Rooster movement:

Its recent position is defined as follows:

$$x_{i,j}^{t+1} = x_i^t * (1 + Randn(0, \sigma^2)) \quad (1)$$

$$\sigma^2 = \begin{cases} 1, & if\ f_i \leq f_k \\ e^{\left(\frac{f_k - f_i}{|f_i| + \varepsilon}\right)}, & otherwise, \quad k \in [1, N], k \neq i \end{cases} \quad (2)$$

Where $x_{i,j}$ is the selected rooster with index i, $Randn(0, \sigma^2)$ is a gaussian distribution with mean 0 and standard deviation σ^2. ε is the smallest constant the computer used to avoid zero-division-error. k is a rooster's index, which is randomly selected from the rooster's group, f is the fitness value of the corresponding rooster x.

Hen movement:

Hens follow their group-mate roosters to search for food. Moreover, they would also randomly steal the good food found by other chickens, though they would be repressed by the other chickens [24]. These phenomena can be formulated mathematically as in equations (3) and (4).

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times Rand\left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S2 \times Rand(x_{r2,j}^{t} - x_{i,j}^{t}) \quad (3)$$

$$S1 = e^{\left(\frac{f_i - f_{r1}}{|f_i| + \varepsilon}\right)} \quad (4)$$

$$S2 = e^{(f_{r2} - f_i)} \quad (5)$$

Where S1 and S2 are the learning factors, Rand is a uniform random number over $[0, 1]$. $r1 \in [1, \ldots, N]$ is an index of the rooster, which is the ith hen's group-mate, while $r2 \in [1, \ldots, N]$ is an index of the chicken (rooster or hen), which is randomly chosen from the swarm $r1 \neq r2$

Chick movement:

The chicks move around their mother to search for food. This is formulated as in equation (6)

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL(x_{m,j}^{t} - x_{i,j}^{t}) \quad (6)$$

Where $x_{m,j}^{t}$ stands for the position of the i^{th} chick's mother ($m \in [1, N]$). $FL(FL \in (0, 2))$ is a parameter, which means that the chick would follow its mother to forage for food. Considering the individual differences, of each chick would randomly choose between 0 and 2. So, the basic CSO algorithm (pseudo-code) is shown in algorithm 1[15].

Algorithm 1: Standard Chicken Swarm Optimization

Input: Set of initial feature parameters W= $\{w_1, w, \ldots w_p\}$

Predefined swarm size: N_c

Several dimensions of a chicken: $D = q$

Output: Optimal feature parameters $\{wopt_I, wopt_H, wopt_c\}$

1. Initialize chickens Ck= [RN=CN =MN=HN]

$\forall i, j, \quad 1 \leq i \leq N_c, \quad 1 \leq j \leq D = q,$

number of CHs, G (maximum generation)

$x_{i,j}(0) = (x_{i,j}(0), y_{i,j}(0))$ */* position of the features */*

2. Evaluate the N chickens' fitness values (Ck).

2. t=0;

4. While (t < G)

i. *If* ($t \bmod G = 0$)

a Rank the chickens' fitness values and establish a hierarchal order in the swarm;

Fitness values =

$$f(x) = \sum_{i=1}^{m} \sum_{j=1}^{n} \Delta\left(W_{i,j}^{m,n}\right)\left((x_i) - (x_j)\right)$$

Where x_i^t represent the s at i=1,2, …, n and k=2,3, …, m

Where $\Delta\left(W_{i,j}^{m,n}\right)((x_i) - (x_j))$ is the change in a feature of input, hidden and output layers x along with the row *n* and column *m* a. Divide the swarm into different groups and determine the relationship between the chicks and mother hens in a group;

End if

Ii For i = 1:N

a If i = rooster Update its solution/location

$$x_{i,j}^{t+1} = x_{i,j}^{t} * (1 + Randn(0, \sigma^2))$$

$$\sigma^2 = \begin{cases} 1, & if\ f_i \leq f_k \\ e^{\left(\frac{f_k - f_i}{|f_i| + \varepsilon}\right)}, & otherwise, \quad k \in [1, N], k \neq i \end{cases}$$

Where $Randn(0, \sigma^2)$ is a gaussian distribution with mean 0 and standard deviation σ^2. ε is used to avoid a zero-division error.

k is a rooster's index, f is the fitness value of the corresponding x.

End if

b If *i = hen* Update its solution/location using equation (3.15);

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times Rand\left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S2 \times Rand(x_{r2,j}^{t} - x_{i,j}^{t}) \quad (3.15)$$

$$S1 = e^{\left(\frac{f_i - f_{r1}}{|f_i| + \varepsilon}\right)}, \quad S2 = e^{(f_{r2} - f_i)}$$

Where *Rand* is a uniform random number over $[0, 1]$. $r1 \in [1, \ldots, N]$ is an index of the rooster, $r2 \in [1, \ldots, N]$ is an index of the chicken (rooster or hen)

End if

b If *i = chick* Update its solution/location

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL(x_{m,j}^{t} - x_{i,j}^{t})$$

Where $x_{m,j}^{t}$ stands for the position of the *ith* chick's mother $(m \in [1, N])$. $FL(FL \in (0, 2))$ is a parameter

End if

b Evaluate the new solution;

c If the new solution is better than its previous one, update it;

End for

End while

Chaos Theory and Chaotic Map

Chaos theory is a scientific discipline that focuses on the study of nonlinear systems that are highly sensitive to initial conditions that are similar to random behavior, and continuous systems. The properties of chaotic systems are (i) Deterministic, which means that they have some determining mathematical equations ruling their behaviour. (ii) Unpredictable and non-linear, this means they are sensitive to initial conditions. (iii) Appear to be random and disorderly but they are not. Beneath the random behaviour, there is a sense of order and pattern [24][25] Chaos theory is a research trend that is based on probability and mathematics. It is used for complex dynamic systems that have case-sensitive and rapid effects features based on the initial values of the systems as inputs. These effects happen in swarm algorithms in the random values generation phase so Chaos theory is suitable and efficient for swarm algorithms to improve and enhance their performance. Tent and Logistics maps are commonly used in solving many research problems such as optimization problems as shown in Equations 7 and 8 [25]. In our study chaos tent map and chaos gauss map equation were introduced into the chicken swarm optimization rooster and hen update equation. This is done to avoid the rooster and hen falling into local optimum which could lead to premature convergence.

Gauss Map

$$x_{k+1} = \exp(-\alpha x_k^2) + \beta, \ \alpha = 4.9, \ \beta = 0\text{-}0.58 \quad (7)$$

Tent Map

$$X_{k+1} = \mu \min(x_k, 1 - x_k), \ \mu = 2 \quad (8)$$

2. METHODOLOGY

Database Setup

A database tagged "KWASU (Kwara State University) database" was developed. It contains 600 facial images of 200 objects' frontal faces with 3 images of each object. To avoid strong shadow, only ambient that is fluorescent room lighting was used. Several images were taken per object, one at every 5 degrees of rotation. All images were histogram stretched, that is the intensity of the brightest pixel was 255, and the intensities of the other pixels were scaled. under different lighting. Figure 3 shows Some of the KWASU database images used for Training the database while Some of the KWASU database images face cropped used for Testing the database is shown in fig. 3 and fig 4.

System Design

MATLAB R2016a was used to implement LBP and ICSO algorithms on Intel(R) Celeron (R) CPU with 1.60GHz Processor speed. The experiment was with a total of 600 facial images, out of which 360 images were used for training and 240 were used for testing as shown in Table 1. The performance metrics on both trained and recognized face types were evaluated based on recognition accuracy. The system consists of several modules: image acquisition, Feature extraction, feature selection, and face recognition. LBP and ICSO are the two-dimensionality reduction algorithms used in the feature extraction and feature selection in face recognition and a support vector machine (SVM) was used as a classification technique. Figure 2 and figure 5 are the Scheme of the Face Recognition System and a schematic diagram describing the Process Flow of the Face Recognition Processing System.

Table 1. Breakdown of images

Category	Figure
Number of objects (persons)	200
Number of samples per object	3
Number of total samples	600
Number of the training set	360
Number of testing samples	240

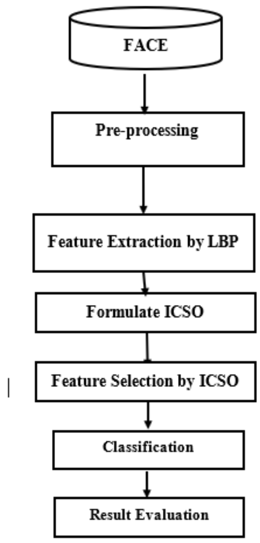

Fig. 2: The Scheme of the Face Recognition System

Fig. 3: Some of the KWASU database images used for Training the database.

Fig.4: Some of the KWASU database images face cropped used for testing the database.

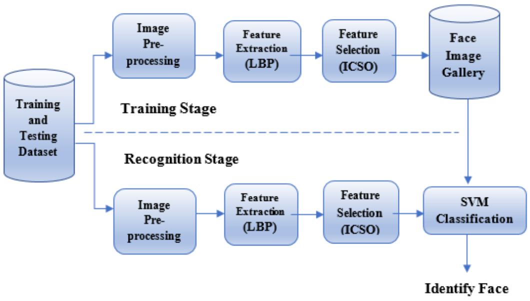

Figure 5: A Schematic Diagram: (describing the Process Flow of Face Recognition Processing System)

Image Acquisition

A Sony Alpha a7 Mirrorless Digital Camera with FE 28-70mm f/3.5-5.6 OSS Lens, 24.3 MP full-frame, Exmor CMS sensor, BIONZ X image processor was used to capture images of faces locally prepared for the database called 'KWASU database". Image pre-processing was carried out by converting the coloured images into grayscale, cropping the image, and normalizing face vectors by computing the average face vector and deducting the average face from each face vector. This was done to remove noise from the face images.

Feature extraction

Feature extraction is a dimensionality reduction process, with the KWASU dataset which contains 600 facial images as data that was divided, 360 facial images were used for Training while 240 facial images were used for testing. A local binary pattern algorithm was used in the face extraction phase to reduce the dimensionality of the facial image features.

Feature Selection

This study combined two chaotic map functions (gauss map and tent map) and was applied to CSO in the rooster and hen generation phased and was used to select optimal features. This is to prevent the roosters and the hens from falling into local optima which could result in premature convergence. the basic steps of the improved CSO can be summarized by the pseudo-code as in algorithm 2:

Algorithm2: Improved Chicken Swarm Optimization

Input: Set of initial feature parameters

W= $\{w_1, w, \dots\ w_p\}$

Predefined swarm size: N_c

Number of dimensions of a chicken: $D = q$

Output: Optimal feature parameters

$\{wopt_I, wopt_H, wopt_c\}$

1. Initialize chickens Ck= [RN=CN =MN=HN]

$\forall i, j,\ \ 1 \le i \le N_c,\ \ 1 \le j \le D = q$, number of CHs, G (maximum generation)

$x_{i,j}(0) = (x_{i,j}(0), y_{i,j}(0))$ /* *position of the features* */

2. Evaluate the N chickens' fitness values (Ck).

3. t=0;

4. ***While*** (t < G)

ii. ***If*** $(t \bmod G = 0)$

a. Rank the chickens' fitness values and establish a hierarchal order in the swarm;

Fitness values =

$$f(x) = \sum_{i=1}^{m} \sum_{j=1}^{n} \Delta\left(W_{i,j}^{m,n}\right)\left((x_i) - (x_j)\right)$$

Where x_i^t represent the s at i=1,2, …, n and k=2,3, …, m

Where $\Delta\left(W_{i,j}^{m,n}\right)((x_i) - (x_j))$ is the change in feature of input, hidden and output layers x along the row *n* and column *m*

b. Divide the swarm into different groups, and determine the relationship between the chicks and mother hens in a group;

End if

iii. ***For*** i = 1: N

a. If i = rooster Update its solution/location

$$Cx_{old} = \frac{mod(abs(ini\ x_{i,j}^{t+1}, rand))}{rand}$$

$$Cx_{new} = \exp\left(-\alpha * Cx_{old}^{\ 2}\right) + \beta$$

$$x_{i,j}^{t+1} = sign\ (ini\ x_{i,j}^{t+1}) \times Cx_{new} \times rand$$

End if

a. FeatureIf *i = hen* Update its solution/location;

$$Chenx_{old} = \frac{mod(abs(ox_{i,j}^{t+1}, (x_{r1,j}^{t} - x_{i,j}^{t})))}{x_{r1,j}^{t} - x_{i,j}^{t}}$$

$$Chenx_{new} = \mu \times min\,(Chenx_{old}\,, 1 - Chenx_{old})$$

$$x_{i,j}^{t+1} = sign\,(\,ox_{i,j}^{t+1}) \times Chenx_{new} \times x_{r1,j}^{t} - x_{i,j}^{t}$$

End if
a. If *i = chick* Update its solution/location
$x_{i,j}^{t+1} = x_{i,j}^{t} + FL(x_{m,j}^{t} - x_{i,j}^{t})$
Where $x_{m,j}^{t}$ stands for the position of the *ith* chick's mother
($m \in [1, N]$). $FL(FL \in (0, 2))$ is a parameter
End if
a. Evaluate the new solution;
e. If the new solution is better than it's previous one, update it;
End for
End while

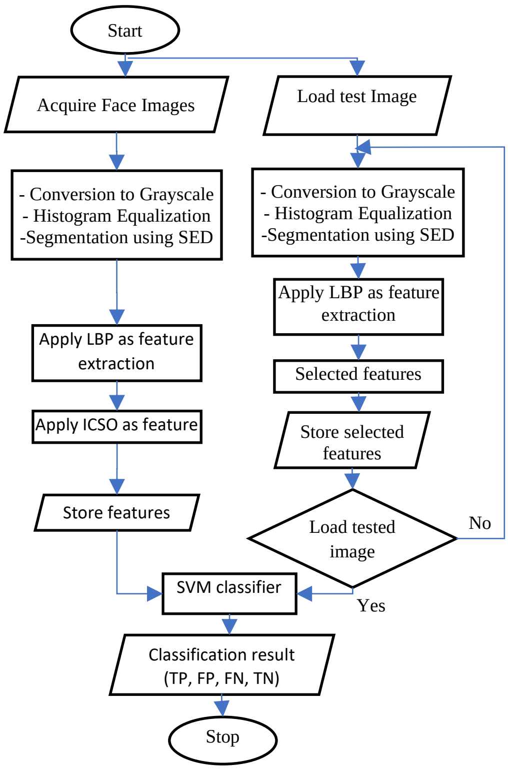

Fig. 6: Flowchart showing Training and Testing using SVM.

Support Vector Machine
The selected features by the ICSO technique were classified using Support Vector Machine (SVM). This technique was employed to measure the similarity between the test vector and the reference vectors in the gallery. The flowchart in fig. 6 shows Training and Testing.

3. RESULT AND DISCUSSION

The results of the evaluation of the improved chicken swarm optimization (ICSO) technique for feature selection of face recognition system were presented in this section. The introduction of chaotic tent map and chaotic gauss map into the rooster and hen update equation of the standard CSO has a strong influence on the performance of the technique. Hence, the performance of the developed technique ICSO-LBP and the CSO-LBP was evaluated at threshold values of 0.25, 0.40, 0.60, and 0.80. The result achieved by each of the developed techniques is based on recognition Accuracy (ACC). The recognition accuracy was measured in percentage.

Result **of LBP with CSO**
The result obtainable in Table 2 show the performance of the LBP based on CSO. 240 datasets were used for testing. The result showcases the performance of the techniques evaluated at a threshold value of 0.25, 0.40, 0.60, and 0.80. The results reveal that at a Threshold value of 0.80 for the face biometric traits; the CSO-LBP technique achieved an accuracy of 91.67%.

Table 2: CSO with LBP

Threshold	ACC (%)
0.25	90
0.40	90.42
0.60	90.83
0.80	91.67

Result of LBP with ICSO
The result attainable in Table 3 depicts the performance of the ICSO-LBP based on face biometric traits. The performance of the technique considered in this study was appraised at threshold value of 0.25, 0.40, 0.60 and 0.80. The results revealed that at threshold value of 0.80 and above; the ICSO-LBP technique achieved accuracy of 96.25%.

Table 3: Result of ICSO-LBP

Threshold	ACC (%)
0.25	94.17
0.40	95.00
0.60	95.83
0.80	96.25

Comparison of CSO-LBP and ICSO-LBP

Table 2 revealed that the CSO-LBP technique achieved an accuracy of 91.67% for a 0.80 threshold value, while table3 the ICSO-LBP technique achieved an accuracy of 96.25% for a 0.80 threshold value. The results disclose that the ICSO-LBP technique outperformed the CSO-LBP technique in terms of recognition accuracy. Fig. 7 shows the accuracy of ICSO-LBP/CSO-LBP in the column cluster chart graph.

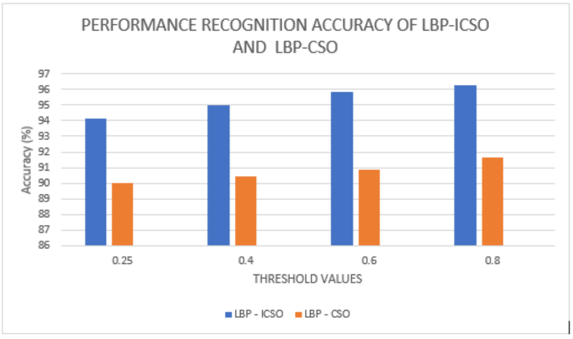

Fig. 7. Performance recognition accuracy for LBP-ICSO and LBP-CSO technique.

Discussion based on Recognition Accuracy Analysis.

The results from Tables 2 and 3 revealed that the developed ICSO-LBP techniques achieved an improved performance compared to CSO-LBP techniques in terms of recognition accuracy. The modification of the standard CSO by the introduction of the chaotic theory map function is justified by the improved performance achieved in this study. It can also be inferred from the cluster charts graph in fig.7 above that the ICSO-LBP technique gave increased accuracy over the CSO-LBP technique in each threshold.

4. CONCLUSION

Optimizing the accuracy of the face recognition system is the main focus of this study. The existing standard chicken swarm optimization algorithm has the issues of slow convergent speed and easily falls into local optima when solving high-dimensional optimization problems. This study presented an improved Chicken Swarm Optimization for face recognition. The Chaotic gauss map and chaotic tent map was introduced into the rooster and hen position update. This is done to avoid the rooster and hens falling into local optimum which could lead to premature convergence. For feature extraction, Local Binary Pattern (LBP) was employed, and for feature selection, the Improved Chicken Swarm Optimization (ICSO) was applied. When LBP and CSO were combined, the accuracy of the facial images was measured. When LBP and ICSO were combined, the accuracy of the facial images was measured. The experimental results shows that LBP-ICSO had a better classification accuracy than the LBP-CSO.

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