An Enhanced Spider Wasp Optimised Convolutional Neural Network for Image Recognition System in Library

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ABSTRACT

Libraries play a vital role in fostering educational, cultural, research, and recreational growth within society, their capacity to serve the diverse needs of users relies on protecting and maintaining both print and electronic information resources. In Nigeria, Incidents such as the loss of books, removal of journals, damage to reference items, and digital breaches have become common occurrence in library, these problems limit student and staff access to vital learning contents. Although 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 low accuracy 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 image recognition. The spider wasp Optimisation algorithm was enhanced using roulette wheel selection method which assigns selection probabilistic based on individual fitness instead of random selection method in the standard SWO. The enhanced Spider Wasp Optimisation (ESWO) which formed ESWO-CNN was then used to optimise CNN settings for feature extraction. The study gathered face images from LAUTECH students, faculty of computing and Informatics and applied a pre-processing work. 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) and standard CNN approaches. The results revealed that the developed ESWO-CNN model attained the sensitivity of 99.18%, specificity of 98.92%, precision of 99.07%, accuracy of 99.07%, 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%, and a reduced false positive rate 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%, with a false positive rate of 4.48% and computational time of 96.04 seconds. The ESWO-CNN approach constitutes a highly effective, scalable, and efficient method for safeguarding both print and electronic resources in academic library.

Keywords: Face recognition system, Convolutional Neural Networks, Hypaparameter Optimisation, Enhanced Spider Wasp Optimiser, Computational time.

INTRODUCTION

Libraries are critical intellectual infrastructures that preserve, organize, and disseminate knowledge across generations. They function as indispensable components of the educational and research ecosystem, yet they face persistent challenges such as theft, vandalisation, and unauthorized access to restricted resources (Adeoye *et al.*, 2018). These issues not only deplete valuable resources but also disrupt academic integrity and user trust. Traditional library surveillance mechanisms—such as manual monitoring, access control logs, and closed-circuit television (CCTV)—are often reactive and human-dependent, leading to lapses in security due to fatigue, bias, or inattention (Oyelola *et al.,* 2023).To overcome these limitations**,** intelligent security systems have emerged as transformative solutions that integrate artificial intelligence (AI), computer vision, and deep learning to enhance the efficiency and reliability of surveillance in libraries. These systems apply pattern recognition, motion analysis, and face recognition algorithms to automatically detect and report suspicious behaviors in real time (Chen *et al.*, 2013). Unlike traditional surveillance, which requires human monitoring, intelligent systems provide autonomous event detection and alert generation, significantly improving response times (Ullah *et al.*, 2022).

The evolution of deep learning**,** especially Convolutional Neural Networks (CNNs)**,** revolutionized facial recognition systems by enabling hierarchical feature extraction directly from image pixels. CNNs learn both local and global features, improving recognition accuracy in unconstrained environments (Krizhevsky *et al.*, 2012). CNN-based systems such as VGGFace and FaceNet have achieved near-human accuracy on benchmark datasets. However, these systems still face challenges in low-resource environments like low accuracy and high computation time (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. However, SWO's random selection process can lead to inconsistent convergence, necessitating improvements in selection mechanisms (Sui *et al.*, 2024). Therefore, this paper introduce the integration of a Roulette Wheel Selection (RWS) to enhance SWO mechanism and use the Enhanced Spider Wasp Optimiser to optimise CNN hyperparameters for botter performance.

METHODOLOGY

In developing an image recognition 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 imaes, conversion to grayscale and adjusting their brightness and contrast.

iii. Formulation of an enhanced Spider-Wasp Optimisation using Roulette Wheel Selection (ESWO).

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 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.

Image Acquisition

Acquisition of both face photographs images were obtained from Faculty of Computing and Informatics students, LAUTECH, Ogbomoso using photo camera.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 while 30%(1500 images) preserved for testing.

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 (Saravanan, 2010; Barnouti 2016; Tan *et al.,* 2012).

Formulation of an Enhanced Spider Wasp Optimiser (ESWO)

The Enhanced Spider Wasp Optimiser introduces a fitness-based selection mechanism known as Roulette Wheel Selection. In ESWO, the probability of selecting a spider wasp is proportional to its fitness, defined as $p_i = \frac{1/f(x_j)}{\sum_{j=1}^{N} 1/f(x_j)}$. This ensures that spider wasps with better fitness values are more likely to be selected to guide others. The position update equation in ESWO is also enhanced by incorporating a global best attraction term. The updated equation is expressed as $x_i^{t+1} = x_i^t + \alpha(x_k^t - x_i^t) + \beta(x^* - x_i^t)$. The additional term $\beta(x^* - x_i^t)$ explicitly pulls each spider wasp toward the best solution found so far. This global guidance accelerates convergence and improves solution refinement. The inclusion of two control parameters allows better regulation of exploration and exploitation.

Algorithm 1: Enhanced Spider Wasp Optimiser (ESWO) Using Roulette Wheel Selection
Input **i.** Objective function $\boldsymbol{f}(\mathbf{x})$ **ii.** Population size $\boldsymbol{N}$ **iii.** Maximum iterations T **iv.** Lower and upper bounds $[\boldsymbol{LB}, \boldsymbol{UB}]$ Step 1: Initialization **i.** Randomly initialize $\boldsymbol{N}$ spider wasps within the search space: **ii.** $\mathbf{x}_{\boldsymbol{i}} = \boldsymbol{LB} + \mathbf{rand}(\mathbf{0},\mathbf{1}) \times (\boldsymbol{UB} - \boldsymbol{LB}), \boldsymbol{i} = \mathbf{1},\mathbf{2},\ldots,\boldsymbol{N}$ Where LB is the Lower bound vector of the search space, UB is the Upper bound vector of the search space, $\mathbf{rand}(\mathbf{0},\mathbf{1})$ is the uniformly distributed random number in the interval $[\mathbf{0},\mathbf{1}]$, $\boldsymbol{N}$ is the Total number of spider wasps (population size)

iii. Evaluate fitness $\boldsymbol{f}(\mathbf{x}_i)$.

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

Step 2: Fitness Normalization

Convert fitness values into selection probabilities:

$$\boldsymbol{p_i} = \frac{\mathbf{1}/\boldsymbol{f}(\mathbf{x}_i)}{\sum_{j=1}^{N}\left(\mathbf{1}/\boldsymbol{f}(\mathbf{x}_j)\right)}$$

(for minimization problems)

Where $\mathbf{x}_i$ is the Position (solution vector) of the $\boldsymbol{i}$-th spider wasp,

$\boldsymbol{f}(\mathbf{x}_i)$ is the Objective (fitness) function value of spider wasp $\boldsymbol{i}$,

$\boldsymbol{p_i}$ is the Selection probability of spider wasp $\boldsymbol{i}$

Step 3: Roulette Wheel Selection

(a) Compute cumulative probabilities:

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

(b) Generate a random number $\boldsymbol{r} \in [\mathbf{0}, \mathbf{1}]$.

(c) Select spider wasp $\boldsymbol{k}$ such that:

$$\boldsymbol{C_{k-1}} < \boldsymbol{r} \leq \boldsymbol{C_k}$$

Where $\boldsymbol{k}$ is the index of the spider wasp selected using Roulette Wheel Selection. Roulette Wheel Selection improves solution quality by assigning higher selection probabilities to fitter spider wasps.

Step 4: Position Update (Hunting & Nesting Phase)

Update the position of spider wasps using:

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

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

$\boldsymbol{\alpha}$ is the Control coefficient regulating local interaction between spider wasps

$\boldsymbol{\beta}$ is the Control coefficient guiding movement toward the global best solution

$\mathbf{x}_i^t$ is the Position of the $\boldsymbol{i}$-th spider wasp at iteration $\boldsymbol{t}$

$\mathbf{x}_i^{t+1}$ is the Updated position at iteration $\boldsymbol{t} + \mathbf{1}$

$\mathbf{x}_k^t$: Position of the spider wasp selected by Roulette Wheel Selection

$\mathbf{x}^*$ is the Global best solution found so far

$\boldsymbol{t}$ is the Current iteration index

Step 5: Boundary Check

Ensure updated solutions remain within bounds:

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

Where $\mathbf{min}(\cdot), \mathbf{max}(\cdot)$ is the Operators ensuring solutions remain within the feasible search space

Step 6: Evaluation

(a) Evaluate new fitness values.

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

(b) Update $\mathbf{x}^*$ if a better solution is found.

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 $\boldsymbol{t+1}$,

x* is the Global best solution found so far,

Step 8: Termination

(a) Repeat Steps 2-6 until $\boldsymbol{t = T}$.

Where T is the Maximum number of iterations,

$\boldsymbol{t}$ is the Current iteration index

(b) Return $\mathbf{x}^*$.

Step 9: Output

Best solution $\mathbf{x}^*$

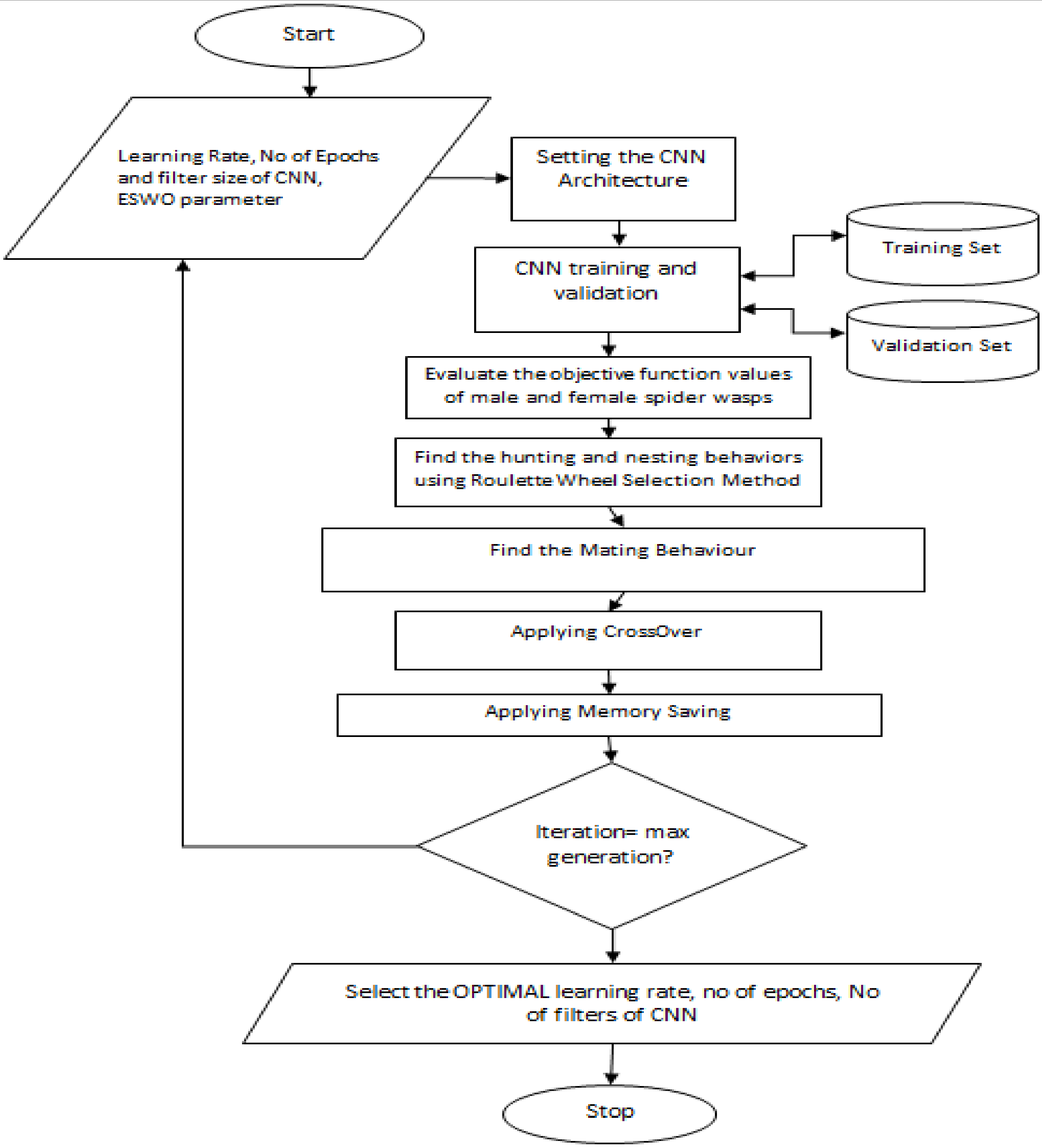

Figure 3.2: Flowchart of Roulette Wheel Spider Wasp Optimiser based Convolutional Neural Network (ESWO-CNN)

Development of an Enhanced Spider Wasp Optimised Convolutional Neural Network (ESWO-CNN) Model for Face Detection

In Algorithm 3.3, 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.

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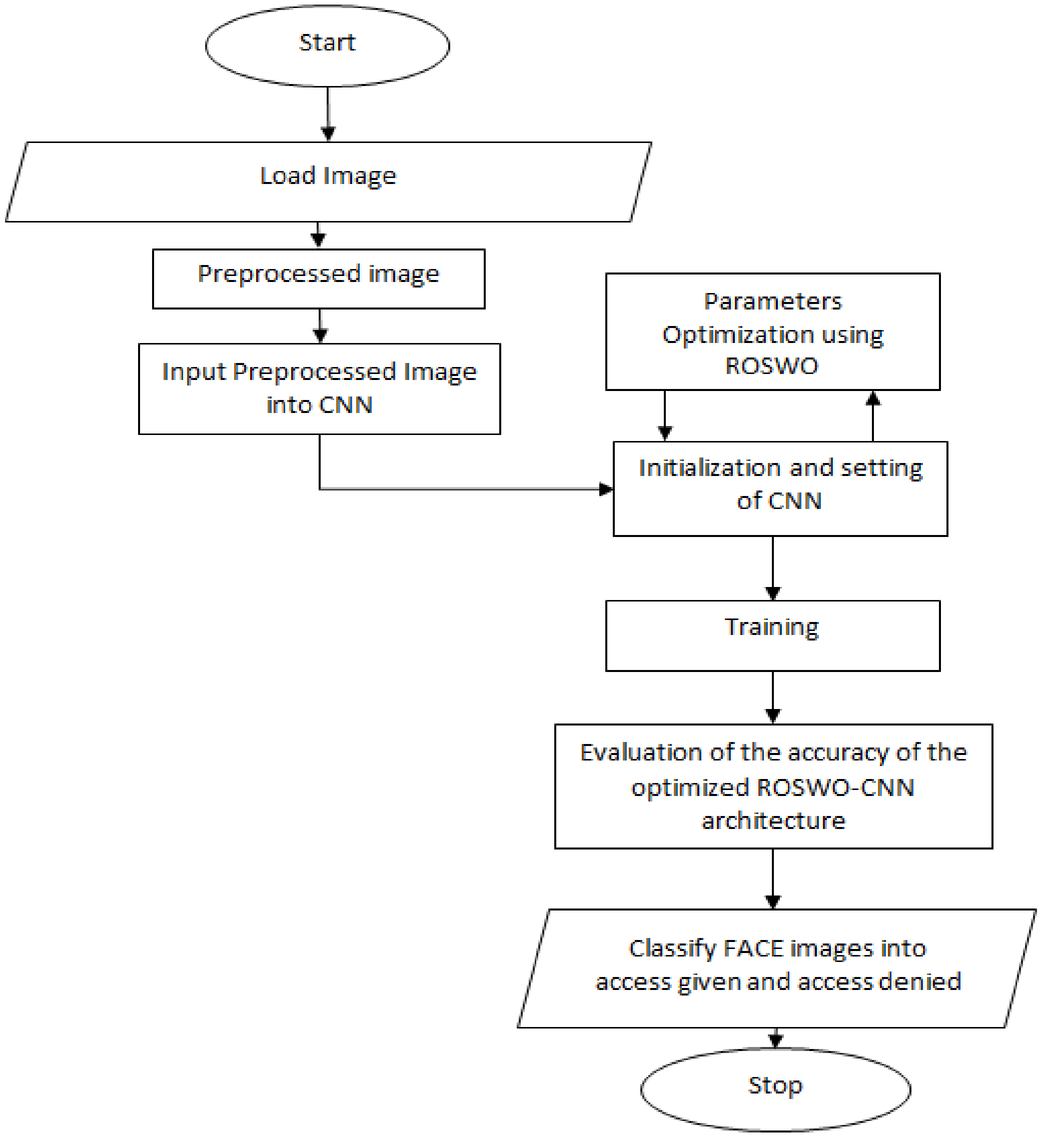

Figure 3.3: Face Recognitoin using Roulette Wheel Spider Wasp Optimiser based Convolutional Neural Network (ESWO-CNN)

RESULT AND DISCUSSION

The recognition window within the GUI displayed both the original cropped input and the system's classification output, thereby validating the operational effectiveness of the model. In addition, the inclusion of user-configurable parameters, such as adjustable threshold values, allowed for dynamic experimentation and fine-tuning of the decision

Table 1: Performance of CNN at Different Threshold Values

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-SCORE (%)	Time (sec)
0.01	826	26	33	615	5.09	96.95	94.91	96.16	96.07	96.55	93.57
0.10	826	26	33	615	5.09	96.95	94.91	96.16	96.07	96.55	93.57
0.15	826	26	33	615	5.09	96.95	94.91	96.16	96.07	96.55	93.57
0.20	826	26	33	615	5.09	96.95	94.91	96.16	96.07	96.55	93.57

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0.21	825	27	31	617	4.78	96.83	95.22	96.38	96.13	96.60	89.51
0.25	825	27	31	617	4.78	96.83	95.22	96.38	96.13	96.60	89.51
0.30	825	27	31	617	4.78	96.83	95.22	96.38	96.13	96.60	89.51
0.35	825	27	31	617	4.78	96.83	95.22	96.38	96.13	96.60	89.51
0.36	824	28	29	619	4.48	96.71	95.52	96.60	96.20	96.66	96.04
0.40	824	28	29	619	4.48	96.71	95.52	96.60	96.20	96.66	96.04
0.45	824	28	29	619	4.48	96.71	95.52	96.60	96.20	96.66	96.04
0.50	824	28	29	619	4.48	96.71	95.52	96.60	96.20	96.66	96.04
0.51	823	29	26	622	4.01	96.60	95.99	96.94	96.33	96.77	87.91
0.60	823	29	26	622	4.01	96.60	95.99	96.94	96.33	96.77	87.91
0.75	823	29	26	622	4.01	96.60	95.99	96.94	96.33	96.77	87.91
0.95	823	29	26	622	4.01	96.60	95.99	96.94	96.33	96.77	87.91

At higher thresholds (0.51–0.95), the CNN demonstrated superior precision, reaching 96.94%, coupled with the highest F1-score of 96.77% and accuracy of 96.33%. Specificity peaked at 95.99%, while sensitivity slightly decreased to 96.60%, indicating the system's preference toward minimizing false positives at the expense of a small reduction in true positives. The false positive rate further dropped to 4.01%, demonstrating CNN's strength in reducing misclassifications. However, execution time dropped considerably to 87.91 seconds, which, while computationally efficient, may reflect fewer detection operations at higher thresholds. Overall, this shows that CNN performs reliably across all threshold values, with the best balance between sensitivity, specificity, and precision occurring in the 0.36–0.51 threshold range.4.3 Discussion of Results with SWO-CNN

The results presented in Table 4.5 highlight the performance of the CNN model Optimised using the Spider Wasp Optimiser (SWO). Compared to the baseline CNN, the SWO-CNN demonstrated a noticeable improvement in terms of sensitivity (SEN), specificity (SPEC), and accuracy (ACC). For instance, at a threshold of 0.21, the model achieved a sensitivity of 98.24% and specificity of 97.07%, indicating its strong ability to correctly classify both positive and negative cases with fewer misclassifications. This enhancement reflects the effectiveness of the SWO in fine-tuning the CNN's parameters, thereby striking a better balance between false positives and false negatives.

Furthermore, the precision (PREC) and F1-score across different thresholds remained consistently high, generally above 97%, with the highest F1-score reaching 98.18% at threshold 0.51. This consistency demonstrates that the integration of SWO reduced fluctuations in the model's predictive ability, yielding stable classification performance across a wide range of decision boundaries. Such stability is particularly valuable in real-world library surveillance applications, where environmental factors and noise can influence detection accuracy. The observed reduction in the false positive rate (FPR), with values dropping as low as 2.16%, also reinforces the strength of the SWO-enhanced CNN.

Despite the gains in accuracy and stability, one of the notable observations is the computational trade-off. The time required for model execution underSWO-CNN varied from approximately 64.87 to 77.10 seconds, which is longer compared to the baseline CNN. This indicates that while SWO Optimisation increases the overall

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Table 2: Performance of SWO-CNN at Different Threshold Values

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-SCORE (%)	Time (sec)
0.01	838	14	22	626	3.40	98.36	96.60	97.44	97.60	97.90	75.62
0.10	838	14	22	626	3.40	98.36	96.60	97.44	97.60	97.90	76.62
0.15	838	14	22	626	3.40	98.36	96.60	97.44	97.60	97.90	77.10
0.20	838	14	22	626	3.40	98.36	96.60	97.44	97.60	97.90	75.01
0.21	837	15	19	629	2.93	98.24	97.07	97.78	97.73	98.01	70.01
0.25	837	15	19	629	2.93	98.24	97.07	97.78	97.73	98.01	68.73
0.30	837	15	19	629	2.93	98.24	97.07	97.78	97.73	98.01	69.19
0.35	837	15	19	629	2.93	98.24	97.07	97.78	97.73	98.01	68.00
0.36	836	16	16	632	2.47	98.12	97.53	98.12	97.87	98.12	68.09
0.40	836	16	16	632	2.47	98.12	97.53	98.12	97.87	98.12	69.26
0.45	836	16	16	632	2.47	98.12	97.53	98.12	97.87	98.12	70.62
0.50	836	16	16	632	2.47	98.12	97.53	98.12	97.87	98.12	71.64
0.51	835	17	14	634	2.16	98.00	97.84	98.35	97.93	98.18	65.62
0.60	835	17	14	634	2.16	98.00	97.84	98.35	97.93	98.18	64.87
0.75	835	17	14	634	2.16	98.00	97.84	98.35	97.93	98.18	66.62
0.95	835	17	14	634	2.16	98.00	97.84	98.35	97.93	98.18	65.00

detection quality, it comes at the cost of slightly higher computational demand. However, for critical security tasks such as detecting Vandalisation and theft in libraries, this trade-off is acceptable, as the marginal increase in processing time is outweighed by the significant improvement in classification reliability. Overall, the SWO-C model demonstrates superior detection capability, laying a strong foundation for further refinement using the enhanced ESWO Optimisation technique.

Discussion of Results with ESWO-CNN

The experimental results in Table 4.6 clearly demonstrate the superiority of the Enhanced Spider Wasp Optimiser (ESWO) over both the baseline CNN and the SWO-CNN as a result of replacement of 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.

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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 3: 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

the three approaches, offering superior accuracy, speed, and robustness for intelligent surveillance among applications in library environments.

The performance of the three models CNN, SWO-CNN, and ESWO-CNN was first assessed independently to understand their strengths and limitations across varying threshold values. ESWO-CNN consistently maintained superior results across multiple thresholds, proving its stability and adaptability to varying decision boundaries. To highlight these performance differences more clearly, Table 4.1 presents a direct comparison of CNN, SWO-CNN, and ESWO-CNN at a threshold of 0.51. The table shows that while CNN achieved an accuracy of 96.33% and F1-score of 96.77%, SWO-CNN improved these results to 97.93% and 98.18%, respectively. ESWO-CNN, however, surpassed both models with an accuracy of99.13% and F1-score of 99.18%. Additionally, ESWO-CNN recorded the lowest false positive rate (0.77%) compared to SWO-CNN (2.16%) and CNN (4.01%), indicating its superior capacity to minimize erroneous detections. This comparison underscores the incremental improvements brought by Optimisation techniques, with ESWO-CNN delivering the most significant gains.

Table 4: Comparison of CNN, SWO-CNN, and ESWO-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	634	2.16	98.00	97.84	98.35	97.93	98.18	65.62
ESWO-CNN	844	8	5	643	0.77	99.06	99.23	99.41	99.13	99.24	52.62

Discussion based on performance metrics

The accuracy trends across CNN, SWO-CNN, and ESWO-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. 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 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 for image recognition tasks.

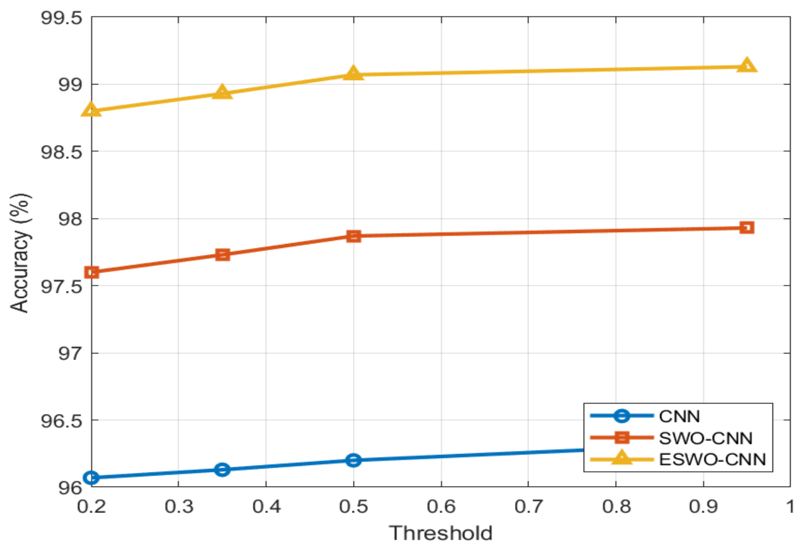

Figure 4.1: Comparison of Accuracy (%) for CNN, SWO-CNN, and ESWO-CNN across different threshold values.

Figure 4.2, presents the execution time of CNN, SWO-CNN, and ESWO-CNN across different threshold values, highlighting the computational efficiency of each model. The baseline CNN exhibits the highest processing times, ranging from 87.91 seconds at threshold 0.95 to 96.04 seconds at threshold 0.50.

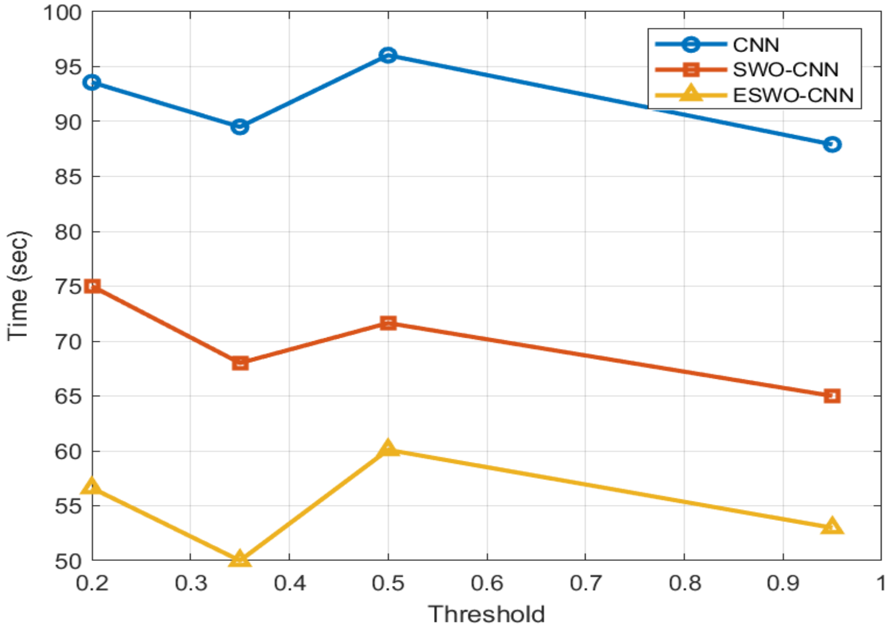

Figure 4.2: Comparison of computation time (sec) for CNN, SWO-CNN, and ESWO-CNN across different threshold values.

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. The ESWO-CNN demonstrates the lowest execution times across all thresholds, ranging from 50.00 seconds to 60.62 seconds. The reduction in execution time demonstrated by ESWO-CNN, with processing durations between 50.00 and 60.62 seconds, represents a significant advancement compared to baseline and SWO-CN, highlighting the critical role of Enhanced Spider Wasp Optimiser in improving computational efficiency

CONCLISION

The consistent reduction in computational time combined with ESWO-CNN's superior accuracy establishes this model as a state-of-the-art solution for efficient, reliable image recognition in library surveillance.

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