

Development of an Enhanced Giant Armadillo Optimizer Technique for Fingerprint Recognition System

Mustapha Sakiru Omoyosade ¹, W. O. Ismail ¹, Adeyemo I. A ¹, Ismaila F. M ², Ogundele A. L ³, Agboola F. F ⁴, Ismail Muhammed Okikiola ⁵

¹Department of Computer Science, Ladoké Akintola University of Technology (LAUTECH), Ogbomosho, Oyo State, Nigeria

²Osun State University (UNIOSUN), Osogbo, Osun State, Nigeria

³Department of Computer Science, Olabisi Onabanjo University (OOU), Ago-Iwoye, Ogun State, Nigeria

⁴Modibbo Adama University, Adamawa State, Nigeria

⁵Department of Nursing, Fountain University, Osogbo, Osun State, Nigeria

Authors email: mustaphasakiru@gmail.com, woismaila@lautech.edu.ng, laadeyemo22@lautech.edu.ng, Folashade.ismaila@uniosun.edu.ng, Lukman@oouagoiwoye.edu.ng, Ffagboola87@mau.edu.ng

ARTICLE INFO

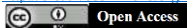
Keywords:
fingerprint recognition,
Giant Armadillo Optimizer,
feature selection,
adaptive parameter tuning,
SVM,
biometrics.

Vol.01, No.04, 2026

<https://doi.org/10.5281/zenodo.22721834>

Copyright © 2026 by author(s) and Scientific Research Publishing Inc. This work is licensed under the Creative Commons Attribution International License (CCBY4.0).

<http://creativecommons.org/licenses/by/4.0/>



ABSTRACT

Fingerprint recognition systems continue to experience significant challenges due to variations in image quality, skin deformation, partial impressions, environmental noise, and the increasing dimensionality of fingerprint databases, all of which negatively affect recognition accuracy and computational efficiency. Metaheuristic optimization techniques have therefore gained attention for feature selection, with Giant Armadillo Optimisation (GAO) demonstrating strong capability in balancing exploration and exploitation during the search process. Nevertheless, GAO still suffers from issues such as slow convergence, parameter sensitivity, and local optima stagnation, thereby creating the need for enhanced GAO models. Hence, this study developed an enhanced giant armadillo optimized feature selection technique for fingerprint recognition system. Fingerprint samples were collected from 500 students of LAUTECH, Ogbomosho, using a Digital Persona fingerprint sensor, with three samples obtained from each participant to ensure data reliability and variability. The second stage, image pre-processing, involves a sequence of enhancement operations such as image enhancement, noise removal, segmentation, binarization, and thinning to improve image clarity and ridge structure. The third stage, feature extraction, focused on identifying key fingerprint characteristics, where minutiae extraction performed using the Crossing Number (CN) algorithm to detect ridge endings and bifurcations. In the fourth stage, feature selection carried out using the formulated Enhanced Giant Armadillo Optimizer (EGAO) integrated with Adaptive Parameter Tuning (APT) to optimally select the most discriminative and relevant features for recognition. The fifth stage involved system implementation in MATLAB R(2020a), where all processes from pre-processing to feature selection and classification programmed and executed. Finally, the sixth stage focused on performance evaluation of the developed fingerprint recognition system using metrics such as False Positive Rate (FPR), Sensitivity, Specificity, Precision, Accuracy, and Recognition Time. The results of the EGAO achieved a False Positive Rate (FPR) of 3.70%, sensitivity of 97.84%, specificity of 96.30%, precision of 98.75%, and accuracy of 97.45%, and recognition time of 78.86 seconds. In comparison, the GAO had an FPR of 12.96%, sensitivity of 94.75%, specificity of 87.04%, precision of 95.64%, and accuracy of 92.82%, with recognition time of 41.91 seconds. The study demonstrated that EGAO consistently outperformed GAO in false positive rate, sensitivity, specificity, precision, and accuracy, confirming that APT enhanced the optimization capability of GAO and enabled the selection of more discriminative fingerprint features. Although EGAO incurred a higher recognition time than GAO, its substantial improvement in recognition performance establishes the EGAO framework as a more accurate, reliable, and effective approach for fingerprint recognition and robust biometric identification applications.

Introduction

Biometric recognition refers to automated methods that use human physiological or behavioural traits to verify identity. Fingerprints remain the most widely deployed modality because they are distinctive, persistent, easy to capture, and inexpensive to process. It plays a vital role in border control, banking, mobile authentication, and other civil and security applications. Modern systems increasingly prioritise speed, robustness, and fairness across populations (Maltoni *et al.*, 2022). A typical fingerprint recognition pipeline begins with image acquisition using optical, capacitive, or ultrasonic sensors, followed by preprocessing steps such as noise suppression, ridge orientation estimation, and normalisation. Feature extraction then derives descriptors including minutiae points, ridge counts, orientation, texture, and, in some cases, learned representations when sufficient data are available. Matching involves comparing these features to stored templates and using calibrated scores for decision making at targeted operating points (Maltoni *et al.*, 2022).

Statement of the Problem

Despite widespread adoption, fingerprint recognition systems face persistent challenges. Variations in image quality, skin deformation, partial impressions, and environmental noise all degrade performance, leading to higher false acceptance and rejection rates. Expanding fingerprint databases also introduce high-dimensional data processing demands. Redundant and irrelevant features often reduce recognition accuracy while slowing computation. Feature selection plays a key role in mitigating these issues by enabling compact and discriminative feature sets that improve accuracy and efficiency.

Aim and objectives

The aim of this research is to develop an enhanced giant armadillo optimized feature selection technique for fingerprint recognition system. The specific objectives are to:

- (i) formulate an Enhanced Giant Armadillo Optimizer (EGAO) using adaptive parameter tuning (APT)
 - (ii) develop an enhanced feature selection technique for fingerprint recognition system using formulated EGAO
 - (iii) implement the developed technique in MATLAB R(2020a) software
- evaluate the performance of the developed model using false positive rate, sensitivity, specificity, precision, accuracy and recognition time.

Justification of the study

Fingerprint recognition systems are widely used but face accuracy challenges due to redundant or noisy data that increases computational costs and reduces performance. Feature selection is critical for retaining only the most meaningful features, yet traditional methods struggle with issues like premature convergence and high computational demands.

Scope of the study

This study will focus on developing and evaluating an enhanced feature selection technique for fingerprint recognition systems using the Giant Armadillo Optimization (GAO) algorithm.

Literature Review

Fingerprint Recognition

Fingerprint recognition is one of the most established and widely adopted biometric modalities, extensively used in law enforcement, border management, banking, and consumer electronics. Its popularity is largely attributed to the uniqueness and permanence of fingerprint ridge patterns, which remain stable over an individual's lifetime and are relatively straightforward to capture compared to other biometric traits (Maltoni *et al.*, 2022). A typical fingerprint recognition system involves acquiring

an image of the fingertip through optical, capacitive, or ultrasonic sensors, followed by preprocessing steps to improve image quality and extract discriminative features such as minutiae points, ridge counts, and texture descriptors. These features are then stored as templates and matched against query samples to support verification or identification decisions.

Fingerprint Acquisition

Fingerprint acquisition constitutes the initial and arguably most critical stage of any fingerprint recognition system. The quality of the captured fingerprint image has a direct impact on subsequent processes including preprocessing, feature extraction, and classification. Therefore, acquisition remains a primary focus in biometric deployments for border control, law enforcement, mobile authentication, and civil identification systems.

Acquisition Methods

The acquisition process is the foundation of fingerprint recognition systems. The quality of the initial capture, whether free from noise, distortion, or incomplete ridge patterns, directly affects subsequent stages such as preprocessing, feature extraction, and classification. Historically, the earliest method of acquisition was ink-based. In this approach, the fingertip was pressed against an ink pad and rolled onto paper to create a permanent forensic record as shown in Figure 2.1. These impressions were later digitized using scanners for computational use. While reliable for archival purposes, this method was frequently affected by smudging, uneven pressure, and geometric distortion during scanning. As a result, many images contained artefacts that complicated automatic feature extraction and reduced recognition accuracy (Jain *et al.*, 2016; Maltoni *et al.*, 2022).

Challenges in Acquisition

Despite advances in fingerprint sensor technology, persistent challenges continue to constrain the accuracy and reliability of captured images. A key source of difficulty lies in human physiological variability, including age, skin conditions, and occupation. Recent surveys indicate that ageing, skin diseases, and occupational wear significantly impact fingerprint richness, causing recognition failures in biometric systems (Riaz *et al.*, 2024). Environmental conditions also impair acquisition quality. Modern fingerprint systems, whether contact-based or contactless, experience distortions from moisture, contamination, and sensor-specific artifacts, which degrade image quality and interoperability (Mohamed Abdul Cader *et al.*, 2023). User behaviour remains critical.

Table 1. Comparison of Fingerprint Sensor Types (Source: Ratha and Bolle, 2021)

Sensor Type	Working Principle	Advantages	Limitations	Typical Applications
Optical Sensor	Captures fingerprint image using light reflection and prism/lens system.	Low cost, mature technology, durable.	Bulky, vulnerable to spoofing (printed images), affected by dirt/oil on surface.	Time and attendance, low-cost smartphones.
Capacitive Sensor	Measures electrical capacitance differences between fingerprint ridges and valleys.	Compact, harder to spoof, widely used in consumer electronics.	Sensitive to dry/dirty skin, requires close contact.	Smartphones, laptops, access control.
Ultrasonic Sensor	Uses high-frequency sound waves to map	Works with wet/dirty fingers,	Expensive, higher power	High-end smartphones,

	3D ridge-valley patterns.	captures depth, higher security.	consumption, slower capture speed.	secure biometric systems.
Thermal Sensor	Detects heat differences when finger touches sensor surface.	Simple design, less affected by surface contamination.	Low resolution, requires finger contact and heat variation.	Specialized access devices, older biometric systems.
Contactless (2D/3D)	Captures fingerprint using cameras, multispectral imaging, or OCT (Optical Coherence Tomography).	Hygienic, user-friendly, reduces wear, robust against skin conditions.	High computational load, illumination challenges, spoofing concerns.	Airports, high-security access, modern biometric research.

Fingerprint Image Preprocessing

Fingerprint preprocessing plays a central role in converting raw, imperfect images into representations suitable for reliable feature extraction and recognition. Since acquisition devices and environmental conditions frequently produce degraded inputs with issues such as low contrast, noise, smudges, partial impressions, and geometric distortions, preprocessing is critical for ensuring consistency and quality. Modern pipelines employ a sequence of operations that standardize intensity distributions, suppress noise, estimate orientation and frequency fields, segment regions of interest, and enhance ridge structures prior to binarization or skeletonization. These steps not only improve the discriminability of extracted features but also enhance robustness against spoofing, contactless variability, and the challenges of latent or mobile sensor captures. Recent studies highlight the role of deep learning and enhancement-driven preprocessing techniques, which automatically adapt to varying image conditions and significantly improve matching accuracy (Fan, 2020; Priesnitz *et al.*, 2022; Gavas *et al.*, 2024; Wang *et al.*, 2025).



Figure 1. Samples of high quality fingerprints (top row) and low quality fingerprint (bottom row) with different age ranges (Blomeke, et al, 2008).

Feature Extraction and Selection in Fingerprint Recognition

Feature extraction and selection constitute two fundamental stages in fingerprint recognition pipelines. While feature extraction focuses on representing the unique ridge structures and minutiae patterns from fingerprint images, feature selection aims to refine these representations by retaining the most discriminative and robust features for matching and classification.

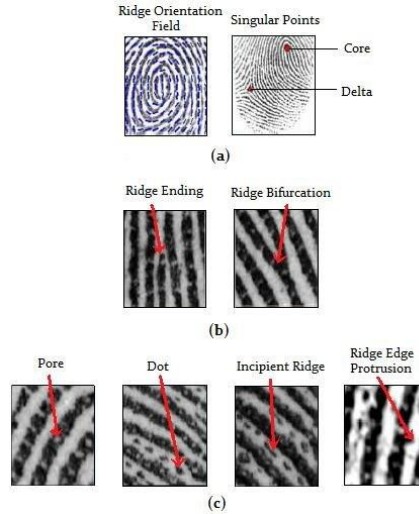


Figure 2. Fingerprint features.

- (a) Level-1 features (Ridge orientation field and singular points),**
- (b) Level-2 features (Ridge ending and ridge bifurcation),**
- (c) Level-3 features (pore, dot, incipient ridge and ridge edge protrusion).**

Optimisation Techniques

Optimisation is a critical component of fingerprint recognition systems because it determines how effectively the system can manage large feature spaces, improve classification accuracy, and reduce computational complexity. In practice, fingerprint data often consist of high-dimensional and redundant features, which can compromise both recognition speed and accuracy if not properly optimised. The process of optimisation involves selecting the most relevant features, adjusting algorithm parameters, and fine-tuning decision boundaries to achieve the best system performance. Without effective optimisation, even advanced recognition algorithms may fail to deliver consistent results under varying acquisition conditions such as noise, partial prints, or distortion (Shukla *et al.*, 2021).

Giant Armadillo Optimiser (GAO)

In this section, the source of inspiration in the design of the proposed Giant Armadillo Optimization (GAO) approach is stated, and then it is mathematically modeled in order to use it in optimization applications.

Inspiration for GAO

The giant armadillo (*Prionomys maximus*) is the largest living species of armadillo in danger of extinction and lives in South America, ranging as far south as northern Argentina (Wilson *et al.*, 2005). Termites and ants are the main diet of giant armadillos. However, this animal also feeds on plants, larvae, worms, and larger creatures, such as snakes and spiders. In order to feed on termites, giant armadillos attack termite mounds and then use their digging power to prey on and rip open termite mounds.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N \times m} \quad 2.1$$

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \quad 2.2$$

Research Gap

Despite significant progress in fingerprint recognition using deep learning, feature selection, and metaheuristic optimisation, current approaches still face challenges of high computational overhead, redundant or irrelevant features, and inconsistent performance across diverse datasets. While the recently

introduced Giant Armadillo Optimiser (GAO) has shown potential in solving complex optimisation tasks, its application in biometrics remains limited and its performance is hindered by slow convergence rates and a tendency to become trapped in local optima. These shortcomings highlight the need for an improved optimisation strategy that balances exploration and exploitation more effectively.

The results showed that when the BALFS system matched sample A on itself; matched sample B on sample A; and matching of sample B on itself produced recognition accuracies of 100.0%; 94.5%; and 98.5% at 0.85 thresholds respectively. However, the matching of sample C (spoofing samples) on sample A and sample B produced accuracies of 100% and 86.5% for non-matching subjects at 0.85 threshold respectively.

Biometrics is a fast growing technology which provides security to prevent unauthorized access to ATMs, computer networks, cellular phones, email authentication on multimedia workstations, PDA, etc. Crime which is happening in Automated Teller Machine (ATM) became a serious issue that affects not only customers but also bank operators. The main solution to this problem is multimodal biometrics. Palm vein authentication is one of the vascular based biometric pattern authentication technologies. Vascular pattern authentication includes vein pattern authentication using the vein patterns of the palm, back of the hand or fingers as personal identification data. This system proposes a multi-modal based fraud prevention ATM security system.

The palm vein is subjected to morphological pre-processing, feature extraction by Independent Gabor (I-Gabor) –cum -Adaptive LBP while thumbprint was also pre-processed by Sobel, histogram equalization and minutiae feature extraction by Crossing Number. While traits matching algorithm used is back-propagation neural network variant. Thus it was observed that the results of the experiment with ALBP produced 9.4% of true positive better than without ALBP, 3.3% of false positive lower than ALBP, 12.5% of recognition rate better than without ALBP.

The increasing demand for high secure and reliable authentication schemes, led to improvement in unimodal biometric system and hence multimodal biometric system has emerged as a mean of more secure and reliable authentication scheme. This work examines the multimodal fusion of palmprint (principal lines) and fingerprint (minutiae points). After an introduction to theoretical principles, related works in palmprint, fingerprint, and fusion of palmprint and fingerprint are highlighted. The developed system modules include image acquisition, morphological stage, feature extraction stage, fusion stage and classification stage. The database is composed of 600 posed fingerprints, 120 posed palmprints and 6480 fused posed palmprints and fingerprints. The data were trained and tested with a variant of neural network back-propagation algorithm. Three thresholds were employed viz; 0.35, 0.65 and 0.95.

The results showed that threshold 0.95 produced average accuracy of 98.3%, threshold 0.65 produced average accuracy of 5%, and threshold 0.35 produced average accuracy 16.4%. Knowledge-based and token-based automatic personal identification approaches have been the two traditional techniques widely used. Because knowledge-based and token-based approaches are unable to differentiate between an authorized person and an impostor who fraudulently acquires the token or knowledge of the authorized person. This paper investigate the use of Physiological traits in online transactions using particle warm optimization. In this experiment 120 tongue images and fingerprints of different individuals were acquired using digital camera and webcam. The traits were preprocessed using segmentation scheme and particle swarm optimization was used to select salient features. Three testing scenarios were created; (i) testing with all images in database and (ii) testing with another selected pose of images in database and (iii) poses of images not in database but captured in a bad illumination.

The decision to recognize or classify the images was determined by threshold at 0.50. Scenario 1 results showed that the experiment produced sensitivity of 94.6%, specificity of 95.7% and accuracy

rate of 94.6% for tongues and sensitivity of 87.2%, specificity of 81.4%, and accuracy of 90.1% for fingerprints. Scenario 2 results showed that the experiment produced sensitivity of 78.6%, specificity of 74.7% and accuracy of 93.3% for tongues while fingerprints has sensitivity of 65.2%, specificity of 69.4%, and accuracy of 75.5%. while scenario 3 results produced sensitivity of 0.6%, specificity of 0.77% and accuracy of 0.0% for fingerprints and sensitivity of 22.6%, specificity of 18.4%, and accuracy of 20.7% for fingerprints. However, using tongue along with PSO will enhance better performance accuracy for this automatic identification and authentication in ATM system.

Methodology

Research Approach

This study involves six major stages designed to develop an Enhanced Giant Armadillo Optimized (EGAO) Feature Selection Technique for fingerprint recognition. In the first stage, fingerprint image acquisition, fingerprint samples will be collected from 500 students of LAUTECH, Ogbomosho, using a Digital Persona fingerprint sensor, with three samples obtained from each participant to ensure data reliability and variability. The second stage, image pre-processing, will involve a sequence of enhancement operations such as image enhancement, noise removal, segmentation, binarization, and thinning to improve image clarity and ridge structure. The third stage, feature extraction, will focus on identifying key fingerprint characteristics, where minutiae extraction will be performed using the Crossing Number (CN) algorithm to detect ridge endings and bifurcations. In the fourth stage, feature selection will be carried out using the formulated Enhanced Giant Armadillo Optimizer (EGAO) integrated with Adaptive Parameter Tuning (APT) to optimally select the most discriminative and relevant features for recognition. The fifth stage will involve system implementation in MATLAB R(2020a), where all processes from pre-processing to feature selection and classification will be programmed and executed. Finally, the sixth stage will focus on performance evaluation of the developed fingerprint recognition system using metrics such as False Positive Rate (FPR), Sensitivity, Specificity, Precision, Accuracy, and Recognition Time.

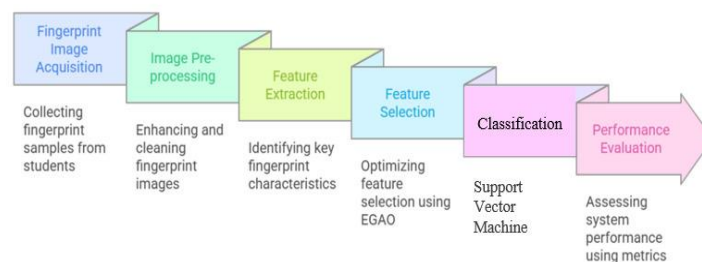


Figure 3. Schematic Diagram of the Fingerprint Recognition System

The second stage focuses on minutiae extraction using the Crossing Number (CN) approach. For each ridge pixel p in the thinned binary image T , the eight neighboring pixels $p_1, p_2, \dots, p_8$ are considered in a clockwise order. Each pixel value is binary- 1 representing a ridge and 0 representing a background. The Crossing Number is computed as Equation 3.1:

$$CN(p) = \frac{1}{2} \sum_{i=1}^8 |v_i - v_{i+1}|, \text{ where } v_9 \equiv v_1 \quad 3.1$$

Formulation and Development of Enhanced Giant Armadillo Optimizer (EGAO)

To reduce redundancy and improve classification performance, the Enhanced Giant Armadillo Optimizer (EGAO) will be applied to select the most discriminative subset of fingerprint features. The EGAO will be developed by integrating Adaptive Parameter Tuning (APT) into the standard Giant Armadillo Optimizer (GAO). The APT mechanism dynamically adjusts the key parameters of GAO

such as exploration coefficient, exploitation rate, and step size based on population diversity and iteration progress.

Fingerprint Recognition using Support Vector Machine

After the optimal subset of fingerprint features has been selected using the Enhanced Giant Armadillo Optimizer (EGAO), the next stage in the recognition pipeline involves classification using a Support Vector Machine (SVM). The SVM is chosen for its robust generalization capability and strong performance in high-dimensional feature spaces, making it highly suitable for biometric recognition tasks. The selected feature matrix, $X_{\text{best}} \in \mathbb{R}^{n \times m'}$, where n is the number of fingerprint samples and m' is the number of features retained after optimization, serves as the input to the SVM classifier. Each feature vector x_i corresponds to a fingerprint sample, and

Implementation of the Developed Technique

The proposed fingerprint recognition system incorporating the EGAO-based feature selection technique will be implemented in MATLAB R(2020a). MATLAB provides a flexible computational platform for image processing, optimization modeling, and statistical analysis. The implementation will include modules for Pre-processing and feature extraction functions, EGAO optimization script for feature selection and SVM-based classifier for fingerprint identification. It will be implemented using some specific system configuration.

Performance Evaluation of the Developed Technique

The performance of the developed Enhanced Giant Armadillo Optimized (EGAO) Feature Selection-based Fingerprint Recognition System was evaluated using standard biometric performance metrics including False Positive Rate (FPR), Sensitivity (Recall), Specificity, Precision, Accuracy, and Recognition Time. These metrics quantitatively assess the classification reliability, robustness, and efficiency of the proposed system after classification by the Support Vector Machine (SVM). The evaluation process compares the system's predicted outcomes with the actual ground truth labels to measure its capability to correctly recognize genuine fingerprint samples and reject impostors.

Let the classification results be represented by four basic quantities:

- a) True Positive (TP): Number of genuine fingerprint samples correctly recognized as genuine.
- b) True Negative (TN): Number of impostor fingerprint samples correctly identified as impostors.
- c) False Positive (FP): Number of impostor fingerprint samples incorrectly recognized as genuine.
- d) False Negative (FN): Number of genuine fingerprint samples incorrectly rejected as impostors.

Results and discussion

Results

The developed Enhanced Giant Armadillo Optimizer (EGAO)-based feature selection technique was successfully implemented for the fingerprint recognition system, with Adaptive Parameter Tuning (APT) incorporated to enhance the optimization process. A total of 1,440 fingerprint images obtained from 480 individuals, with three samples collected from each individual, were used for the experimental evaluation. Using the random subsampling cross-validation approach, 70% of the images were randomly allocated for training, while the remaining 30% were used for testing. The developed model was implemented in MATLAB R2020a and integrated into a graphical user interface that supports fingerprint training, testing, feature selection, and recognition. In the recognition stage, Support Vector Machine (SVM) was employed as the classifier, while the performance of the proposed EGAO feature-selection technique was compared with the conventional Giant Armadillo Optimizer (GAO) used as the baseline feature-selection method.

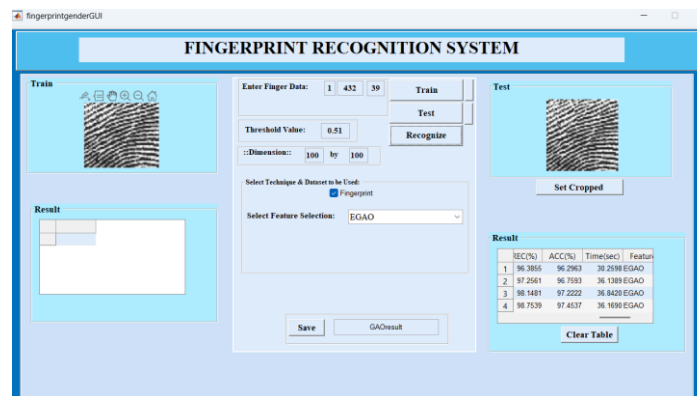


Figure 4. Graphical User Interface describing the Training and Recognition process of the Developed Model

Result of Giant Armadillo Optimizer (GAO)

The performance of the Giant Armadillo Optimizer (GAO) as a feature selection technique for the fingerprint recognition system was evaluated at threshold values of 0.20, 0.35, 0.50, and 0.51. At a threshold of 0.20, the GAO-based feature selection achieved 310 true positives (TP), 14 false negatives (FN), 21 false positives (FP), and 87 true negatives (TN), resulting in an FPR of 19.44%, sensitivity of 95.68%, specificity of 80.56%, precision of 93.66%, and accuracy of 91.90%. Increasing the threshold to 0.35 reduced the FP from 21 to 19 and increased TN from 87 to 89, thereby reducing the FPR to 17.59% while maintaining a high sensitivity of 95.37%. At this threshold, the specificity and precision increased to 82.41% and 94.21%, respectively, while accuracy improved slightly to 92.13% with a recognition time of 43.45 seconds. These results indicate that increasing the threshold from 0.20 to 0.35 improved the overall classification performance of GAO, particularly in terms of reduced false-positive identification and increased specificity.

Table 2. Performance Evaluation Result of GAO

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time (sec)
0.2	310	14	21	87	19.44	95.68	80.56	93.66	91.90	42.77
0.35	309	15	19	89	17.59	95.37	82.41	94.21	92.13	43.45
0.5	308	16	17	91	15.74	95.06	84.26	94.77	92.36	46.33
0.51	307	17	14	94	12.96	94.75	87.04	95.64	92.82	41.91

Result of Enhanced Giant Armadillo Optimizer

The performance of the Enhanced Giant Armadillo Optimizer (EGAO), developed by incorporating Adaptive Parameter Tuning (APT) into the original Giant Armadillo Optimizer (GAO), was evaluated at threshold values of 0.20, 0.40, 0.50, and 0.51. At a threshold of 0.20, EGAO achieved 320 true positives (TP), 4 false negatives (FN), 12 false positives (FP), and 96 true negatives (TN), resulting in an FPR of 11.11%, sensitivity of 98.77%, specificity of 88.89%, precision of 96.39%, and accuracy of 96.30%. When the threshold was increased to 0.40, the number of FP decreased from 12 to 9 and TN increased from 96 to 99, resulting in a lower FPR of 8.33% and higher specificity of 91.67%. At this threshold, sensitivity decreased slightly to 98.46%, while precision and accuracy increased to 97.26% and 96.76%, respectively, with a recognition time of 79.84 seconds. These results demonstrate that the incorporation of APT enabled EGAO to maintain high classification sensitivity while progressively reducing false-positive fingerprint recognition errors as the threshold increased.

Table 3. Performance Evaluation Result of Enhanced Giant Armadillo Optimizer

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time (sec)
0.2	320	4	12	96	11.11	98.77	88.89	96.39	96.30	78.31
0.4	319	5	9	99	8.33	98.46	91.67	97.26	96.76	79.84
0.5	318	6	6	102	5.56	98.15	94.44	98.15	97.22	79.84
0.51	317	7	4	104	3.70	97.84	96.30	98.75	97.45	78.86

Comparison of the Result of GAO and EGAO

The comparative results in Table 4.3 show that both the conventional Giant Armadillo Optimizer (GAO) and the Enhanced Giant Armadillo Optimizer (EGAO) were employed as feature-selection techniques, while Support Vector Machine (SVM) was used as the classifier for fingerprint recognition. At the optimum threshold of 0.51, the GAO-SVM model achieved an FPR of 12.96%, sensitivity of 94.75%, specificity of 87.04%, precision of 95.64%, and accuracy of 92.82%. In contrast, the EGAO-SVM model achieved a substantially lower FPR of 3.70%, while sensitivity, specificity, precision, and accuracy increased to 97.84%, 96.30%, 98.75%, and 97.45%, respectively. The corresponding improvements of EGAO over GAO were 9.26 percentage points in FPR reduction, 3.09 percentage points in sensitivity, 9.26 percentage points in specificity, 3.11 percentage points in precision, and 4.63 percentage points in accuracy. These findings demonstrate that the enhanced feature-selection capability of EGAO provided SVM with more discriminative fingerprint features, thereby improving the overall classification performance compared with GAO-based feature selection.

Table 4. Comparative Performance Evaluation of GAO and EGAO at Optimum Threshold

Performance Metric	GAO (Threshold = 0.51)	EGAO (Threshold = 0.51)	Improvement of EGAO
FPR (%)	12.96	3.70	-9.26
Sensitivity (%)	94.75	97.84	+3.09
Specificity (%)	87.04	96.30	+9.26
Precision (%)	95.64	98.75	+3.11
Accuracy (%)	92.82	97.45	+4.63
Recognition Time (sec)	41.91	78.86	+36.95

Discussion of Results

Figure 4.2 presents the false positive rate (FPR) obtained from GAO and EGAO at threshold values of 0.20, 0.35, 0.50, and 0.51. The GAO-based feature selection produced FPR values of 19.44%, 17.59%, 15.74%, and 12.96%, respectively, whereas EGAO achieved substantially lower values of 11.11%, 8.33%, 5.56%, and 3.70%. The progressive reduction in FPR demonstrates that EGAO was more effective than GAO in selecting fingerprint features capable of distinguishing genuine samples from non-genuine samples. This improvement can be attributed to the Adaptive Parameter Tuning (APT) incorporated into EGAO, because dynamic parameter control allows an optimizer to modify its search behaviour during the optimization process rather than retaining fixed parameter values throughout the search (de Lacerda et al., 2021). The finding is also consistent with Nssibi et al. (2023), who reported that metaheuristic feature-selection methods can improve the search for concise and informative feature subsets in complex search spaces, thereby improving learning and classification performance.

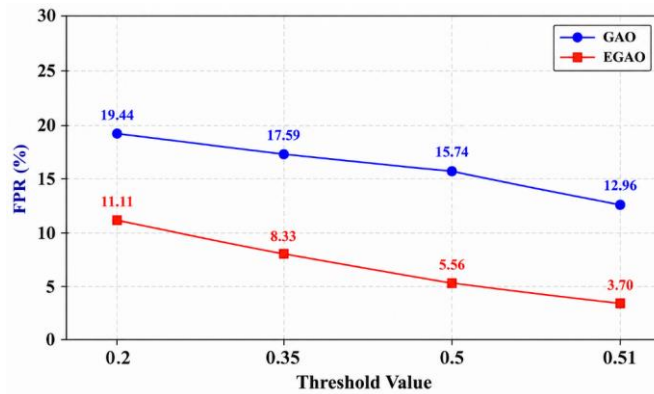


Figure 5. Graph of False Positive Rate with GAO and EGAO

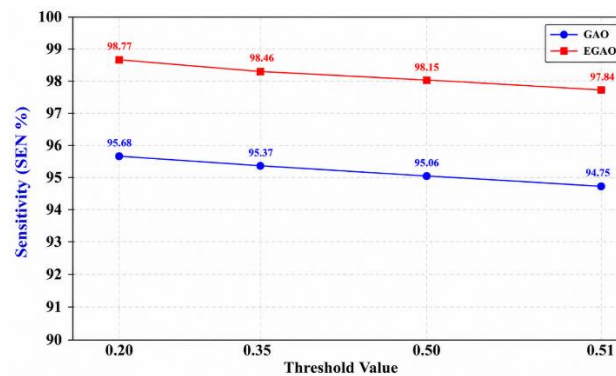


Figure 6. Graph of Sensitivity with GAO and EGAO

Conclusion

This study successfully developed an Enhanced Giant Armadillo Optimizer (EGAO)-based feature-selection technique for fingerprint recognition by incorporating Adaptive Parameter Tuning (APT) into the conventional Giant Armadillo Optimizer (GAO). The developed EGAO was implemented in MATLAB R2020a and integrated with Support Vector Machine (SVM) for the recognition of fingerprint patterns. Experimental evaluation using the fingerprint dataset demonstrated that both GAO and EGAO were capable of selecting relevant fingerprint features for effective recognition. However, EGAO consistently achieved superior performance across the major evaluation metrics, including false positive rate, sensitivity, specificity, precision, and accuracy. The results therefore confirm that adaptive parameter tuning enhanced the optimization capability of GAO and contributed to the selection of more discriminative features for the SVM-based fingerprint recognition system.

At the optimum threshold, the EGAO-SVM model achieved a lower value of FPR, and high sensitivity, specificity, precision, and accuracy, compared with GAO-SVM model. These findings demonstrate that EGAO provided substantial improvements in both the reliability and discriminatory capability of the fingerprint recognition system, particularly through the reduction of false-positive recognition errors. Although EGAO required a longer recognition time compared with GAO, the computational increase was accompanied by considerable gains in recognition performance. The study consequently establishes Adaptive Parameter Tuning as an effective enhancement mechanism for the GAO feature-selection process when applied to fingerprint recognition. Overall, the developed EGAO-SVM framework provides a more accurate and reliable fingerprint recognition approach than the conventional GAO-SVM framework and demonstrates its potential for applications requiring robust biometric identification.

Recommendation

Based on the findings of this study, it is recommended that the Enhanced Giant Armadillo Optimizer (EGAO) with Adaptive Parameter Tuning (APT) be adopted as a feature-selection technique for fingerprint recognition systems because of its superior classification performance compared with conventional GAO. Future studies should investigate strategies for reducing the computational time of EGAO while maintaining its improved accuracy, sensitivity, specificity, precision, and low false positive rate. The developed EGAO-SVM framework should also be evaluated using larger and more diverse fingerprint datasets obtained from different sensors, environmental conditions, age groups, and fingerprint qualities to establish its robustness and generalization capability. Further research should consider integrating EGAO with other advanced classifiers, deep-learning models, or hybrid biometric systems to determine whether additional improvements in recognition performance can be achieved. Finally, real-time implementation and deployment of the EGAO-based fingerprint recognition system should be investigated to assess its computational efficiency, scalability, security, and suitability for practical biometric identification applications.

Contribution to Knowledge

This study contributes to knowledge by developing an Enhanced Giant Armadillo Optimizer (EGAO) through the incorporation of Adaptive Parameter Tuning (APT) into the conventional Giant Armadillo Optimizer (GAO), thereby providing a more flexible optimization mechanism for feature selection. The APT mechanism addresses the limitation of relying on fixed algorithmic parameters by enabling parameter values to be adjusted in response to the optimization search, which is recognized as an important consideration in improving metaheuristic performance. The enhanced EGAO was subsequently applied as a feature-selection technique for fingerprint recognition, where its role was to identify relevant and discriminative fingerprint features while reducing the influence of irrelevant or redundant features, consistent with the established objective of metaheuristic feature selection.

References

1. Fan, J. (2020). Fingerprint image enhancement based on Gabor filter. *Journal of Physics: Conference Series*, 1631(1), 012134. <https://doi.org/10.1088/1742-6596/1631/1/012134>
2. Gavass, A. P., and Namboodiri, A. M. (2023). Finger-UNet: A lightweight U-Net model for fingerprint image enhancement. *Pattern Recognition Letters*, 169, 15–22. <https://doi.org/10.1016/j.patrec.2023.03.005>
3. Ismaila W. O., Ogunjinmi Temitope O., Babalola O. Richard, Ismaila Folasade. M. (2019). Biometric Automated Teller Machines Based Anti-Spoofing Fingerprint System, *International Journal of Embedded and Software Computing*. Vol. 9, No.9, pp- 23789- 23792.
4. Jain, A. K., Ross, A., and Nandakumar, K. (2016). *Introduction to biometrics* (2nd ed.). Springer. <https://doi.org/10.1007/978-0-387-77326-1>
5. Maltoni, D., Maio, D., Jain, A. K., and Feng, J. (2022). *Handbook of fingerprint recognition* (3rd ed.). Springer. <https://doi.org/10.1007/978-3-031-01772-8>
6. Maltoni, D., Maio, D., Jain, A. K., and Prabhakar, S. (2022). *Handbook of fingerprint recognition* (3rd ed.). Springer. <https://doi.org/10.1007/978-3-030-83624-5>
7. Mohamed Abdul Cader, A. J., Banks, J., and Chandran, V. (2023, July 21). Fingerprint systems: Sensors, image acquisition, interoperability and challenges. *Sensors*, 23(14), 6591. <https://doi.org/10.3390/s23146591>
8. Mustapha S. O., Ismaila W. O., Adeyemi I.O. Ismaila F.M., Priesnitz, J., Mirzaalian, H., and Micheloni, C. (2022). Contactless to contact fingerprint image enhancement via generative adversarial networks. *Pattern Recognition Letters*, 155, 75–82. <https://doi.org/10.1016/j.patrec.2022.01.018>

9. Shukla, A., Yadav, N., and Singh, R. (2021). Optimisation techniques for high-dimensional biometric data: A survey. IEEE Access, 9, 145732–145748. <https://doi.org/10.1109/ACCESS.2021.3120623>
10. Tabassi, E., Wilson, C. L., and Watson, C. I. (2021). NIST fingerprint image quality (NFIQ) 2.0. National Institute of Standards and Technology. <https://doi.org/10.6028/NIST.IR.8034>
11. Yang, X., Li, Y., Wang, S., and Chen, H. (2023). Giant armadillo optimiser: A nature-inspired metaheuristic for high-dimensional optimisation problems. Applied Soft Computing, 136, 110103. <https://doi.org/10.1016/j.asoc.2023.110103>.