UKR Journal of Multidisciplinary Studies (UKRJMS)
Homepage: https://ukrpublisher.com/ukrjms/
Email: submit.ukrpublisher@gmail.com
Volume 2, Issue 5, 2026 ISSN: 3049-432X (Online)

An Optimised Spider Intelligent Deep Learning Model for Detection of Vandalisation and Theft in Library

Orukotan Felicia Funmilayo[1], Adeosun Olajide Olusegun[2], Ebijuwa Adefunke Serah[3], Olabiyisi, Stephen Olatunde[4], Aderibigbe Ojo Stephen[5] and Famutim Rantiola Fidelis[6]

[1,2,4] Department of Computer Science, Ladoke Akintola University of Technology, Ogbomoso, Nigeria
[3]Department of Library and Information Science, Ladoke Akintola University of Technology, Ogbomoso, Nigeria
[5] Department of Computer Science, Lagos State University of Science and Technology, Ikorodu, Nigeria
[6]Department of Mathematics and Computer Science, University of Medical Sciences, Ondo, Nigeria

***Corresponding Author**: Orukotan Felicia Funmilayo, Adeosun Olajide Olusegun, Ebijuwa Adefunke Serah, Olabiyisi, Stephen Olatunde, Aderibigbe Ojo Stephen and Famutim Rantiola Fidelis

DOI: *https://doi.org/10.5281/zenodo.20251527*

Article History
Original Research Article
Received: 11-03-2026
Accepted: 21-04-2026
Published: 17-05-2026

Citation: Orukotan Felicia Funmilayo, Adeosun Olajide Olusegun, Ebijuwa Adefunke Serah, Olabiyisi Stephen Olatunde, Aderibigbe Ojo Stephen, & Famutim Rantiola Fidelis. (2026). An optimised spider intelligent deep learning model for detection of vandalisation and theft in library. UKR Journal of Multidisciplinary Studies (UKRJMS), 2(5). 120-128.

Abstract

Recent advances in deep learning, especially the use of Convolutional Neural Networks (CNNs), show promise for automating the detection of suspicious activity using image analysis, common CNNs face obstacles such as high computational time and weak generalization challenges. To improve the CNN model, Optimisation strategies like the Spider Wasp Optimiser (SWO) have been explored, but issues with consistency and convergence remain. Therefore, this paper introduced an Enhanced Spider Wasp Optimiser (ESWO) that incorporates roulette wheel selection, designed to better fine-tune CNN hyperparameters for automated face detection and recognition. The spider wasp Optimisation algorithm was enhanced using roulette wheel selection method instead of random selection method in the standard SWO. Roulette wheel selection assigns selection probabilistic based on individual fitness, favouring solutions with higher fitness values and thereby guiding the search toward more promising regions in the solution space. The resulting enhanced Spider Wasp Optimisation (ESWO) which formed ESWO-CNN was then used to optimize CNN settings for feature extraction. The study gathered face images from LAUTECH students, faculty of computing and Informatics and applied a pre-processing workflow including resizing, cropping, grayscale transformation, and enhancing brightness and contrast training. The ESWO-CNN was implemented with the preprocessed facial images in MATLAB R2023a. The performance of the formulated model was measured using sensitivity, specificity, precision, accuracy, false positive rate, computation time, and compared against existing Spider Wasp Optimised-CNN (SWO-CNN) approach. The results revealed that the developed ESWO-CNN model exhibited superior performance, attaining the sensitivity of 99.18%, specificity of 98.92%, precision of 99.07%, accuracy of 99.07%, and F1-score of 99.18%, with False Positive Rate of 1.08% and minimal computational time of 60.09 seconds. The SWO-CNN model showed notable performance enhancement 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 conclusion, the ESWO-CNN approach constitutes a highly effective, scalable, and efficient method for the detection of suspicious activity using image analysis. Its robust parameter Optimisation supports security monitoring, addressing both traditional and modern security challenges.

Keywords*: Convolutional Neural Networks, parameter Optimisation, Spider Wasp Optimiser, Intelligent Deep Learning Model.*

1.0 Introduction

Concurrently, the advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Long Short- Term Memory (LSTM) networks, offers potent solutions for real-time behavior and image recognition tasks within security systems (Zhou *et al.,* 2021). CNNs exhibit an exceptional capacity for automatic feature extraction and complex pattern recognition, making them highly suited for face recognition applications. Nevertheless, CNN performance depends heavily on selecting appropriate network architectures and hyperparameters, a non- trivial task given the expansive and complex parameter space (Bacanin *et al.,* 2021). Optimising CNN architectures often involves metaheuristic algorithms due to the NP- hard nature of hyperparameter tuning. Metaheuristics balance exploration and exploitation in search strategies to identify near- optimal solutions efficiently. Two primary classes of metaheuristics are evolutionary algorithms and swarm intelligence. Among these, 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).

Despite its promise, the SWO algorithm' s reliance on random selection mechanisms can result in premature convergence, suboptimal solution quality, and inconsistent outcomes across multiple runs (Mathur and Verma, 2021). This necessitates algorithmic enhancements, such as integrating more systematic selection methods like roulette wheel selection, to improve convergence reliability and solution robustness.

Given these considerations, the present study proposes to develop an Enhanced Spider Wasp Optimised Convolutional Neural Network (ESWO- CNN) model. This model aims to leverage an improved SWO algorithm to optimize CNN hyperparameters for real- time face recognition, particularly to detect and prevent vandalism and theft in university libraries. The integration of an advanced metaheuristic Optimiser with CNN technology aspires to deliver a resource- efficient, accurate, and practical solution for library security challenges.

While deep learning models such as CNNs hold potential for automating suspicious behavior detection through sophisticated image analysis (Zhou *et al.,* 2021), CNN implementations face challenges including excessive computational, time, limited generalization capabilities, overfitting tendencies, and interpretability issues (Jindal and Ghosh, 2023). These limitations hinder the practical deployment of CNN models for real time face detection in resource constrained library environments.

Recent papers have focused on optimising CNNs model for security measure in libraries such as VGGFace, FaceNet and deep learning algorithm. However, these systems still face challenges like low accuracy, high computation time where low camera resolution and poor lighting conditions persist (Zhou *et al.,* 2021). These limitations indicate a critical need for an advanced face recognition system for the protection of library resources.

Optimisation algorithms like the Spider Wasp Optimiser (SWO) offer avenues to improve CNN efficiency by automating the exploration of hyperparameters for optimal model configurations (Mishra *et al.,* 2023). However, SWO's stochastic nature causes challenges such as premature convergence and inconsistent performance attributable to an imbalance between exploration and exploitation processes (Mathur and Verma, 2021). Thus, this study addresses the gaps mentioned by developing an Enhanced Spider Wasp Optimiser that incorporates roulette wheel selection for more balanced and reliable hyperparameter optimisation of CNN models. The ultimately ESWO- CNN model was implemented and evaluated for real time face detection and recognition efficacy in university library contexts. The aim of this paper is to develop an Optimised Spider Intelligent Deep Learning Model for the detection of vandalisation and theft

2.0 Related Works

Senthilkumar *et al.* (2023) proposed an algorithm for face detection and recognition based on convolution neural networks (CNN), which outperform the traditional techniques. In order to validate the efficiency of the proposed algorithm, a smart classroom for the student's attendance using face recognition has been proposed. The face recognition system is trained on publicly available labeled faces in the wild (LFW) dataset. The system can detect approximately 35 faces and recognizes 30 out of them from the single image of 40 students. The proposed system achieved 97.9% accuracy on the testing data. Moreover, generated data by smart classrooms is computed and transmitted through an IoT-based architecture using edge computing. A comparative performance study shows that our architecture outperforms in terms of data latency and real-time response.

Chen *et al.* (2023) proposed a lightweight face recognition algorithm to reduce the number of parameters and calculations of the face feature extraction network. The most important part of the approach lies in designing a novel inverted residual Shuffle unit (IR-Shufe). After being trained by ArcFace loss on a Graphics Processing Unit (GPU) workstation, the model built on improved IR-Shufe blocks of size 1.45 MB achieves an accuracy of 98.65%. In terms of running time, our model is 5 ms faster than the current fastest MobileFaceNet, with only about 0.5% drop in accuracy. The algorithm was implemented and Optimised on the Jetson Nano embedded platform, and accurate and real-time deployment of the face recognition system was realized. The system takes 37 ms to perform the complete face detection and recognition and is robust to complex backgrounds and ambient light changes. Experimental results show that our system is of practical application value.

Vijaya *et al.* (2023) proposed a Region-based Fully CNN (R-FCN) based framework for face detection. The R-FCN refers to a completely convolutional structure using a new position-sensitive pooling layer that extracts a score for the prediction of each such region. This helps in speeding up the network and sharing the computation of Region of Interests (ROIs), thus preventing the loss of information by the feature map in ROI-pooling. In this work, a hybrid Grammatical Evolution (GE) with a Grey Wolf Optimiser (GWO) (GE-GWO) algorithm has been proposed for Optimising the R-FCN structure to enhance face detection. The WIDER face dataset with a Face Detection Dataset and Benchmark (FDDB) was employed to evaluate techniques. The results have proved that the proposed technique will achieves better performance.

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 the detection of theft and vandalization in library. However, several critical research gaps persist at the intersection of face recognition, deep learning optimisation, and library security applications. These systems still face challenges like: low accuracy, high computational time, and a high false-positive rate.

3.0. Methodology

In developing a face detection system using an Enhanced Spider Wasp Optimisation based Convolutional Neural Network algorithm (ESWO-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 an enhanced Spider-Wasp Optimisation using Roulette Wheel Selection (ESWO).
iv. Use of ESWO to select CNN hyperparameters such as learning rate, number of epochs, filter size and number of filters.
v. Feature Extraction, Training and Recognition of face images were achieved by using Roulette Wheel Selection-Spider Wasp Optimised based Convolutional Neural Network (ESWO-CNN).
vi. Evaluation of ESWO-CNN model against existing Spider Wasp Optimised- (SWO-CNN) and standard CNN approaches. for real-time face detection was done using Sensitivity, Specificity, Precision, Accuracy false Positive rate and computation time.

3.1. Image acquisition

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. Development of an Optimised Convolutional Neural Network Model for Face Detection

In Algorithm 1, the Optimisation objective is formalized through a fitness function $f(x_i)$, which evaluates CNN performance. ESWO operates by iteratively updating candidate solutions represented as vectors $x_i = [\eta_i, E_i, F_i]$. Thus, the entire model formulation is based on minimizing the fitness function derived from CNN accuracy equations

Algorithm 1 outlines the complete framework of the ESWO-based CNN for face detection. The algorithm begins with the definition of the training dataset, validation dataset, CNN architecture template, and Optimisation parameters. Each spider wasp in the population represents a candidate solution corresponding to a specific CNN hyperparameter configuration. The objective of ESWO is to identify the optimal combination of learning rate, number of epochs, and convolutional filter size. This formulation enables a tight coupling between the Optimisation process and CNN training.

Algorithm 1 defines the ESWO-CNN framework through explicit mathematical inputs and constraints. The training dataset D_{train} and validation dataset D_{val} provide samples (x_n, y_n) used in CNN forward and backward propagation equations. Each spider wasp encodes a set of CNN hyperparameters in vector form. The Optimisation

Algorithm 1: ESWO-Based Convolutional Neural Network (CNN) for Face Detection

Input

i. **Training dataset** $\mathcal{D}_{\text{train}} = \{(x_n, y_n)\}_{n=1}^{N_n}$
ii. **Validation dataset** $\mathcal{D}_{\text{val}}$
iii. **CNN architecture template**
iv. **Population size** N
v. **Maximum ESWO iterations T**
vi. **Hyperparameter bounds:**
vii. **Learning rate** $\eta \in [\eta_{\min}, \eta_{\max}]$
viii. **Number of epochs** $E \in [E_{\min}, E_{\max}]$
ix. **Filter size** $F \in [F_{\min}, F_{\max}]$

Step 1: Encoding of Spider Wasp Positions

Encode each spider wasp as a CNN hyperparameter vector:

$$\mathbf{x}_i = [\eta_i, E_i, F_i]$$

where η_i **is the learning rate,** E_i **is the number of epochs, and** F_i **is the convolution filter size.**

Step 2: Population Initialization

(a) Initialize N **spider wasps randomly:**

$$\eta_i = \eta_{\min} + \text{rand}(0,1)(\eta_{\max} - \eta_{\min})$$
$$E_i = E_{\min} + \text{rand}(0,1)(E_{\max} - E_{\min})$$
$$F_i = F_{\min} + \text{rand}(0,1)(F_{\max} - F_{\min})$$

Where $\eta_{\min}, \eta_{\max}$ **is the Minimum and maximum learning rate**

$E_{\min}, E_{\max}$ **is the Minimum and maximum number of epochs**

$F_{\min}, F_{\max}$ **is the Minimum and maximum convolution filter size**

(b) Discretize integer parameters E_i **and** F_i**.**

Step 3: CNN Forward Propagation (Hyperparameter-Dependent)

(a) Convolution Layer (filter size F_i **):**

$$z_l^{(i)} = W_l^{(Fi)} * a_{l-1} + b_l$$
$$a_l = \sigma(z_l)$$

where $W_l^{(F_i)}$ **denotes convolutional kernels of size** $F_i \times F_i$,

$W_l^{(F)}$ **is the Convolutional kernel weights of size** $F_i \times F_i$

b_l **is the Bias vector of layer** l

a_{l-1} **is the Input feature map to convolution layer** l

z_l **is the Pre-activation output of layer** l

a_l **is the Activated feature map after nonlinearity**

a_l **is the Activated feature map after nonlinearity**

*** is the Convolution operation**

(b) Pooling Layer:

$$a_l^{pool} = \text{pool}(a_l)$$

Where $\text{pool}(\cdot)$ is the Pooling operation (max or average pooling)

(c) Fully Connected Layer:

$$z_{fc} = W_{fc}a_{fc} + b_{fc}$$

Where W_{fc} is the Weight matrix of the fully connected layer,

b_{fc} is the Bias vector of the fully connected layer, a_{fc} is the Activation vector (feature representation) input to the fully connected (FC) layer, obtained after the final convolution and pooling layers and flattening operation.

(d) Softmax Output:

$$\hat{y} = \frac{e^{z_{fc}}}{\sum_{c=1}^{C} e^{z_{fce}}}$$

Where $\hat{y}$ is the detected class probability vector

Step 4: CNN Loss Function

Compute loss using cross-entropy:

$$\mathcal{L} = -\sum_{c=1}^{C} y_c \log(\hat{y}_c)$$

Where y_c is the Ground truth label for class c

Step 5: CNN (Learning Rate Optimised by ESWO)

(a) Update CNN weights using gradient descent:

$$W^{(t+1)} = W^{(t)} - \eta_i \frac{\partial \mathcal{L}}{\partial W^{(t)}}$$

$$b^{(t+1)} = b^{(t)} - \eta_i \frac{\partial \mathcal{L}}{\partial b^{(t)}}$$

where η_i is selected by ESWO-RWS

$\frac{\partial \mathcal{L}}{\partial W}, \frac{\partial \mathcal{L}}{\partial b}$ is the Gradients of loss function,

$W^{(t)}, W^{(t+1)}$ is the CNN weights before and after update,

$b^{(t)}, b^{(t+1)}$ is the CNN biases before and after update,

η_i is the Learning rate used in gradient descent (ESWO-Optimised)

(b) Repeat Steps 4-9 for E_i epochs (epochs Optimised by ESWO-RWS).

Step 6: Fitness Evaluation

(a) Evaluate validation accuracy:

$$Acc_i = \frac{1}{N_v} \sum_{n=1}^{N_v} 1(\hat{y}_n = y_n)$$

Where $1(\cdot)$ is an Indicator function,

(y_n) is the input sample and corresponding class label,

N_v : Number of validation samples

(b) Define ESWO fitness function:

$$f(\mathrm{x}_i) = 1 - Acc_i$$

Step 7: Roulette Wheel Selection (RWS)

(a) Compute selection probabilities:

$$p_i = \frac{1/f(\mathrm{x}_i)}{\sum_{j=1}^{N} 1/f(\mathrm{x}_j)}$$

(b) Compute cumulative probabilities:

$$C_i = \sum_{j=1}^{i} p_j$$

(c) Generate random number $r \in [0, 1]$ and select spider wasp k :

$$C_{k-1} < r \le C_k$$

Step 8: ESWO Position Update

Update spider wasp position:

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

where $\boldsymbol{\alpha}, \boldsymbol{\beta} \in (\mathbf{0}, \mathbf{1})$.

Step 9: Constraint Handling

(a) Enforce hyperparameter bounds:

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

(b) Round integer hyperparameters $\boldsymbol{E_i}$ and $\boldsymbol{F_i}$.

Step 10: Global Best Update

Update best solution:

$$\mathbf{x}^* = \mathbf{arg}\ \min_{\mathbf{x}_i} \boldsymbol{f}(\mathbf{x}_i)$$

Step 11: Termination

Repeat Steps 3-10 until $\boldsymbol{t} = \boldsymbol{T}$.

Step 12: Output Optimised hyperparameters ($\boldsymbol{\eta}^*, \boldsymbol{E}^*, \boldsymbol{F}^*$),

Train final CNN using Optimised hyperparameters on full training data.

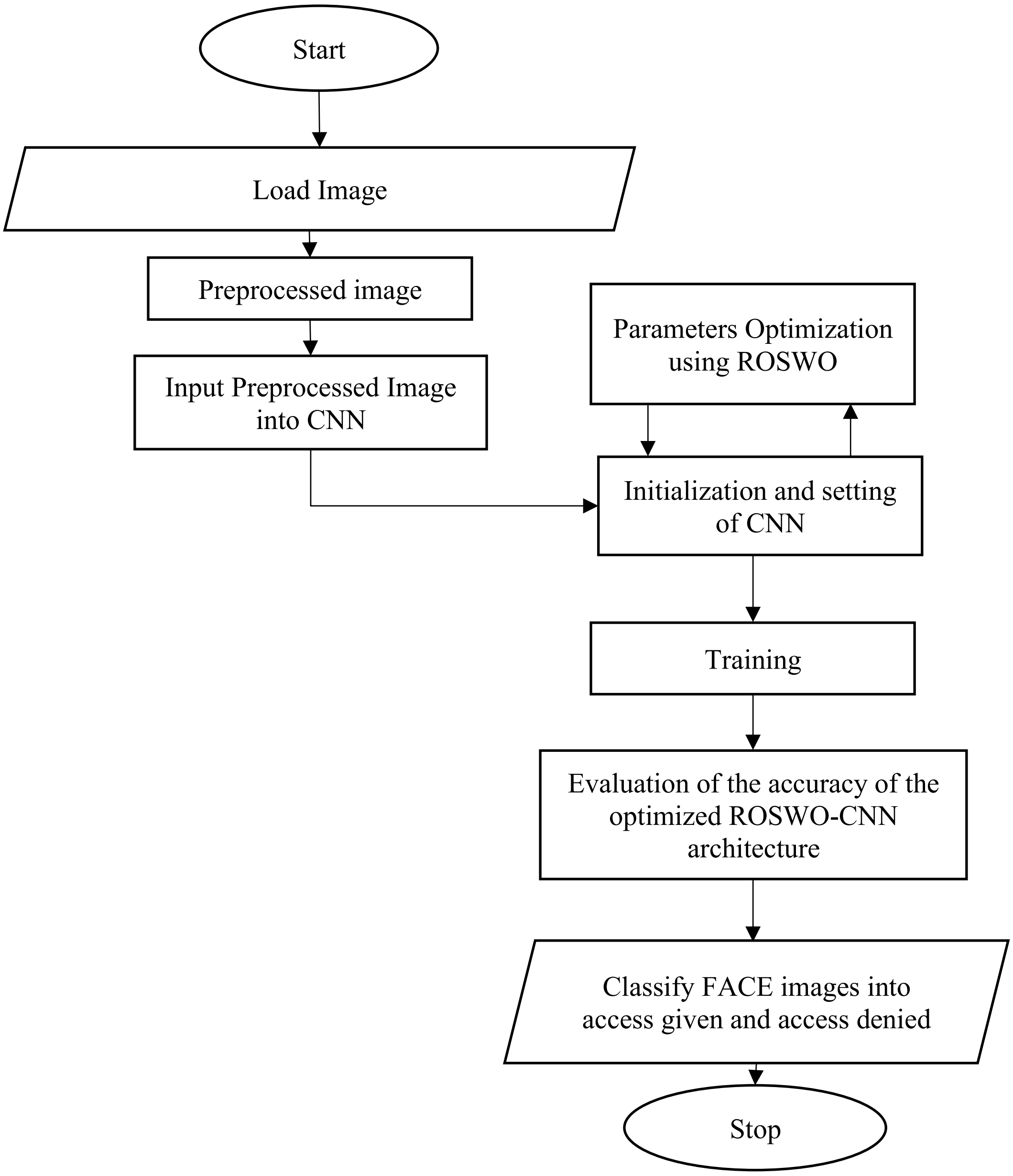

Figure 1: Face Recognition using Roulette Wheel Spider Wasp Optimiser based Convolutional Neural Network (ROSWO-CNN)

4.0 Results and Discussion

4.1 Result

The experimental results in Table 1: clearly demonstrate the superiority of the Enhanced Spider Wasp Optimiser (ESWO) over the SWO-CNN as a result of replacement the random selection method with roulette wheel selection method. At nearly all threshold levels, ESWO-CNN achieved outstanding sensitivity and specificity, consistently above 99% in the optimal regions. For example, at a threshold of 0.51, the model achieved a sensitivity of 99.06% and specificity of 99.23%, reflecting a highly balanced performance across both positive and negative classifications. This indicates that the ESWO not only minimized false positives and false negatives but also ensured that the model generalized exceptionally well across different test cases.

Another important observation is the significant improvement in precision and F1-score compared to previous models. The precision peaked at 99.41%, while the F1-score remained consistently above 98.9%, with the highest value reaching 99.24%. These results suggest that ESWO-CNN is highly reliable in detecting instances of Vandalisation and theft while avoiding overfitting or excessive bias towards a particular class. The balance of precision and recall further confirms that ESWO's Optimisation effectively strengthened the CNN's decision boundaries, providing both stability and robustness in real-world detection scenarios.

Additionally, one of the most notable advantages of the ESWO-CNN is its reduced computational cost compared to SWO-CNN. The processing time for ESWO-CNN ranged between 50.01 and 60.62 seconds, which is significantly faster than the 64.77 seconds observed in the SWO-CNN experiments. This efficiency gain underscores the value of the enhancements introduced in the ESWO, which not only improved predictive performance but also accelerated convergence during Optimisation. Taken together, the results highlight ESWO-CNN as the most effective and efficient model

Table 1: Performance of ESWO-CNN at Different Threshold Values

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-SCORE (%)	Time (sec)
0.01	847	5	13	635	2.01	99.41	97.99	98.49	98.80	98.95	54.62
0.10	847	5	13	635	2.01	99.41	97.99	98.49	98.80	98.95	53.20
0.15	847	5	13	635	2.01	99.41	97.99	98.49	98.80	98.95	55.00
0.20	847	5	13	635	2.01	99.41	97.99	98.49	98.80	98.95	56.62
0.21	846	6	10	638	1.54	99.30	98.46	98.83	98.93	99.06	50.69
0.25	846	6	10	638	1.54	99.30	98.46	98.83	98.93	99.06	50.01
0.30	846	6	10	638	1.54	99.30	98.46	98.83	98.93	99.06	51.00
0.35	846	6	10	638	1.54	99.30	98.46	98.83	98.93	99.06	50.00
0.36	845	7	7	641	1.08	99.18	98.92	99.18	99.07	99.18	60.62
0.40	845	7	7	641	1.08	99.18	98.92	99.18	99.07	99.18	60.01
0.45	845	7	7	641	1.08	99.18	98.92	99.18	99.07	99.18	59.60
0.50	845	7	7	641	1.08	99.18	98.92	99.18	99.07	99.18	60.09
0.51	844	8	5	643	0.77	99.06	99.23	99.41	99.13	99.24	52.62
0.60	844	8	5	643	0.77	99.06	99.23	99.41	99.13	99.24	52.70
0.75	844	8	5	643	0.77	99.06	99.23	99.41	99.13	99.24	53.01
0.95	844	8	5	643	0.77	99.06	99.23	99.41	99.13	99.24	52.99

4.2 Discussion based on Performance Evaluation Metrics

The accuracy trends across SWO-CNN, and ESWO-CNN at varying threshold values are presented in Figure 2 providing a comprehensive evaluation of how each model balances correct classifications. 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.

The ESWO-CNN achieves the highest accuracy across all thresholds, starting at 98.80% at threshold 0.20 and reaching 99.13% at threshold 0.95. This superior performance demonstrates the efficiency of the Enhanced Spider Wasp Optimiser approach in further refining the CNN's hyperparameters and learning dynamics. The incremental gains at higher thresholds suggest that ESWO-CNN is more resilient to stricter classification boundaries, consistently delivering near-perfect accuracy. The results in Figure 2 therefore confirm that ESWO-CNN outperforms SWO-CNN, establishing itself as the most reliable and effective model in terms of classification accuracy for face mask identification tasks.

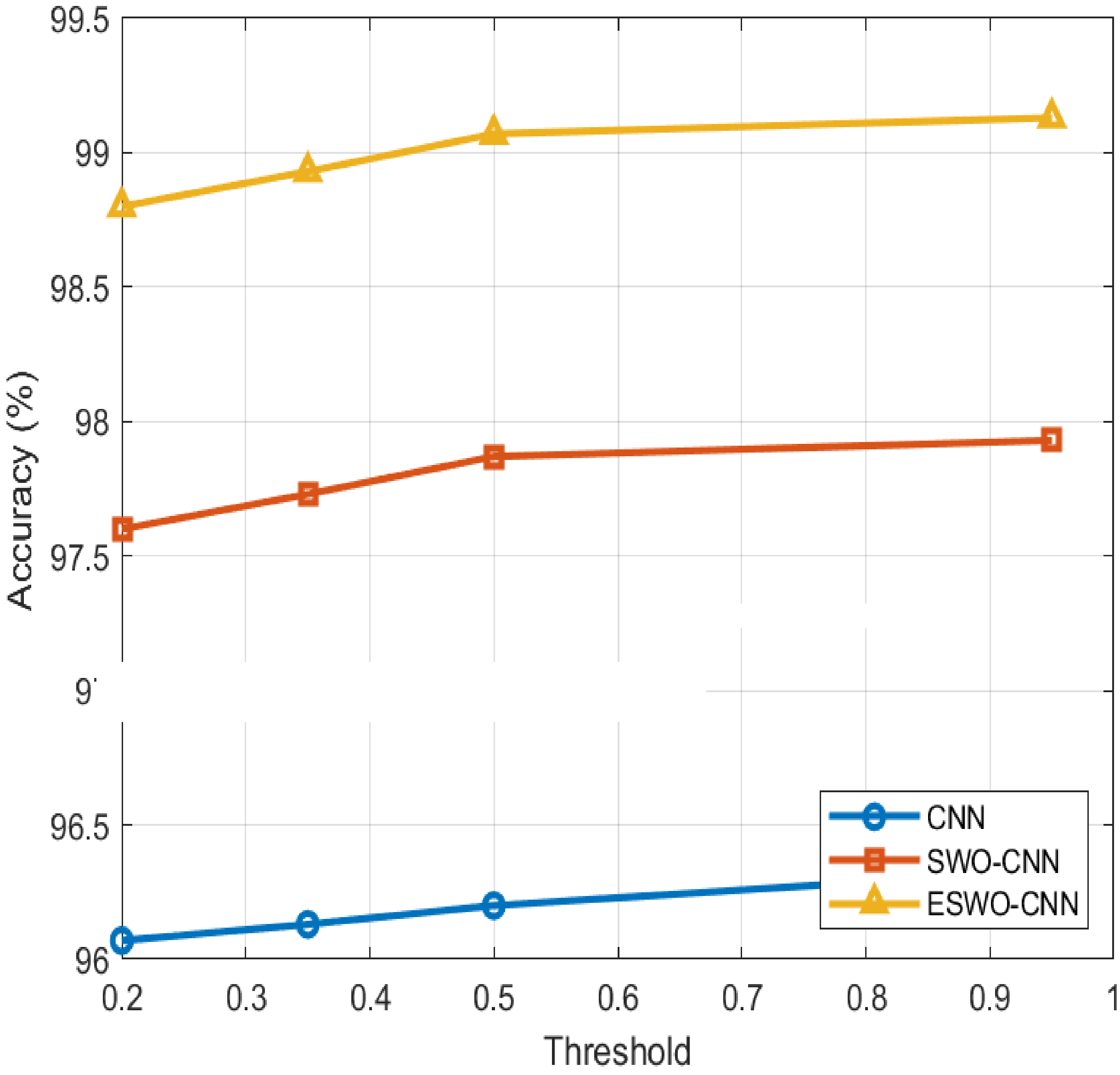

Figure 2: Comparison of Accuracy (%) for SWO-CNN, and ESWO-CNN across different threshold values.

ESWO-CNN demonstrates substantial improvement compared to SWO-CNN (97.60%–97.93%), underscoring the efficacy of Enhanced Spider Wasp Optimiser in fine-tuning CNN hyperparameters for real-world security surveillance. This performance aligns with recent studies where swarm-based or metaheuristic Optimisation strategies have been shown to significantly enhance accuracy by Optimising complex hyperparameters, as seen in the works of Asiri *et al.* (2024) and Choudhary *et al.* (2024), who reported improved classification robustness and adaptability across dynamic thresholds in anomaly detection applications. Unlike SWO-CNN models, ESWO-CNN's superior adaptability to stricter decision boundaries and maintenance of near-perfect accuracy across thresholds point to its high reliability and operational credibility, crucial for deployment in library surveillance where minimizing misclassification is critical. Furthermore, Yeh *et al.* (2023) emphasize the importance of simplified swarm Optimisation techniques in raising CNN accuracy, supporting the claim that Optimisation-enhanced models like ESWO-CNN advance the state of the art by combining robustness and precision. Thus, ESWO-CNN stands out as a highly effective model, proving essential for surveillance systems requiring high accuracy, flexible threshold management, and resilience against varying environmental conditions (Asiri *et al.,* 2024; Choudhary *et al.,* 2024; Yeh *et al.,* 2023).

5.0 Conclusion

The developed ESWO-CNN model has demonstrated significantly superior effectiveness compared to both the traditional CNN and the Spider Wasp Optimiser CNN (SWO-CNN) in detecting vandalism and theft within library environments. By integrating the Enhanced Spider Wasp Optimiser (ESWO) 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 ESWO-CNN achieving consistently higher precision, accuracy, and F1-Score across all tested thresholds.

These results clearly demonstrate that the enhanced metaheuristic Optimisation enhances the model's ability to accurately identify theft and vandalism instances while minimizing false alarms, making the system highly reliable for practical deployment in library security monitoring.

References

1. Abdel- Basset, M., Shankar, K., and Mohamed, M. (2023). Spider wasp Optimiser: A novel metaheuristic algorithm inspired by spider wasps' hunting and nesting behaviors. *Evolutionary Computation and Optimisation Journal.*
2. Abdel-Basset, M., Shankar, K., and Mohamed, R. (2023). Spider Wasp Optimiser: A novel metaheuristic algorithm for Optimisation problems. *Applied Soft Computing, 136*, 110010. https://doi.org/10.1016/j.asoc.2022.110010
3. Asiri, A. A., *et al.* (2024). Enhancing brain tumor diagnosis: An Optimised convolutional neural network model through hyperparameter tuning. *Journal of Medical Imaging and Health Informatics*, 14(3), 123-138. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11041936/
4. Bacanin, N., T uba, M., and T uba, M. (2021). Optimisation of convolutional neural networks using metaheuristic algorithms: A review. Neural Computing and Applications, 33(7), 59– 78.
5. Chen, Z., Chen, J., Ding, G. and Huang, H. (2023). A lightweight CNN-based algorithm and implementation on embedded system for real-time face recognition. *Multimedia Systems*, *29*(1), 129-138.
6. Karlupia, N., Mahajan, P., Abrol, P., and Lehana, P. K. (2023). A genetic algorithm based Optimised convolutional neural network for face recognition. *International Journal of Applied Mathematics and Computer Science*, *33*(1), 22-31.
7. Mathur, S., and Verma, A. (2021). Limitations of spider wasp Optimiser and potential improvements: A review. Swarm Intelligence and Optimisation, 5(4), 224– 230.
8. Mishra, S., Singh, V., and Roy, A. (2023). Hyperparameter Optimisation of convolutional neural networks using spider wasp Optimiser. Journal of Computational Intelligence, 17(3), 99–110.
9. Vijaya, R., Kumar, S., and Singh, P. (2023). Intelligent video surveillance using multimodal deep learning. *Pattern Recognition Letters, 175*, 90–101. https://doi.org/10.1016/j.patrec.2023.06.007
10. Zhou, F., Jiang, W., and Chen, H. (2021). Deep learning for library security: Image recognition and behavior analysis using CNNs and LST Ms. Computers and Security, 102, 102120.
11. Zhou, Z., Jiang, W., and Chen, X. (2021). Deep convolutional neural networks for face recognition: A survey. *Pattern Recognition, 117*, 107980. https://doi.org/10.1016/j.patcog.2021.107980