MULTI-INSTANCE IRIS BIOMETRIC AUTHENTICATION SYSTEM BASED ON CULTURAL CHICKEN SWARM OPTIMIZATION TECHNIQUE

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[1]Jonathan Ponmile Oguntoye, [2]Oluyinka Titilayo Adedeji, [3]Oluwaseun Modupe Alade, [4*]Abisola Ayomide Olayiwola, [5]Elijah Olusayo Omidiora, [6]Abigael Bola Adetunji

[1,5] Department of Computer Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[2]Department of Information Systems, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[3]Department of Cyber Security, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[4*]Department of Computer Engineering, Olabisi Onabanjo University, Ago-Iwoye, Nigeria.
[6]Department of Computer Science, Ladoke Akintola University f Technology, Ogbomoso, Nigeria.
Corresponding author**:** olayiwola.abisola@oouagoiwoye.edu.ng,

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Abstract: Iris-based biometric systems have gained importance for secure access control. However, the need for improved accuracy and efficiency remains a challenge. This research addresses these challenges by leveraging the Cultural Chicken Swarm Optimization technique (CCSO), which integrates a belief space for enhanced feature selection, optimizing both accuracy and computational efficiency. A total of 240 students from Ladoke Akintola University of Technology participated in the data collection process, with left and right iris images captured using a CMITech iris camera. The data underwent preprocessing, followed by feature extraction using the Haar Wavelet-Based Technique. CCSO was applied for feature selection, optimizing the discriminative power of the features. The optimized features from both irises were fused, and matching scores were computed using Mahalanobis distance to classify users as genuine or impostors. The experimental results demonstrate that the CCSO technique outperforms the standard Chicken Swarm Optimization (CSO) in both accuracy and computational efficiency. For the left iris, CCSO achieved a 23.33% FAR, 9.44% FRR, and 87.08% accuracy, while for the right iris, it achieved a 21.67% FAR, 8.89% FRR, and 87.92% accuracy, significantly improving upon CSO. For the multi-instance dataset, CCSO further improved accuracy to 96.25%, reducing the FAR and FRR to 5.00% and 3.33%, respectively, while cutting computation time by nearly 35.00%. CCSO also reduced the Equal Error Rate (EER) to 4.17%, as opposed to CSO's 7.50%. These results highlight the potential of CCSO in real-time biometric systems, and future research will explore its application to other biometric modalities and larger datasets.

Keywords: Access control, Biometric system, Chicken Swarm Optimization, Cultural Algorithm, Cultural Chicken Swarm Optimization, Multi-instance iris authentication

Introduction

Iris biometrics, one of the most accurate and secure biometric modalities, has become a cornerstone of modern authentication systems due to its high uniqueness and stability over time. The human iris contains rich texture patterns that remain unchanged throughout a person's lifetime, making it ideal for secure identification (Daugman, 2004). Compared to other biometric traits like fingerprints or facial recognition, the iris is less affected by aging or environmental factors, making it more reliable for long-term use (Bowyer et al., 2008). This makes iris-based systems particularly valuable in security-sensitive applications such as border control, military installations, and access control systems (Olayiwola et al., 2024). However, as these systems evolve, the need for enhanced performance, particularly in terms of accuracy, robustness, and computational efficiency, continues to grow.

Optimization techniques are critical for improving the performance of biometric systems, particularly in feature extraction, matching, and decision-making processes (Ola et al., 2020; Adedeji et al., 2021; Oguntoye et al., 2023). The Chicken Swarm Optimization (CSO) algorithm, which mimics the hierarchical behaviour of chickens, has been explored for its efficiency in solving complex optimization problems, including biometric recognition tasks (Meng et al., 2014). Despite its promising results, CSO suffers from limitations such as premature convergence and trapping in local optima, which can degrade its performance, particularly in high-dimensional spaces (Shi et al., 2016). To address these challenges, the Cultural Chicken Swarm Optimization (CCSO) technique has emerged as an extension of CSO. CCSO integrates cultural evolution concepts to enhance global search capabilities and avoid the common pitfalls of premature convergence, making it a more robust and effective optimization method for biometric applications (Zhang et al., 2017).

Current biometric systems, particularly those relying on single-instance models, face limitations in handling noisy data, susceptibility to spoofing, and reduced accuracy in challenging environments (Adedeji et al., 2021b; Kadhim and Abdulameer, 2024). Single-instance models depend on data from a single source (e.g., one iris), making them vulnerable to inconsistencies or partial obstructions. To overcome these issues, multi-instance iris recognition has been proposed, where both left and right iris images are used to enhance the robustness of the authentication system.

The primary objective of this study is to investigate the effectiveness of the Cultural Chicken Swarm Optimization (CCSO) technique in comparison to the standard CSO algorithm for multi-instance iris biometric authentication.

CSO Algorithm and Its Applications

The Chicken Swarm Optimization (CSO) algorithm, developed by Meng et al. (2014), is inspired by the natural behaviours of chickens, particularly their social hierarchy and interaction dynamics. In CSO, chickens are categorized into groups, such as roosters, hens, and chicks, with each group exhibiting different behaviours that guide the search for optimal solutions. Roosters represent the most competitive individuals, while hens and chicks follow their strategies but also perform independent explorations. This social dynamic allows the algorithm to balance between exploration and exploitation in complex search spaces.

In iris biometric systems, the CSO algorithm can enhance the accuracy of recognition by optimizing the selection of discriminative iris features. However, despite its effectiveness, CSO suffers from premature convergence, where the algorithm stagnates in local optima, especially when dealing with high-dimensional and multimodal problems. This limitation necessitates further refinements to enhance its performance in complex tasks like multi-instance iris recognition (Zhang et al., 2017).

Cultural Algorithms (CAs)

Cultural Algorithms (CAs), introduced by Reynolds (1994), add a layer of sophistication to traditional optimization techniques by incorporating the concept of cultural evolution. Unlike other algorithms that rely solely on population dynamics, CAs maintain a knowledge base that influences the search process over time. This knowledge base, known as the "belief space," stores successful strategies and solutions from previous iterations, which are then used to guide future searches.

The integration of CAs with CSO, resulting in the Cultural Chicken Swarm Optimization (CCSO) technique, introduces a mechanism to mitigate the premature convergence problem in CSO. The CCSO algorithm utilises a belief space to enhance global exploration capabilities, mitigating the risk of premature convergence to local optima and thereby improving overall optimization performance. This makes it particularly suitable for complex biometric tasks, such as multi-instance iris recognition, where the search space is vast, and optimal solutions are difficult to find using traditional methods. In the context of this study, the CCSO technique will be employed to optimize the multi-instance iris biometric system. This study aims to demonstrate that CCSO outperforms the traditional CSO in multi-instance biometric applications, thus contributing to the enhancement of biometric authentication systems.

Various studies have shown that using multiple instances within a biometric modality, such as the left and right irises, can significantly enhance performance when compared to single-instance systems.

Wang, Yao, and Han (2008) introduced a method to enhance iris recognition performance by fusing multiple instances at the score level. They proposed combining left and right iris images using the Minimax Probability Machine (MPM) to generate a more reliable decision score, leading to better verification accuracy. Their experiments on the CASIA and UBIRIS databases demonstrated that this multi-instance fusion approach significantly outperformed single-instance methods, highlighting the effectiveness of MPM in improving system robustness. Building on this, Bharadi et al. (2018) presented the Webber Local Descriptor (WLD) as a new method for feature extraction in multi-instance iris recognition. Their approach focused on capturing texture information from both irises, showing that a multi-instance system improved performance by 6.44%, with an 88.39% Equal Error Rate (EER). This study reinforced the benefits of multi-instance approaches, particularly when using advanced feature extraction methods like WLD, which significantly outperformed single-instance systems. Tibo, Jaeger, and Frasconi (2020) introduced a theoretical framework called multi-multi-instance learning, allowing for nested bags of instances. While their research centered on text and image classification, the principles are applicable to multi-instance iris recognition, as the model can aggregate and interpret data across multiple levels. This framework provides a foundation for improving multi-instance biometric systems by enabling more comprehensive data interpretation. Podder and Mondal (2022) developed the LBPX feature extraction method, a rotation-invariant extension of the Local Binary Pattern (LBP). When applied to multi-instance iris recognition, LBPX achieved over 96% accuracy across several datasets, demonstrating superior performance in both accuracy and feature vector length reduction. The method’s ability to reduce feature length leads to faster recognition, critical in real-time applications, and highlights the importance of efficient feature extraction techniques in multi-instance systems.

Piugie (2023) explored a time-series-based approach to biometric data processing, transforming raw data into 2D images for deep learning applications. This method has the potential to enhance feature extraction and performance in multi-instance iris recognition, while addressing security concerns like adversarial attacks, which are crucial in biometric systems. Kadhim and Abdulameer (2024) addressed the limitations of unimodal biometric systems by proposing a multimodal system combining face, palmprint, and iris features. They achieved up to 99.88% accuracy, surpassing unimodal systems and underscoring the benefits of combining multiple biometric features. Although their focus was on multimodal biometrics, the integration of multi-instance data in iris recognition can offer similar improvements in accuracy and robustness. The reviewed studies collectively emphasize the superiority of multi-instance iris recognition systems over single-instance models.

Methodology

The implementation of the Cultural Chicken Swarm Optimization (CCSO) technique for an iris-based multi-instance biometric access control system involves several critical steps. First, left and right iris datasets are acquired, forming the foundation for the multi-instance approach. The acquired data undergoes pre-processing, which involves cleaning and normalizing the iris images to enhance the quality and consistency of the dataset. Following pre-processing, the Haar Wavelet-Based Technique is utilized for feature extraction. This method effectively captures significant patterns and details from both the left and right iris images. After feature extraction, the Cultural Chicken Swarm Optimization (CCSO) technique is applied for feature selection, optimizing the process by using a belief space to guide the swarm's search for the most discriminative features. The next step involves fusing the optimized features from both the left and right iris images. This fusion process ensures that the most relevant information from both irises is combined to enhance the overall performance of the biometric system. A matching score is then generated using Mahalanobis distance, a statistical measure that evaluates the similarity between the optimized fused features and stored biometric templates. Finally, based on the generated matching score, the system classifies the subject as either a genuine user or an impostor.

Acquisition of Iris Images

A total of 240 students from LAUTECH participated in the iris data collection process using a CMITech iris camera. For each subject, three images of both the left and right irises were captured, resulting in stored biometric data. However, due to capture inconsistencies, only 200 subjects' irises were deemed suitable for analysis. As a result, a dataset of 600 iris images was utilized for training and evaluation. The training phase employed 360 iris images, while 240 images were reserved for testing the technique.

Pre-processing of Iris Images

Segmentation, normalization, and enhancement were applied to process the captured iris images. The segmentation step aimed to eliminate irrelevant information, specifically the pupil and external areas such as the sclera, eyelids, and skin. This involved estimating the iris boundary. Initially, the iris images were processed using the Canny edge detection algorithm to generate an edge map. This edge map was then utilized to accurately determine the boundaries of the pupil and iris using Hough transforms. Horizontal segmentation operators, along with image binarization, were employed to extract eyelid edge details. The eyelid boundaries were modelled using parabolic curves based on the identified edge points. In the normalization phase, the polar coordinates of the iris were transformed into Cartesian coordinates, resulting in a rectangular strip using Daugman's rubber sheet model. This homogenous model remapped each point within the iris region into a set of polar coordinates (r, θ), where r lies between [0, 1] and θ between [0, 2π]. The remapping of the iris from Cartesian (x, y) coordinates to normalized non-concentric polar coordinates is mathematically represented in Equations 1, 2, and 3.

$$\mathrm{I}\big(\mathrm{x}(\mathrm{r},\theta),\mathrm{y}(\mathrm{r},\theta)\big) \rightarrow \mathrm{I}(\mathrm{r},\theta) \quad 1$$

$$\mathrm{X}(\mathrm{r},\theta) = (1-\mathrm{r})\mathrm{x_i}(\theta) + \mathrm{r.x_0} + \cos\theta\,.\big(\mathrm{r_i} + \mathrm{r.}(\mathrm{r_0}-\mathrm{r_i})\big) \quad 2$$

$$\mathrm{Y}(\mathrm{r},\theta) = (1-\mathrm{r})\mathrm{y_i}(\theta) + \mathrm{r.y_0} + \sin\theta.\big(\mathrm{r_i} + \mathrm{r.}(\mathrm{r_0}-\mathrm{r_i})\big) \quad 3$$

In this model, $\mathrm{I}(\mathrm{x},\mathrm{y})$ represents the iris region, where (x,y) are the original Cartesian coordinates, and (r,θ) are the normalized polar coordinates along the angular θ direction. The rubber sheet model accounts for variations in pupil dilation and size, generating a consistent, normalized iris representation with fixed dimensions. After normalization, histogram equalization is applied to enhance the image quality.

Haar Wavelet-Based Technique for Feature Extraction

The Haar wavelet-based approach was utilized on the pre-processed irises dataset for feature extraction. This method employs wavelet transformation, a decomposition technique that generates multiple resolutions of the image, starting from a high-resolution version to lower-resolution approximations. The multilevel 2-D wavelet decomposition produces four sub-images: LH, HL, and HH represent detail images in the horizontal, vertical, and diagonal directions, respectively, while LL is the approximation image.

A two-level decomposition was performed to reduce the dimensionality of the image matrix, which resulted in the image size being reduced to one-quarter of its original size. The approximation coefficient (LL), which retains most of the essential image information, was extracted after each level of decomposition, following the same process as the original image. The output from the Haar wavelet-based method was then transformed into a feature vector, which served as input for the classification modules across all biometric systems examined in this study. The MATLAB code to perform the 2-D Haar wavelet decomposition is as follows:

```
[cA, cH, cV, cD] = dwt2(image, 'haar');
```

This command decomposes the input image into approximation (cA), horizontal detail (cH), vertical detail (cV), and diagonal detail (cD) coefficients, implementing the Haar wavelet transformation.

Normalization of Features Using Min-Max Technique

The features extracted from both the left and right iris using the Haar wavelet method were found to be heterogeneous in scale. To address this, the Min-max normalization technique was employed to standardize the iris feature sets, denoted as F_{Iris}. This method preserves the relative distribution of the features while transforming them into a consistent range. By mapping the raw biometric features onto the interval [0, 1], the Min-max normalization ensures that the variability in feature values is appropriately scaled without altering their original distribution. The normalization process for the biometric traits is expressed mathematically in Equation 4.

$$F'_{Iris} = \frac{F_{Iris} - min\,(F_{Iris})}{max\,(F_{Iris}) - min\,(F_{Iris})} \quad 4$$

Feature Selection using Cultural Chicken Swarm Optimization

The Chicken Swarm Optimization (CSO) algorithm is recognized for its effectiveness in tackling complex optimization challenges. Despite its strengths, CSO often encounters issues with convergence and accuracy, particularly in high-dimensional problems. These challenges stem from a loss of diversity during the exploration of the solution space, which can impede the algorithm's performance. To address these limitations, the Cultural Chicken Swarm Optimization (CCSO) technique integrates a cultural algorithm framework, which incorporates a belief space, acceptance function, and influence function into the iterative search process. This integration enhances the algorithm's ability to converge and improves its precision by maintaining diversity and refining the search mechanism. The CCSO technique, therefore, represents an advancement in optimization methodologies, providing a more robust approach to complex problem-solving. The implementation of the Cultural Chicken Swarm Optimization (CCSO) technique for enhancing biometric access control follows these steps:

1. ***Initialization***: Begin by initializing the chicken swarm parameters: $\boldsymbol{x_i}$ (the positions of chickens), and parameters **N** (total chickens), I_r (maximum iterations), **G** (hierarchical change frequency), $\boldsymbol{R_N}$ (number of roosters), $\boldsymbol{H_N}$ (number of hens), $\boldsymbol{C_N}$ (number of chicks), and $\boldsymbol{M_N}$ (number of mothers).
2. ***Creation of Belief Space***: Initialize the belief space $\boldsymbol{B_s}$ as an empty set.
3. ***Fitness Evaluation***: Evaluate the fitness values of the chicken swarm $\boldsymbol{x_i}$, initializing personal best p_{best} and global best g_{best} positions. Set iteration counter t = 1.
4. ***Hierarchical Update***: When $t\ mod\ G = 1$, sort the fitness values and establish the hierarchical order within the swarm. Divide the swarm into subgroups and model the relationships among hens and chicks.
5. ***Position Update***:

   5.1 Roosters: Update positions using Equation 5:

$$x_{i,j}(t+1) = x_{i,j}(t) * \big(1 + Randn(0,\sigma^2)\big) \quad 5.$$

where σ^2 is determined by the fitness values of the roosters (Equation 6).

$$\sigma^2 = \begin{cases} 1 & if\ f_i < f_k \\ exp\left(\dfrac{f_k - f_i}{|f_i| + \epsilon}\right) & otherwise, k \neq i \end{cases} \quad 6.$$

Hens: Update positions according to Equation 7:

$$x_{i,j}(t+1) = x_{i,j}(t) + s1 * Rand1 * \left(x_{r1,j}(t) - x_{i,j}(t)\right) + s2 * Rand2 * \left(x_{r2,j}(t) - x_{i,j}(t)\right) \quad 7.$$

where $S1$ and $S2$ are computed from the fitness differences as follows.

$$S1 = exp\left(\frac{f_i - f_{r1}}{|f_i| + \in}\right)$$

$$S2 = \exp(f_{r2} - f_i)$$

Chicks: Update positions using Equation 8:

$$x_{i,j}(t+1) = x_{i,j}(t) + FL * \left(x_{m,j}(t) - x_{i,j}(t)\right) \quad 8.$$

where FL is a random factor in [0,2].

Belief Space Adjustment: Use the acceptance function to adjust the belief space B_s.

$$N_{accepted} = n\% \times N + \frac{n\%}{t} \times N \quad 9.$$

Where n% is a parameter that is set by the user, N is the number of chickens, and t represents the th generation.

$$NB_s = [l_w, u_p] = \{x_i | l_w \le p \le u_p, x \in 3i\} \quad 10$$

Update bounds l_w and u_p using Equations 11.

$$l_w = \begin{cases} x_i & if\ x_i \le l_w \\ l_w, & otherwise \end{cases}$$

$$u_p = \begin{cases} x_{i,} & \text{if } x_i \ge u_p \\ u_p, & \text{otherwise} \end{cases} \quad 11$$

Influence Function: Apply the influence function to adjust chicken positions and avoid local optima:

$$x_i(t) = \begin{cases} x_i(t) + \left|\text{Rand}() \times (u_p - l_w)\right| & \text{if } x_i < l_w \\ x_i(t) - \left|\text{Rand}() \times (u_p - l_w)\right| & \text{if } x_i > u_p \end{cases} \quad 12$$

Best Solution Update: Update the individual best fitness (p_{best}) and the global best ($\mathrm{g_{best}}$) based on fitness comparisons as shown in (Equation 13).

$$x_i(t) = \begin{cases} x_i(t-1), & f(x_i(t)) > f(x_i(t-1)), \\ x_i(t), & f(x_i(t)) \le f(x_i(t-1)). \end{cases} \quad 13$$

Iteration: If $\mathbf{t} < \mathbf{Ir}$, return to Step 4. Otherwise, terminate and output the global best solution.

Parameter Selection: Identify the optimal parameters from the global best position $\mathrm{x_i(t)}$, and determine the optimized feature set $\mathrm{F_i(t)}$ as in (Equation 14).

$$F_i(t) = G_{Best}(x_i(t)) \quad 14$$

Fusion of optimal features

The optimum features generated by CCSO from the normalized right iris ($\mathrm{F'_{irisR}}$) and left iris ($\mathrm{F'_{irisL}}$) features were fused using the serial rule as shown in Equation 15

$$\mathrm{F_{fused}} = \left\{ \mathrm{F^{\varphi'}_{irisR}(t), F^{\varphi'}_{irisL}(t)} \right\} \quad 15.$$

where $\mathrm{F^{\varphi'}_{irisR}(t)}$ and $\mathrm{F^{\varphi'}_{irisL}(t)}$ are the optimal normalized right and left iris features respectively.

The Matching Modules

In the matching phase, the optimized fused feature set is compared against the fused stored templates by employing a matching algorithm to compute the optimized matching scores. Specifically, the Mahalanobis distance is utilized to generate these scores, ensuring a robust comparison by considering the variance within the dataset. The matcher evaluates the similarity between the extracted features and the database template, producing corresponding matching scores. This process is mathematically represented in Equation 16

$$\mathrm{S_g(x,y)^2 = (x-y)'S^{-1}(x-y)} \quad 16.$$

where $\mathrm{S_g}$ represents the within-group covariance matrix. The vector with the minimum distance is identified as the most similar match.

Decision module

The matching score of the fused optimized features was used to identify a user as either genuine or an impostor. The matching score $\mathrm{S_{fused}}$ was compared to a pre-specified threshold (th). If $\mathrm{S_{fused}} >$ th, then the user was identified to be genuine otherwise, be identified as an impostor. The decision function defined in Equation 17 verified the identity of users.

$$\mathrm{Decision(S_{fused})} = \begin{cases} \text{Accept (Genuine)}, & \text{if } \mathrm{S_{fus}} > \text{th} \\ \text{Reject(Impostor)}, & \text{otherwise} \end{cases} \quad 17.$$

Implementation and Evaluation Measure

The research was conducted using MATLAB version 9.4 (R2018a) on a Hewlett-Packard G56 system, equipped with an Intel® Core™ i5 dual-core processor running at 2.7 GHz, 6 GB of RAM, and a 1 TB hard drive, operating on a 64-bit Windows 10 Professional platform. The software environment facilitated the seamless implementation and testing of the developed algorithms. The performance of the evaluated biometric systems was assessed through key metrics, including False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and recognition accuracy. To derive these metrics, a confusion matrix was employed, capturing the system's outcomes in terms of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN). These values were instrumental in calculating the system's overall performance, ensuring a thorough analysis of its effectiveness and reliability, as detailed in Equation 18, 19 and 20.

$$\text{FAR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad 18.$$

$$\text{FRR} = \frac{\text{FN}}{\text{FN} + \text{TP}} \quad 19.$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{FN} + \text{TP} + \text{TN}} \quad 20.$$

Results and Discussion

The analysis of the performance of the developed Cultural Chicken Swarm Optimization (CCSO) technique in comparison to the standard Chicken Swarm Optimization (CSO) technique for multi-instance iris recognition is presented. The evaluation was carried out using both left and right iris biometric data. The standard CSO is a parametric method, with its performance heavily dependent on parameter settings, particularly the FL parameter, which is crucial in determining its effectiveness. To ensure a fair comparison, both the CCSO and CSO techniques were evaluated with an FL value of 0.4, following the recommendations of prior studies by Meng et al. (2014) and Deb et al. (2020), which demonstrated that FL ∈ [0.4, 1] yields optimal results for many optimization problems. Empirical evidence further supports this choice. Table 1, 2 and 3 depicts the contingency table for the performance of CSO and CCSO technique for right iris, left iris and multi-instance iris recognition.

The results in Table 1 and Table 2 present contingency tables for the performance of the CCSO and CSO techniques based on a confusion matrix for right and left iris data, respectively. The dataset comprises 240 instances for each iris (180 genuine and 60 imposters).

Table 1: Contingency table for performance of CSO and CCSO Technique for Right Iris

Techniques		CSO		CCSO	
		Predicted Class		Predicted Class	
		Genuine	Imposter	Genuine	Imposter
Actual Class	Genuine (180)	161 (TP)	19 (FN)	164 (TP)	16 (FN)
	Imposter (60)	16 (FP)	44 (TN)	13 (FP)	47 (TN)

Table 2: Contingency table for performance of CSO and CCSO Technique for Left Iris

Techniques		CSO		CCSO	
		Predicted Class		Predicted Class	
		Genuine	Imposter	Genuine	Imposter
Actual Class	Genuine (180)	160 (TP)	20 (FN)	163 (TP)	17 (FN)
	Imposter (60)	17 (FP)	43 (TN)	14 (FP)	46 (TN)

Table 3: Contingency table for performance of CSO and CCSO Technique for Multi-instance Iris

Techniques		CSO		CCSO	
		Predicted Class		Predicted Class	
		Genuine	Imposter	Genuine	Imposter
Actual Class	Genuine (180)	171 (TP)	9 (FN)	174 (TP)	6 (FN)
	Imposter (60)	6 (FP)	54 (TN)	3 (FP)	57 (TN)

For right iris data, Table 1 shows that with the CCSO technique, 164 genuine instances were correctly classified, while 16 were misclassified as imposters. Additionally, 47 imposter instances were accurately identified, with 13 misclassified as genuine. Using the CSO technique, 161 genuine instances were correctly classified, while 19 were misclassified as imposters. Moreover, 44 imposter instances were correctly identified, with 16 misclassified as genuine. Similarly, Table 2 reports left iris performance. With CCSO, 163 genuine instances were accurately classified, and 17 were misclassified. Of the imposter instances, 46 were correctly identified, and 14 were misclassified. Using CSO, 160 genuine instances were correctly classified, while 20 were misclassified as imposters. 43 imposter instances were correctly identified, while 17 were misclassified. In Table 3, multi-instance iris performance is summarized. Using CCSO, 174 genuine instances were correctly classified, while 6 were misclassified. Among imposter instances, 57 were accurately classified, with 3 misclassified. For CSO, 171 genuine instances were correctly classified, while 9 were misclassified. Furthermore, 54 imposter instances were correctly identified, and 6 were misclassified. These results suggest the CCSO technique generally outperforms the standard CSO technique across all datasets.

The results in Table 4 demonstrate the performance of the CSO and CCSO techniques at FL value of 0.4 for the iris biometric datasets**.** For the left iris, the CSO technique achieved a FAR of 28.33%, FRR of 11.11%, and an accuracy of 84.58% with a computation time of 163.94 seconds. In comparison, the CCSO technique yielded better results with a FAR of 23.33%, FRR of 9.44%, and accuracy of 87.08%, while also reducing computation time to 135.19 seconds.

Table 4: Performance of the CSO and CCSO Technique at FL=0.4

Dataset	Technique	FAR (%)	FRR (%)	Accuracy (%)	Time (sec)
Left Iris	CSO	28.33	11.11	84.58	163.94
	CCSO	23.33	9.44	87.08	135.19
Right Iris	CSO	26.67	10.56	85.42	159.11
	CCSO	21.67	8.89	87.92	122.61
Multi-instance Iris	CSO	10.00	5.00	93.75	322.63
	CCSO	5.00	3.33	96.25	207.68

For the right iris, the CSO technique recorded a FAR of 26.67%, FRR of 10.56%, and an accuracy of 85.42%, taking 159.11 seconds. The CCSO technique improved upon these results, achieving a FAR of 21.67%, FRR of 8.89%, and accuracy of 87.92%, with a reduced time of 122.61 seconds. For the multi-instance iris dataset, the CSO technique achieved a FAR of 10.00%, FRR of 5.00%, and an accuracy of 93.75% with a time of 322.63 seconds. The CCSO technique outperformed CSO by achieving a FAR of 5.00%, FRR of 3.33%, and an accuracy of 96.25%, with a much faster computation time of 207.68 seconds. These results indicate that the CCSO technique consistently outperforms the CSO technique in terms of FAR, FRR, accuracy, and computational efficiency across all datasets. In view of the performance with the iris biometrics, it was revealed that the CCSO technique achieved improved performance with lower FAR, FRR, and recognition time, along with higher recognition accuracy compared to the standard CSO. In this study, the multi-instance iris biometric outperformed single-instance left or right iris biometric, demonstrating superior accuracy. However, the multi-instance iris biometric had a higher recognition time due to the increased complexity of features in both the training and testing sets. This highlights the balance between accuracy and computational efficiency when utilizing multi-instance biometric systems. Figure 1 illustrates the FAR (False Acceptance Rate) and FRR (False Rejection Rate) for both the CSO and CCSO techniques across varying FL values.

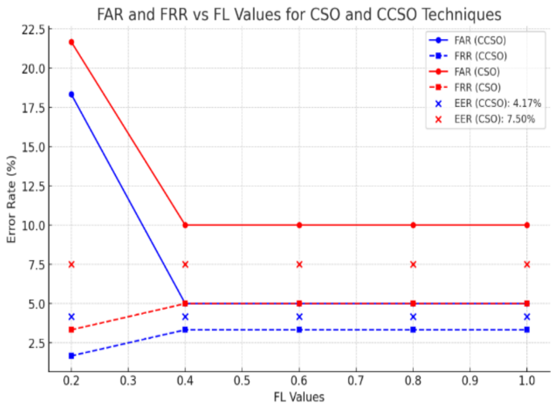

Figure 1: The graph of FAR and FRR against the FL values

The Equal Error Rate (EER), representing the point where FAR and FRR converge, is a key performance metric. In this analysis, the CSO technique records an EER of 7.5%, while the CCSO technique achieves a significantly lower

EER of 4.165% for multi-instance iris biometric authentication. These EER values suggest that the CCSO technique outperforms the CSO approach, indicating superior accuracy and overall effectiveness for multi-instance biometric systems.

The experimental results of this study evaluated the performance of CSO and CCSO techniques in terms of recognition time, accuracy, FAR, and FRR for multi-instance iris biometric authentication. Both techniques showed optimal performance at an FL value of 0.4, aligning with the findings of Meng et al. (2014) and Deb et al. (2020), which indicated that FL ∈ [0.4, 1] yields optimal results. Beyond this threshold, no further improvement in performance was noted. However, CCSO consistently outperformed the standard CSO, validating the effectiveness of integrating cultural algorithm operators into the CCSO technique. This enhancement balanced exploration and exploitation stages, significantly reducing recognition time and improving accuracy. The study demonstrated that the CCSO technique achieved better recognition accuracy, lower FAR, and reduced EER compared to the CSO, exceeding the 80% accuracy benchmark established by Phillips et al. (1998). The reduced EER, supported by the findings of Monwar and Gavrilova (2009) and Hossain (2018), is a critical metric, as a lower EER indicates better system performance. The study further revealed an inverse relationship between FAR and FRR, where decreasing one often leads to an increase in the other.

The improved recognition performance of CCSO, marked by enhanced accuracy and reduced computational time, demonstrates its robustness for multi-instance iris authentication systems. This supports the hypothesis by Qu et al. (2017) and Chebihi et al. (2021) that modifying the standard Chicken Swarm Optimization algorithm enhances optimization precision, convergence speed, and robustness. The results highlight the effectiveness of the CCSO technique in ensuring a secure and efficient biometric authentication system, with substantial improvements in key performance metrics.

Conclusion and Future Work

This study demonstrated that the Cultural Chicken Swarm Optimization (CCSO) technique significantly outperforms the standard Chicken Swarm Optimization (CSO) in multi-instance iris biometric authentication. The CCSO consistently achieved lower False Acceptance Rates (FAR) and False Rejection Rates (FRR), higher accuracy, and reduced computational time across all datasets.

This research contributes to the field of biometric authentication by proposing a more robust and efficient method, addressing the limitations of traditional optimization techniques, and offering improvements in both recognition accuracy and system security.

Future research can explore hybrid metaheuristics, combining CCSO with other optimization techniques to further enhance system performance. Additionally, the potential application of CCSO to other biometric fields, such as fingerprint and facial recognition, should be investigated to determine its broader utility.

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