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Comparative Analysis of Spider Wasp Optimisation-Based CNN and Standard CNN for Face Detection

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Abstract **Original Research Article**

In the detection of suspicious activity using image analysis, standard Convolutional Neural Networks (CNNs) face obstacles such as low accuracy and high computational time. However to improve the CNN model, optimisation strategies like the Spider Wasp Optimiser (SWO) have been explored. In this paper, the spider intelligent optimizer was integrated into a standard CNN model and the resultant optimized convolutional model was trained and tested with 5000 face images acquired from Ladoke Akintola University of Technology students, Faculty of Computing and Informatics, and applied a pre-processing workflow including resizing cropping and grayscale transformation. The optimised model was implemented in MATLAB R20023a. The performance of the formulated model was measured using sensitivity, specificity, precision, accuracy, false positive rate, computation time, and compared against existing standard CNN approach. The results revealed that the SWO-CNN model showed notable performance with a sensitivity of 98.12%, specificity of 97.53%, precision of 98.12%, accuracy of 97.87%, F1-score of 98.12%, and a reduced FPR of 2.47%, taking 71.64 seconds to execute. In contrast, the standard CNN model achieved a sensitivity of 96.71%, specificity of 95.52%, precision of 96.60%, accuracy of 96.20%, and F1-score of 96.66%, with a false positive rate of 4.48% and computational time of 96.04 seconds. This result show that the SWO-CNN offers a superior performance over existing standard CNN.

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1.0 INTRODUCTION

Face recognition has long been regarded as one of the most challenging tasks in the field of pattern recognition (Chen *et al.*, 2013). At its simplest level, the technology involves detecting and localizing a face in an image or video frame (Kalamkar and Mohod, 2015). Over time, the technology has progressed from simple image-based methods to sophisticated intelligent systems capable of automated recognition in complex environments. The growing global demand for personal identification, surveillance, and security has increased the necessity for reliable face recognition systems across diverse sectors, including law enforcement, public safety, and library management (Bhatt *et al.*, 2014; Vijaya *et al.*, 2023).

Early face-recognition methods were primarily based on pattern recognition principles, using geometric and statistical techniques to detect key facial features such as eyes, nose, and mouth (Devi and Marimuthu, 2016). Although such methods provided foundational insights, they were heavily affected by changes in pose, illumination, and facial expression, leading to inconsistent performance in real-world settings (Saste and Jagdale, 2017). With globalization and increasing digital interactions, face recognition has become an essential component of modern security infrastructure, particularly in access control, attendance management, and surveillance (Panjaitan *et al.*, 2018).

Deep learning, an advancement of artificial neural networks, allows machines to learn from vast data through hierarchical representations. CNNs, in particular, have demonstrated exceptional performance in image recognition, object detection, and feature extraction (Goodfellow *et al.,* 2016). Their layered architecture enables automatic learning of low- and high-level visual features, minimizing the need for manual feature engineering. In surveillance contexts, CNNs can detect facial features, track movement, and classify individuals across frames, making them indispensable in automated library monitoring systems (Srivastava, *et al.,* 2014). The introduction of Convolutional Neural Networks (CNNs) revolutionized face recognition by enabling automatic learning of hierarchical, discriminative features from raw pixel data. Krizhevsky *et al.* (2012) demonstrated the power of deep architectures with the AlexNet model, which achieved remarkable performance on large-scale visual datasets. Building on this success, Taigman *et al.* (2014) proposed DeepFace, which combined deep learning with precise 3D alignment to approach human-level accuracy.

Recent studies demonstrate the dominance of deep learning in achieving robust recognition under unconstrained conditions. Zhou *et al.* (2021) conducted a large-scale review of convolutional architectures and concluded that modern CNNs such as ArcFace, CosFace, and MobileFaceNet outperform handcrafted and shallow models on benchmarks like LFW and MegaFace. Similarly, Vijaya *et al.* (2023) applied a multimodal deep-learning framework to video surveillance and reported 96% accuracy in identifying suspicious activities using CNN-LSTM fusion, showing that hybrid temporal–spatial models outperform static detection methods.

Later *et al.* (2015) developed FaceNet, introducing the triplet-loss function to learn compact embeddings that preserve identity similarity in Euclidean space. Deng *et al.* (2019) extended this concept with ArcFace, an additive angular margin loss that improves inter-class separability, producing robust embeddings for recognition across varying conditions. These deep-learning paradigms shifted face recognition from handcrafted descriptors to end-to-end learning, enabling superior accuracy in unconstrained and dynamic surveillance scenarios (Zhou *et al.,* 2021). However, the training and fine-tuning of CNNs require the Optimisation of numerous hyperparameters—such as learning rate, filter size, epoch number, and batch size—which directly influence model accuracy and computational efficiency. Traditional tuning approaches (e.g., grid search or manual tuning) are inefficient and often yield suboptimal solutions due to high dimensionality and nonlinearity (Mathur and Verma, 2021).

Recently**,** the Spider Wasp Optimiser (SWO) was introduced by Abdel-Basset, Shankar, and Mohamed (2023), inspired by the predatory and nesting behavior of spider wasps. SWO exhibits efficient balance between global exploration and local exploitation, making it effective for solving high-dimensional optimisation problems. The Spider Wasp Optimiser (SWO) is a novel algorithm inspired by the hunting and nesting behaviors of spider wasps. It simulates the wasps' strategy of searching, paralyzing prey, and nesting in a structured search space to optimize problem- solving (Abdel-Basset *et al.,* 2023). Therefore, this paper presents a comparative analysis of spider wasp optimizer optimised CNN and standard CNN.

2.0 RELATED WORKS

Basil et al. Their framework is directed at recognizing and matching facial photos of people with respect to theft incidents such as burglaries made through home entry. Along with it, the system also included an alarm feature that could sound alerts as soon as there was any Aurora borealis suspicious action. To improve the model, the researchers increased image frames captured and optimized parameters such as learning rate and iterations. This model used a CNN architecture that could identify facial areas inside 150 × 150 pixel picture frames. The system facilitated uninterrupted frame collection via webcam and it enabled the comparison of real-time images against a pre-saved original image of an individual which yields cropped detections of faces. Threshold values at frame counts of 25, 50, 100 and 150 to evaluate model performance accuracy and loss. The experimental outcomes demonstrated that the model has reached 100% accuracy with all cases being evaluated. The model was implemented and tested with MATLAB.

Similarly, Obaida et al. Facial detection and tracking system for identifying witnesses in courtroom environments (2022). Viola-Jones Algorithm was subsequently employed in their research to detect human facial features, and then based on transformations of the image, facial cropping and other preprocessing can be applied. A Convolutional Neural Network model was used to produce a classification of the two types of images: witness and non-witness images, and facial tracking was based on trained image features through the Kanade-Lucas-Tomasi Algorithm. The framework aided in lowering both latency and computational space while improving accuracy in detection by combining these methods. Experimental results indicated that the proposed system is robust for practical facial recognition and tracking applications, achieving an accuracy of 99.5% when applied under real-time conditions with sufficient illumination.

Ullah et al. (2022) proposed a human face detection and recognition framework based on machine learning and deep learning techniques jointly with the application of Closed-Circuit Television systems that operates in real-time. They pointed out that traditional Closed-Circuit Television (CCTV) surveillance systems rely significantly on the constant monitoring of humans, which is time-consumingly and cost-inefficient with a high margin for human error. To overcome these limitations, the study proposed an automated facial recognition system that could identify both suspects and missing persons as well as guards against wrongful entry of unauthorized individuals at restricted locations with low human intervention level and lower operating cost while enhancing security infrastructure. It also described the challenges of image-based facial recognition such as different terms of lighting conditions, scaling and rotation or cluttered backgrounds. This framework consists of multiple processing stages to tackle above stated challenges in which image acquisition, preprocessing, face detection and localization, and feature extraction as well as recognition. Two feature extraction methods were performed (PCA & CNN) and classification performance was assessed using K-nearest neighbour (KNN), decision tree, random forest, & CNN model algorithms. It used over 40,000 real-time images in different lighting, rotation and scaling conditions for simulation and evaluation. A facial recognition was performed using the developed system, and it achieved satisfactory computational efficiency with an accuracy of over 90%.

Similarly, Saurav et al. DICNN- A Dual Integrated Convolution Neural Network model for Real-Time Facial Expression Recognition in Unconstrained Environments (2022). It is a comprehensive model designed to run on embedded platforms, with the goal of preserving computational efficiency while maintaining stringently accurate recognition. DICNN architecture, which comprised only of 1.08 million parameters and a memory storage size of the model is —approximately— 5.40 MB was very efficient to run. For performance evaluation, four benchmark facial expression recognition datasets (FER2013, FERPlus, RAF-DB and CKPlus) were used while metrics including recognition accuracy, precision, recall and F1-score were applied for assessment. The model was optimized by TensorRT SDK to help in portability and inference speed and used on the NVIDIA Xavier embedded system. The performance of the proposed system represented a favourable trade-off with respect to existing state-of-the-art facial expression recognition systems using advance methods, reaching a competitive classification accuracy, while attaining remarkable speed-up alongside real-time processing capabilities.

In a separate relevant sense, by Senthilkumar et al. Convolutional Neural Network based Dense (2017). developed a facial detection and recognition algorithm that was able to perform better than those of many contemporary traditional face recognition approaches. In order to prove an efficacy of the suggested system, researchers applied a smart classroom application for automatic student attendance management based on facial recognition technology. The training was done on the publicly available Labeled Faces in the Wild dataset. Experimental results began with 40 students sitting in a classroom and the system could find roughly 35 faces and recognize about 30 individuals from a single image. The testing accuracy with this framework proposed was 97.9%. Moreover, it included a smart classroom architecture with IoT based architectures equipped with edge computing to process and transmit the data generated in the classroom. More importantly, comparing with previous systems under the proportional effect, we proved that the proposed architecture was capable of supporting better real-time response and data latency.

Karlupia *et al.* (2023) proposed a Genetic Algorithm (GA)-based approach for Optimising Convolutional Neural Network (CNN) hyperparameters in face recognition. The GA was employed to fine-tune key parameters such as filter size, number of filters, and hidden layers. A benchmark dataset consisting of ninety subjects was used for evaluation, and the experimental results demonstrated that the GA-CNN model achieved superior accuracy compared to traditional CNN models. By iteratively refining the objective function, the GA identified optimal hyperparameter combinations, resulting in an improved face recognition accuracy of 94.5%. The study could not explore the inclusion of additional hyperparameters, such as learning rate and number of epochs, and suggested the integration of other metaheuristic algorithms for further Optimisation. Although the reviewed literature provides a strong foundation for face detection, however, several gaps persist at the intersection of face recognition, deep learning optimisation. These systems still face challenges like: low accuracy and high computation time.

3.0 METHODOLOGY

In developing a face detection system using Spider Wasp Optimisation based Convolutional Neural Network algorithm (SWO-CNN), the following stages were involved.

i. Acquisition of Face photographs obtained from students of Faculty of computing and informatics LAUTECH Ogbomoso using photo and camera
ii. Pre-processing of the face captured was done by resizing the images, cropping the images, conversion to grayscale and adjusting their brightness and contrast.
iii. Formulation of Spider-Wasp Optimisation using Random Selection (SWO).
Use of ESWO to select CNN hyperparameters such as learning rate, number of epochs, filter size and number of filters.
iv. Feature Extraction, Training and Recognition of face images were achieved by using Spider Wasp Optimised based Convolutional Neural Network (SWO-CNN).
v. Evaluation of SWO-CNN model against existing Spider standard CNN approach. for real-time face detection was done using Sensitivity, Specificity, Precision, Accuracy false Positive rate and computation time.

3.1. Image acquisition

Acquisition of both face photograph images were obtained from Faculty of Computing and Informatics students, LAUTECH, Ogbomoso using photo camera. One thousand student photographs were taken. The photographs were augmented, The augmentation was carried out as flip left to right, flip up and down, rotate angle ninety degree, and rotate angle one hundred and eighty degree, each augmentation reproduce another one thousand photographs making four thousands images added to the original images. The study was developed using a dataset of 5,000 facial images specifically curated for this study. To achieve an optimal balance between learning and evaluation, the dataset was divided into two subsets. Where 70% (3,500 images) were assigned for training and the remaining 30% (1,500 images) were reserved for testing.

3.2. Image pre-processing

Image pre-processing has to do with actions such as image brightness, contrast alteration, image scaling, filtering, cropping and other operations that help in the enhancement of images. In this phase, pre-processing was carried out by converting the colored images into grayscale, cropping the image and normalizing the face vectors by computing the average face vector and deducting average face from each face vector. This was done to remove noise from the face images.

3.3. Formulation of Spider Wasp Optimiser (SWO)

Algorithm 3.1: Spider Wasp Optimiser

Input

i. Objective function $\boldsymbol{f}(\mathbf{x})$
ii. Population size $\boldsymbol{N}$
iii. Maximum number of iterations $\boldsymbol{T}$
iv. Lower and upper bounds $\boldsymbol{LB}, \boldsymbol{UB}$

Step 1: Initialization

i. Initialize a population of $\boldsymbol{N}$ spider wasps randomly within the search space:

$$\mathbf{x}_i = \boldsymbol{LB} + \mathbf{rand}(\mathbf{0}, \mathbf{1}) \times (\boldsymbol{UB} - \boldsymbol{LB}), \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{N}$$

ii. Evaluate the fitness of each spider wasp $\boldsymbol{f}(\mathbf{x}_i)$.
iii. Identify the initial global best solution $\mathbf{x}^*$.

Step 2: Iterative Optimisation Process

Set iteration counter $\boldsymbol{t} = \mathbf{1}$.

Step 3: Random Selection

For each spider wasp $\boldsymbol{i}$, randomly select another spider wasp $\boldsymbol{k}$ such that:

$$\boldsymbol{k} \sim \boldsymbol{U}(\mathbf{1}, \boldsymbol{N}), \boldsymbol{k} \neq \boldsymbol{i}$$

where $\boldsymbol{U}$ denotes a uniform distribution,
$\boldsymbol{k} \sim \boldsymbol{U}(\mathbf{1}, \boldsymbol{N})$ is the index of spider wasp selected uniformly at random

Step 4: Position Update (Hunting Phase)

Update the position of spider wasp $\boldsymbol{i}$ using:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \boldsymbol{\alpha}(\mathbf{x}_k^t - \mathbf{x}_i^t)$$

where $\boldsymbol{\alpha} \in (\mathbf{0}, \mathbf{1})$ is a random control parameter,
$\mathbf{x}_i$ is the Position (candidate solution vector) of the $\boldsymbol{i}$-th spider wasp,
$\mathbf{x}_i^t$ is the Position of the $\boldsymbol{i}$-th spider wasp at iteration $\boldsymbol{t}$,
$\mathbf{x}_i^{t+1}$ is the Updated position of the $\boldsymbol{i}$-th spider wasp at iteration $\boldsymbol{t} + \mathbf{1}$,
x* is the Global best solution found so far,
$\boldsymbol{N}$ is the Total number of spider wasps (population size),
$\boldsymbol{i}$ is the Index of the current spider wasp, $\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{N}$,
$\boldsymbol{k}$ is the Index of a randomly selected spider wasp, $\boldsymbol{k} \neq \boldsymbol{i}$,
$\boldsymbol{\alpha}$ is the Random control parameter governing the movement step size and exploration behavior, where $\boldsymbol{\alpha} \in (\mathbf{0}, \mathbf{1})$,

Step 5: Boundary Control

Apply boundary constraints to ensure feasibility:

$$\mathbf{x}_i^{t+1} = \mathbf{min}\left(\mathbf{max}\left(\mathbf{x}_i^{t+1}, \boldsymbol{LB}\right), \boldsymbol{UB}\right)$$

Step 6: Fitness Evaluation

Evaluate the fitness $\boldsymbol{f}\left(\boldsymbol{x}_i^{t+1}\right)$.

Step 7: Global Best Update

If $\boldsymbol{f}\left(\boldsymbol{x}_i^{t+1}\right) < \boldsymbol{f}(\boldsymbol{x}^*)$, update:

$$\mathbf{x}^* = \mathbf{x}_i^{t+1}$$

Where, $\boldsymbol{f}(\mathbf{x}^*)$ is the Best fitness value obtained so far,

$\mathbf{x}_i^{t+1}$ is the Updated position of the $\boldsymbol{i}$-th spider wasp at iteration $\boldsymbol{t}+\mathbf{1}$,

x* is the Global best solution found so far,

Step 8: Termination Check

Increment iteration counter $\boldsymbol{t}=\boldsymbol{t}+\mathbf{1}$.

Repeat Steps 3-7 until $\boldsymbol{t}=\boldsymbol{T}$.

Where, $\boldsymbol{t}$ is the Current iteration number, T is the Maximum number of iterations (stopping criterion)

Step 9: Output:

Return the global best solution $\mathbf{x}^*$.

3.4. Development of spider Wasp Optimised Convolutional Neural Network

The main aspect of this paper is to create a method for the recognition of face images using convolutional neural networks. The face images are recognized as either accessible or deniable. These face images are given as the input and the output could be the exact recognized image. CNN is fine tuued by using the SWO algorithm. By using this optimization approach, CNN is retrained with images to achieve the exact recognition output

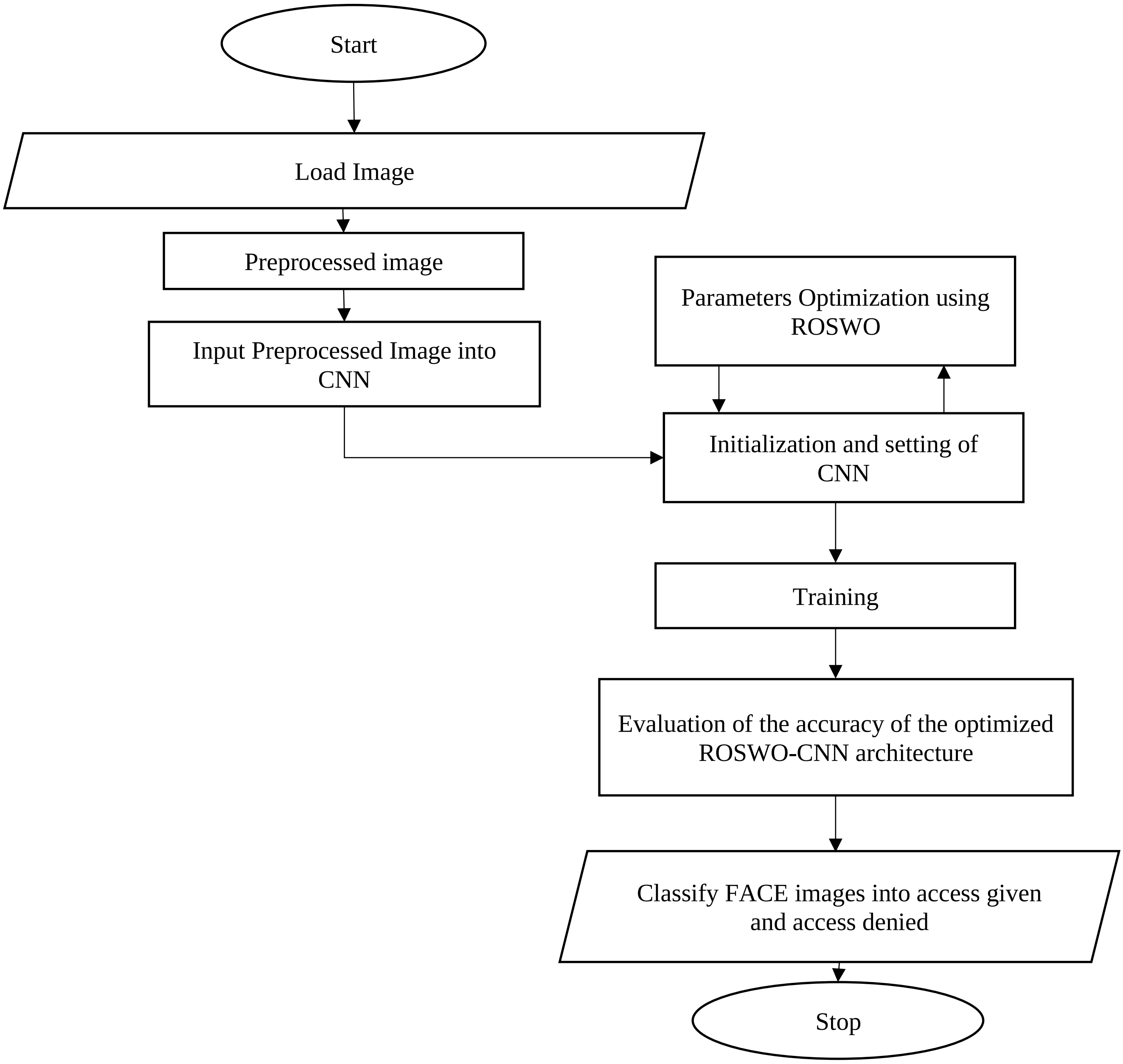

Figure 3.1: Face Recognition using Spider Wasp Optimiser based Convolutional Neural Network (SWO-CNN)

4.0 RESULTS AND DISCUSSION

In comparison, the SWO-CNN model, as presented in Table 4.1, showed noticeable improvements in both precision and sensitivity. At the threshold of 0.51 SWO-CNN achieved an accuracy of 97.93% and an F1-score of 98.18%, both of which surpass the baseline CNN model. The false positive rate was reduced to 14%, a significant enhancement over CNN, indicating the model's ability to minimize misclassifications. Moreover, the sensitivity rose to 98.35%, confirming that SWO-CNN was better at detecting true cases of Vandalisation and theft while maintaining a balanced trade-off with specificity. These results illustrate the effectiveness of spider Optimisation in enhancing CNN performance.

CNN achieved an accuracy of 96.33% and F1-score of 97.77%, SWO-CNN improved these results to 97.77% and 98.18% respectively, Additionally, SWO-CNN recorded the lowest false positive rate of (2.16%) compared to CNN with (4.01%), indicating its superior capacity to minimize erroneous detections. This comparison underscores the incremental improvements brought by Optimisation techniques, with SWO-CNN delivering the most significant gains.

Table of Comparison of CNN and SWO-CNN at Threshold 0.51

Model	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-SCORE (%)	Time (sec)
CNN	823	29	26	622	4.01	96.60	95.99	96.94	96.33	96.77	87.91
SWO-CNN	835	17	14		2.16	98.00	97.84	98.35	97.93	98.18	65.62

4.1. Discussion based on Performance Evaluation Metrics

The accuracy trends across CNN and SWO-CNN at varying threshold values are presented in

Figure 4.1, providing a comprehensive evaluation of how each model balances correct classifications. For the baseline CNN, the accuracy values remain relatively stable, ranging between 96.07% and 96.33% across thresholds 0.20, 0.35, 0.50, and 0.95. In contrast, the SWO-CNN demonstrates a noticeable improvement in accuracy, ranging from 97.60% at threshold 0.20 to 97.93% at threshold 0.95. The steady upward trend indicates that the integration of the Spider Wasp Optimiser technique enhances the CNN's ability to optimize its decision-making process, particularly in maintaining higher true positive and true negative rates across different thresholds. This improvement is significant when compared to the baseline CNN, as it reflects SWO-CNN's capability to fine-tune hyperparameters and better manage the trade-offs between sensitivity and specificity, resulting in a higher proportion of correctly classified instances

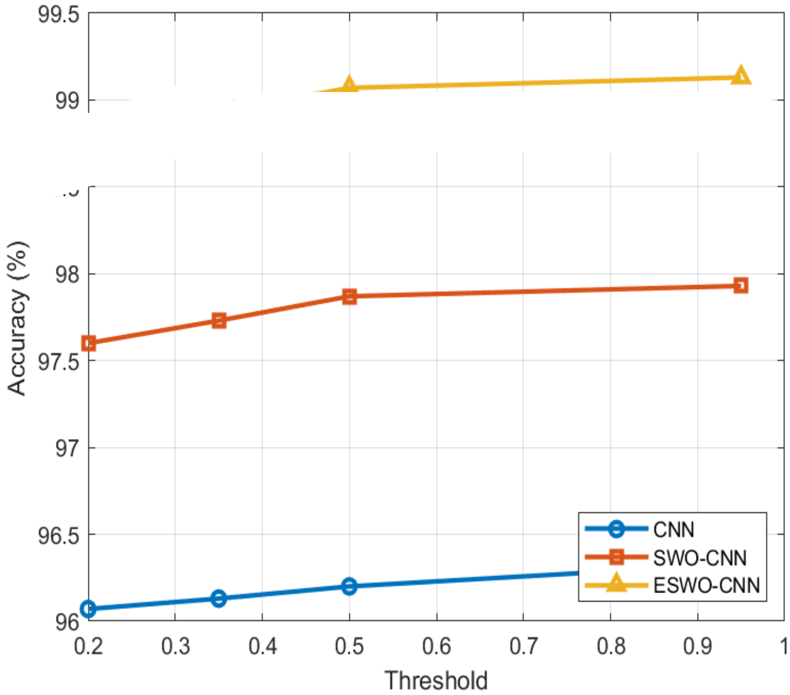

Figure 4.1: Comparison of Accuracy (%) for CNN and SWO-CNN across different threshold values.

The SWO-CNN shows a significant reduction in execution time compared to the baseline CNN, with values ranging from 65.00 seconds at threshold 0.95 to 75.01 seconds at threshold 0.20. The integration of the Spider Wasp Optimiser method not only improves model performance metrics but also streamlines certain computations by effectively Optimising the network parameters. This reduction in processing time indicates that SWO-CNN achieves a better balance between model accuracy and computational efficiency, making it more suitable for real-time face detection

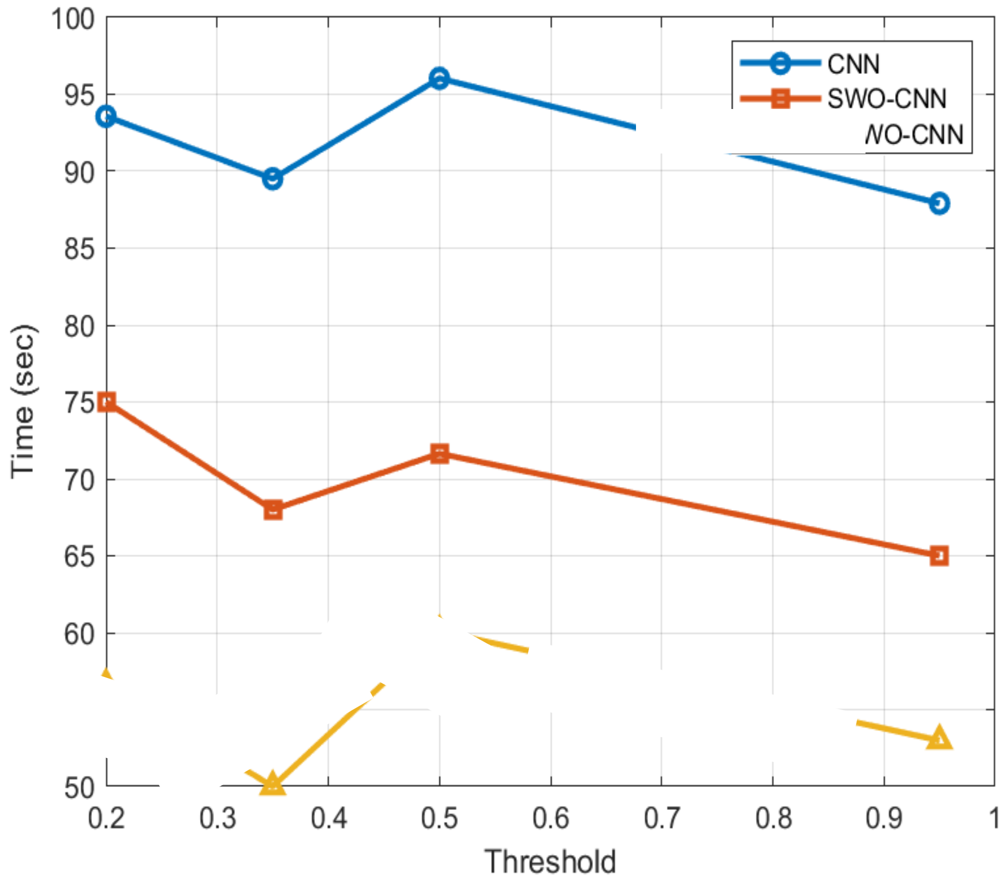

Figure 4.2: Comparison of computation time (sec) for CNN and SWO-CNN across different threshold values.

5.0 CONCLUSION

The developed SWO-CNN model has demonstrated significantly superior effectiveness compared to the standard CNN in detecting face images. By integrating the Spider Wasp Optimiser (SWO) algorithm, the model efficiently explores the hyperparameter space, selecting optimal CNN parameters such as learning rate, number of layers, and dropout rates. This Optimisation yielded substantial improvements in classification performance, with the SWO-CNN achieving consistently higher precision, accuracy, and F1-Score across all tested thresholds.

This paper confirmed that the SWO approach not only optimizes CNN for superior predictive performance but also maintains practical feasibility for real-time applications. The SWO-CNN constitutes a robust, scalable, and efficient deep learning solution for automated detection of face images, providing significant advancements over standard CNN.

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