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Development Of An Enhanced Self-Organizing Feature Map Iris-Based Access Control System

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ABSTRACT

Access control systems play a critical role in maintaining data integrity and confidentiality. Utilizing biometric recognition improves security by utilizing distinct behavioral and physiological characteristics. This study aims to address issues of accuracy and computing efficiency by creating a sophisticated access control system with iris-based biometrics and a novel fusion of Chicken Swarm Optimization (CSO) and Self-Organizing Feature Maps (SOFM). Iris images were acquired, preprocessed, and subjected to feature extraction via Log-Gabor filters to highlight critical attributes. The CSO algorithm optimized the SOFM's learning parameters, resulting in an improved clustering and recognition process. Comparative analysis against the standard SOFM demonstrated significant enhancements in sensitivity (96.09%), specificity (90.59%), precision (96.85%), and accuracy (94.72%). Additionally, processing time was reduced, ensuring feasibility for real-time applications. These results establish the Modified CSO-SOFM as a robust and efficient method for biometric access control. Future efforts will focus on incorporating multimodal biometrics and advanced optimization strategies to further elevate system performance.

Keywords: Enhanced Self-Organizing Feature Map, Iris-Based Access Control System, Biometrics

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1. INTRODUCTION

Access control system protect against unauthorized access, data alteration, and confidentiality breaches by allowing authorized users to access data or system components while blocking unauthorized users from doing so. (Cookey *et. al.,* 2024). Biometric recognition refers to the recognition of individuals based on their physiological and behavioral characteristics. Some distinct physiological characteristics that are measurable include the hand geometry, face, fingerprint, iris, and retina of individuals; while behavioral traits ones are handwriting, voice patterns and keystroke dynamics (Jain and Kumar, 2012). Self-Organizing Feature Maps (SOFM) are machine learning algorithms that categorize input vectors based on their spatial arrangement, effectively learning the distribution and topology of the training data. This makes SOFMs highly effective for categorizing complex biometric data, as they map high-dimensional multimodal data onto a lower-dimensional map, extracting significant features and revealing underlying patterns (Wickramasinghe, *et al.,* 2019).

The robustness of SOFMs is maintained through self-organization and continuous updates, with efficiency depending on well-tuned training parameters such as learning rate, neighborhood function, input weights and weight update (Ahmed, *et al.,* 2023). Adil, *et al.,* (2015), presented a method for optimizing the Self Organizing Feature Map. The approach involved the ability to identify and select the best map. The goal is to delete unimportant units in the Kohonen map because the selected neuron was removed after each iteration; learning is then done again with the remainder of the variables. To test the approach, two databases which are Iris and Seeds were used. A more effective system was achieved. However, the approach led to higher computational time, which delayed the system for a significant duration of time.

Olajide, *et al.,* (2019) presented a novel method for an access control system using ear and tongue images. PCA was employed for feature extraction of ear and tongue images, and SOFM was used for training and testing the system. The method was evaluated using 5000 ear images and tongue images. The images were collected using a digital camera and were fused at the feature extraction level. The fusion results of ear and tongue images showed improved performance and a considerable step closer to user access control. The result of the experiment showed that a multimodal biometric authentication system is much more reliable and might be used in real-time authentication systems. However, the work did not consider the effect of some optimization algorithms on the performance of the projected multimodal method and the taking on of more biometric traits.

Ahmed *et al.,* (2020), proposed a roadmap for optimizing the Self Organizing Feature Map (SOFM) parameters by employing the genetic algorithm for selecting the SOFM parameters. The researchers also applied the roadmap to the grayscale color clustering problem. Experimental results confirm 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 they also suggested future work be done using a more complex input like in a biometric system. Jia *et al.* (2021), employed the use of 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 effectiveness compared to standard SOFM.

2. METHODOLOGY

The study implemented access control system integrating iris biometrics using Chicken Swarm Optimization and Self-Organizing Feature Maps (CSO-SOFM) in MATLAB 2016a. The system development proceeded through five stages: data acquisition, preprocessing, feature extraction, fusion, and classification. Figure 1 illustrates the framework of the CSO-SOFM access control system, detailing its design and development stages.

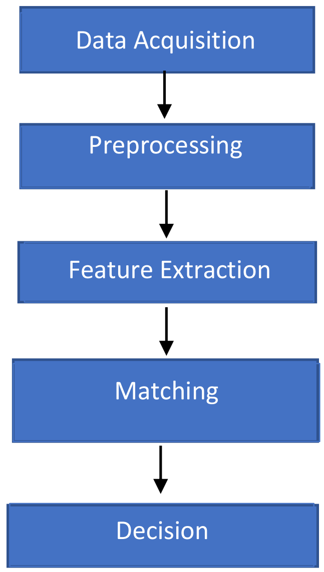

Figure 1: Framework of the CSO-SOFM access Control System

Data Acquisition

This study captured high-quality iris images from 341 individuals at the LAUTECH Campus, under a uniform lighting condition throughout the image acquisition process. Each biometric trait comprised six instances of the iris trait (6 instances*361), resulting in a dataset of 2,166 images with a resolution of 100x100 pixels. Samples of acquired images are as shown in Figure 2

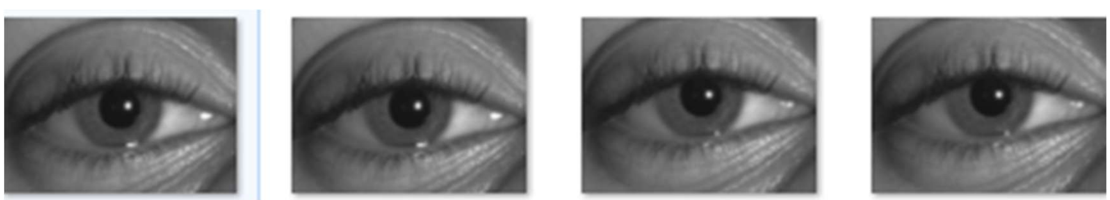

Figure 2: Samples of Acquired iris Images

Pre-Processing

After the local dataset, as mentioned in the previous section, has been acquired. The iris images were cropped, resized and converted to grayscale using the histogram equalization method. The average iris vector is calculated and extracted from the original image vectors. This is done to remove noise, and other unwanted elements from the images. Each grayscale was expressed and stored in a matrix form in MATLAB, and eventually converted to vector images for further processing. Normalization was also used to retain the unique feature of the images by removing the common features that the images share. The common features were discovered by finding the average dataset vector of the whole training set (iris images). Then, the average image vector was subtracted from each dataset vector, resulting in a normalized (iris) vector using histogram equalization. Figure 3.3 shows examples of some of the images that have been enhanced using histogram equalizer.

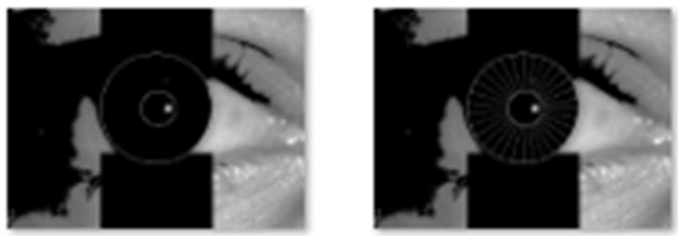

Figure 3: Samples of enhanced images using histogram equalizer.

Feature Extraction using Log-Gabor filter

Iris feature extraction was done using Log-Gabor filter to extract the best features from the iris images. This process began with the setting of key parameters, including the center frequency p0 and bandwidth σ. The normalized iris image was then converted to the frequency domain using the Fourier Transform. Next, the Log-Gabor filter transfer function, as specified in equation (1), was applied to the frequency domain representation of the iris image:

$$G(p) = \exp\left(-\frac{\left(\log\left(\frac{p}{p_0}\right)\right)^2}{2\left(\log\frac{\sigma}{p_0}\right)\right)^2}\right) \qquad (1)$$

Here, G(p) represents the transfer function of the Log-Gabor filter at frequency p, where p is the frequency variable, p0 is the center frequency of the filter, and σ is the bandwidth parameter of the filter.

Classification using Enhanced SOFM (CSO-SOFM) Technique

The SOFM is a simple artificial network that learns via an unsupervised method. The potential of this network to self-organize makes it map the input vector to a particular output node. In the learning process, it does not need predefined input target pair. This is the same inherent learning process adapted in human brains. Algorithm 1 shows the algorithm for the enhanced Self-Organizing Feature Map (CSO-SOFM).

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

Input: Set of initial SOFM learning rate and SOFM weight parameters
W= $\{r_1, r, \ldots\ \boldsymbol{r_p} \ldots w_1, w, \ldots\ w_{\boldsymbol{p}}\}$
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* $(t \bmod G = 0)$
      a. Rank the chickens' fitness values and establish a hierarchal order in the swarm;

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

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

         Where $\Delta\left(W_{i,j}^{m,n}\right)((x_i) - (x_j))$ is the change in weight 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
   ii. *For* i = 1:N
      a. *If i = rooster* Update its solution/location

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

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

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

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

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

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

         End if
      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 it's previous one, update it;

      End for

   End while

Output Optimal SOFM learning rate and SOFM weight parameter

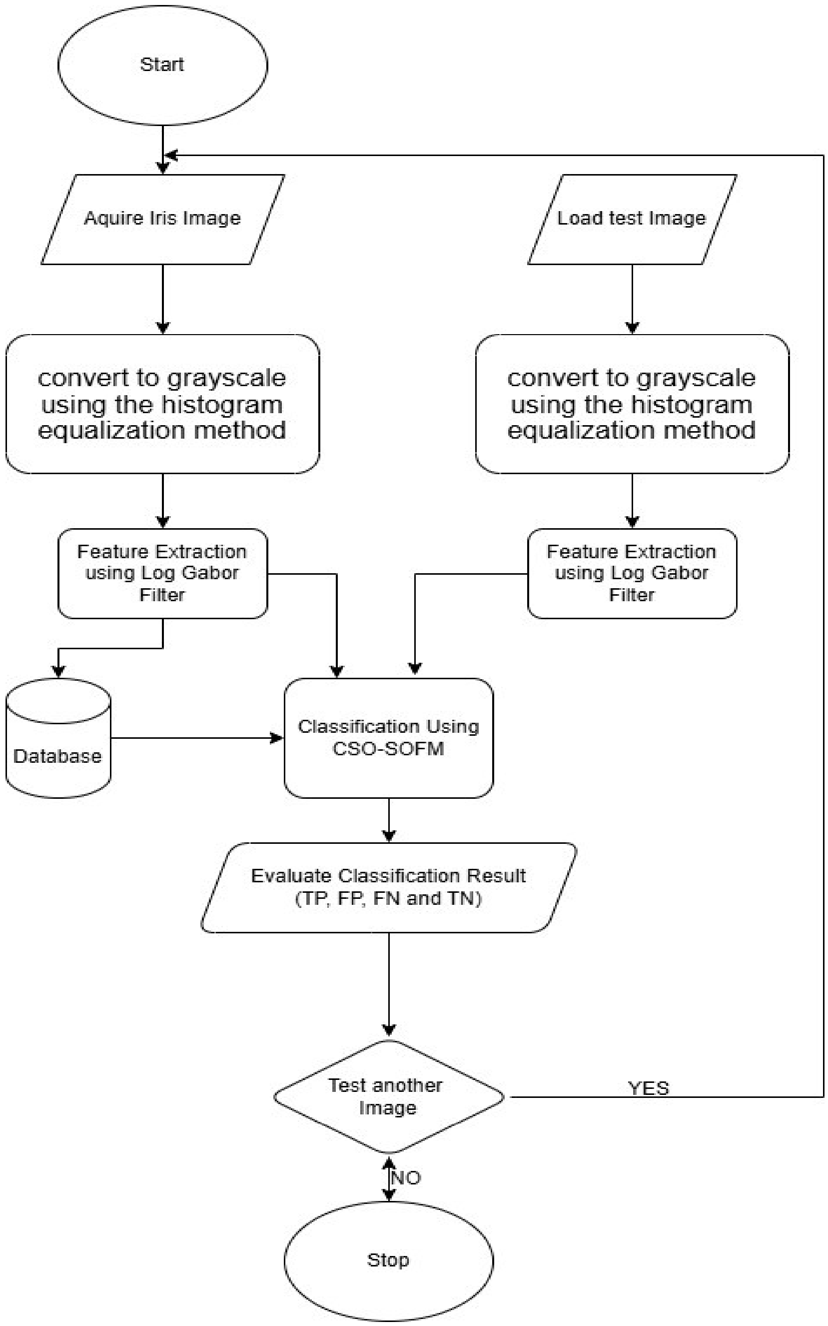

Figure 4: Flowchart showing trained and tested of selected images with CSO-SOFM

Graphical user interface of the developed system

A graphical user interface designed for the developed Iris access control system was shown in figure 5. The graphical user interface has different segment such as training, testing, classification, display of image and results.

Figure 5: GUI for the developed system

3. RESULTS AND DISCUSSION

Several experimental tests were conducted to validate the performance of the developed multimodal system under varying conditions. Arbitrary constants called threshold values from 0 – 1 were used to moderate the results obtained during running and testing. The general observation is that all the performance evaluation metrics gave the same results for the following ranges of threshold values respectively: 0 – 0.20, 0.21 – 0.35, 0.36 – 0.50 and 0.51 – 1. From table 1, at threshold of 0.8 considering only iris as the biometric trait, the best values for TP, FN, FP, TN, FPR, SEN, SPEC, PREC, ACC, and time was achieved, and these are: 241, 15, 12, 73, 14.12%, 94.15%, 85.88%, 95.26%, 92.08%, 63.46 seconds.

3.1 Standard SOFM versus Modified SOFM (CSO-SOFM)

Table 1: Results of iris-based access control system with standard SOFM as classifier

Classifier	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time (sec)	Threshold
SOFM	244	12	19	66	22.35	95.31	77.65	92.78	90.91	63.92	0.20
CSO-SOFM	248	8	16	69	18.82	96.88	81.18	93.94	92.96	59.52	
SOFM	243	13	17	68	20.00	94.92	80.00	93.46	91.20	63.76	0.35
CSO-SOFM	247	9	13	72	15.29	96.48	84.71	95.00	93.55	58.60	
SOFM	242	14	15	70	17.65	94.53	82.35	94.16	91.50	63.34	0.50
CSO-SOFM	246	10	10	75	11.76	96.09	88.24	96.09	94.13	58.66	
SOFM	241	15	12	73	14.12	94.14	85.88	95.26	92.08	63.46	0.80
CSO-SOFM	246	10	8	77	9.41	96.09	90.59	96.85	94.72	58.50	

The results realized from the developed system when SOFM and CSO-SOFM techniques were employed are as shown in Table 1 at varying threshold values.

3.2 Standard SOFM Classifier result

At threshold of 0.2, TP records 224, FN records 12, FP records 19, TN records 66, FPR records 22.35%, Sensitivity records 95.31%, Specificity records 77.65%, Precision records 92.78%, Accuracy records 90.91% and Time at 63.92 sec. At threshold of 0.35, TP records 243, FN records 13, FP records 17, TN records 68, FPR records 20.00%, Sensitivity records 94.92%, Specificity records 80.00%, Precision records 93.46%, Accuracy records 91.20% and Time at 63.76 sec. At threshold of 0.5, TP records 242, FN records 14, FP records 15, TN records 70, FPR records 17.65%, Sensitivity records 96.09%, Specificity records 88.24%, Precision records 96.09%, Accuracy records 94.13% and Time at 63.34 sec. At threshold of 0.8, TP records 241, FN records 15, FP records 12, TN records 73, FPR records 14.12%, Sensitivity records 94.14%, Specificity records 85.88%, Precision records 95.26%, Accuracy records 92.08% and Time at 63.46 sec.

3.3 Modified SOFM (CSO-SOFM) Classifier Result

At threshold of 0.2, TP records 248, FN records 8, FP records 16, TN records 69, FPR records 18.82%, Sensitivity records 96.88%, Specificity records 81.18%, Precision records 93.94%, Accuracy records 92.96% and Time at 59.52 sec. At threshold of 0.35, TP records 247, FN records 9, FP records 13, TN records 72, FPR records 15.29%, Sensitivity records 96.48%, Specificity records 84.71%, Precision records 95.00%, Accuracy records 93.55% and Time at 58.60 sec. At threshold of 0.5, TP records 246, FN records 10, FP records 10, TN records 75, FPR records 11.76%, Sensitivity records 96.09%, Specificity records 88.24%, Precision records 96.09%, Accuracy records 94.13% and Time at 58.66 sec. At threshold of 0.8, TP records 246, FN records 10, FP records 8, TN records 77, FPR records 9.41%, Sensitivity records 96.09%, Specificity records 90.59%, Precision records 96.85%, Accuracy records 94.72% and Time at 58.50 sec.

3.4 Statistical Analysis

Inferential Statistical analysis using paired sampled t-test was done to analyze the result obtained for test of significance for True Positive (TP), False Negative (FN), False Positive (FP), True Negative (TN), False Positive Rate (FPR), Sensitivity, Specificity, Precision (PREC), Recognition Accuracy (Accuracy), and Time between SOFM and CSO-SOFM. The hypothesis is defined as:

H_0: There is no significant difference between SOFM and CSO-SOFM technique.
H_1: There is significant difference between SOFM and CSO-SOFM technique.

Metric	t-statistic	p-value	Interpretation
Accuracy (ACC)	-17.30	0.00042	Significant difference
Sensitivity (SEN)	-17.17	0.00043	Significant difference
Specificity (SPEC)	-9.78	0.00227	Significant difference
Precision (PREC)	-9.87	0.00221	Significant difference
Execution Time (TIME)	28.96	0.00009	Significant difference

4. CONCLUSION

The proposed Iris based biometric access control system utilizing an enhanced CSO-SOFM algorithm, indicates that the Modified CSO-SOFM outperforms the Standard SOFM in all key performance metrics, in terms of accuracy, sensitivity, specificity, false positive rate and recognition time. These improvements suggest that the Modified CSO-SOFM is a more reliable and efficient approach for enhancing access control systems, and the efficient processing times also suggest better applicability for real-time systems. All p-values are less than 0.05, indicating statistically significant differences between SOFM and CSO-SOFM techniques for all metrics. Future works will explore the integration of additional biometric traits and further optimization techniques to enhance system performance.

REFERENCES

Adil, B. H., Youssef, G. H. A. N. O. U., and Abderrahim, E. Q. (2015). A new Algorithm for Optimizing the Self-Organizing Map. *Journal of Theoretical and Applied Information Technology, 78*(3).

Ahmed, R. F. M., Salama, C., and Mahdi, H. (2020). Optimizing Self-Organizing Maps Parameters Using Genetic Algorithm: A Simple Case Study. *In Proceedings of the International Conference on Advanced Intelligent Systems and Informatics* (pp. 3-12). Springer International Publishing. .

Ahmed, S.F., Alam, M.S.B., Hassan, M. (2023). Deep learning modelling techniques: current progress, applications, advantages, and challenges. *Artif Intell Rev 56*, 13521–13617. doi:https://doi.org/10.1007/s10462-023-10466-8

Cookey Iyen, Abel Jacob, Ayoola Oluwasegun. (2024). Development of Biometric User Identification and Access Control System. *European Journal of Applied Science, Engineering and Technology*, 194-204.

Jain, A. K., and Kumar, A. (2012). Biometric recognition: an overview. . *Second generation biometrics: The ethical, legal and social.*, 49-79.

Olajide, A. Y., Adepeju, A. A., and Oluwaseun, I. E. (2019). A ear and tongue based multimodal access control system. annals. *Computer Science Series,, 17*(2).

Wickramasinghe, C. S., Amarasinghe, K., and Manic, M. (2019). Deep self-organizing maps for unsupervised image classification. *IEEE Transactions on Industrial Informatics, 15*(11), 5837-5845.