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Development of an Enhanced Convolutional Neural Network for Fingerprint-Based Ethnicity Identification

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ABSTRACT: Researchers have been extremely concerned in the classification of ethnicity using fingerprint since every individual has distinguished features, that distinguished them based on their ethnicity. The use of fingerprint for identification has been proven to be highly reliable. This research enhanced CNN for fingerprint ethnicity identification system. Fingerprints were collected from three major ethnic groups in Nigeria (Yoruba, Igbo and Hausa), 400 subjects from each of the ethnic groups were collected using Secugen Hamster Plus Fingerprint Scanner. To improve the dataset, image augmentation techniques were applied to 50% of the subject’s fingerprint images collected from three ethnic groups which increased the dataset to 2,400 images which were used for training while the remaining unaugment 50% were used for testing. The raw images were pre-processed; CNN was enhanced using CSO. The performance of the system was evaluated and compare at 0.75 threshold using, Recall (R), F1 score (F1), Recognition Accuracy (RA). The R, F1 and RA were 91.5%, 92.19% and 94.83 for Yoruba, 91%, 91.69% and 94.5% for Igbo and 90%, 91.18% and 94.17% for Hausa for CNN while the corresponding values for CSO-CNN were 94%, 94.7% and 96.5% for Yoruba, 93.5%, 94.20% and 96.17% for Igbo and 94.5%, 95.21% and 96.83% for Hausa ethnicity. CSO-CNN technique performed better than CNN in all metrics. Fingerprint ethnicity identification based on CSO-CNN can be employed to streamline the search range of crime offender by law enforcement authorities where ethnicity is of high concerned.

KEYWORDS: Development, enhanced Identification, fingerprint recognition, ethnicity

1.0 INTRODUCTION

Identification and verification of human being have been in existence before the invention of modern biometric technology; humans have been using physical characteristics to identify one another. In ancient Babylon, for example, clay tablets were used to record fingerprints 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 identifying 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). Fingerprints 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). 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 (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. 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). CNNs have shown remarkable success in various computer vision applications, including face recognition, object detection, and medical image analysis (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. The performance of the developed system was evaluated.

2.0 METHODS

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 augmentation and image segmentation. 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 CSO-CNN method under study.

2.1 Image Acquisition

Six hundred (1200) fingerprint images were obtained using Secugen Hamster Plus Fingerprint Scanner.

2.2 Image Pre-processing

Fingerprint images were acquired as primary biometric characteristics, while ethnicity which was considered as soft biometric trait were also acquired from Yoruba, Igbo and Hausa ethnics. This was initially analyzed which consist of 400 subjects each from Yoruba, Igbo and Hausa ethnic groups respectively. To enhance the dataset, image rotation, image shifting, image flipping and image noising of augmentation techniques were applied to 50% of the collected data from ethnic groups. This ensures that all fingerprint images are consistent in size, orientation, and quality, thereby improving feature extraction accuracy. The augmentation technique increased the dataset to a total of 2,400 images; the image samples were 80% training images and 20% testing images. This implies that 2,400 image samples were used for training and 600 image samples for testing.

2.3 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.

2.3.1 *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.

2.3.1.1 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.

2.3.1.2 Classification

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

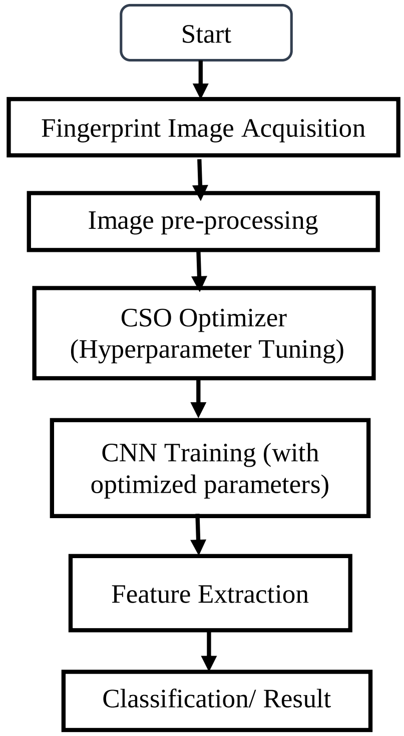

Figure 1. The Structure of the CSO-CNN Methods

3.0 RESULTS AND DISCUSSION

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

3.1 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 3000 fingerprints image datasets – Yoruba, Igbo and Hausa. The fingerprint images comprise 2400 trained datasets and 600 test datasets.

3.1.1 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.

3.1.2 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.

3.1.3 *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 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.

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

b. Result for Igbo Ethnicity

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

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

3.2 Results for CSO-CNN Techniques on Fingerprint

In this study, Convolutional Neural Network was optimized using Chicken Swarm Optimization Algorithm to find the best setting. A target accuracy of 0.75 thresholds was set. The CSO-CNN was then used to analyze the three major Nigerian ethnic groups on 3000 fingerprints image datasets, that is, Yoruba, Igbo and Hausa. The fingerprint images comprised 2400 trained datasets and 600 test datasets.

3.2.1 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.

3.2.2 Analysis of Igbo Ethnic Group

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.

3.2.3 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.

Table 3. Summary of the Evaluation of CNN and CSO-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

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

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

In order to establish the technique with the best performance based on the aforementioned performance metrics, the results obtained in Table 1 (a) - (c) were compared with that of Table 2(a) - (c). Table 3 shows the combined results of the CNN and CSO-CNN technique at the threshold value of 0.75 for all metrics. Result obtained in Table 3 inferred that CSO-CNN technique has lower recognition time compared with the corresponding value with CNN technique in each of the ethnic group. The CSO-CNN technique has recognition time of 49.87s, 48.82s and 49.79s for Yoruba, Igbo and Hausa respectively while the 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 CSO-CNN technique and CNN technique are compared at threshold value of 0.75; the study revealed that CSO-CNN technique has better performance in Recall, Precision, F1 score and Recognition accuracy than CNN technique as enumerated in Table 3 in all the ethnic groups. The CSO-CNN had Recall value of 94%, 93.5% and 94.5% for Yoruba, Igbo and Hausa respectively while, CNN had 91.5%, 91% and 90.5% for Yoruba, Igbo and Hausa respectively. 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. CSO-CNN had Recognition accuracy of 96.5%, 96.17% and 96.83% for Yoruba, Igbo and Hausa respectively while CNN technique had Recognition accuracy of 94.83%, 94.5% and 94.17% for Yoruba, Igbo and Hausa respectively

3.3 Discussion of Results

As indicated in Table 1 and Table 2, it is evident that In all three ethnic groups (Yoruba, Igbo, and Hausa), the CSO-CNN technique consistently outperforms the traditional CNN. Although CNN already demonstrated strong performance with accuracy values above 93%, the incorporation of Chicken Swarm Optimization (CSO) increased computational efficiency, decreased error rates, and improved classification reliability.

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

3.3.1 Discussion on Performance Metrics

The performance metrics of the results as showed in Table 1 and Table 2, indicates 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%, while CSO-CNN increased recall up to 96% 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%, while CSO-CNN increased it to as high as 95.9%, 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%, whereas CSO-CNN achieved 94%–95%, demonstrating a stronger trade-off between sensitivity and precision. iv. Specificity and False Positive Rate (FPR): CNN specificity was between 94% – 96%, while CSO-CNN enhanced it to 97% – 98%. 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%, while CSO-CNN improved this consistently to 95.3% – 96.8%. vi. Recognition Time: This is a critical factor for real-world applications. CNN averaged 58-61 seconds, while CSO-CNN averaged 48–50 seconds. This reduction highlights CSO's role in accelerating convergence.

3.4 Statistical Analysis

The results from table 3 revealed that there is a significant difference between CSO-CNN and CNN techniques, for more clarity, the statistical analysis was carried out on the result obtained for the accuracy and computation time. To further validate the performance differences between CSO-CNN and 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 CSO-CNN and CNN. The paired t-test analysis conducted between recognition accuracies of CSO-CNN and 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-test result further validates the fact that the CSO-CNN outperformed the CNN technique with respect to recognition accuracy. Figure 2, 3 and 4 show the graphical illustration of

Accuracy against Threshold with respect to Yoruba, Igbo and Hausa Ethnicity respectively.

Additionally, the paired t-test analysis conducted between recognition time of CSO-CNN and CNN shows that there a difference in these test results; having a mean difference (μ =12.25). Nevertheless, the result confirmed that the CSO-CNN technique is highly statistically significant at $P < 0.001; P = 0.006$with $\mu = 12.25,\ df = 2\ and\ t\ value =$ 12.25. This shows that CSO-CNN not only improves accuracy but also substantially enhances computational efficiency, making it more suitable for real-time or large-scale applications. Figure 5, 6 and 7 show the graphical illustration of Recognition Time against Threshold with respect to Yoruba, Igbo and Hausa Ethnicity respectively.

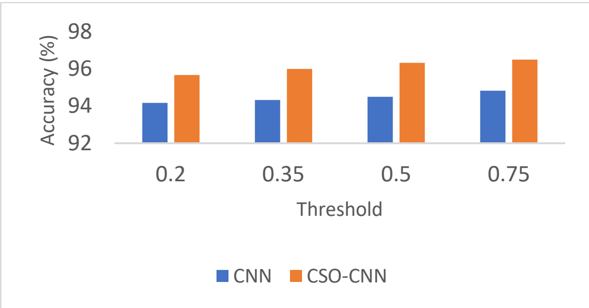

Figure 2. Graph showing Accuracy against Threshold with respect to Yoruba Ethnicity.

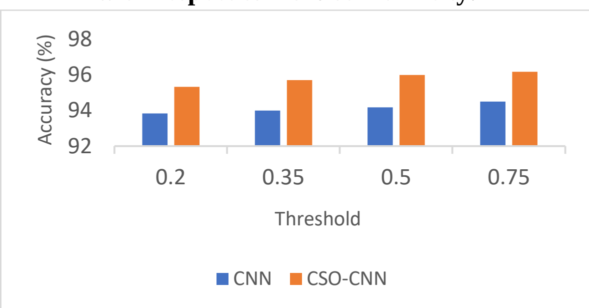

Figure 3. Graph showing Accuracy against Threshold with respect to Igbo Ethnicity.

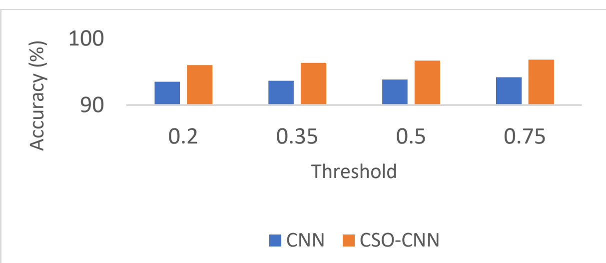

Figure 4. Graph showing Accuracy against Threshold with respect to Hausa Ethnicity.

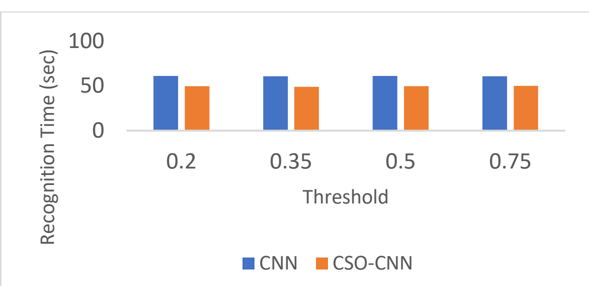

Figure 5. Graph showing Recognition Time against Threshold with respect to Yoruba Ethnicity.

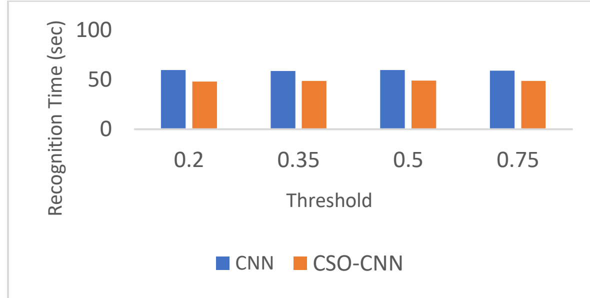

Figure 6. Graph showing Recognition Time against Threshold with respect to Igbo Ethnicity.

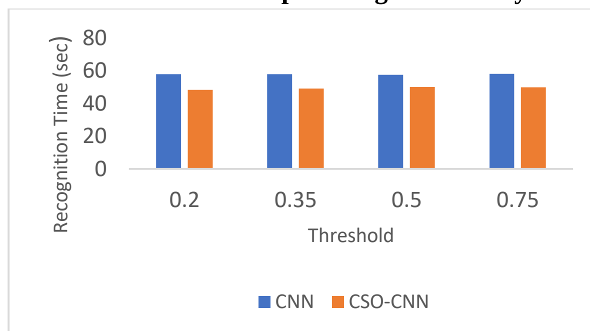

Figure 7. Graph showing Recognition Time against Threshold with respect to Hausa Ethnicity.

4.0 CONCLUSION

The study developed an enhanced convolutional neural network for fingerprint-based ethnicity identification. It was found that CSO-CNN technique consistently outperforms the conventional 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.

Declaration of competing Interest

No conflict of interest by the authors

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