PERFORMANCE ASSESSMENT OF LOCAL BINARY PATTERN ALGORITHM AND CHICKEN SWARM OPTIMIZATION ALGORITHM USING THE KWASU DATABASE

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Abstract: *Facial recognition has emerged as the most promising and robust method of recognizing people in recent years. The research focuses on performance assessment of Local Binary Patterns (LBP), and Chicken Swarm Optimization (CSO) face recognition techniques. The Local Binary Patterns (LBP) technique and Enhanced LBP were used to extract features, Chicken Swarm Optimization (CSO) algorithm and Improved CSO were used for feature selection, and the Support Vector Machine (SVM) was used as a classifier. Performance assessment was done by comparing the combination of techniques LBP-CSO, CSO-ELBP, ICSO-LBP, and ICSO-ELBP. Experimental results in terms of recognition time and recognition accuracy were employed, using the KWASU database. The results show that the LBP-CSO has an accuracy of 91.67% at 119.10 seconds, ELBP-CSO has an accuracy of 95.00% at 79.16 seconds, and LBP-ICSO has an accuracy of 96.25% at 105.20 seconds and ELBP-ICSO has an accuracy of 97.92% at 58.37 seconds.*

1. INTRODUCTION

Due to the constant global technology development and the various possibilities for computer use, computer security has become a serious concern in recent years. Cyber dangers are increasing at an alarming rate, coinciding with the increased usage of personal computers and mobile devices online [2]. User authentication, which confirms the identity of the claimed user, is one important approach to accomplishing the needed level of safety. User authentication is a common way to safeguard any information technology system from unwanted user activity [9]. Biometrics refers to a person's unique features, physiological or behavioral features that do not change over time. Fingerprint, iris, palmprint, and face are examples of physiological while behavioral traits include handwritten signature, voice, gait and walking manner of an individual, and keyboard typing style [10]. As the growing emphasis is being paid to security, man-machine communication, content-based image retrieval, and image or video coding, researchers in the biometrics, computer vision, pattern recognition, and cognitive psychology fields have given face recognition a lot of thought [7]. In face recognition, the algorithm chooses a face that looks the most like the required face from the trained faces and uses it as the final answer [13].

The face has several benefits that make it one of the most common biometric traits for determining identity. It is a nonintrusive method, unlike fingerprint or iris images, facial images can be obtained quickly without physical contact, and people are more relaxed when their visage is used as a biometric identifier. Apart from the fact that facial recognition devices can collect data that people accept, administrators can easily monitor and rate people who have been approved after verification based on their facial features [6].

The researchers used a database they constructed expressly for the study to evaluate the performance of dimensionality reduction strategies including standard local binary Patterns, Enhanced Local Binary patterns, Standard Chicken Swarm Optimization, and Improved Chicken Swarm Optimization. The database was given the name KWASU, which stands for "Kwara State University." The performance of LBP-CSO, CSO-ELBP, ICSO-LBP, and ICSO-ELBP computational recognition time and face recognition accuracy were implemented using MATLAB 2016a. As for performance measures, training time, testing time, and classification Index were employed, and the results were examined using column data and cluster column charts graph.

Related Work

i Singh and Kant (2021) introduced Face and Age Recognition (FAR) using the Discrete Wavelet Transform (DWT), the Radial Basis Function Support Vector Machine (RBF-SVM) classifier, and the Rotational Local Binary Pattern (RLBP). The RLBP algorithm was used to pick and extract information from a facial image. The results are implemented using the FG-NET (Face and Gesture Recognition Network) and AT&T datasets. Face recognition has a detection rate of 92–98 percent, and age recognition has a detection rate of 87 percent. When compared to earlier methods, the suggested approach outperforms them and also estimates the value of accuracy [11].

ii. For global optimization, Rosalinda, Thobirin, and Wijayanti (2017) introduced a novel modified Chicken Swarm Optimization (CSO) technique dubbed multi-step CSO. By deleting the parameters roosters, hens, and chicks, the update minimizes the number of steps in the CSO algorithm. Multi-step CSO is more efficient than CSO in solving optimization challenges. Experiments on seven benchmark problems and a speed reduction design were conducted to compare the performance of multi-step CSO with CSO algorithms and other algorithm-based populations such as Cuckoo Search (CS), Differential Evolution (DE), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). According to simulation results, the multi-step CSO method outperforms the others. The advantages of the multi-step CSO method are simplicity, high resilience, fast convergence, and fewer control steps [8].

iii. Ryu and Yeom (2021), offer an enhanced real-time facial recognition system with pose and emotion, and resolution fluctuations at a low resolution of 15 pixels. The datasets LRD200 and LRD100 were used for training and classification. In the face detection part, the Viola-Jones algorithm is used, and in the face recognition part, the face image is received from the face detection part and processed using the Local Binary Pattern Histogram (LBPH) algorithm with Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocessing and face alignment. Using the LRD200 database, which contains 200 photos per individual, the real-time face recognition accuracy was 78.40 percent at 15 pixels and 98.05 percent at 45 pixels. The achieved accuracies are 60.60 percent at 15 pixels and 95 percent at 45 pixels with 100 photos per individual in the database (LRD100). [9]

iv. Sona and Sasirekha (2019) developed a Chicken Swarm Optimization and Naive-Bayes-Based Improved Hybrid Intrusion Detection Mechanism (HCSONB). For the categorization of intrusion data, a hybrid module is created by combining the Chicken Swarm Optimization and Naive Bayes classifier (HCSONB). Since the strategy was developed to be capable of recognizing enormous data in the network, the hybrid method is introduced to detect features efficiently in a complicated dataset. In the case of complicated datasets, certain traditional approaches have significant drawbacks. The properties of the algorithms are given to uncover better optimization outcomes and classification precision values. Using the NSL KDD-99 dataset, the research compares the performance of feature selection using the Swarm Intelligence (SI), Nave-Bayes classifier, and proposed HCSO-NB algorithms. The proposed classification procedure was created using the NETBEANS 8.2 software. Experiments have shown that the proposed HCSO-NB improves accuracy. [3].

Local Binary Patterns

A feature extractor termed Local Binary Pattern was used in this investigation. Local Binary Pattern is a type of visual course used for categorization in computer vision. The Texture Spectrum imitation, which was first proposed in 1990, is exemplified by LBP. In 1994, LBP was first depicted. It has since been discovered to be a significant element in texture classification. Individual photos are evaluated as a structure of micro-patterns using the LBP operator. The LBP histogram is then applied to the face, displaying only the micropatterns' conditions. The documentation figure is created by dividing the face picture into m minor non-overlapping regions, such as R0, R1..., and Rm. The pixels are identified by thresholding the 3 by 3 matrix neighborhoods about the original LBP's center pixel value. The common features, such as edges, lines, and points, can be represented by a value on a numerical scale. As a result, using a set of values derived a priori, it is feasible to distinguish objects in a picture [1]. Equation (1) shows the formula for calculating the LBP feature extractor, which is as follows:

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

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

Algorithm 1: Existing LBP Algorithm (Pseudocode)

Step 1: *Set $\boldsymbol{g_c}$ which corresponds to the gray value of the center pixel*

Step 2: *Set $\boldsymbol{g_n}$ as the gray values of the "n" neighbour pixels*

Step 3: *Set* $S=\begin{Bmatrix} 1, & \text{if } g_c \geq 0 \\ 0, & \text{if } g_c < 0 \end{Bmatrix}$

Step 4: *Compute LBP features as described thus;*

$$\mathrm{LBP}_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} S(g_p - g_c) * 2^p$$

Where x_c and y_c represent the horizontal and vertical component of the image; Sg_p and Sg_c their neighborhood patterns, P represents the bit binary number resulting in 2^P distinct values for the LBP code.

Step 5: *Output selected LBP features*

Chicken Swarm Optimization (CSO)

Meng et al. (2014) [7] suggested chicken swarm optimization as an optimization technique that resembles chicken swarm characteristics. The chicken swarm is divided into various groups. A rooster, hens, and chicks make up each group. Different laws of motion apply to different chickens. The chickens' identities (roosters, hens, and chicks) are determined by the groups. Roosters are the chickens with the highest fitness values. Chicks would be identified as having the lowest fitness levels. The hens live in groups that they choose at random. Chickens follow the rooster in their group in a quest for food. They may hinder those who are unable to eat their meals from doing so. The motion of the chickens is described by equations 2–7. [14].

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

$$\sigma^2 = \begin{cases} 1, & if\ f_i \leq f_k \\ e^{\left(\frac{f_k - f_i}{|f_i| + \varepsilon}\right)}, & otherwise,\ k \in [1, N], k \neq i \end{cases} \quad (3)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times Rand\left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S2 \times Rand(x_{r2,j}^{t} - x_{i,j}^{t}) \quad (4)$$

$$S1 = e^{\left(\frac{f_i - f_{r1}}{|f_i| + \varepsilon}\right)} \quad (5)$$

$$S2 = e^{(f_{r2} - f_i)} \quad (6)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL(x_{m,j}^{t} - x_{i,j}^{t}) \quad (7)$$

Where $rand$ is a uniform random number over $[0, 1]$. $r1 \in [1, \ldots, N]$ is an index of the rooster, which is the i[th] 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 $r1 \neq r2$. the standard CSO algorithm (pseudo code) is shown in algorithm2[7].

Algorithm 2: Standard Chicken Swarm Optimization

Input: Set of initial feature parameters W= $\{w_1, w, \ldots\ w_p\}$
Predefined swarm size: $\boldsymbol{N_c}$
Several dimensions of a chicken: $\boldsymbol{D = q}$
Output: Optimal feature parameters $\{wopt_I, wopt_H, wopt_c\}$

1. Initialize chickens Ck= [RN=CN =MN=HN] $\forall \boldsymbol{i, j}, \boldsymbol{1 \leq i \leq N_c},\ \boldsymbol{1 \leq j \leq D = q}$, number of CHs, G (maximum generation)

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

2. Evaluate the N chickens' fitness values (Ck).
3. t=0;
4. ***While*** (t < G)

i. ***If*** $(\boldsymbol{t\ mod\ G = 0})$ ***a*** Rank the chickens' fitness values and establish a hierarchal order in the swarm;

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

Where $\boldsymbol{x_i^t}$ represent the s at i=1,2, …, n and k=2,3, …, m

Where $\boldsymbol{\Delta\left(W_{i,j}^{m,n}\right)((x_i) - (x_j))}$ 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 the mother hens in a group;

End if

ii For i = 1:N

a ***If*** *i = rooster* Update its solution/location

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

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

Where $\boldsymbol{Randn(0, \sigma^2)}$ is a gaussian distribution with a mean of 0 and standard deviation $\boldsymbol{\sigma^2}$. $\boldsymbol{\varepsilon}$ is used to avoid a zero-division error. *k* is a rooster's index, $\boldsymbol{f}$ which is the fitness value of the corresponding $\boldsymbol{x}$.

End if

b If *i = hen* Update its solution/location using equation (8);

$$\boldsymbol{x_{i,j}^{t+1} = x_{i,j}^t + S1 \times Rand\left(x_{r1,j}^t - x_{i,j}^t\right) + S2 \times Rand(x_{r2,j}^t - x_{i,j}^t)} \quad (8)$$

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

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

End if

c If *i = chick* Update its solution/location $\boldsymbol{x_{i,j}^{t+1} = x_{i,j}^t + FL(x_{m,j}^t - x_{i,j}^t)}$

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

End if

b Evaluate the new solution;

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

End for

End while

2. METHODOLOGY

This study takes these approaches: First, a camera is used to capture multiple facial images into the KWASU database named after Kwara State University. Facial images were preprocessed by converting colour input images to grayscale images, image cropping, noise removal, and histogram equalization for image normalization. Second, with a standard Local Binary Pattern (LBP) and the Chinese Remainder Theorem (CRT), we formulated an Enhanced Local Binary Pattern (ELBP) and utilize it as a feature extraction approach. Finally, for feature selection, an Improved Chicken Swarm Optimization (ICSO) was formulated from standard Chicken Swarm Optimization (CSO), chaotic gauss map, and chaotic tent map functions by introducing it into the rooster and hens update equation of the Chicken Swarm Optimization.

A Support Vector Machine (SVM) was used for classification. Following that, the classification's performance across facial images was enumerated.

Figure 1 depicts the Face Recognition System's Scheme, whereas Figure 2 depicts the Face Recognition Processing System Flow.

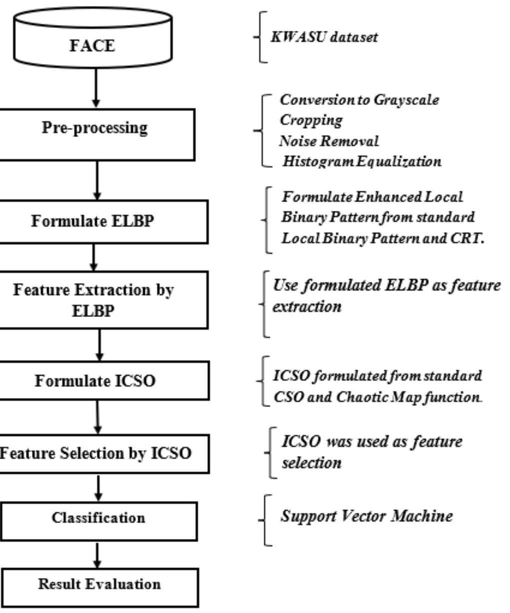

Fig 1. The Scheme of the Face Recognition System

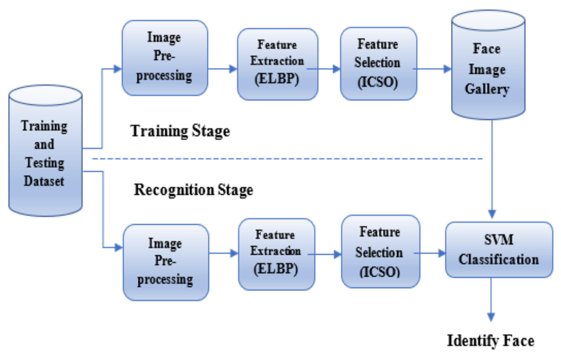

Fig 2. A Process Flow of Face Recognition Processing System.

Database Setup

A database known as the "KWASU database" was created. As indicated in Table 1, it contains 600 facial images of 200 persons, with three images of each object (person). 360 images were utilized for training, while 240 were used for testing. To improve the outcome, geometric normalization is applied to the collected images. All images were histogram stretched, the brightest pixel's intensity was set to 255 and the other pixels' intensities were scaled. To make the images appropriate for the face recognition system, they were transformed into grayscale (2-D). The images were coloured images in three-dimensional form (3-D) that needed to be converted to grayscale (2-D) in order to make them suitable for the face recognition system because the majority of face recognition algorithms require two-dimensional arrays for analysis.

System Design

The LBP-CSO, ELBP-CSO, ICSO-LBP, and ELBP-ICSO algorithms were implemented in MATLAB R2016a. For the implementation, a computer system with an Intel ® CoreTM i7 processor, Windows 10 Professional 64-bit operating system, a 3.0GHz processor, 8GB of random access memory (RAM), and a 500GB hard disk drive. The experiment used a total of 600 facial images, with 360 images used for training and 240 images used for testing, as shown in Table 1 as well as classification, was employed as a performance metric to determine the recognition time and recognition accuracy at the end of the experiment. The system's components include picture acquisition, image pre-processing, feature extraction, feature selection, and recognition accuracy. LBP and ELBP are all-purpose texturing algorithms used in feature extraction, whereas CSO and ICSO are dimensionality reduction techniques used in feature selection. An SVM was employed to categorize the data.

Table 1. Breakdown of images used for the KWASU database

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

Data Acquisition

Facial images were taken with a camera into the KWASU database, which was the setup database. For better output, the captured images were subjected to image preprocessing such as conversion to greyscale, image contrast augmentation, and image cropping. 360 photos were utilized for training, as indicated in table 1. as well as 240 for testing.

Feature Extraction

The process of obtaining relevant information from a facial image is known as feature extraction. This stage's main purpose is to extract the features of the facial photos that were discovered in the dataset. This stage illustrates a face by describing the prominent features of the face image, such as the lips, nose, and eyes, as well as their geometric distribution [15]. To extract features, standard Local binary patterns (LBP) and Enhanced Local binary patterns (ELBP) were used. The Pseudocode in algorithm 3 depicts the Enhanced local binary pattern for the face recognition system.

Algorithm 3: CRT-LBP Algorithm

Step 1: *Set $\boldsymbol{g_c}$ which corresponds to the gray value of the center pixel*

Step 2: *Set $\boldsymbol{g_n}$ as the gray values of the "n" which is one of the neighbor's pixels*

Step 3: *Let $\boldsymbol{g_c}$ and $\boldsymbol{g_n}$ be coprime. The system of equations has a unique solution of $\boldsymbol{x_c}$ modulo $\boldsymbol{g_c g_n}$ where M is 1 or 0 which is one of the horizontal and vertical components of the image.*

$$\boldsymbol{x_c = M\ (mod\ g_c)}$$

$$\boldsymbol{x_n = M\ (mod\ g_n)}$$

The reverse direction is trivial: given $\boldsymbol{x_c \epsilon R_{g_c g_n}}$ the study reduces $\boldsymbol{x_c}$ modulo $\boldsymbol{g_c}$ and $\boldsymbol{x_n}$ modulo $\boldsymbol{g_n}$ to obtain the equation 1 and .2

Step 4: *Let $\boldsymbol{p_1 = {g_c}^{-1}\ (mod\ g_n)}$ and $\boldsymbol{q_1 = {g_n}^{-1}\ (mod\ g_c)}$. These must exist since $\boldsymbol{g_c}$ and $\boldsymbol{g_n}$ are coprime. Then this study claims that if y is an* ***intege****r such that $\boldsymbol{y_c = M g_n q_1 + M g_c p_1\ (mod\ g_c g_n)}$ then $\boldsymbol{y_c}$ satisfied equations 3.1 and 3.2*

For modulo $\boldsymbol{g_c}$, $\boldsymbol{y_c = M g_n q_1 = M\ (mod\ g_c)}$ since $\boldsymbol{g_n q_1 = 1\ (mod\ g_c)}$ Similarly, $\boldsymbol{y_c = M\ (mod\ g_n)}$.

Thus, $\boldsymbol{y_c}$ is a solution for $\boldsymbol{x_c}$

Step 5: *Set* ***S***= $\boldsymbol{\begin{Bmatrix} 1, & if\ g_c \geq 0 \\ 0, & if\ g_c < 0 \end{Bmatrix}}$

Step 6: *Compute LBP features as described thus;*

$$\boldsymbol{LBP_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} S(g_p - g_c) * 2^p}$$

Where x_c and y_c represent the horizontal and vertical component of the image; Sg_p and Sg_c their neighborhood patterns, P represents the bit binary number resulting in 2^p distinct values for the LBP code

Step 7: *Output selected LBP features*

Feature Selection

Feature selection is the act of choosing a subset of features from a larger set, to reduce the dimensionality of the feature space and complete a classification task [4].

CSO and ICSO were used to optimize features in this study.

The basic steps of the ICSO can be summarized by the pseudo-code as in algorithm 4.

Algorithm 4: Improved Chicken Swarm Optimization

Input: Set of initial feature parameters

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

Predefined swarm size: N_c

The 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]
   $\forall i, j, 1 \leq i \leq N_c,\ 1 \leq j \leq D = q$, 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).
3. t=0;
4. ***While*** (t < G)

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

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

b. Feature ***If*** *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

c. ***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

d.Evaluate the new solution;

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

End for

End while

Support Vector Machine

The features chosen by the CSO technique will be classified using the Support Vector Machine (SVM). This method was used to determine the degree of similarity between the test vector and the gallery's reference vectors. Figure 3 is a flowchart depicting SVM Training and Testing.

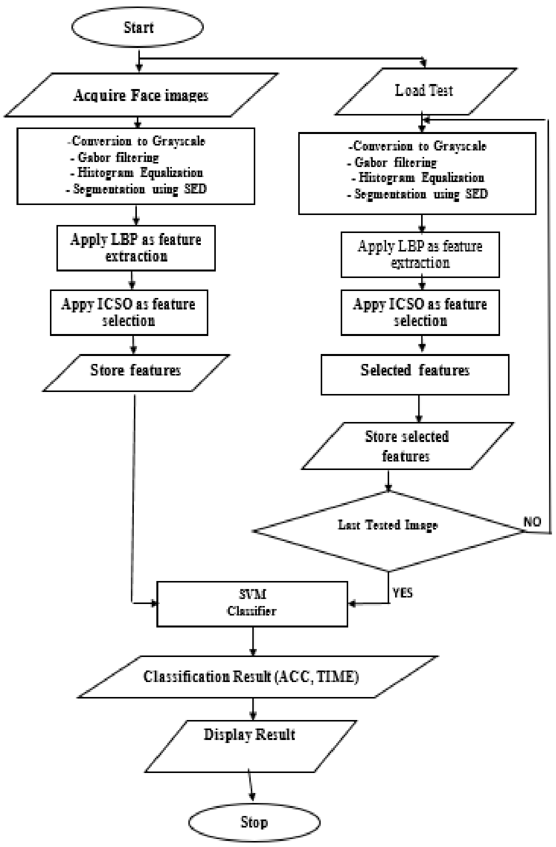

Fig 3. Process Flowchart

The MATLAB 2016a software package was used on a computer system with Intel ® Core™ i7, Windows 10 Professional 64-bit operating system, a processing speed of 3.0GHz, 8GB Random Access Memory (RAM), and 500 GB hard disk drive for the implementation.

Thereafter, the implementation, and the output result will be displayed in figure 4 below,

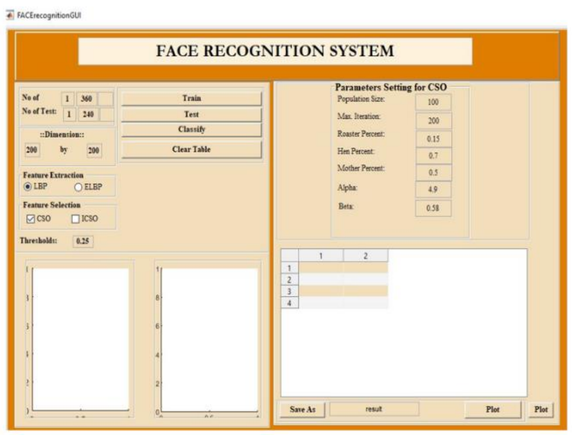

Fig 4. LBP-CSO, ELBP-CSO, LBO-ICSO, and ELBP-ICSO system Implementation.

3. RESULTS

The feature extractors are the LBP and ELBP, the feature selectors are the CSO and ICSO, and the classifier is the SVM with 0.25, 0.40, 0.60, and 0.80 thresholds. For classification, the CSO-LBP, CSO-ELBP, ICSO-LBP, and ICSO-ELBP were employed.

The experimental findings showed that the created technique ICSO-ELBP had a progressive increase in face recognition accuracy and lower recognition time on each threshold than ICSO-LBP, CSO-ELBP, and CSO-LBP. Furthermore, when comparing ICSO-LBP with CSO-ELBP and CSO-LBP, the combination of ICSO-LBP demonstrated higher accuracy in face recognition than CSO-ELBP and CSO-LBP.

The created technique CSO-ELBP, on the other hand, took less time to recognize faces than CSO-LBP and ICSO-LBP. Tables 2, 3, 4, and 5 show the results of the LBP-CSO, ELBP-CSO, LBP-ICSO, and ELBP-ICSO approaches in terms of accuracy and recognition time using face biometric features. The accuracy is represented as a percentage and the time is expressed in seconds.

The cluster column graph in fig. 5 depicts the performance response of CSO-LBP, ICSO-LBP, CSO-ELBP, and ICSO-ELBP approaches based on recognition accuracy. The y-axis shows the percentage of facial recognition accuracy, while the x-axis shows the threshold values. In a cluster column chart graph, Figure 6 shows the performance response of CSO-LBP, ICSO-LBP, CSO-ELBP, and ICSO-ELBP techniques based on Recognition Time.

Result of LBP-CSO

Table 2 shows the performance of the LBP-CSO based on biometric facial features. 240 datasets were used in the testing.

The findings show how well the techniques performed at 0.25, 0.40, 0.60, and 0.80 as threshold values.

The face recognition accuracy for the CSO-LBP technique was 91.67 percent at 119.10 seconds with a Threshold value of 0.80

Table 2: Result of CSO-LBP

Threshold		ACC (%)	Time (sec)
0.25		90	119.54
0.40		90.42	116.14
0.60		90.83	119.47
0.80		91.67	119.10

Result of ELBP- CSO

Table 3 shows the performance of the CSO-ELBP based on facial biometric features. The performance of the technique investigated in this study was evaluated at threshold values of 0.25, 0.40, 0.60, and 0.80. According to the data, the CSO-ELBP technique achieved 95.00 percent accuracy in 79.16 seconds at a threshold value of 0.80 and higher

Table 3: Result of CSO-ELBP

Threshold	ACC (%)	Time (sec)
0.25	93.33	75.76
0.40.	95.75	74.82
0.60	94.17	76.36
0.80	95.00	79.16

Result of LBP-ICSO

Table 4 shows the performance of the ICSO-LBP based on facial biometric features. The performance of the technique investigated in this study was evaluated at threshold values of 0.25, 0.40, 0.60, and 0.80. When the threshold value was 0.80 and above, the ICSO-LBP technique had an accuracy of 96.25 percent at 105.20 seconds.

Table 4: Result of ICSO-LBP

Threshold	ACC (%)	Time (sec)
0.25	94.17	106.67
0.40	95.00	106.70
0.60	95.83	106.69
0.80	96.25	105.20

Result of ELBP with ICSO

Table 5 shows the performance of the ICSO-ELBP based on facial biometric features. Similarly, the act of the technique tested in this study was graded at a threshold value of 0.25, 0.40, 0.60, and 0.80. Table 5 demonstrates that the ICSO-ELBP technique achieved 97.92 percent accuracy in 58.37 seconds at a threshold value of 0.80 and higher.

Table 5: Result of ICSO-ELBP

Threshold	ACC (%)	Time (sec)
0.25	95.83	60.95
0.40	96.67	61.50
0.60	67.50	63.95
0.80	97.92	58.37

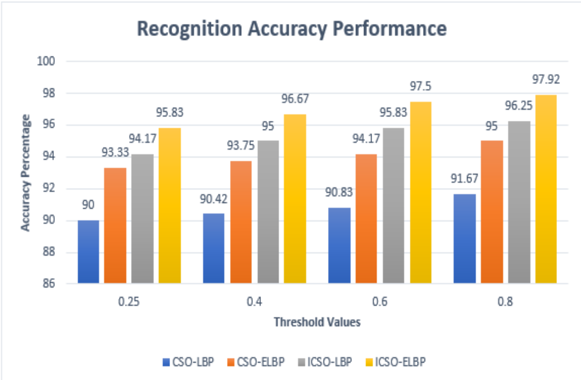

Fig. 5. Performance recognition response of CSO-LBP, CSO-ELBP, ICSO-LBP, and ICSO-ELBP technique based on recognition accuracy.

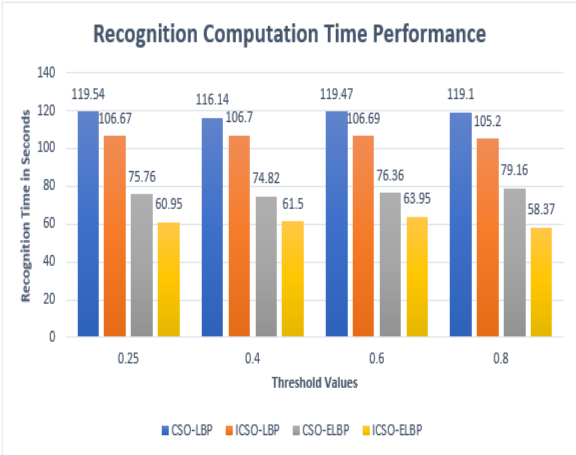

Fig. 6: Performance recognition response of CSO-LBP, ICSO, CSO-ELBP, and ICSO-ELBP technique based on recognition time.

4. CONCLUSION

There was a brief overview of biometric and face recognition techniques offered. The performance of CSO-LBP, CSO-ELBP, ICSO-LBP, and ICSO-ELBP recognition time and accuracy are evaluated in this study. Experimental results indicated that the LBP-CSO has an accuracy of 91.67% at 119.10 seconds, ELBP-CSO has an accuracy of 95.00% at 79.16 seconds, and LBP-ICSO has an accuracy of 96.25% at 105.20 seconds and ELBP-ICSO has an accuracy of 97.92% at 58.37 seconds.

The trial results in Tables 2, 3, 4, and 5 demonstrated that the created ICSO-ELBP and ICSO-LBP approaches performed better in terms of accuracy than the CSO-ELBP and CSO-LBP techniques. The better performance achieved in this study justifies the modification of the standard CSO by introducing the chaotic map function into the standard CSO update equation. Furthermore, when compared to CSO-LBP and ICSO-LBP, the experimental findings demonstrated that the created techniques CSO-ELBP and ICSO-ELBP took less time to recognize. This proved that the time complexity of CSO-ELBP and ICSO-ELBP was lower than that of CSO-LBP and ICSO-LBP. The introduction of the Chinese Remainder Theorem (CRT) strategy in the standard LBP improved the sequential operation of LBP with parallelism (simultaneous) nonmodular thresholding of central pixels with adjacent pixels, resulting in a reduction in recognition time.

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