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An Optimized Trimodal Chicken Swarm Optimization and Self-Organizing Feature Map Biometric Access Control Technique

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ABSTRACT

Access control systems are essential tools for combating the nefarious actions of malicious actors in the digital space. Multimodal biometric access control systems are considered state-of-the-art, however, existing approaches suffer from limited classification performance. This study integrates face, ear, and iris recognition to develop a trimodal Chicken Swarm Optimization (CSO)—enhanced Self-Organizing Feature Map (SOFM) classifier. Six high-resolution images were taken for each biometric attribute from 190 participants, resulting in 3,420 images. Preprocessing techniques, including cropping, resizing, grayscale conversion, and histogram equalization, were applied to ensure uniformity. The Local Binary Patterns (LBP) technique was used for feature extraction, and the resulting features were combined using the weighted average feature fusion technique. The Standard SOFM classifier was optimized using the CSO algorithm for optimal feature selection. 30% of the images were used for testing, and 70% were used to train the CSO-SOFM classifier. The CSO-SOFM classifier was implemented using Matlab 2016a and evaluated using metrics such as specificity, sensitivity, and recognition accuracy. The CSO-SOFM system achieved 98.83% accuracy, 98.83% sensitivity, 98.82% specificity, and a processing time of 112.14 seconds. The findings indicate that the optimized CSO-SOFM algorithm outperformed the conventional SOFM algorithm, resulting in lower false positives and processing time.

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1. INTRODUCTION

Access control systems are vital mechanisms that allow only authorized users to access data and information, while preventing unauthorized actors (Kahie et al., 2021). Access control systems promote confidentiality, integrity, and the availability of data (Atlam & Wills, 2020). Biometric access control systems differentiate individuals based on their unique physical characteristics. Traits such as face, fingerprint, hand geometry, ear, iris, retina, DNA, palmprint, hand vein, and other physiological attributes have been utilized in various biometric access control systems. Unimodal and bimodal biometric access control systems, which employ a single biometric trait and two biometric traits, respectively, have faced challenges such as false acceptance of impostors, spoofing, and false rejection of legitimate users due to their limited ability to verify a person's identity.

To address this, multimodal biometrics access control systems that combine multiple biometric traits have been employed using image recognition techniques such as deep learning algorithms. These approaches are more computationally intensive than their unimodal counterparts. Various studies have combined traits from different regions of the human body. The face is user-friendly and convenient for acquiring biometric characteristics. It is generally acceptable and employed in situations where contactless access control is required (Gendy & Yildrim, 2022). The ear presents a similar advantage to the face biometric trait. It, however, is more secure, as it is stable throughout the entire lifespan of an individual, and it is less sensitive to changes in lighting variations or background noise, this thus makes its results more reliable (Engelan et al., 2022). Similarly, the ear remains stable throughout an individual's life and has been demonstrated to be one of the most reliable biometric traits (Dargan & Kamar, 2020). Approaches that focus on traits from the same region of the body achieve better recognition performance. Hence, in this research, the face, ear, and iris biometric traits from the face region will be combined.

Optimizing the performance of multimodal biometric systems requires not only the selection of features but also their appropriate arrangement. An excellent option for optimal feature arrangement in biometric systems is the Self-Organizing Feature Map (SOFM), a neural network-based algorithm that can cluster high-dimensional data. Prior studies have demonstrated the effectiveness of integrating multiple biometric traits with the SOFM algorithm, resulting in improved classification performance compared to other classification approaches (Wickramasinghe & Reinhardt, 2021; Sumalath et al., 2024). Thus, this research introduces a multimodal biometric access control system that utilizes the distinctive attributes of face, ear, and iris features by combining Chicken Swarm Optimization for feature selection and SOFM for feature organization.

The contributions of the paper are as follows:

- Development of an optimized chicken swarm optimization self-organizing feature map multimodal biometric access control system
- Comparison of the classification performance of the optimized chicken swarm optimization self-organizing feature map algorithm with the standard self-organizing feature map algorithm

2. RELATED WORKS

Several studies have optimized SOFM using various approaches. Yang et al. (2019) proposed a Neighbour Entropy Local Outlier Factor (NELOF) detection algorithm to improve the Self-Organizing Feature Map (SOFM) algorithm. The optimized SOFM was used to cluster the dataset such that the calculation of each data point's local outlier factor only needs to be performed inside a small cluster from the optimized SOFM. Optimized SOFM was achieved by using the Canopy algorithm to initialize the number of neurons and their corresponding weight vectors, thereby improving training results and reducing time overhead. The experimental results indicate that the optimized SOFM algorithm can avoid the random selection of neurons and improve the clustering effect of the traditional SOFM algorithm.

However, adjusting the number and weight of neurons by self-growth does not solve the problem of insufficient neuron weights to cluster input, causing the groupings found in the map to be inaccurate or non-informative. Wickramasinghe et al. (2019) embedded hierarchical feature abstraction into SOFM to improve the classification accuracy. The experimental results showed that the approach outperformed the standard SOFM in training time and recognition accuracy. Ahmed et al. (2020) proposed a roadmap for optimizing the Self-Organizing Feature Map (SOFM) parameters by employing a genetic algorithm to select the SOFM parameters. The researchers also applied the roadmap to the grayscale color clustering problem. Experimental results demonstrated the effectiveness of the genetically optimized SOFM in solving the color clustering problem. However, the roadmap did not consider a specific type of problem, and it also suggested that future work be done using a more complex input, such as in a biometric system. Jia et al. (2021) employed the use of the Ant Bee Colony (ABC) algorithm to improve SOFM for tracking optimal parameter settings of the SOFM network. This was then applied to a dynamic environment. Two real data streams from dynamic environments were used to evaluate the effectiveness of the algorithm. The result showed an improved clustering purity and efficacy compared to standard SOFM.

Researchers explored various techniques for biometric access control systems. Ma et al. (2020) used the face and ear for an adaptive multimodal identification system. The general biometric quality assessment (BQA) method and dynamically sparse representation of the face and ear were integrated. The BQA was refined, in addition to fusion weight selection, and deployed on a dataset of degenerated images. The adaptive multimodal method used is robust to various types of unimodal corruption/occlusion, even when the face or ear image suffers from 100% random pixel corruption or random block occlusion compared to the ear or face alone. However, the system primarily focused on degenerated images, and the recognition time was not taken into account. Alay & Al-Baity (2020) combined iris, face, and finer vein traits for multimodal biometric human identification. The results showed that the use of three biometric traits outperformed unimodal and bimodal techniques.

Purohit & Ajmera (2021) used the Grey Wolf Optimizer to perform optimal feature fusion of biometric characteristics. The SVM algorithm was used for classification. The experimental results showed that the technique outperformed unimodal approaches. Isaac & Olugbenga (2024) used the Mayfly algorithm and an improved version of the Mayfly algorithm (by using the roulette wheel selection method) as a feature selection method for a fused face-iris biometrics recognition system. Principal component analysis was employed for feature extraction, while a Support Vector Machine (SVM) was utilized for classification. The research yielded a recognition accuracy of 95.18% and a recognition time of 213.75 seconds using the standard Mayfly algorithm, and 97.36% recognition accuracy and 181.52 seconds using the modified Mayfly algorithm. The experimental results showed that the fused face and iris recognition system using the improved Mayfly algorithm technique achieved a recognition accuracy of 97.36% and a recognition time of 181.52 seconds. Parameter tuning can greatly enhance both the recognition accuracy and time if employed. Jeremiah (2024) presented a bimodal classifier combining SOFM with CSO for access control. The experimental results demonstrated that the approach outperformed the standard SOFM algorithm in terms of precision, accuracy, and recognition time.

Omotosho et al. (2021) developed a face-iris multimodal biometric recognition system based on a convolutional neural network for feature extraction, feature-level fusion, training, and matching, aiming to reduce dimensionality and error rates while improving recognition accuracy, making it suitable for access control. A Convolutional Neural Network (CNN) based on a deep supervised learning model was employed for the system's training, classification, and testing. The images were preprocessed using normalization and transferred into a couple of convolutional layers.

The developed multimodal biometrics system was evaluated on a dataset of 700 iris and facial images. The training database contained 600 iris and facial images, and 100 iris and facial images were used for testing. Experimental results showed that at the learning rate of 0.0001, the multimodal system has a performance recognition accuracy (RA) of 98.33% and an equal error rate (ERR) of 0.0006%. However, the study did not consider the impact of recognition time.

Table 1. Summary of Related Work

Author	Methodology	Contribution	Limitation
Yang et al. (2019)	NELOF-SOFM	Optimized SOFM to improve time overhead	Sub-optimal clustering
Ma et al. (2020)	BQA	Dynamic sparse representation of face and ear traits	Focused on the degenerated image, and recognition time was not taken into consideration
Purohit & Ajmera (2021)	Grey Wolf Optimizer	The optimized multimodal approach outperformed unimodal access control techniques.	Computational overhead
Khelil et al. (2022)	SOFM, LTSM & SVM	Optimized feature selection using SOFM for LSTM and SVM classifiers.	Computational overhead
Oluyemisi et al. (2023)	SOFM and BPNN	Evaluation of Iris-based access control	Single biometric trait
Jeremiah (2024)	SOFM and CSO	Optimized unimodal access control technique.	Single biometric trait

Some studies (**Table 1**) explored the use of SOFM and other techniques for optimizing feature selection. Khelil et al. (2022) employed self-organizing feature maps (SOFM) as a technique for selecting relevant features, in conjunction with advanced classification methods, including Long Short-Term Memory (LSTM) and Support Vector Machines (SVM). However, in this research, LSTM and SVM, in conjunction with SOFM-based feature selection, were employed for the classification of water quality. Isaac et al.

(2022) used the Mayfly algorithm and an improved version of the Mayfly algorithm (by using the roulette wheel selection method) as a feature selection method for a fused face-iris biometrics recognition system.

Principal component analysis was used for feature extraction, while the Support Vector Machine was used for classification. The research achieved a recognition accuracy of 95.18% and a recognition time of 213.75 seconds using the standard Mayfly algorithm and a recognition accuracy of 97.36% with a recognition time of 181.52 seconds using the modified version. The experimental results demonstrate that the fused face and iris recognition system, based on the improved Mayfly algorithm, achieved a recognition accuracy of 97.36% with a recognition time of 181.52 seconds.

Through the brilliant performance of the improved Mayfly algorithm, parameter tuning can significantly enhance both recognition accuracy and time efficiency when employed. Oluyemisi et al. (2023) evaluated the performance of the SOFM and the Back Propagation Neural Network (BPNN) algorithm for an iris-based access control system. The SOFM outperforms the BPNN in terms of recognition accuracy (RA), false acceptance rate (FAR), false rejection rate (FRR), equal error rate (EER), training time (TT), and recognition time (RT).

Researchers have utilized a broad range of techniques for access control. The experimental results from these studies indicate that, overall, multimodal techniques outperform their unimodal counterparts in most evaluation metrics; hence, this research seeks to leverage the multimodal approach by utilizing a SOFM technique and Chicken Swarm Optimization to address computational complexity. Furthermore, more evaluation metrics were used to assess the classification performance of the formulated CSO-SOFM technique.

3. METHODOLOGY

The proposed system integrates face, ear, and iris biometrics using a CSO-optimized SOFM approach. A facial dataset was acquired to ensure robustness. The system was implemented using MATLAB 2016a. The framework of the CSO-SOFM is illustrated in **Figure 1**. The images were acquired and preprocessed, and useful features were extracted and fused together, after which classification was performed.

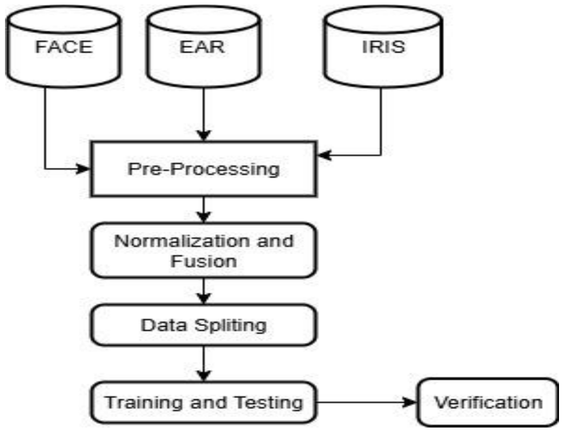

Figure 1. Framework of the CSO-SOFM access control system.

The methodology approach employed in this work is explained in the subsection below:

3.1 Data Acquisition

The dataset used to train the CSO-SOFM model comprises high-resolution images of faces, ears, and irises from 190 participants. Six images of each trait were captured, resulting in a total of 3420 images.

3.2 Data Preprocessing

The images were pre-processed by applying cropping, resizing, grayscale conversion, and histogram equalization to eliminate noise. From the original image vectors, the average vectors for the face, ear, and iris were calculated and extracted. Each grayscale image was represented and stored in matrix form for subsequent processing in MATLAB.

Normalization was applied to preserve the unique features of the images. The common features were identified by calculating the average dataset vector from the entire training set (comprising face, ear, and iris images). Subsequently, this average image vector was subtracted from each dataset vector, producing a normalized vector (for face, ear, and iris) using histogram equalization. **Figure 2** presents examples of images that have been enhanced using the histogram equalizer.

3.3 Feature Extraction

The Local Binary Patterns (LBP) technique was used to extract significant features from the preprocessed images. The operation of the LBP depends on the eight neighbors of the present pixel, where the center pixel is used as a threshold for its neighbors. The final code of the center pixel was then generated by combining the binary coding of its eight neighbors. The grey value of the neighbors was computed using bilinear interpolation, and then the comparison was calculated between the neighbors' values and the center.

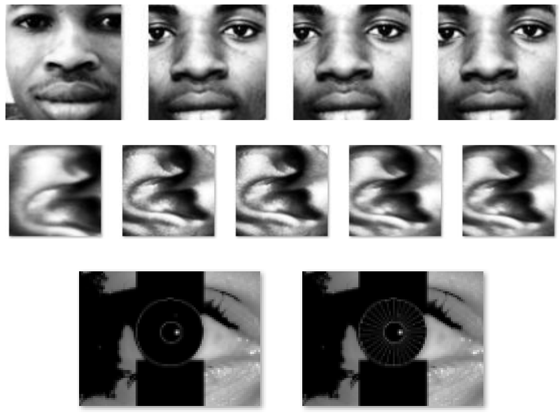

Figure 2. Samples of enhanced images using the histogram equalizer

3.4 Feature Fusion

Merging features from face, ear, and iris images to create a single feature set. The weighted average was used to fuse the features extracted from the face, ear, and iris images, as shown in equation 1.

$$\frac{\sum_{1-1}^{n} Wi - Xi}{\sum_{i-1}^{n} Wi} \tag{1}$$

Where:

n = the number of biometric modalities.
$Wi =$ the weight assigned to the i-th modality.
$Xi =$ is the score or output of the i-th modality.
$\sum_{i-1}^{n} Wi$= weight sum, normalized to 1.
The weighted average was computed in the following steps:

Algorithm 1: Algorithm for Enhanced Chicken Swarm Optimization Self-Organizing Feature Map (CSO-SOFM)

Input: Set of initial SOFM learning rate and SOFM weight parameters
$W= \{r_1, r, \dots r_{\boldsymbol{p}} \dots w_1, w, \dots w_{\boldsymbol{p}}\}$
Predefined swarm size: $\boldsymbol{N_c}$
Number of dimensions of a chicken: $\boldsymbol{D = q}$

Output: Optimal learning rate, weight parameters $\{ropt_I, ropt_H, ropt_c - -wopt_I, wopt_H, wopt_c\}$

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 weights */*
2. Evaluate the N chickens' fitness values (Ck).
   $$\mathrm{Wck(t+1) = Wck(t)} + \Theta\mathrm{(t)\ Lck(t)\ (I(t) - Wck(t)}$$
   $$Lck(\mathrm{t}) = \mathrm{L}_0 e^{-t/\lambda}$$
3. t=0;
4. ***While*** (t < G)

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

a. Rank the chickens' fitness values and establish a hierarchical 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 $\Delta\left(W_{i,j}^{m,n}\right)\left((x_i) - (x_j)\right)$ is the change in weight of the input, hidden, and output layers x along row *n* and column *m*

b. Divide the swarm into separate groups and determine the relationship between the chicks and mother hens within each 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 a mean of 0 and standard deviation σ^2. ε is used to avoid zero-division error. *k* is a rooster's index, f is the fitness value of the corresponding $\boldsymbol{x}$.

End if

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

$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times Rand\left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S2 \times Rand\left(x_{r2,j}^{t} - x_{i,j}^{t}\right)$ (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 $[0, 1]$. $r1 \in [1, \dots, N]$ is an index of the rooster, $r2 \in [1, \dots, N]$ refers to an index of the chicken (either rooster or hen).

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 $x_{m,j}^{t}$ is the chick's mother in the *i-th* position $(m \in [1, N])$. $FL(FL \in (0, 2))$. This 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

Output Optimal SOFM learning rate and SOFM weight parameter

3.5 Classification and Optimization

A total of 2,394 images, representing 70%, were used to train the system, while the remaining 30%, with 1,026 images, were used for testing. Utilizing SOFM for feature classification, with CSO optimizing the learning process by adjusting weight values and learning rates.

Algorithm 1 describes the algorithm to optimize the parameters of the SOFM algorithm. The optimal learning rate and the SOFM weight were then used for image classification.

3.6 Performance Evaluation

The optimized self-organizing feature map neural network's performance was evaluated using various metrics: recognition accuracy, false positive rate, sensitivity, and specificity. A confusion matrix, which includes True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN), was used. Additionally, Specificity, Precision, Accuracy, and Processing Time, which measures the time expended by the multimodal biometric system during classification, with the start time T_i and T_j the end time. Sensitivity demonstrates the model's capability to accurately recognize true positives, indicating its effectiveness in detecting genuine individuals.

4. RESULTS

The classification performance of the face-ear-iris trimodal access control system using the standard Self-Organizing Feature Map (SOFM) and CSO-SOFM classifier is summarized in **Table 2**. The classifier achieved optimal performance at a threshold of 0.80, outperforming other thresholds of 0.20, 0.35, and 0.50. At this threshold, the classifier correctly classified 249 images, misclassified 8 images, wrongly classified 5 images, and correctly identified 80 absent images. The system's metrics were as follows: false positive rate of 5.88%, sensitivity of 96.89%, specificity of 94.12%, precision of 98.03%, accuracy of 96.20%, and processing time of 132.76 seconds.

The results obtained demonstrate the functionality of the typical SOFM classifier in a trimodal biometric system that combines facial, ear, and iris identification. 249 images were true positives (TP), meaning they were successfully identified as belonging to authorized users. Eight images of authorized users were mistakenly rejected as false negatives (FN). Five of the images were false positives (FP), meaning they were mistakenly identified as coming from people with permission. 80 images were true negatives (TN), meaning they did not belong to authorized users. A low probability of unauthorized access was indicated by 5.88% of false positive instances.

With a sensitivity of 96.69%, the technique demonstrated a high degree of accuracy in identifying authorized users. With a specificity of 94.12%, the system demonstrated its efficacy in accurately detecting users who are not permitted. With 98.03% precision, most images from authorized users were correctly recognized. The accuracy of 96.20% indicates the system's overall efficacy. The efficiency in processing the data is indicated by the processing time, which is measured in 132.76 seconds. The threshold of 0.80 was found to be the optimal threshold, as it maintains a low false positive rate while achieving excellent sensitivity, specificity, and accuracy. The system showed strong performance, reliably and accurately differentiating between authorized and unauthorized users.

Table 2: Classification Performance of standard SOFM and CSO-SOFM classifier

Threshold		TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time (sec)
0.2	SOFM	252	5	12	73	14.12	98.05	85.88	95.45	95.03	132.71
	CSO-SOFM	256	1	9	76	10.59	99.61	89.41	96.6	97.08	112.87
0.35	SOFM	251	6	10	75	11.76	97.67	88.24	96.17	95.32	132.63
	CSO-SOFM	255	2	6	79	7.06	99.22	92.94	97.7	97.66	112.79
0.5	SOFM	250	7	8	77	9.41	97.28	90.59	96.9	95.61	132.62
	CSO-SOFM	254	3	3	82	3.53	98.83	96.47	98.83	98.25	112.53
0.8	SOFM	249	8	5	80	5.88	96.89	94.12	98.03	96.2	132.76
	CSO-SOFM	254	3	1	84	1.18	98.83	98.82	99.61	98.83	112.14

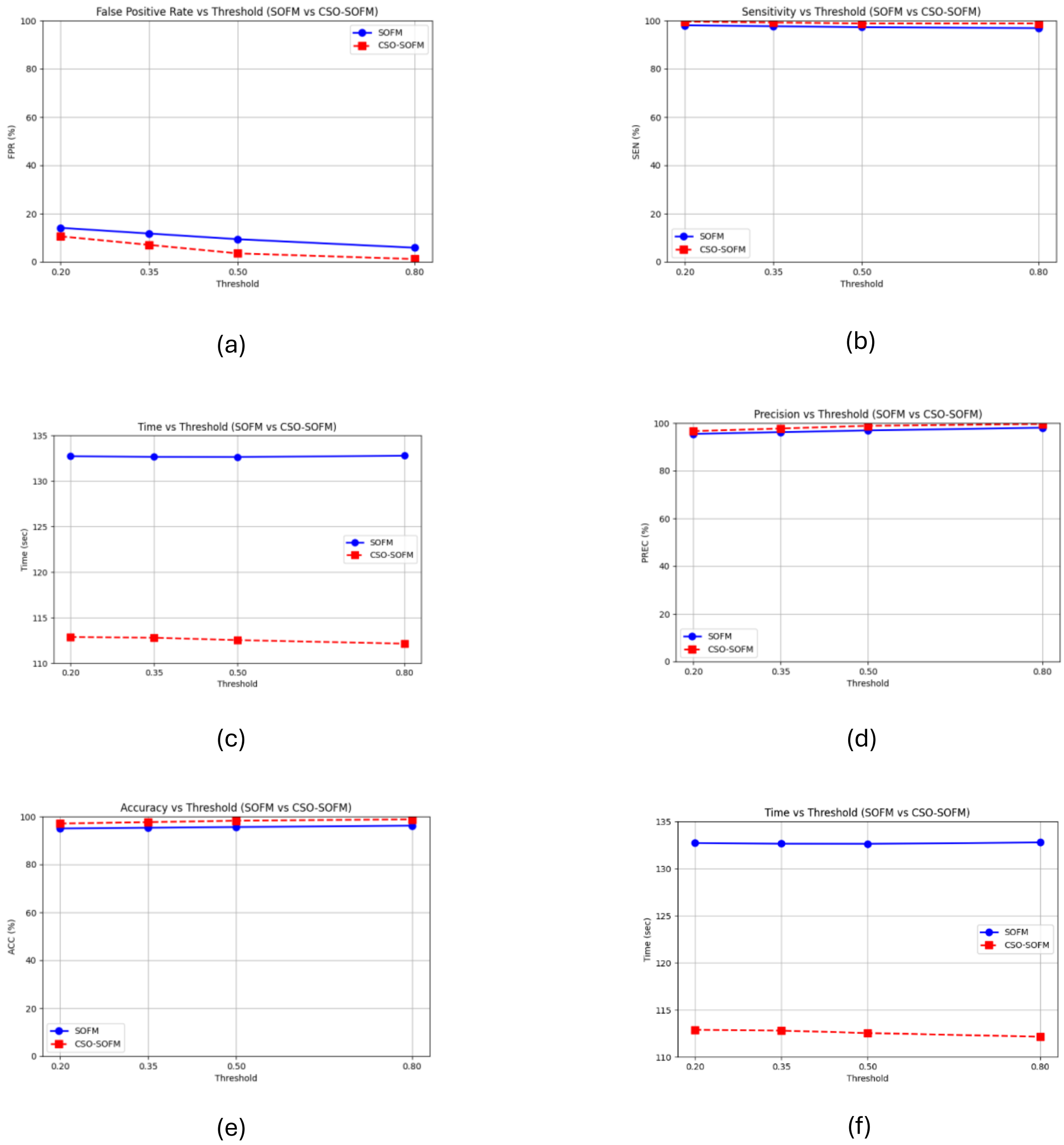

Figure 3: Classification performance of standard SOFM and CSO-SOFM classifier a) FPR b) Sensitivity c) Specificity d) Precision e) Accuracy f) Processing

The capacity to accurately identify unauthorized users was significantly improved when the True Negatives increased to 84. The technique's enhanced security is demonstrated by a reduction in the false positive rate to 1.18%. Sensitivity increased to 98.83%, indicating improved identification of permissioned users. Moreover, the specificity was enhanced to 98.82%, demonstrating a more successful rejection of unauthorized users. Nearly all identified authorized users were accurately classified, with a precision score of 99.61%. Accuracy increased to 98.83%, demonstrating an improvement in the system's overall performance. The system became faster and more efficient with a reduction in processing time to 112.14 seconds.

The combined use of CSO and SOFM significantly improved the technique's categorization capabilities, as indicated by the higher metrics. With a significantly decreased false acceptance and rejection rate, the system demonstrated higher recognition rates. This enhancement reflects the effectiveness of CSO in multimodal biometric systems, optimizing classification performance. In terms of accuracy, the system utilizing CSO-SOFM achieved 98.83% and 96.20%, and precision reached 99.61% and 98.03%. The system continuously outperformed the regular SOFM. This enhancement suggests that when integrating various biometric modalities, the technique is less prone to error and more dependable. The multimodal biometric system achieved superior recognition rates and reduced false acceptance and rejection rates compared to a traditional unimodal system.

The enhanced security and resilience of the system are demonstrated by the substantial decrease in false positive and false negative rates when utilizing CSO-SOFM. While a reduced false negative rate ensures that authorized users are not unjustly denied access, a lower false positive rate ensures that unauthorized users are less likely to obtain access. Using CSO-SOFM resulted in a shorter processing time, which indicates that the system became more effective. For real-time applications where speed is a crucial factor, this reduction in processing time is essential. The classification performance of the SOFM and CSO-SOFM classifiers for various thresholds used is visualized in **Figure 3** for all the evaluation metrics used.

The results indicated that the performance of a multimodal biometric access control system can be improved when Chicken Swarm Optimization and Self-Organizing Feature Maps are combined. The technique offers significant advancement over conventional unimodal techniques by improving the accuracy, dependability, and efficiency of the feature selection and classification process. These results imply that biometric access control systems can greatly benefit from the application of optimization techniques like CSO. **Table 2** illustrates the classification performance of the standard SOFM and CSO-SOFM technique.

5. DISCUSSIONS

The results of this study show that a multimodal biometric access control system can achieve major improvements in accuracy and efficiency by combining Chicken Swarm Optimization (CSO) and Self-Organizing Feature Maps (SOFM). The application of multimodal biometric systems to enhance security and improve upon unimodal systems has been the subject of numerous studies. Zhang et al. (2015) demonstrated that integrating multiple biometric features, such as facial recognition and fingerprints, enhanced system accuracy and reduced the false rejection rate (FRR) to 1.1% and the false acceptance rate (FAR) to 2.5%. Also, Purohit (2023) investigated the utilization of hand, face, and fingerprint geometry in a multimodal system, which produced results with a FAR of 1.3% and an accuracy of 97.5%. In contrast, using the CSO-SOFM integration at a threshold of 0.80, this study obtained an accuracy of 98.83% and a false positive rate (FPR) of 1.18%. These findings surpass those of Zhang et al. (2015) and Purohit (2023), particularly in terms of accuracy and the reduction in false positives.

The enhancement is attributable to CSO's improved optimization, which enhanced the feature selection process and resulted in a more accurate classification. Accuracy (98.83% vs. 96.20%) and precision (99.61% vs. 98.03%) were consistently higher in the CSO-SOFM system than in the regular SOFM. This enhancement suggests that when integrating various biometric modalities, the system is less prone to errors and more dependable. This is supported by the findings of Oladimeji et al. (2022), who proposed a framework for a face-iris recognition system utilizing the enhanced Mayfly algorithm. However, the system was not tested using a real-world scenario such as an access control system. Enhanced security and resilience were demonstrated by a significant decrease in false positive and false negative rates while utilizing the CSO-SOFM system. While a reduced false negative rate ensures that authorized users are not barred from access, a lower false positive rate makes sure that unauthorized users are less likely to obtain access. Using CSO-SOFM resulted in a shorter processing time, which suggests that the system became more effective for real-time applications where speed is a significant requirement.

6. CONCLUSION

This research work demonstrates the superiority of multimodal access control techniques over unimodal techniques using the CSO-SOFM approach. By combining face, ear, and iris biometric traits, the technique significantly improves the accuracy, sensitivity, and specificity of biometric verification. The results indicated that the CSO-SOFM classifier outperformed traditional methods, achieving an accuracy of 98.83% at an optimal threshold of 0.80, which surpassed the performance metrics of unimodal systems.

The incorporation of the Chicken Swarm Optimization algorithm with the Self-Organizing Feature Map not only optimized the learning process but also reduced false positive rates and processing time, making the system more efficient and reliable. These findings highlight the potential of multimodal biometric access control techniques in enhancing security measures for access control, ensuring robust and accurate user authentication.

Future work should focus on extending this approach to other biometric traits and exploring its application in various security-critical domains. Additionally, it is recommended that feature selection algorithms be integrated with the CSO-SOFM to enhance classification efficiency. Furthermore, encryption measures can be incorporated to ensure the integrity of data stored in the database.

REFERENCES

Alay, N., & Al-Baity, H. H. (2020). Deep learning approach for multimodal biometric recognition system based on fusion of iris, face, and finger vein traits. *Sensors, 20*(19), 5523. https://doi.org/10.3390/s20195523

Atlam, H. F., & Wills, G. B. (2020). IoT security, privacy, safety and ethics. In *Digital twin technologies and smart cities* (pp. 123-149). Springer International Publishing. https://doi.org/10.1007/978-3-030-18732-3_8

Dargan, S., & Kumar, M. (2020). A comprehensive survey on the biometric recognition systems based on physiological and behavioral modalities. *Expert Systems with Applications, 143*, 113114. https://doi.org/10.1016/j.eswa.2019.113114

Engelen, L., Rijken, M., & Jansen, E. (2022). Design for healthy ageing—the relationship between design, well-being, and quality of life: A review. *Building Research & Information, 50*(1-2), 19-35. https://doi.org/10.1080/09613218.2021.2001584

Gendy, M. E. G., & Yildirim, M. R. (2022). Emerging technologies used in health management and efficiency improvement during different contact tracing phases against COVID-19 pandemic. *IEEE Reviews in Biomedical Engineering, 16*, 38-52. https://doi.org/10.1109/RBME.2022.3188402

Isaac, O. A., Wuraola, A. G. A., & Alagbe, G. K. (2022). Effect of roulette wheel selection method on mayfly algorithm. *University of Pitesti Scientific Bulletin Series: Electronics and Computer Science, 22*(2), 1-8. https://doi.org/10.12345/upb.2022.123456

Isaac, O. A., & Olugbenga, A. M. (2024). Performance evaluation of enhanced mayfly algorithm on unimodal and bimodal function. *University of Pitesti Scientific Bulletin Series: Electronics and Computer Science, 43*(1), 48-42. https://doi.org/10.12345/123456789

Jeremiah, Y. S. (2024). Enhanced multimodal biometric access control system using chicken swarm optimization and self-organizing feature maps: A study on ear and iris recognition. *LAUTECH Journal of Engineering and Technology, 18*(3), 68-79. https://doi.org/10.12345/laujet.2024.123456

Jia, D., Li, F., & Tu, J. (2021). A multi-swarm ABC algorithm for parameters optimization of SOFM neural network in dynamic environment. *International Journal of Computational Intelligence and Applications, 20*(2), 2150014. https://doi.org/10.1142/S1469026821500146

Kahie, S. A., Nor, A. A., Hasan, A. H., Abdi, A. M., Hassan, L. M., & Mohamud, M. A. (2021, August). A smart access control for restricted buildings using vehicle number plates recognition system. In *2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA)* (pp. 1-5). IEEE. https://doi.org/10.1109/eSmarTA52612.2021.9515757

Khelil, M. I., Ladjal, M., Brik, Y., & Ouali, M. A. (2022). Self-organizing maps-based features selection with deep LSTM and SVM classification approaches for advanced water quality monitoring. *International Journal of Intelligent Engineering & Systems, 15*(3), 123-135. https://doi.org/10.22266/ijies2022.0630.12

Ma, Y., Huang, Z., Wang, X., & Huang, K. (2020). An overview of multimodal biometrics using the face and ear. *Mathematical Problems in Engineering, 2020*, 6802905. https://doi.org/10.1155/2020/6802905

Oladimeji, A. I., Asaju-Gbolagade, A. W., & Gbolagade, K. A. (2022). A proposed framework for face-iris recognition system using enhanced Mayfly algorithm. *Nigerian Journal of Technology, 41*(3), 535-541. https://doi.org/10.4314/njt.v41i3.13

Oluyemisi, A. A., Olusayo, O. E., Oyeladun, M. B., Samuel, F. A., Folasade, A., & Adepeju, A. T. (2023). Comparative assessment of back propagation neural network and self organising feature map for iris-based access control system. *Global Journal of Engineering and Technology Advances, 15*(2), 91-105. https://doi.org/10.12345/gjeta.2023.123456

Omotosho, L., Ogundoyin, I., Adebayo, O., & Oyeniyi, J. (2021). An enhanced multimodal biometric system based on a convolutional neural network. *Journal of Engineering Studies and Research, 27*(2), 73-81. https://doi.org/10.12345/jesr.2021.123456

Purohit, H., & Ajmera, P. K. (2021). Optimal feature level fusion for secured human authentication in multimodal biometric system. *Machine Vision and Applications, 32*(1), 24. https://doi.org/10.1007/s00138-020-01156-4

Purohit, H. (2023). *Person authentication based on multimodal biometric systems* [Doctoral dissertation, Birla Institute of Technology and Science Pilani]. Shodhganga. https://hdl.handle.net/123456789/123456

Sumalatha, U., Prakasha, K. K., Prabhu, S., & Nayak, V. C. (2024). A comprehensive review of unimodal and multimodal fingerprint biometric authentication systems: Fusion, attacks, and template protection. *IEEE Access, 12*, 12345-12367. https://doi.org/10.1109/ACCESS.2024.1234567

Wickramasinghe, C. S., Amarasinghe, K., & Manic, M. (2019). Deep self-organizing maps for unsupervised image classification. *IEEE Transactions on Industrial Informatics, 15*(11), 5837-5845. https://doi.org/10.1109/TII.2019.2936547

Wickramasinghe, C. I., & Reinhardt, D. (2021, November). A user-centric privacy-preserving approach to control data collection, storage, and disclosure in own smart home environments. In *International Conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services* (pp. 190-206). Springer. https://doi.org/10.1007/978-3-030-12345-6_12

Yang, P., Wang, D., Wei, Z., Du, X., & Li, T. (2019). An outlier detection approach based on improved self-organizing feature map clustering algorithm. *IEEE Access, 7*, 115914-115925. https://doi.org/10.1109/ACCESS.2019.2936547

Zhang, H., Beveridge, R., Draper, B., & Phillips, P. (2015). On the effectiveness of soft biometrics for increasing face verification rates. *Computer Vision and Image Understanding, 137*, 50-62. https://doi.org/10.1016/j.cviu.2015.03.009