LAUTECH Journal of Engineering and Technology 19 (5) 2025: 76-89
10.36108/laujet/5202.91.0550

Enhanced Chicken Swarm Optimization-Tuned Convolutional Neural Network For Fingerprint-Based Ethnicity Identification

[1]Ige, O. B., [1]Falohun, A. S., [2]Olabiyisi, S. O., [3]Ayangbekun, O. J, [3]Akanni O. A, [1]Omidiora E. O., [4]Ige, R.O., and [1]Awodoye O. O.

[1]*Department of Computer Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria*
[2]*Department of Computer Science, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria*
[3]*Department of Computer Engineering, Federal Polytechnic Ayede, Oyo State, Nigeria*
[4]*Department of Community Medicine, College of Health Sciences, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria*

[1]ask4bestlink@yahoo.com [1]asfalohun@lautech.edu.ng, [2]soolabiyisi@lautech.edu.ng, [3]ayangbekunoj@gmail.com, [3]akannioa@federalpolyayde.edu.ng, [1]eoomidiora@lautech.edu.ng, [1]jpoguntoye@lautech.edu.ng [4]roige@lautech.edu.ng, [1]ooawodoye50@lautech.edu.ng

Article Info

Article history:

Received: Sept 29, 2025
Revised: Oct 29, 2025
Accepted: Nov 16, 2025

Keywords:

Fingerprint recognition, ethnicity classification, convolutional neural network, chicken swarm optimization, data augmentation, biometrics

Corresponding Author:
ask4bestlink@yahoo.com
+2348060407045

ABSTRACT

Identification of human being based on fingerprints have proven to be highly reliable. Researches have been done on fingerprint ethnicity identification, which are characterized with high false positive rate and high recognition time. This research developed Fingerprint Identification System with an enhanced CSO combined with CNN for better fingerprint ethnicity identification. One thousand two hundred (1200) subjects' fingerprint images were acquired from three major ethnic groups in Nigeria (Yoruba, Igbo and Hausa) with equal ratio of male to female between the ages of 17–50 years, using Secugen Hamster Plus Fingerprint Scanner; Six hundred (600) acquired subjects' fingerprints were augmented and used for training while the remaining 50% were used for testing. The raw images were pre-processed; CNN hyperparameters were tuned using CSO and CSO enhanced with Chaotic theory. The implementation was done using MATLAB R2023a software. The performance of the ICSO-CNN was evaluated and compare with CNN and CSO-CNN at a benchmark of 0.75 threshold value using, False Positive Rate (FPR) and Recognition Time (RT). The FPR and RT using CNN for Yoruba, Igbo and Hausa were 3.5% and 60.54s; 3.75% and 59.31s and 4% and 58.04s, respectively. The FPR and RT using CSO-CNN for Yoruba, Igbo and Hausa were 2.25% and 49.87s; 2.5% and 48.82s and 2% and 49.79s, respectively, while the corresponding values for the enhanced CSO-CNN were 1.75% and 36.64s, 2% and 38.56s and 1.5% and 39.35s. The developed fingerprint-based ethnicity identification system gave an improved identification performance over CNN and CSO-CNN. The developed ICSO-CNN can be used by security agencies for proper identification of criminals based on ethnicity.

INTRODUCTION

Human identification and verification have been in existence before the invention of technology; humans have been using physical traits to identify one another. During the time of ancient Babylonia and China, thumbprints and fingerprints were used as signatures on clay tablets and seals (Bhatele et al., 2025) and also to identify workers in government jobs (Nayak et al., 2022). The practice of using handprints for identification continued into the Tang dynasty (618–907 CE) when fingerprints were also used as a means of detecting criminals (Petrétei, 2025). Despite the fact that this approach then was void of scientific analysis, it was generally accepted. Fingerprint, is the impression made by the papillary ridges on the ends of the fingers and thumbs (Riaz and Ibrahim, 2024), it affords an infallible means of personal identification, because the ridge arrangement on every finger of every human being is unique and does not alter with growth or age (Greenland, 2023). Biometrics identify people by measuring some aspect of individual's anatomy or physiology such as fingerprint which consists of a pattern of interleaved ridges and valleys (Adetunji et al 2015; Falohun *et al.,* 2016). Fingerprints identification is an efficient biometric technique (Adedeji et al., 2021; Akintunde et al., 2025) which serve to disclose an individual's true identity despite personal rejection, assumed names, or changes in personal appearance ensuing from disease, plastic surgery, age or accident.

Biometric identification has become a vital tool in modern society offering reliable methods of recognizing individuals based on their unique physiological or behavioral traits (Torrecilla-García and Skotnicka, 2025; Oguntoye *et al.,* 2025). Among the various biometric traits, fingerprints remain one of the most widely used due to their uniqueness, permanence, ease of acquisition, and cost-effectiveness (Shekhar *et al.,* 2025). Beyond personal authentication, fingerprint analysis has also been explored in forensic science, anthropology and demographic studies, including ethnicity identification (Ashraf et al., 2025). Ethnicity identification from fingerprints is particularly important in contexts such as forensic investigations, resources allocation, demographic research and social security management (Okediran and Oguntoye 2023; Ragmac and Allanic, 2025), where narrowing down the identity of individuals within vast populations can significantly enhance decision-making. Traditional fingerprint identification methods often rely on handcrafted features such as ridges, minutiae points and texture descriptors (Rehan et al., 2025). While these approaches have achieved reasonable accuracy, they are often limited by sensitivity to noise, variations in fingerprint quality, and the inability to capture deep, non-linear relationships between features (Ogundepo *et al*, 2022). In recent years, Convolutional Neural Networks (CNNs) have emerged as powerful models capable of automatically learning hierarchical features directly from raw images (Zangana et al., 2024; Olagunju et al., 2025). CNNs have shown remarkable success in various computer vision applications, including face recognition, object detection, and medical image analysis (Ola et al., 2020, Zhao *et al.,* 2024, He *et al.,* 2025). However, applying CNNs directly to ethnicity identification based on fingerprints presents several challenges, such as overfitting on small datasets, slow convergence speed, and the risk of poor generalization across diverse ethnic groups. Feature extraction and classification of fingerprint images were done using CNN while CSO was used to optimized the network's weights and hyperparameters (Olayiwola *et al.,* 2023). The performance of the developed system was evaluated using false positive rate, recognition accuracy and recognition time. In line with recent advances in optimized intelligent systems (Oyedokun et al., 2025; Oguntoye et al., 2024), and consistent with proven AI performance enhancement strategies (Mustapha et al., 2025), this study adopts an improved CSO-tuned CNN to strengthen accuracy and generalization in ethnicity identification.

METHODOLOGY

The evaluation of the developed enhanced Convolutional Neural Network for fingerprint-based ethnicity identification was carried out. The following stages were implemented: image acquisition, image pre-processing step comprised operations like image normalization, thinning, image segmentation and image augmentation. CSO was applied as an optimizer to fine-tune CNN hyperparameters and CNN was employed as feature extraction and classification for better performance as shown in Figure 1 of the **enhanced CSO-CNN (ECSO-CNN)** method under study.

Image Acquisition

One thousand two hundred (1200) subjects fingerprint images of both male and female between the ages of 17-50years were obtained using Secugen Hamster Plus Fingerprint Scanner.

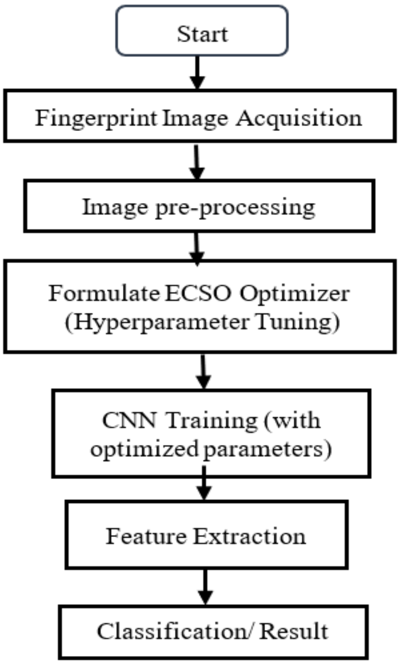

Figure 1. The Structure of the ECSO-CNN method

Image Pre-processing

Fingerprint images were acquired as primary biometric characteristics, while ethnicity which was considered as soft biometric trait were also acquired from 1200 subjects from Yoruba, Igbo and Hausa ethnic groups. This was initially analyzed which consist of the right thumb fingerprints from 1200 subjects from Yoruba, Igbo and Hausa ethnic groups respectively. To enhance the dataset, image rotation, image shifting, image flipping and augmentation techniques were applied to each category of ethnic group. This ensures that all fingerprint images are consistent in size, orientation and quality, thereby improving feature extraction accuracy. The augmentation technique was performed on 50% of the subjects fingerprints collected which increased the dataset to 2,400 image samples, which were used for training and the remaining 600 subject image samples were used for testing using random sampling method.

CSO Optimize (Hyperparameter Tuning)

Chicken Swarm Optimization (CSO) was employed to fine-tune CNN hyperparameters such as learning rate, number of filters, filter sizes and batch size. This prevents overfitting, accelerates convergence, and avoids the problem of local optima.

Fingerprint Feature Selection and Classification

CNN Training (with optimized parameters)

The optimized parameters by the CSO were used with the Convolutional Neural Network (CNN), this was trained on the fingerprint dataset. This enhances the learning process and improves classification performance.

Feature Extraction

The CNN automatically extracts hierarchical and discriminative features (such as ridges and minutiae patterns) from the fingerprint images through convolutional and pooling layers.

Classification

The fully connected layers of the CNN perform classification automatically by assigning the extracted features to the corresponding ethnicity group.

RESULTS AND DISCUSSION

Results for CNN Technique on Fingerprint

The result in Table1 presents the performance of CNN based fingerprint recognition techniques across the three major Nigerian ethnic groups on fingerprints image datasets – Yoruba, Igbo and Hausa. The fingerprint images comprise 2400 trained datasets and 600 test datasets.

Analysis of Yoruba Ethnic Group

Table1 presents the result of the CNN technique, at optimum threshold of 0.75 as shown in Table 1(a), the CNN correctly classified 183 of 600 datasets as true positive and 386 of 600 datasets as true negative with the Yoruba ethnicity as shown in Table 1(a). However, it misclassified 17 datasets as negative and 14 datasets as positive indicated that CNN on Yoruba ethnicity dataset had an average False Positive Rate of 3.5%, Specificity 96.5%, Recall 91.5%, Precision 92.89%, F1 92.19% and Accuracy of 94.83% at 60.54 seconds.

Analysis of Igbo Ethnic Group

Table 1, presents the results of CNN technique applied to Igbo ethnic group, for the Igbo ethnicity as indicated in Table 1(b), at an optimum threshold of 0.75, the CNN correctly classified 182 as true positive and 385 of 600 datasets as true negative, it misclassified 18 datasets as negative and 15 datasets as positive. Also, Igbo ethnicity dataset had an average False Positive Rate of 3.75%, specificity 90.5%, recall 91%, precision 92.39%, F1 91.69% and accuracy of 94.5% at 59.31seconds.

Analysis of Hausa Ethnic Group

Table 1 presents the result of the CNN technique applied to the Hausa dataset as shown in Table 1(c) at an optimum threshold of 0.75 has 181 of 600

Table 1. Results for Performance of the CNN Techniques on Fingerprint

a. Result for Yoruba Ethnic Group

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	186	14	21	379	5.25	94.75	93	89.86	91.40	94.17	60.84
0.35	185	15	19	381	4.75	95.25	92.5	90.69	91.59	94.33	60.41
0.5	184	16	17	383	4.25	95.75	92	91.54	91.77	94.5	60.88
0.75	183	17	14	386	3.5	96.5	91.5	92.89	92.19	94.83	60.54

b. Result for Igbo Ethnic Group

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	185	15	22	378	5.5	94.5	92.5	89.37	90.91	93.83	59.98
0.35	184	16	20	380	5	95	92	90.2	91.09	94	58.91
0.5	183	17	18	382	4.5	95.5	91.5	91.1	91.30	94.17	59.94
0.75	182	18	15	385	3.75	96.25	91	92.4	91.69	94.5	59.31

c. Result for Hausa Ethnic Group

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	FI (%)	Accuracy (%)	Time (sec)
0.2	184	16	23	377	5.75	94.25	92	88.89	90.42	93.5	57.79
0.35	183	17	21	379	5.25	94.75	91.5	89.71	90.60	93.67	57.96

0.5	182	18	19	381	4.75	95.25	91	90.55	90.77	93.83	57.59
0.75	181	19	16	384	4	96	90.5	91.88	91.18	94.17	58.04

Table 2. Results for the Performance of the CSO-CNN Techniques on Fingerprint

a. Result for Yoruba Ethnicity

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	191	9	17	383	4.25	95.75	95.5	91.83	93.63	95.67	49.6
0.35	190	10	14	386	3.5	96.5	95	93.14	94.06	96	48.85
0.5	189	11	11	389	2.75	97.25	94.5	94.5	94.5	96.33	49.38
0.75	188	12	9	391	2.25	97.75	94	95.43	94.71	96.5	49.87

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	190	10	18	382	4.5	95.5	95	91.35	93.14	95.33	48.13
0.35	189	11	15	385	3.75	96.25	94.5	92.65	93.60	95.67	48.76
0.5	188	12	12	388	3	97	94	94	94.00	96	49
0.75	187	13	10	390	2.5	97.5	93.5	94.92	94.20	96.17	48.82

b. Result for Igbo Ethnicity

c. Result for Hausa Ethnicity

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	192	8	16	384	4	96	96	92.31	94.12	96	48.32
0.35	191	9	13	387	3.25	96.75	95.5	93.63	94.56	96.33	49.02
0.5	190	10	10	390	2.5	97.5	95	95	95	96.67	50.13
0.75	189	11	8	392	2	98	94.5	95.94	95.21	96.83	49.79

dataset as true positive and 384 of 600 datasets as true negative while it misclassified 19 datasets as negative and 16 datasets as positive. Also, Hausa ethnicity dataset had an average FPR of 4%, Specificity 96%, Recall 90.5%, Precision 91.88%, F1 91.18% and Accuracy of 94.17% at 58.04 seconds.

Results for CSO-CNN Techniques on Fingerprint

The result in Table 2 presents the performance of CSO-CNN based fingerprint recognition techniques across the three major Nigerian ethnic groups on datasets of Yoruba, Igbo and Hausa. The fingerprint images comprise 2400 trained datasets and 600 test datasets.

Analysis of Yoruba Ethnic Group

From Table 2(a), with CSO-CNN technique, at optimum threshold of 0.75, the CSO-CNN correctly classified 188 of 600 datasets as true positive and 391 of 600 datasets as true negative. However, it misclassified 12 datasets as negative and 9 datasets as positive. In addition, Table 2 presented the result obtained by the CSO-CNN technique at different value with respect to the performance metrics. The results obtained from threshold value of 0.75 indicated that CSO-CNN on Yoruba ethnicity dataset had an average False Positive Rate of 2.25%, Specificity of 97.75%, Recall 94%, Precision 95.43147%, F1 94.71% and Accuracy 96.5% at 49.87seconds.

For the Igbo ethnicity as shown in Table 2(b) at an optimum threshold of 0.75, the CSO-CNN correctly classified 187 as true positive and 390 of 600 datasets as true negative, it misclassified 13 datasets as negative and 10 datasets as positive. Also, Igbo ethnicity dataset had an average False Positive Rate of 2.5%, Specificity 97.5%, Recall 93.5%, Precision 94.92%, F1 94.20% and Accuracy of 96.17% at 48.82seconds.

Analysis of Igbo Ethnic Group

Table 3. Results for the Performance of the ECSO-CNN Techniques on Fingerprint

a. Result for Yoruba Ethnicity

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	193	7	15	385	3.75	96.25	96.5	91.83	94.61	96.33	37.72
0.35	192	8	12	388	3	97	96	93.14	95.05	96.67	36.66
0.5	191	9	9	391	2.25	97.75	9.5	95.5	95.5	97	36.96
0.75	190	10	7	393	1.5	98.25	94	95	95.72	97.17	36.64

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	192	8	16	384	4	96	96	92.31	94.12	96	38.06
0.35	191	9	13	387	3.25	96.75	95.5	93.63	94.56	96.33	38.32
0.5	190	10	10	390	2.5	97.5	95	95	95	96.67	38.9
0.75	189	11	8	392	2	98	94.5	95.94	95.21	96.83	38.56

b. Result for Igbo Ethnicity

c. Result for Hausa Ethnicity

Threshold	TP	FN	FP	TN	FPR (%)	Specificity (%)	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
0.2	194	6	14	386	3.5	96.5	97	93.27	95.10	96.67	39.48
0.35	193	7	11	389	2.75	97.25	96.5	94.61	95.55	97	39.68
0.5	192	8	8	392	2	98	96	96	96	97.33	39.35

0.75	191	9	6	394	1.5	98.5	95.5	96.95	96.22	97.5	39.35

Analysis of Hausa Ethnic Group

As shown in Table 2(c), the Hausa dataset, at an optimum threshold of 0.75 has 189 of 600 dataset as true positive and 392 of 600 datasets as true negative while it misclassified 11 datasets as negative and 8 datasets as positive. Also, Hausa ethnicity dataset had an average False Positive Rate 2%, Specificity 98%, Recall 94.5%, Precision 95.94%, F1 95.21% and Accuracy of 96.83% at 49.79seconds.

Results for ECSO-CNN Techniques on Fingerprint

In this study, Convolutional Neural Network was optimized with chaotic enhanced Chicken Swarm Optimization Algorithm to find the best quality results. A target accuracy of 0.75 thresholds was set. The ECSO-CNN was then used to analyze the three major Nigerian ethnic groups Yoruba, Igbo and Hausa fingerprints. The fingerprint images comprised 2400 trained datasets and 600 test datasets.

Analysis of Yoruba Ethnic Group

From Table 3(a), with ECSO-CNN technique, at optimum threshold of 0.75, the ECSO-CNN correctly classified 190 of 600 datasets as true positive and 393 of 600 datasets as true negative. However, it misclassified 10 datasets as negative and 7 datasets as positive. Furthermore, the results obtained also indicated that at 0.75 threshold value ECSO-CNN on Yoruba ethnicity dataset had an average False Positive Rate of 1.75%, Specificity of 98.25%, Recall 95%, Precision 9.45%, F1 95.72% and Accuracy 97.17% at 3.64 seconds.

Table 4. Summary of the Evaluation of CNN, CSO-CNN and ECSO-CNN at threshold 0.75 on Fingerprint Ethnicity Identification

a. Result for Yoruba Ethnicity

Algorithm	FPR (%)	Recall (%)	Specificity (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
CNN	3.5	91.5	96.5	92.89	92.19	94.83	60.54
CSO-CNN	2.25	94	97.75	95.43	94.71	96.5	49.87
ECSO-CNN	1.75	95	98.25	96.45	95.72	97.17	36.64

b. Result for Igbo Ethnicity

Algorithm	FPR (%)	Recall (%)	Specificity (%)	Precision (%)	F1 (%)	Accuracy (%)	Time (sec)
CNN	3.75	91	96.25	92.39	91.69	94.5	59.31
CSO-CNN	2.5	93.5	97.5	94.92	94.20	96.17	48.82
ECSO-CNN	2	94.5	98	95.94	95.21	96.83	38.56

c. Result for Hausa Ethnicity

Algorithm	FPR	Recall	Specificity	Precision	F1	Accuracy	Time

	(%)	**(%)**	**(%)**	**(%)**	**(%)**	**(%)**	**(sec)**
CNN	4	90.5	96	91.88	91.18	94.17	58.04
CSO-CNN	2	94.5	98	95.94	95.21	96.83	49.79
ECSO-CNN	1.5	95.5	98.5	96.95	96.22	97.5	39.35

Analysis of Igbo Ethnic Group

For the Igbo ethnicity as shown in Table 3(b) at an optimum threshold of 0.75, the ECSO-CNN correctly classified 189 as true positive and 392 of 600 datasets as true negative, it misclassified 11 datasets as negative and 8 datasets as positive. Also, Igbo ethnicity dataset had an average False Positive Rate of 0.75%, Specificity 98%, Recall 94.5%, Precision 95.94%, F1 95.21% and Accuracy of 96.83% at 38.56seconds.

Analysis of Hausa Ethnic Group

As revealed in Table 3(c), the Hausa dataset, at an optimum threshold value of 0.75 has 191 of 600 dataset as true positive and 394 of 600 datasets as true negative while it misclassified 9 datasets as negative and 6 datasets as positive. In addition, Hausa ethnicity dataset had an average False Positive Rate 1.5%, Specificity 98.5%, Recall 95.5%, Precision 96.95%, F1 96.22% and Accuracy of 97.5% at 39.35seconds. In order to establish the technique with the best performance based on the aforementioned performance metrics, the results in Table 3 shows the combined results of the CNN, CSO-CNN and ECSO-CNN technique at the threshold value of 0.75 for all metrics. Result obtained in Table 3 inferred that ECSO-CNN technique has lowest recognition time compared with the corresponding value with CNN and CSO-CNN technique in each of the ethnic group. The ECSO-CNN technique has recognition time of 36.64s, 38.56s and 39.35s for Yoruba, Igbo and Hausa respectively while CSO-CNN technique has recognition time of 49.87s, 48.82s and 49.79s for Yoruba, Igbo and Hausa respectively and CNN technique has the corresponding recognition time of 60.54s, 59.31s and 58.04s for Yoruba, Igbo and Hausa respectively at threshold value of 0.75.

Similarly, Recall, Precision, F1 score and Recognition accuracy of ECSO-CNN, CSO-CNN and CNN technique were compared at threshold value of 0.75; the study revealed that ECSO-CNN technique has best performance in Recall, Precision, F1 score and Recognition accuracy than both CNN and CSO-CNN techniques as enumerated in Table 4 in all the ethnic groups. The ECSO-CNN had Recall value of 95%, 94.5% and 95.5% for Yoruba, Igbo and Hausa respectively while, CSO-CNN had 94%, 93.5% and 94.5% for Yoruba, Igbo and Hausa respectively and CNN had 91.5%, 91% and 90.5% for Yoruba, Igbo and Hausa respectively. The ECSO-CNN has a Precision value of 96.45%, 95.94% and 96.95% for Yoruba, Igbo and Hausa ethnicity respectively and F1 score of 95.72%, 95.21% and 96.22% for Yoruba, Igbo and Hausa while the CSO-CNN technique has a Precision value of 95.43%, 94.92% and 95.94% for Yoruba, Igbo and Hausa ethnicity respectively and F1 score of 94.71%, 94.20% and 95.21% for Yoruba, Igbo and Hausa while the CNN technique has a Precision value of 92.89%, 92.4% and 91.88% for Yoruba, Igbo and Hausa ethnicity and F1 score of 91.9%, 91.69% and 91.18% for Yoruba, Igbo and Hausa respectively. ECSO-CNN has Recognition accuracy of 97.17%, 96.83% and 97.5% for Yoruba, Igbo and Hausa respectively while CSO-CNN has Recognition accuracy of 96.5%, 96.17% and 96.83% for Yoruba, Igbo and Hausa respectively and CNN technique had Recognition accuracy of 94.83%, 94.5% and 94.17% for Yoruba, Igbo and Hausa respectively

Discussion of Results

As indicated in Table 3, it is evident that ECSO-CNN technique consistently outperforms the conventional CNN and CSO-CNN across all three ethnic groups (Yoruba, Igbo, Hausa), while CNN already achieved strong performance with accuracy values above 93%, the integration of Chicken Swarm Optimization (CSO) improved classification reliability, reduced error rates, and enhanced computational efficiency.

For the Yoruba ethnic group, CNN achieved a maximum accuracy of 94.83% with an F1-score of 92.19%, CSO-CNN achieved an accuracy of 96.5% and F1-score to 94.71% whereas ECSO-CNN improved accuracy to 97.17% with an F1-score of 95.72%. A similar pattern was also observed for the Igbo ethnic group, where CNN attained 94.5% accuracy CSO-CNN's 96.17% compared to ECSO-CNN with accuracy of 96.83% with an F1-score of 95.21%. The Hausa ethnic group also showed notable improvement, with CNN's 94.17% accuracy, CSO-CNN 96.83% accuracy increasing to 97.50% using ECSO-CNN. In term of recognition time, the CNN required between 58seconds to 61 seconds across groups, CSO-CNN has between 48seconds and 50seconds while ECSO-CNN reduced this to between 36seconds and 40seconds. This indicates that the optimization process not only enhanced classification accuracy but also improved convergence speed, making the system more efficient (Oguntoye et al., 2023). Hence, the results confirmed that ECSO plays a vital role in fine-tuning CNN hyperparameters, thereby reducing overfitting, improving generalization and achieving higher robustness across all the ethnic groups.

Discussion on Performance Metrics

The performance metrics of the results as showed in Table 1, Table 2 and Table 3, indicate the techniques under consideration. Standard biometric evaluation metrics were employed: i. Recall: measures the ability to correctly identify true ethnic group members. CNN recall values ranged between 90.5%–93%, CSO-CNN ranged between 93.5%–96%, while ECSO-CNN increased recall up to 97% for the Hausa group, confirming improved detection of true positives. ii. Precision: Indicates the correctness of positive predictions. CNN precision values were between 88%–92%, CSO-CNN precision values were between 91%–95% while ECSO-CNN increased it to as high as 96.95%, reducing false positives and improving reliability. iii. F1-Score: which is the harmonic mean of recall and precision, reflecting a balanced performance. The CNN technique achieved 91%–92%, CSO-CNN achieved 94%–95% whereas ECSO-CNN achieved 95%–96%, demonstrating a stronger trade-off between sensitivity and precision. iv. Specificity and False Positive Rate (FPR): CNN specificity was between 94% – 96%, CSO-CNN 97%–98% while ECSO-CNN enhanced it to 98.25% – 98.5%. This corresponds to lower FPR, this indicates fewer cases of wrongly classifying a fingerprint into another ethnic group. v. Accuracy: The accuracies of CNN ranged from 93.5% – 94.8%, CSO-CNN achieved between 95.3% – 96.8%. while ECSO-CNN had between 96.33% – 97.5%. vi. Recognition Time: This is a critical factor for real-world applications, CNN averaged 58-61 seconds, CSO-CNN 48–50 seconds while ECSO-CNN averaged between 36seconds and 40seconds. This reduction highlights ECSO's role in accelerating convergence.

Statistical Analysis

To validate the result in Table 4, performance differences was conducted between CNN and CSO-CNN and also between CSO-CNN and ECSO-CNN at the threshold value of 0.75, a paired sample t-test was conducted across the three major ethnic groups (Yoruba, Igbo and Hausa). The test evaluated both classification accuracy and recognition time of CNN vs CSO-CNN and also CSO-CNN vs ECSO-CNN. The paired t-test analysis conducted between recognition accuracies of CNN and CSO-CNN revealed that there is significant difference in the test result; having a mean difference of 2%. Nevertheless, the result confirmed that the CSO-CNN technique is statistically significant at $p < 0.05; p = 0.026$ with $\mu = 2\%, df = 2$ and t $value = 6.06$. The t-Additionally, the paired t-test analysis conducted between recognition accuracy of ECSO-CNN and CSO-CNN shows that there a difference in these test results; having a mean difference ($\mu = 0.67$). Nevertheless, the result confirmed that the ECSO-CNN technique is significant outperform CSO-CNN at $P < 0.05; P = 0.006$ with $\mu = 115.97$, $df = 2$ and t $value = 115.97$ This shows that ECSO-CNN not only improves accuracy but also substantially enhances computational efficiency, making it more suitable for real-time or large-scale applications.

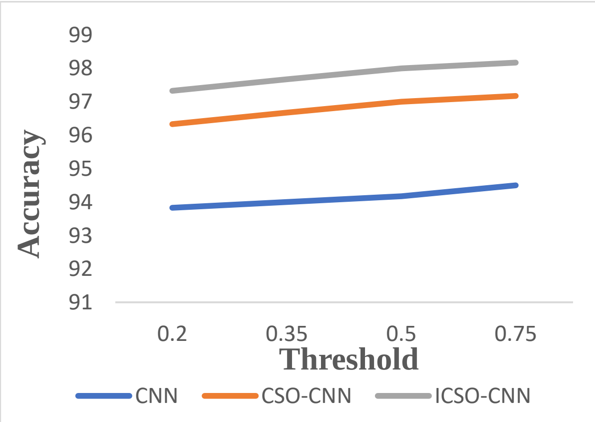

Figure 2. Graph showing Accuracy against Threshold

with respect to Yoruba Ethnicity.

Therefore, ECSO-CNN shows the strongest evidence, both in accuracy and efficiency. Therefore, improvements are not due to chance, but due to real model enhancement (Atanda *et al.*, 2023). Figure 2, 3 and 4 show the graphical illustration of Recognition accuracy against Threshold with respect to Yoruba, Igbo and Hausa Ethnicity respectively.

test result further validates the fact that the CSO-CNN outperformed the CNN technique with respect to recognition accuracy.

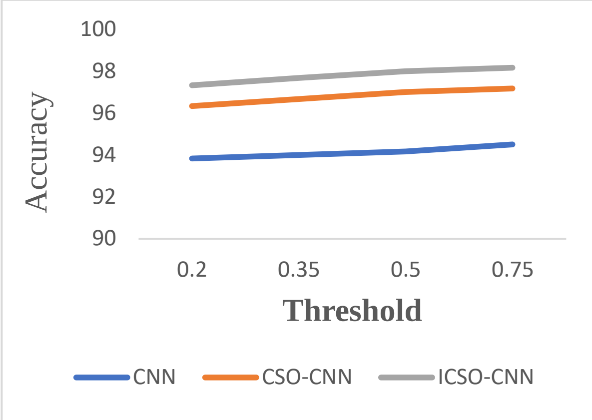

Figure 3. Graph showing Accuracy against Threshold

with respect to Igbo Ethnicity.

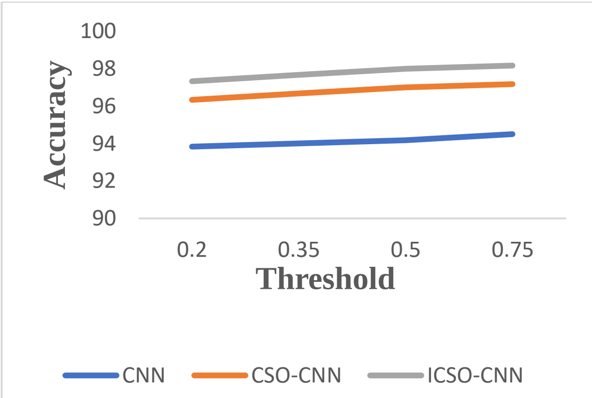

Figure 4. Graph showing Accuracy against Threshold

with respect to Hausa Ethnicity.

Declaration of competing Interest

No conflict of interest by the authors

REFERENCES

Adedeji, O. T., Alade, O. M., and Oguntoye, J. P. (2021). Comparative Analysis of Feature Selection Techniques For Fingerprint Recognition Based on Artificial Bee Colony and Teaching Learning Based Optimization.

LAUTECH Journal of Computing and Informatics, *2*(1), 25-34.

Adetunji, A. B., Oguntoye, J. P., Fenwa, O. D., & Omidiora, E. O. (2015). Facial Expression Recognition Based on Cultural Particle Swamp Optimization and Support Vector Machine. *LAUTECH Journal of Engineering and Technology*, *10*(1), 94-102.

Akintunde, O. A., Adetunji, A. B., Fenwa, O. D., Oguntoye, J. P., Olayiwola, D. S., & Adeleke, A. J. (2025). Comparative analysis of score level fusion techniques in multi-biometric system. *LAUTECH Journal of Engineering and Technology*, *19*(1), 128-141.

Ashraf, R., Zafar, D., Shabbir, S., Manzoor, S., Buzdar, Z. A., and Tahir, T. (2025). Beyond the Ridge: Exploring Fingerprints to Determine the Predominant Pattern in the Pakistani Population: Beyond the Ridge: Fingerprints to Determine the Predominant Pattern. *Pakistan Journal of Health Sciences*, 127-132.

Atanda, O. G., Ismaila, W., Afolabi, A. O., Awodoye, O. A., Falohun, A. S., & Oguntoye, J. P. (2023, April). Statistical Analysis of a deep learning based trimodal biometric system using paired sampling T-Test. In *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals (SEB-SDG)* (Vol. 1, pp. 1-10). IEEE.

Bhatele, K. R., Tiwari, D., and Bisen, A. S. (2025). Border surveillance: Prominent usage scenarios. In *Artificial Intelligence for Cyber Security and Industry 4.0* (pp. 129-150). CRC Press.

Falohun, A. S., Fenwa, O. D., and Ajala, F. A. (2016). A fingerprint-based age and gender detector system using fingerprint pattern analysis. *International Journal of Computer Applications*, *136*(4), 0975-8887.

Greenland, F. (2023). Fingerprinting, civil codes, and the origins of surveillance culture in the United States. *American Journal of Cultural Sociology*, *11(2)*, (137-161).

He, W., Zhang, Y., Xu, T., An, T., Liang, Y., and Zhang, B. (2025). Object detection for medical image analysis: Insights from the RT-DETR model. In *Proceedings of the 2025 International Conference on Artificial Intelligence and Computational Intelligence* (pp. 415-420).

Ige, O. B., Falohun, A. S., Omidiora, E. O., Olabiyisi, S. O., Ige, R. O., Oguntoye, J.P., Awodoye, O.O., Adedeji, O. T. and Oke, A. O. (2025). Development of an enhanced support vector e face recognition system. *LAUTECH Journal of Engineering and Technology*, *19*(2), 30-40.

Mustapha, B. O., Oguntoye, J. P., Obansola, O. Y., Adetunji, B., & Okediran, O. O. (2025). Performance Evaluation of Self-Organizing Feature Maps and Support Vector Machines in Predicting Stock Prices: A Comparative Study. *ABUAD Journal of Engineering Research and Development (AJERD)*, *8*(3), 160-172.

Nayak, A., Satpathy, I., Mishra, B. S., Patnaik, B. C. M. and Das, B. (2022). Biometric A Helping Hand in Talent Management: A Modern Time Tracking Tool. In *2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC)* (pp. 1-7). IEEE.

Ogundepo, O. Y., Omeiza, I. O. A., & Oguntoye, J. P. (2022). Optimized textural features for mass classification in digital mammography using a weighted average gravitational search algorithm. *International Journal of Electrical and Computer Engineering (IJECE)*, *12*(5), 5001-5013.

Oguntoye, J. P., Ajagbe, S. A., Adedeji, O. T., Awodoye, O. O., Adetunji, A. B., Omidiora, E. O., & Adigun, M. O. (2025). An Improved Chicken Swarm Optimization Techniques Based on Cultural Algorithm Operators for Biometric Access Control. *Computers, Materials & Continua*, *84*(3).

Oguntoye, J. P., Olayiwola, A. A., Ogunkola, T. G., FANIBUYAN, J., GANIYU, R., & Olayiwola, D. S. (2024). Real-Time IoT-Based Smart Fertigation System for Sustainable and Precision Agriculture. *Journal of Computer Science and Its Applications (JCSIA)*, *31*(2), 94-103.

Okediran, O. O., & Oguntoye, J. P. (2023). Analysis of critical success factors for information management performance. *LAUTECH Journal of Engineering and Technology*, *17*(1), 175-186.

Ola, B. O., Oguntoye, J. P., Awodoye, O. O., & Oyewole, M. O. (2020). Development of a Plant Disease Classification System using an Improved Counter Propagation Neural Network. *International Journal of Computer Applications*, *975*, 8887.

Olagunju, K. M., Adebiyi, A. A., Adeliyi, T. T., Oguntoye, J. P., Igbekele, E. O., & Osunade, S. (2025). State-of-the-Art Research in Intrusion Detection Systems (IDS) for Network Attack Detection: A Review. *NIPES-JSTR ISSUE*, *7*(1), 974-981.

Olayiwola, D. S., Olayiwola, A. A., Oguntoye, J. P., Awodoye, O. O., Ganiyu, R. A., & Omidiora, E. O. (2023). Development of a Fingerprint Verification and Identification System Using a Gravitational Search Algorithm-Optimized Deep Convolutional Neural Network. *Adeleke University Journal of Engineering and Technology*, *6*(2), 296-307.

Oyedokun, I. O., Ganiyu, R. A., Oguntoye, J. P., & Mojeed, Y. O. (2025). Development of an Enhanced Internet of Things-Based Wearable Human Tracking Security System with Integrated Distress Alert Mechanism. *Journal of Engineering Research and Reports*, *27*(12), 135-147

Petrétei, D. (2025). Fingerprints in Ancient China—A Mini-Review. *Forensic Science Review*, *37*(1), 45-50.

Ragmac, A. R. A., and Allanic, E. A. (2025). Enhancing Fingerprint System: A Case Study on Bridging Gaps to Improve Efficiency, Standardization and Public Trust. *Mediterranean Journal of Basic and Applied Sciences (MJBAS)*, *9*(2), 166-179.

Rehan, P., Bhandari, A. and Bathla, A. (2025). FeatureBased Fingerprint Presentation Attack Detection: System Integration, Taxonomy, Cross-Material Analysis, and Open Challenges. *Taxonomy, Cross-Material Analysis, and Open Challenges*.

Riaz, I., Ali, A. N., and Ibrahim, H. (2024). Loss of fingerprint features and recognition failure due to physiological factors-a literature survey. *Multimedia Tools and Applications*, *83*(39), 87153-87178.

Shekhar, M., Trivedi, A. K., and Patgiri, R. (2025). Enhancing security and accuracy in biometric systems through the fusion of fingerprint and gait recognition technologies. *International Journal of Biometrics*, *17*(5), 449-468.

Torrecilla-García, J. A., and Skotnicka, A. G. (2025) Biometrics as a Key Factor for Emergent User Experience Evaluation. In *Biometrics* (pp. 27-53). CRC Press.

Zangana, H. M., Mohammed, A. K., and Mustafa, F. M. (2024). Advancements and applications of convolutional neural networks in image analysis: A comprehensive review. *Journal Ilmiah Computer Science*, *3*(1), 16-29.

Zhao, X., Wang, L., Zhang, Y., Han, X., Deveci, M., and Parmar, M. (2024). A review of convolutional neural networks in computer vision. *Artificial Intelligence Review*, *57*(4), 99.