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Development of Cassava Leaf Disease Detection System using Convolutional Neural Network-Based Zebra Optimization Algorithm

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ABSTRACT

Cassava is a widely cultivated root crop valued for its starchy tubers and nutritional importance in tropical regions; however, its productivity is severely affected by diseases and pests, resulting in substantial yield losses for farmers. Although recent advances in deep learning offer effective solutions for automated disease detection, challenges related to model accuracy and hyperparameter tuning remain. This study optimizes a Convolutional Neural Network (CNN) using the Zebra Optimization Algorithm (ZOA) for cassava leaf disease detection. A total of 19,620 cassava leaf images were obtained from Kaggle and categorized into four classes: Cassava Mosaic Disease, Cassava Green Mite, Cassava Bacterial Blight, and healthy leaves. Image preprocessing techniques, including cropping, grayscale conversion, and normalization, were applied to enhance training efficiency. The ZOA was employed to optimize key CNN hyperparameters, specifically the number of neurons and dropout rate. The ZOA-CNN model was implemented using MATLAB R2023a and evaluated using false positive rate, specificity, sensitivity, accuracy, and recognition time. Experimental results show that the ZOA-CNN achieved an FPR of 1.11%, specificity of 98.89%, sensitivity of 95.28%, accuracy of 98.12%, and recognition time of 37.70 s, outperforming the conventional CNN. These results demonstrate that the ZOA-CNN improves detection accuracy, reduces false detections, and enhances computational efficiency, making it suitable for real-world cassava disease monitoring applications.

INTRODUCTION

Cassava (Manihot esculenta) is a starchy root crop widely cultivated for its tubers, which serve as a primary food source for millions globally. Native to South America, cassava is now grown in tropical and subtropical regions, including Africa, Asia, and Latin America, where it is a staple crop for both subsistence and commercial farming. Economically, cassava is crucial as it provides food security, raw materials for industries (that is, starch and bioethanol production), and income for smallholder farmers. Its resilience to drought makes it ideal for low-rainfall areas (Chikoti *et al*., 2019). In Nigeria, cassava holds significant importance as the country is the largest producer in the world, and the crop plays a vital role in ensuring food security, providing employment opportunities, and supporting various agro-based industries that rely on cassava derivatives such as garri, fufu, starch, and flour (FAO, 2023).

However, Cassava yield is significantly affected by diseases such as Cassava Mosaic Disease (CMD), Cassava Brown Streak Disease (CBSD), Cassava Green Mosaic (CGM) among others, which are caused by viruses and transmitted primarily through whiteflies or infected planting material (Legg *et al*., 2020). Cassava Mosaic Disease often causes yellow or green mosaic patterns on cassava leaves, while Cassava Brown Streak Disease leads to yellowing or brown streaks along the veins, with both conditions weakening the plant and reducing tuber quality (Bundi *et al*., 2022). These diseases are particularly challenging for farmers to detect early because symptoms can vary depending on environmental factors and crop varieties, and latent infections may go unnoticed until significant yield losses occur (Hillocks *et al*., 2019).

Several approaches have been employed for cassava disease detection, some of which include laboratory molecular techniques and contemporary data analysis approaches. Traditional approaches like Polymerase Chain Reaction (PCR) allow for accurate disease diagnosis of viral agents using genetic testing, and other techniques like Loop-Mediated Isothermal Amplification are faster and easier and therefore applicable in field environments. There are also imaging systems like hyperspectral and multispectral imaging, that have been used to detect changes in leaf traits of cassava resulting from diseases (Ola et al., 2020). However, with current advancements in technology, artificial intelligence approaches like machine learning and deep learning algorithms are also in vogue given their capacity to instantly detect diseases using automated leaf imaging analysis techniques, which are particularly beneficial in areas that lack access to laboratory analysis and experts in these locations and therefore very beneficial in environments aimed at efficient disease control and enhanced crop output (Okonya *et al*., 2021).

Convolutional Neural Networks (CNNs) have proven highly effective for processing image data, where convolutional layers enable automatic learning of spatial features such as edges, shapes, and textures, making them highly effective for image classification and related vision tasks (Oguntoye *et al*., 2023; Atanda *et al.,* 2023, Olayiwola et al., 2023). However, despite their strong performance, CNNs are often affected by challenges including overfitting, sensitivity to hyperparameter selection, imbalanced datasets, and gradient instability, which can limit their generalization ability (Khan *et al*., 2020; Oguntoye *et al*., 2023).

To address these issues, optimization algorithms have been widely adopted to improve CNN training by efficiently searching complex parameter spaces. Techniques such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization have demonstrated potential in enhancing model performance; however, they may still encounter drawbacks such as premature convergence, limited exploration, and suboptimal generalization. These limitations highlight the need for more effective optimization strategies to fully exploit the capabilities of CNN-based models in practical applications.

The Zebra Optimization Algorithm (ZOA) was used in this research to improve the performance of CNN by effectively handling problems like overfitting and sensitivity to hyperparameters using an exploration-exploitation technique. Being a biologically inspired algorithm, ZOA allows for an efficient search of complex solution spaces and was used for the optimization of some of the most crucial hyperparameters, such as the number of neurons and the rate of dropouts, to control the complexity of models and ensure generalization (Alzubi, 2023). According to well-established optimization techniques for training CNNs, the detail optimization of network parameters ensures efficient minimization of the loss function and improves the predictive performance by steering the weights and biases towards optimal settings (Kingma and Ba, 2017). The combination of ZOA and CNN is an effective and applicable optimization technique for reliable deployment in real-world image recognition tasks.

METHODOLOGY

Research Approach

This study developed a cassava leaf disease detection framework based on the integration of Convolutional Neural Networks and the Zebra Optimization Algorithm (ZOA-CNN), as shown in Figure 1. A publicly available cassava leaf dataset was collected, labelled by disease categories, and preprocessed through image resizing, normalization, and data augmentation to improve robustness. A baseline CNN was designed for feature extraction and classification, while ZOA optimized key hyperparameters such as the number of neurons and dropout rate to reduce overfitting and enhance generalization. The optimized CNN was trained and evaluated using accuracy, sensitivity, specificity, false positive rate, and recognition time.

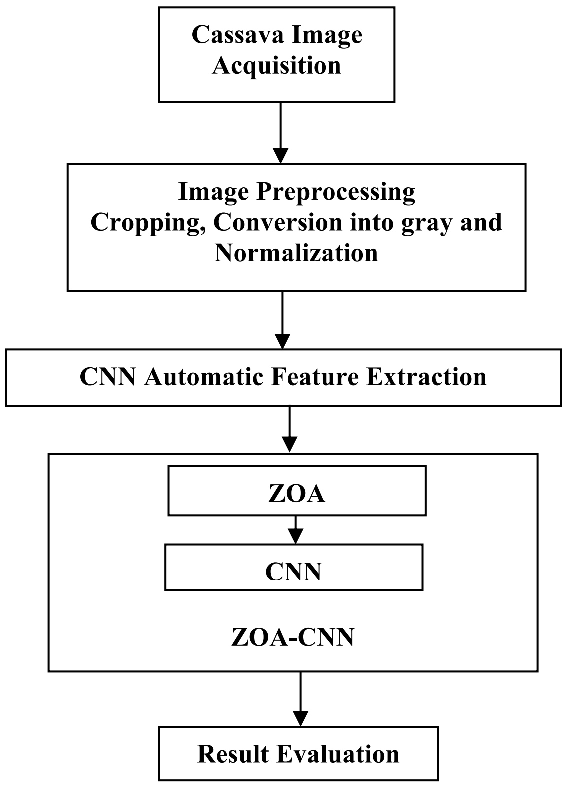

Figure 1: The Structure of the Cassava Disease System

Over the years, research has demonstrated that parameter optimization significantly enhances model performance by improving accuracy, reliability, and computational efficiency (Ogundepo *et al.,* 2022; Oguntoye *et al.,* 2025). The workflow highlights the effectiveness of combining deep learning with metaheuristic optimization for efficient cassava disease detection.

Image Acquisition

A total of 19,620 cassava leaf images were collected from a publicly available Kaggle repository, comprising healthy samples and four major disease categories. The dataset was organized into five classes, including Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), and Cassava Green Mite (CGM), each represented by 4,194 images, while 2,844 images corresponded to healthy cassava leaves. This class arrangement provides balanced representation among diseased categories to support unbiased model training, while the relatively smaller healthy class reflects realistic field conditions.

Data Preprocessing

In image pre-processing, the collected cassava leaf images were standardized to improve training efficiency and recognition accuracy. All images were resized to 224 × 224 pixels and pixel intensities were normalized to enhance CNN convergence. Automatic cropping was applied to focus on the cassava leaf region and remove irrelevant background information. RGB images were converted to grayscale to emphasize structural patterns such as edges and textures while reducing model complexity (Adetunji *et al,* 2015; Adetunji *et al,* 2018). In addition, data augmentation techniques including rotation, flipping, cropping, and brightness variation, were applied to increase data diversity and improve generalization accuracy (Oguntoye *et al.,* 2023).

The design of CNN-based Zebra optimization Algorithm

The design of the ZOA-CNN framework for cassava leaf disease detection employs the Zebra Optimization Algorithm to tune critical CNN hyperparameters that directly influence learning capacity and generalization. In this framework, each zebra represents a candidate solution defined by a pair of hyperparameters, namely the number of neurons in the fully connected layer and the dropout rate.

An initial population of zebras is randomly generated within predefined search bounds to ensure sufficient diversity and broad exploration of the solution space. Each candidate solution is evaluated by training the CNN and using validation accuracy as the fitness function, while the zebra with the highest fitness is identified as the current best solution and serves as the leader for the optimization process.

The optimization proceeds iteratively through exploration and exploitation strategies inspired by zebra social behaviour. During exploration, zebras interact with randomly selected peers to search new regions of the hyperparameter space, whereas exploitation guides zebras toward the current best solution to refine promising configurations. Boundary constraints and small random perturbations are applied to prevent premature convergence and maintain diversity within the population.

This iterative process continues until the stopping criterion is met, after which the optimal hyperparameter set is obtained. The resulting ZOA-optimized CNN demonstrates improved classification accuracy, reduced overfitting, and enhanced generalization on unseen cassava leaf images, confirming its suitability for reliable and practical agricultural disease detection applications.

Implementation of CNN-based Pelican Optimization Algorithm

The CNN-based Zebra Optimization Algorithm (ZOA-CNN) for cassava leaf disease detection system was implemented through a Graphical User Interface (GUI) developed in MATLAB R(2023a). The design utilized MATLAB toolboxes, including Image Processing, Deep Learning, and Optimisation, to integrate model development with user interaction. The GUI provided an interactive environment where cassava leaf images were uploaded, preprocessed, and classified using either the baseline CNN or the optimized ZOA-CNN model. The platform also allowed dynamic adjustment of parameters such as population size, exploration coefficient, and maximum iterations, enabling flexible experimentation. Both the training and recognition processes were visually represented, which allowed real-time monitoring of model performance (Akintunde et al., 2025; Mustapha et al., 2025). The implementation demonstrated that the ZOA-CNN provided an efficient and accurate solution for cassava leaf disease detection, and established MATLAB as a robust environment for developing GUI-based intelligent systems for precision agriculture.

System Evaluation

The performance of the cassava leaf disease detection model using the CNN-Zebra optimization algorithm was evaluated using metrics, namely accuracy, false positive rate, specificity, sensitivity, and recognition time. These metrics provided insights into the effectiveness of the model in detecting and classifying diseased cassava leaves and is calculated using the following formulas:

Accuracy (Acc): Accuracy refers to the ability of the classification model to correctly identify the health status of cassava leaves across all samples in the dataset. A higher accuracy value indicates better model performance and reliable detection of both diseased and healthy leaves.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (1)$$

False Positive Rate (FPR): False Positive Rate (FPR) represents the proportion of healthy cassava leaves that were incorrectly classified as diseased by the model. A lower FPR is desirable, as it signifies fewer misclassifications and improved model reliability.

$$FPR = \frac{FP}{FP+TN} \times 100\% \quad (2)$$

Specificity (SPEC): Specificity denotes the ability of the classification model to correctly identify cassava leaves that are not infected. A higher specificity value indicates that the model effectively rejects false disease detections and accurately recognizes healthy leaves.

$$\text{SPEC} = \frac{TN}{TN+FP} \; X \; 100\% \quad (3)$$

Sensitivity (SEN): Sensitivity measures the model's capability to correctly identify cassava leaves that are truly infected. A higher sensitivity value reflects a stronger ability of the model to detect diseased samples accurately.

$$SEN = \frac{TP}{TP+FN} \times 100\% \quad (4)$$

Recognition Time: Recognition Time refers to the total time required by the system to correctly classify a cassava leaf image.

Where;

TP (True Positive) means correctly predicted positive cases.

TN (True Negative) means correctly predicted negative cases.

FP (False Positive) means incorrectly predicted positive cases.

FN (False Negative) means incorrectly predicted negative cases.

RESULTS AND DISCUSSION

Figure 2 presents representative samples from the cassava leaf dataset used in this study, covering Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mite (CGM), and healthy leaves, thereby ensuring balanced visual representation of all classes for reliable model training and evaluation. The developed Graphical User Interface (GUI), shown in Figure 3, illustrates the training process of both the conventional CNN and the optimized ZOA-CNN models, providing real-time visualization of accuracy and loss trends across training epochs to support effective performance monitoring and comparison. During the testing phase, the GUI further enables evaluation on unseen cassava leaf images, as depicted in Figure 4, where prediction outputs and performance indicators clearly demonstrate the improved detection accuracy and generalization capability of the ZOA-CNN model over the baseline CNN, making the framework suitable for practical deployment.

Results with CNN

The performance of the baseline CNN in detecting different cassava leaf diseases, including Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mite (CGM), and healthy samples, is presented below

Evaluation Results with Cassava Bacterial Blight (CBB) Disease

The performance of the baseline CNN for Cassava Bacterial Blight (CBB) classification is summarized in Table 1 across decision thresholds of 0.25, 0.35, 0.50, and 0.85. As the threshold increases, the model shows improved reliability, evidenced by reduced false positive rate and increased specificity and accuracy.

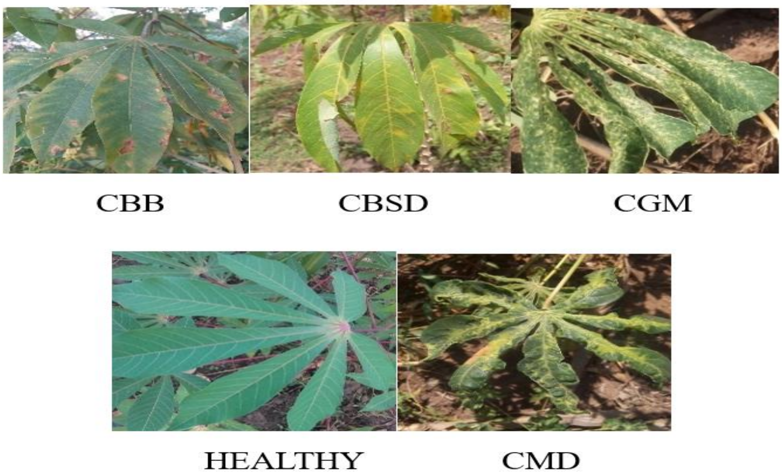

Figure 2: Sample of cassava leaf dataset showing disease categories

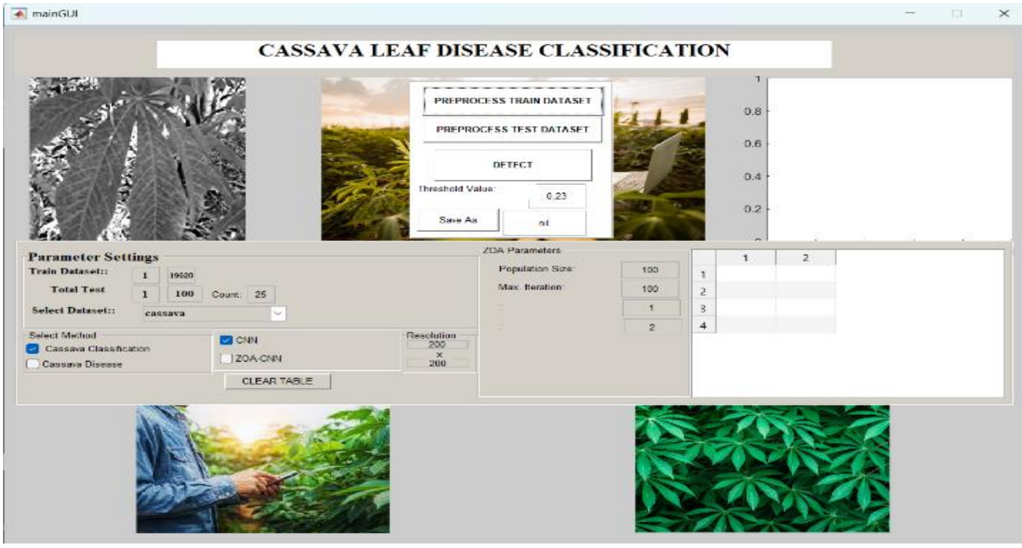

Figure 3: GUI showing the training process with cassava disease using CNN and ZOA-CNN

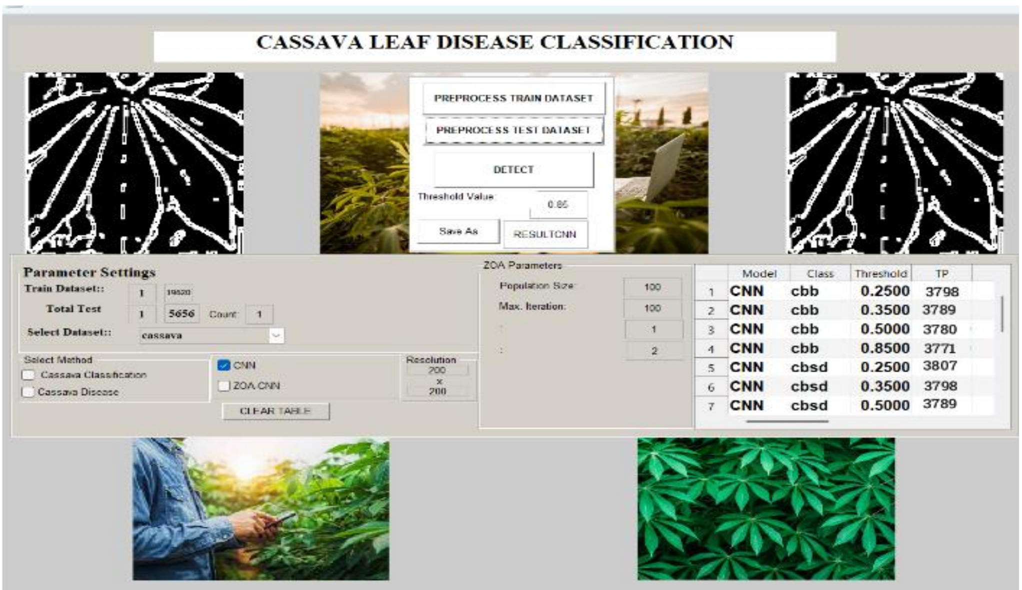

Figure 4: GUI showing the Testing Process with cassava disease using CNN and ZOA-CNN

Lower thresholds yield higher sensitivity but more misclassification of healthy leaves, while the highest threshold of 0.85 achieves the best performance with the lowest false positive rate (2.57%), highest specificity (97.43%), peak accuracy (95.83%), and reduced recognition time. Although sensitivity slightly decreases, this trade-off ensures more stable predictions with fewer false disease alarms. Hence, Table 1 indicates that a threshold of 0.85 provides the most balanced and practical operating point for reliable CBB detection using the baseline CNN model.

Table 1: Performance of CNN Model on Cassava Bacterial Blight (CBB) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
CNN	0.25	3798	396	459	14967	2.98	97.02	90.56	95.64	49.90
CNN	0.35	3789	405	441	14985	2.86	97.14	90.34	95.69	49.00
CNN	0.5	3780	414	423	15003	2.74	97.26	90.13	95.73	49.24
CNN	0.85	3771	423	396	15030	2.57	97.43	89.91	95.83	47.18

Evaluation Results with Cassava Brown Streak Disease (CBSD)

The performance of the CNN model for CBSD classification is presented in Table 2 at decision thresholds of 0.25, 0.35, 0.50, and 0.85. The results show stable performance across all thresholds, with accuracy and specificity improving as the threshold increases. Lower thresholds exhibit higher sensitivity but also higher false positive rates, where some healthy leaves are misclassified as diseased. As the threshold increases, false positives reduce, leading to the best balance of accuracy and specificity at the 0.85 threshold. At this point, the CNN achieves 95.92% accuracy, 97.49% specificity, and 90.13% sensitivity, while maintaining the same recognition time. Therefore, the optimal threshold for accurate and reliable CBSD detection using the CNN model is 0.85.

Table 2: Performance of CNN Model on Cassava Brown Streak Diseases (CBSD) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
CNN	0.25	3807	387	450	14976	2.92	97.08	90.77	95.73	50.68
CNN	0.35	3798	396	432	14994	2.80	97.20	90.56	95.78	50.28
CNN	0.5	3789	405	414	15012	2.68	97.32	90.34	95.83	50.30
CNN	0.85	3780	414	387	15039	2.51	97.49	90.13	95.92	50.81

Evaluation Results with Cassava Green Mite (CGM)

The performance of the CNN model for Cassava Green Mite (CGM) detection is shown in Table 3 at decision thresholds of 0.25, 0.35, 0.50, and 0.85. Classification accuracy remained stable across all thresholds, with a trade-off between sensitivity and specificity as the threshold increased. Lower thresholds produced higher sensitivity but more false positives, occasionally misclassifying healthy leaves. As the threshold rose, false positives decreased, improving specificity and hence accuracy, while sensitivity slightly declined. The best results were at the 0.85 threshold, with 95.73% accuracy, 97.37% specificity, and a 2.63% false positive rate, alongside consistent recognition time. Thus, a 0.85 threshold provides the most balanced and reliable performance for CGM detection, making the CNN model suitable for accurate and practical cassava disease monitoring.

Table 3: Performance of CNN Model on Cassava Green Mite (CGM) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
CNN	0.25	3789	405	468	14958	3.03	96.97	90.34	95.55	49.53
CNN	0.35	3780	414	450	14976	2.92	97.08	90.13	95.60	49.00
CNN	0.5	3771	423	432	14994	2.80	97.20	89.91	95.64	50.59
CNN	0.85	3762	432	405	15021	2.63	97.37	89.70	95.73	50.06

Evaluation Results with Cassava Mosaic Disease (CMD)

Table 4 summarizes the CNN model's performance in detecting Cassava Mosaic Disease (CMD) at cut-offs of 0.25, 0.35, 0.50, and 0.85. The best performance was at 0.85, with 3753 true positives, 441 false negatives, 414 false positives, 15,012 true negatives, and a run time of 49.69 seconds. Accuracy, specificity, and sensitivity were 95.64%, 97.32%, and 89.48%, respectively. The true positive rate was slightly lower, leaving a few CMD cases undetected, reflecting the trade-off between sensitivity and specificity. High specificity and a lower false positive rate indicate the model effectively differentiates healthy from diseased leaves. The 0.85 cut-off ensures a reliable and practical model for cassava disease monitoring, with stable run time.

Table 4: Performance of CNN Model on Cassava Mosaic Disease (CMD) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
CNN	0.25	3780	414	477	14949	3.09	96.91	90.13	95.46	50.02
CNN	0.35	3771	423	459	14967	2.98	97.02	89.91	95.50	51.88
CNN	0.5	3762	432	441	14985	2.86	97.14	89.70	95.55	50.80
CNN	0.85	3753	441	414	15012	2.68	97.32	89.48	95.64	49.69

Evaluation Results with Healthy Cassava Leaves

Table 5 presents the CNN model's performance in classifying healthy cassava leaves across thresholds of 0.25, 0.35, 0.50, and 0.85. The best results were at 0.85, with 2475 true positives, 369 false negatives, 342 false positives, and 16,434 true negatives, achieving 96.38% accuracy, 97.96% specificity, 87.03% sensitivity, and a recognition time of 45.29 seconds. While sensitivity was slightly lower, the model showed the highest accuracy and specificity, effectively distinguishing healthy leaves from diseased ones and minimizing false alarms. This trade-off reduces misclassification of healthy plants, which is critical in agricultural applications. The low false positive rate and stable processing time highlight the CNN's reliability and computational efficiency. Hence, the 0.85 threshold provides an optimal balance of precision, accuracy, and efficiency for practical deployment in cassava disease monitoring.

Results with ZOA-CNN

The performance of the ZOA-CNN in detecting different cassava leaf diseases, including Cassava Mosaic Disease (CMD), Cassava Bacterial Blight

Table 5: Performance of CNN Model on Healthy Classification at Different Thresholds

Model	Class	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
CNN	healthy	0.25	2502	342	405	16371	2.41	97.59	87.97	96.19	45.50
CNN	healthy	0.35	2493	351	387	16389	2.31	97.69	87.66	96.24	46.94
CNN	healthy	0.5	2484	360	369	16407	2.20	97.80	87.34	96.28	45.34
CNN	healthy	0.85	2475	369	342	16434	2.04	97.96	87.03	96.38	45.29

(CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mite (CGM), and healthy samples, is presented below.

Evaluation Results with Cassava Bacterial Blight (CBB) Disease

The performance of the ZOA-CNN model in classifying Cassava Bacterial Blight (CBB) was evaluated at thresholds of 0.25, 0.35, 0.5, and 0.85, as shown in Table 6. The model showed strong performance across all thresholds, with accuracy between 97.80% and 98.03%, specificity from 98.37% to 98.83%, and sensitivity from 95.06% to 95.71%. At 0.25, the highest true positives (4014) and sensitivity (95.71%) were achieved, but with a higher false positive rate (1.63%). Increasing the threshold reduced false positives and improved specificity. The 0.5 threshold provided balanced sensitivity, specificity, and 97.98% accuracy. Although 0.85 achieved the highest accuracy (98.03%) and specificity (98.83%), sensitivity declined slightly. Hence, the 0.5 threshold offered the most balanced performance, confirming the robustness of the ZOA-CNN model for CBB classification.

Table 6: Performance of ZOA-CNN Model on Cassava Bacterial Blight (CBB) Classification at Different Thresholds

Model	**Threshold**	**TP**	**FN**	**FP**	**TN**	**FPR (%)**	**SPEC (%)**	**SEN (%)**	**ACC (%)**	**Time (sec)**
ZOA-CNN	0.25	4014	180	252	15174	1.63	98.37	95.71	97.80	35.58
ZOA-CNN	0.35	4005	189	225	15201	1.46	98.54	95.49	97.89	35.26
ZOA-CNN	0.5	3996	198	198	15228	1.28	98.72	95.28	97.98	35.21
ZOA-CNN	0.85	3987	207	180	15246	1.17	98.83	95.06	98.03	31.55

Evaluation Results with Cassava Brown Streak Disease (CBSD)

Table 7 shows the model's performance across thresholds of 0.25, 0.35, 0.5, and 0.85 in detecting Cassava Brown Streak Disease (CBSD). The model registered accuracy (97.98%–98.21%), specificity (98.48%–98.95%), and sensitivity (95.49%–96.14%). At 0.25, it achieved the highest true positives (4032) and sensitivity (96.14%) but specificity dropped to 98.48% due to a 1.52% false positive rate. Increasing the threshold to 0.35 reduced false positives to 207, raising specificity to 98.66% while sensitivity decreased to 95.92%, illustrating the trade-off. At 0.5, true positives were 4014 with 180 false negatives and false positives, specificity 98.83%, and accuracy 98.17%. Threshold 0.85 achieved the highest accuracy (98.21%) and specificity (98.95%) but slightly lower sensitivity (95.49%) with a recognition time of 36.40 s.

Table 7: Performance of ZOA-CNN Model on Cassava Brown Streak Diseases (CBSD) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
ZOA-CNN	0.25	4032	162	234	15192	1.52	98.48	96.14	97.98	36.66
ZOA-CNN	0.35	4023	171	207	15219	1.34	98.66	95.92	98.07	37.51
ZOA-CNN	0.5	4014	180	180	15246	1.17	98.83	95.71	98.17	36.47
ZOA-CNN	0.85	4005	189	162	15264	1.05	98.95	95.49	98.21	36.40

Evaluation Results with Cassava Green Mite Disease (CGM)

Table 8 summarizes the performance of the ZOA-CNN model for Cassava Green Mite (CGM) classification across thresholds of 0.25, 0.35, 0.5, and 0.85. The model showed strong performance, with accuracy between 97.89–98.12%, specificity 98.42–98.89%, and sensitivity 95.28–95.92%. At 0.25, the model achieved the highest true positives (4023) and sensitivity (95.92%) but with a higher false positive rate (1.58%). Increasing the threshold reduced false positives and improved specificity. The 0.5 threshold provided the best balance, achieving 98.07% accuracy, 98.77% specificity, and 95.49% sensitivity. Although 0.85 produced the highest accuracy (98.12%) and specificity (98.89%) with the lowest false positive rate (1.11%), sensitivity slightly decreased. Processing time remained stable at about 36 s, making the 0.5 threshold most suitable for practical deployment.

Table 8: Performance of ZOA-CNN Model on Cassava Green Mite (CGM) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
ZOA-CNN	0.25	4023	171	243	15183	1.58	98.42	95.92	97.89	36.30
ZOA-CNN	0.35	4014	180	216	15210	1.40	98.60	95.71	97.98	37.68
ZOA-CNN	0.5	4005	189	189	15237	1.23	98.77	95.49	98.07	37.70
ZOA-CNN	0.85	3996	198	171	15255	1.11	98.89	95.28	98.12	36.43

Hence, the 0.5 threshold provides the best balance between sensitivity and specificity.

Evaluation Results with Cassava Mosaic Disease (CMD)

Table 9 presents the performance of the ZOA-CNN model at different thresholds for Cassava Mosaic Disease (CMD) classification. The model achieved consistently high performance, with accuracy between 97.71% and 97.94%, specificity from 98.31% to 98.77%, and sensitivity from 94.85% to 95.49%. At the 0.25 threshold, the model recorded the highest true positives (4005) and sensitivity (95.49%) but with a higher false positive rate (1.69%). Increasing the threshold improved specificity by reducing false positives. The default 0.5 threshold provided balanced performance, achieving 97.89% accuracy, 98.66% specificity, and 95.06% sensitivity. Although the 0.85 threshold yielded the highest specificity (98.77%) and lowest false positive rate (1.23%), sensitivity slightly decreased. Hence, the 0.5 threshold offers the most balanced and practical performance for CMD detection.

Table 9: Performance of ZOA-CNN Model on Cassava Mosaic Disease (CMD) Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
ZOA-CNN	0.25	4005	189	261	15165	1.69	98.31	95.49	97.71	36.46
ZOA-CNN	0.35	3996	198	234	15192	1.52	98.48	95.28	97.80	37.49
ZOA-CNN	0.5	3987	207	207	15219	1.34	98.66	95.06	97.89	36.69
ZOA-CNN	0.85	3978	216	189	15219	1.23	98.77	94.85	97.94	36.31

Evaluation Results with Healthy Cassava Leaves

Table 10 presents the performance of the ZOA-CNN model for classifying healthy cassava leaves at thresholds of 0.25, 0.35, 0.5, and 0.85. The model achieved consistently high performance across all thresholds, with accuracy between 98.44% and 98.67%, specificity from 98.87% to 99.30%, and sensitivity from 94.94% to 95.89%. At the lowest threshold (0.25), the model recorded the highest true positives (2727) and sensitivity (95.89%), indicating effective identification of healthy leaves, though with a slightly higher false positive rate (1.13%). Increasing the threshold reduced false positives and improved specificity, with the 0.5 threshold providing the most balanced performance, achieving 98.62% accuracy, 99.20% specificity, and 95.25% sensitivity. The highest threshold (0.85) yielded the best accuracy and specificity, but with a small reduction in sensitivity. Hence, the results demonstrate that ZOA-CNN reliably distinguishes healthy cassava leaves from diseased ones, with the 0.5 threshold offering the most practical balance for real-world deployment.

Table 10: Performance of ZOA-CNN Model on Healthy Classification at Different Thresholds

Model	Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
ZOACNN	0.25	2727	117	189	16587	1.13	98.87	95.89	98.44	31.69
ZOACNN	0.35	2718	126	162	16614	0.97	99.03	95.57	98.53	31.53
ZOACNN	0.5	2709	135	135	16641	0.80	99.20	95.25	98.62	31.72
ZOACNN	0.85	2700	144	117	16659	0.70	99.30	94.94	98.67	31.57

Performance Comparison of CNN and ZOA-CNN for Plant Disease Classification

The comparative evaluation shows that the designed ZOA-CNN consistently outperforms the baseline CNN across all cassava disease categories in accuracy, specificity, sensitivity, false positive rate, and recognition time.

ZOA-CNN achieved higher accuracy (up to 98.67%), improved specificity (up to 99.30%), and reduced false positives for all disease and healthy leaf classes, while lowering processing time from about 45–50 s to 31–36 s. These improvements demonstrate the effectiveness of the Zebra Optimization Algorithm in selecting optimal CNN hyperparameters, resulting in better feature learning, faster convergence, and more reliable classification. Hence, ZOA-CNN provides a robust and efficient framework for practical and real-time cassava disease monitoring.

Discussion of Results

The comparative results demonstrate that the ZOA-CNN model consistently outperforms the baseline CNN in cassava disease classification across all evaluated thresholds. While the conventional CNN shows stable behaviour with only marginal improvements as thresholds increase, its performance remains comparatively limited (Olagunju et al., 2025). In contrast, ZOA-CNN achieves noticeably higher accuracy, stronger specificity, and improved sensitivity, indicating a superior ability to learn discriminative features and correctly identify diseased samples while minimizing false alarms. The optimized model also maintains lower false positive rates, reflecting better discrimination between healthy and infected leaves, which is essential for practical agricultural use. Moreover, ZOA-CNN exhibits enhanced computational efficiency by requiring significantly less recognition time than the baseline CNN, while preserving robustness across varying decision thresholds. These improvements confirm that the integration of the Zebra Optimization Algorithm effectively enhances CNN hyperparameter tuning, leading to faster convergence, reduced misclassification, and more reliable predictions. Hence, the results validate ZOA-CNN as a robust, accurate, and efficient framework suitable for real-time cassava disease monitoring and precision agriculture applications.

CONCLUSION

This study concludes that the Zebra Optimization Algorithm–based Convolutional Neural Network (ZOA-CNN) provides a clear improvement over the conventional CNN for cassava leaf disease detection. By integrating ZOA into the CNN framework, the designed model achieves higher accuracy, sensitivity, and specificity, while significantly reducing false positive rates and computational time. These improvements indicate a stronger ability to distinguish between healthy and diseased leaves, ensure reliable performance under varying decision thresholds, and support timely disease identification. The enhanced efficiency and robustness of ZOA-CNN make it well suited for practical agricultural deployment, where fast and accurate diagnosis is essential to reduce yield losses and support sustainable crop management. Hence, the findings demonstrate that bio-inspired optimization can effectively strengthen deep learning models for plant disease detection, contributing a reliable and scalable solution for real-world cassava disease monitoring.

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