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Development of a Fingerprint-based Gender Detection System using an Optimised Convolutional Neural Network

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ABSTRACT

Biometrics is a technology that identifies or verifies individuals based on unique physical or behavioural traits, offering a reliable form of authentication in sectors like healthcare, law enforcement, and security. Existing gender detection systems using fingerprints face challenges due to poor image quality and complex ridge patterns, while Convolutional Neural Networks (CNNs), though promising, are hindered by issues like overfitting, slow convergence, and getting trapped in local minima. Other optimisation algorithms like Genetic Algorithm (GA), Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) often face issues like premature convergence, high computational costs and poor global search ability. Whale Optimisation Algorithm (WOA) was chosen for its faster convergence, simplicity, and better balance between exploration and exploitation in optimising CNN parameters. Therefore, this study developed a fingerprint-based gender detection system through the Optimisation of CNN with Whale Optimisation Algorithm. A dataset of 2,200 gender-labelled fingerprint images (1,320 male and 880 female) was acquired from Kaggle.com. The images underwent preprocessing involving cropping, grayscale conversion, histogram equalization for enhancement, and edge detection filtering to eliminate noise. Optimised CNN model was formulated using Whale Optimisation Algorithm (WOA) by tuning CNN hyperparameters: number of neurons and dropout rate. The resulting WOA-CNN was employed for feature extraction (edges, texture patterns, shapes) and detection of fingerprint images. The model was implemented in MATLAB R2023a. Performance was evaluated using accuracy, sensitivity, specificity, false positive rate, precision, and recognition time, with an 80-20% training-testing split. CNN achieved 95.86% accuracy, 96.44% sensitivity, 95.00% specificity, 5.00% false positive rate, 96.66% precision, and 99.90 s recognition time. WOA-CNN achieved 97.23% accuracy, 97.58% sensitivity, 96.70% specificity, 3.30% false positive rate, 97.80% precision, and 87.40 s recognition time. This research showed WOA-CNN outperformed CNN in all metrics. It is recommended for use in biometric authentication, security checkpoints, and forensic investigations.

INTRODUCTION

A Biometric is the technology that uses part of the human body to identify a person. In contrast to something known that can be forgotten, like a password or registration number, or something owned that can be lost, like identity card, physical lock, or smart card, biometric authentication for personal identification is incredibly and more reliable (Adetunji *et al.* 2018; Adedeji *et al.* 2021). Biometric is derived from the Greek words "Bio," meaning "life," and "Metric," meaning "measurement". To identify or verify an individual's identification, biometrics assesses distinct physical or behavioural traits (Faluyi *et al.*, 2022). The identification and verification of people by analyzing human body features like fingerprints, palm veins, iris, and the like is known as biometric technology, and has been widely employed in many facets of life, including the voting system. Many underage voters have registered in recent years, which has tainted electioneering, especially in developing nations. The concept of impersonation occurs often in both public and commercial sectors, as well as the ghost worker phenomenon, leading to anomalies in the election process. Additionally, it has become a growing threat across all levels of government in developing and low-income countries. Many people who use biometric technology are faced with challenge of identifying the most appropriate and accurate biometric system that is economically feasible to address specific issues in a given environment, despite the many benefits that come with biometric systems and influence on different industries worldwide (Cappelli *et al*., 2006; Adetunji *et al.* 2015), and voting system like what was obtained in the Nigerian 2015 State and Presidential elections.

A biometric system is typically "a pattern recognition system which identifies an individual by authenticating the distinctiveness of a particular physical and/or behavioural attribute specific to the person" in the context of information systems (Cappelli *et al*., 2006; Oguntoye *et al.,* 2025a). China, in the 14th century, was where the first recorded application of systematic biometric techniques to differentiate one person from another can be found. It was common for Chinese traders to distinguish between youngsters by stamping their footprints and inked palms on paper. The English botanist Nehemiah Grew produced the first known differentiation of a biometric attribute in Western culture when he published a paper in 1684 detailing the unique features of ridge, furrow, and pore patterns in human fingerprints (Falohun *et al*., 2016; Akintunde *et al.,* 2025). A fingerprint is a pattern of interleaved ridges and grooves that is the outer layer of skin on a finger. Over time, the ridges on the fingertips developed to help people grip things and hold onto items (Adedeji *et al.,* 2021b). Fingerprint ridges are formed by a mix of environmental and genetic variables, much like everything else in the human body. For this reason, even identical twins' fingerprints differ (Maltoni *et al*., 2006; Ola *et al*., 2017).

The biometric applications based on gender categorization are meant for: (i) E-commerce, such as mobile phones, Personal Digital Assistant (PDA), restorative records for executives, library access, virtual learning, internet connectivity, electronic data security, digital banking and automatic teller machine (ATM) facilities, credit cards, personal identification or system verification (ID), as well as others. (ii) E-Government: such as document control, driver's licenses, national ID cards, digital marks or steganography, etc. (iii) Scientific applications: such as missing children, fear-based oppressor identification, criminal examination, carcass recognizable proof, and parentage assurance. This demonstrated that the Optimised technique outperformed the baseline and is recommended for applications in biometric authentication, security, checkpoints and forensic investigations. Nowadays, many social and official communications and administrative roles are influenced by the gender of the person performing them (Sudharshan *et al*., 2019; Ige *et al.,* 2024).

Investigative leads for locating unidentified individuals depend on gender information. The availability of teeth, bones, or other distinguishable body components with physical characteristics that enable gender estimation by traditional methods makes the gender categorization techniques now in use for crime scene investigation. A variety of biometric characteristics, including face, gait, iris, hand shape, voice, and fingerprint, have been used to determine gender (Gnanasivam *et al*., 2012).

Deep learning has become a central part of the development of machine learning-based models in recent years of these models, Convolutional Neural Networks (CNNs) have proven to be highly effective in the area of pattern recognition and image classification (Dixit *et al*., 2019). Some drawbacks of CNNs, such as overfitting and other limitations, led to the decision to optimised the CNN (Oguntoye *et al,* 2023). Optimisation of CNNs is one of the key aspects of their efficiency, scalability, and robustness, enabling improvement in generalization across varied datasets. Several recent works demonstrate that optimising CNNs could lead to significant accuracy while reducing computational costs, hence making CNNs suitable for practical deployments (Huang *et al*., 2024).

The Whale Optimisation Algorithm (WOA) is an emerging computational algorithm inspired by the hunting behaviour of whales, characterized by strength, endurance, agility, intelligence, and lifespan. Whales are social animals known for their cooperative hunting tactics. The reason behind the widespread attention of WOA in many areas is its novelty in solving Optimisation problems. This algorithm's applications have also extended to engineering, environmental management, data analysis, and many more. A systematic review highlighted that the algorithm is very efficient for real-world Optimisation problems, unlike traditional algorithms, WOA leverages the balancing of exploration and exploitation making this algorithm especially suitable for tasks that need an exact solution with constraints. Other studies have integrated WOA to address the limitations of Optimisation algorithms like Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), and Ant Colony Optimisation (ACO), which often struggle with issues such as premature convergence, high computational costs, and poor global search ability, making WOA a more efficient and reliable choice for performance enhancement.. The development of WOA provides a physical and biologically-inspired approach to addressing complex Optimisation problems, with potential applications in various Optimisation tasks across diverse domains (Oguntoye *et al.,* 2025b). In this study, a fingerprint-based gender detection system was identified using a Whale Optimisation Algorithm with Convolutional Neural Network (WOA-CNN). The whale Optimisation algorithm (WOA) was introduced to choose the CNN's ideal parameter. This research demonstrated that the Optimised technique outperformed the baseline and is recommended for applications in biometric authentication, security, checkpoints and forensic investigations.

METHODOLOGY

The Design Approach

The developed technique in this research comprises five distinct stages: image dataset acquisition, image pre-processing, design of the Whale Optimisation Algorithm-based Convolutional Neural Network (WOA-CNN) for fingerprint-based gender prediction, implementation of the deep learning model for gender classification, and performance evaluation. The evaluation is based on metrics including accuracy, specificity, recognition time, sensitivity, false positive rate, and overall classification accuracy.

Image Acquisition

A dataset of 2,200 gender-labelled fingerprint images, consisting of 1,320 males and 880 females, were acquired from Kaggle.com, to provide enough data for effective model training while preserving the original class distribution. The image samples are classified into different data division percentage splits: 60-40, 70-30, 75-25, and 80-20% for training and testing, respectively. These splits help identify the best balance between training and testing, with the 80-20% split providing the highest specificity, precision, accuracy, and sensitivity, while also reducing the false positive rate and recognition time by offering more data for learning and enough data for validation.

Image Preprocessing

Image preprocessing plays an important role in training the model, conforming to system requirements. The acquired images underwent preprocessing stage, which involves cropping to remove unwanted elements from fingerprint images, conversion into gray-scale to simplify image processing by reducing computational requirements, image enhancement using the histogram equalization method to improve visual quality, and filtering with the edge detection method to eliminate unwanted noise.

Design of WOA-CNN for Fingerprint-based Gender Detection System

As described in Figure 1, the process begins by initializing key CNN hyperparameters, such as the number of neurons and dropout rates, which serve as the search agents for Optimisation. The CNN architecture is then established, and the network undergoes training and validation to assess its performance. The fitness of each search agent is calculated based on the network's accuracy or loss, guiding the iterative search for optimal hyperparameters. Iterative updates proceed through multiple phases, including position adjustments using mathematical formulations inspired by whale social behaviour, such as spiral updating and prey encircling strategies.

During each iteration, the search agent's position is updated across three phases, leveraging adaptive coefficients and random probability to balance exploration and exploitation. Phase 1 focuses on exploitation, with agents moving closer to the best-known solution, while Phase 2 and Phase 3 explore new areas of the search space. Positions are adjusted based on fitness evaluations, which are recalculated to ensure dynamic refinement of the agents.

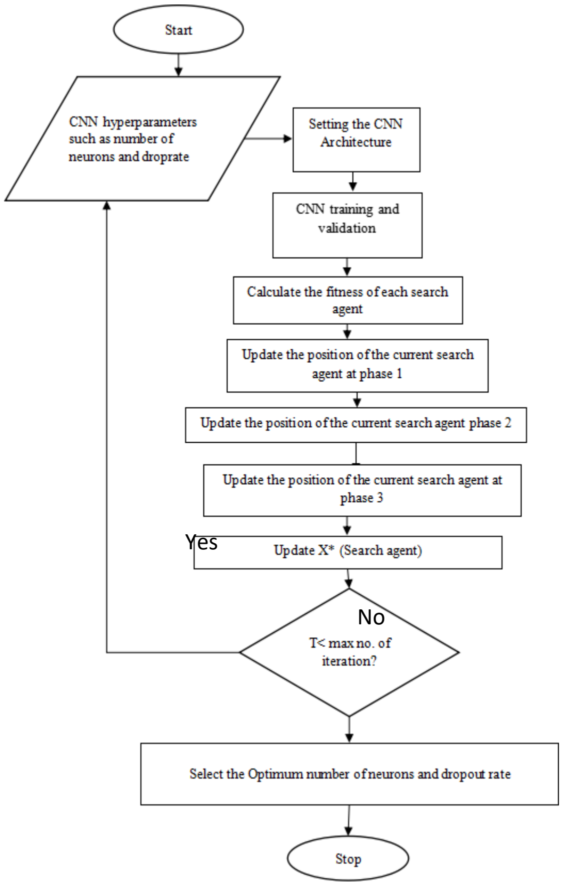

Figure 1: Flow Chart of Convolutional Neural Network with Whale Optimisation Algorithm (WOA-CNN)

The global best solution (X*) is updated whenever a superior agent is identified, ensuring the Optimisation process remains focused on improving CNN performance. This iterative refinement continues till the specified highest number of iterations is reached, ensuring comprehensive search space coverage.

After the iterations, the optimal hyperparameters are selected, representing the best-performing combination of neurons and dropout rates. The resulting WOA-CNN was employed for feature extraction (edges, texture patterns, and shapes) and detection of fingerprint images to improve the approach that enhances the CNN technique.

Implementation

The system was implemented in MATLAB R2023a using built-in toolboxes for image processing, computer vision, and Optimisation. A graphical user interface (GUI) was developed to allow fingerprint image input, parameter tuning, training, and result visualization for both CNN and WOA-CNN techniques.

Performance Evaluation

Performance was evaluated using metrics like accuracy, sensitivity, specificity, precision, false positive rate, and recognition time. These metrics were calculated based on TP, TN, FP, and FN values. These performance metrics are calculated using the following formulas:

False Positive Rate: is defined as the rate at which the classification model incorrectly predicts a fingerprint as belonging to a specific gender when it does not.

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{TN+FP}} X\ 100 \qquad (3.1)$$

Sensitivity: is defined as the ability of a classification model to correctly identify fingerprints that do belong to a specific gender.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} X\ 100 \qquad (3.2)$$

Specificity: is defined as the ability of a classification model to correctly identify fingerprints that do not belong to a specific gender.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} X\ 100 \qquad (3.3)$$

Accuracy: is defined as the ability of a classification model to correctly identify the gender of all fingerprint samples in the dataset.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} X\ 100 \qquad (3.4)$$

Recognition Time refers to the total time the system needs in order to correctly identify a fingerprint sample.

Where TP stands for True Positive, TN for True Negative, FP for False Positive, and FN for False Negative, experiments with different data splits showed that the WOA-CNN technique outperformed standard CNN in all measured criteria.

RESULTS AND DISCUSSION

Figures 2 and 3 present the Graphical User Interface (GUI) for the training and testing phases using CNN and WOA-CNN. The interface displays a sample fingerprint image, classification outputs, and a detailed confusion matrix. Notably, WOA-CNN presented a higher number of True Positives (TP) while also reducing the number of False Positives (FP) and False Negatives (FN), highlighting its improved accuracy. The GUI also shows a cropped fingerprint in the test section, reflecting preprocessing for enhanced recognition. Across varying training ratios, WOA-CNN demonstrated consistent performance, with the 80-20 split yielding optimal generalization and classification accuracy.

Result with CNN

Table 1 demonstrates that increasing the training ratio from 60-40 to 80-20 led to improved performance metrics. The False Positive Rate (FPR) decreased from 5.80% to 5.00%, while precision rose from 96.16% to 96.66%. Sensitivity remained high (96.67% to 96.44%), and specificity improved from 94.20% to 95.00%. Accuracy also increased slightly from 95.68% to 95.86%. The confusion matrix showed minor variations in classification, with a consistent ability to distinguish male and female fingerprints. Recognition time remained stable between 99.20 and 99.90 seconds.

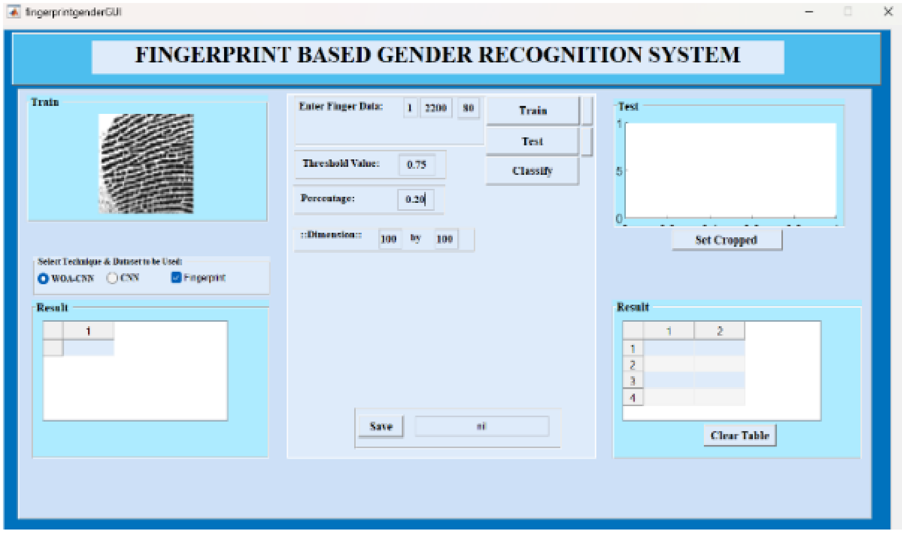

Figure 2: GUI demonstrating Training Process using CNN and WOA-CNN

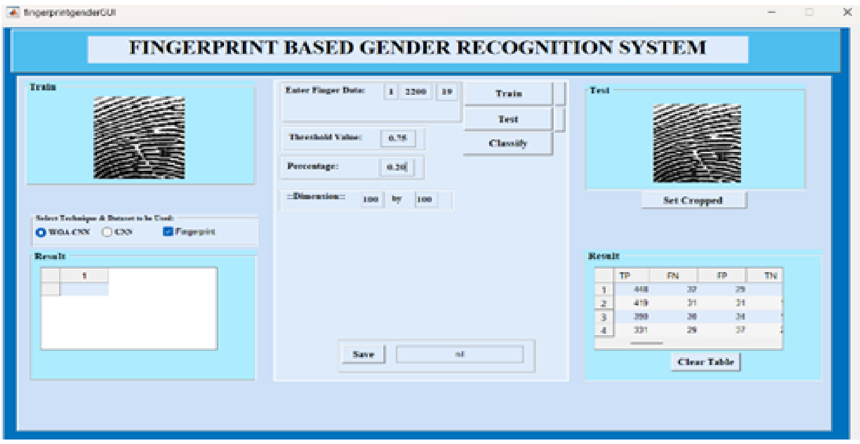

Figure 3: GUI demonstrating Testing Process using CNN and WOA-CNN

Table 1: Performance Evaluation Results with CNN

Data-Division Percentage	60 x 40	70 x 30	75 x 25	80 x 20
Male	1320	1320	1320	1320
Female	880	880	880	880
TP	1276	1275	1274	1273
FN	44	45	46	47
FP	51	49	47	44
TN	829	831	833	836
FPR (%)	5.80	5.57	5.34	5.00
SEN (%)	96.67	96.59	96.52	96.44
SPEC (%)	94.20	94.43	94.66	95.00
PREC (%)	96.16	96.30	96.44	96.66
ACC (%)	95.68	95.73	95.77	95.86
Time (sec)	99.20	100.10	101.30	99.90

Among all tested splits (80-20, 75-25, 70-30, 60-40), the 80-20 split yielded the best results, affirming that a larger training set enhances model performance. CNN maintained reliable performance across different training ratios, confirming its effectiveness for fingerprint-based gender detection.

Result with WOA-CNN

Table 2 presents the performance of the WOA-CNN model across different training splits, highlighting its robustness in a fingerprint-based gender detection system. True Positives remained high (1291 to 1288), while False Positives decreased from 37 to 29 and False Negatives rose slightly from 29 to 32, resulting in increased True Negatives.

Table 2: Performance Evaluation Results with WOA-CNN

Data-Division Percentage	60 x 40	70 x 30	75 x 25	80 x 20
Male	1320	1320	1320	1320
Female	880	880	880	880
TP	1291	1290	1289	1288
FN	29	30	31	32
FP	37	34	31	29
TN	843	846	849	851
FPR (%)	4.20	3.86	3.52	3.30
SEN (%)	97.80	97.73	97.65	97.58
SPEC (%)	95.80	96.14	96.48	96.70
PREC (%)	97.21	97.43	97.65	97.80
ACC (%)	97.00	97.09	97.18	97.23
Time (sec)	89.40	88.10	89.40	87.40

The False Positive Rate dropped from 4.20% to 3.30%, and Specificity improved from 95.80% to 96.70%. Sensitivity showed a marginal decline from 97.80% to 97.58%, whereas Precision increased to 97.80%, surpassing the baseline CNN. Overall Accuracy improved from 97.00% to 97.23%, with the 80–20 split delivering the best results, confirming the benefit of larger training sets. Recognition time also decreased from 89.40 to 87.40 seconds, demonstrating enhanced efficiency. These results confirm the efficacy of integrating Whale Optimisation with CNN for an accurate and efficient fingerprint-based gender detection system.

Comparison Result of CNN and WOA-CNN

Table 3 compares the performance of CNN and Whale Optimisation Algorithm-based CNN (WOA-CNN) for fingerprint-based gender detection, highlighting notable improvements with WOA integration. Across all data splits, WOA-CNN consistently reduced the false positive rate from 5.80% to 3.30% and improved sensitivity from 96.67% to 97.80%, indicating better identification of male fingerprints. Specificity also increased from 94.20% to 96.70%, reflecting enhanced discrimination of female fingerprints, while precision rose to 97.80%, surpassing CNN's 96.66%, confirming more reliable classification. Overall accuracy improved from 95.68% to 97.23%, with greater stability across training ratios, suggesting improved generalization and reduced overfitting. Additionally, WOA-CNN demonstrated faster training times, decreasing from 99.20 to 87.40 seconds, reflecting improved computational efficiency. These gains are attributed to WOA's ability to optimise CNN's feature selection and hyperparameters, which enhances the model's learning process by focusing on the most relevant features and avoiding noise. This fine-tuning reduces overfitting and accelerates convergence, leading to a more accurate and efficient fingerprint-based gender detection system.

Discussion of Results

The performance analysis of CNN and Whale Optimisation Algorithm-based CNN (WOA-CNN) for fingerprint-based gender detection reveals significant differences across multiple metrics. The false positive rate consistently decreases as the data division percentage changes from 60x40 to 80x20, with WOA-CNN demonstrating a notably lower false positive rate (ranging from 4.20% to 3.30%) compared to traditional CNN (ranging from 5.80% to 5.00%). The specificity comparison between CNN and WOA-CNN, with WOA-CNN demonstrating consistently higher specificity values (97.80% to 97.58%) compared to conventional CNN (96.67% to 96.44%) across all data division percentages. The sensitivity comparison reveals an interesting trend where both techniques show increasing sensitivity as the training data percentage increases from 60% to 80%.

Table 3: Comparison Results of CNN and WOA-CNN

Data-Division Percentage	60 x 40		70 x 30		75 x 25		80 x 20	
Technique	**CNN**	**WOA-CNN**	**CNN**	**WOA-CNN**	**CNN**	**WOA-CNN**	**CNN**	**WOA-CNN**
Male	1320	1320	1320	1320	1320	1320	1320	1320
Female	880	880	880	880	880	880	880	880
FPR (%)	5.80	4.20	5.57	3.86	5.34	3.52	5.00	3.30
SEN (%)	96.67	97.80	96.59	97.73	96.52	97.65	96.44	97.58
SPEC (%)	94.20	95.80	94.43	96.14	94.66	96.48	95.00	96.70
PREC (%)	96.16	97.21	96.30	97.43	96.44	97.65	96.66	97.80
ACC (%)	95.68	97.00	95.73	97.09	95.77	97.18	95.86	97.23
Time (sec)	99.20	89.40	100.10	88.10	101.30	89.40	99.90	87.40

WOA-CNN consistently outperforms traditional CNN across all data divisions, with sensitivity values ranging from 95.80% to 96.70% compared to CNN's 94.20% to 95.00%. The precision metrics show a clear advantage for WOA-CNN (97.21% to 97.80%) over traditional CNN (96.16% to 96.66%) across all data division percentages. The precision values for both models increase as the training data percentage increases, indicating better model performance with more training examples.

The overall accuracy comparison shows WOA-CNN achieving superior results (97.00% to 97.23%) compared to traditional CNN (95.68% to 95.86%) across all tested data divisions. Also, WOA-CNN achieved a lower recognition time (87.40s–89.40s) compared to CNN (99.20s–101.30s).

CONCLUSIONS

The Whale Optimisation Algorithm-based Convolutional Neural Network (WOA-CNN) proved highly effective for fingerprint-based gender detection by enhancing CNN's parameter tuning and feature extraction. It achieved high sensitivity, specificity, precision, and accuracy across various data splits while reducing false positive rate and recognition time. Among the tested data division splits (60-40, 70-30, 75-25, and 80-20), the 80-20 split consistently performed best, demonstrating that a higher proportion of training data leads to improved model performance. These results confirm WOA-CNN's reliability and efficiency for real-time biometric applications. It is recommended for use in biometric authentication, security checkpoints, and forensic investigations, with future work focusing on dataset expansion and hybrid Optimisation for greater adaptability.

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