

Metaheuristic-Tuned Convolutional Networks for Plant Disease Recognition: Waterwheel Plant Algorithm as a Standout Optimizer

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Abstract— Plant diseases cause ~1/3 of annual agricultural losses, threatening food security; timely detection ensures sustainability. This study optimizes CNNs with metaheuristics (WWPA, GWO, PSO, WOA, GA) for classifying 87,000 RGB images across 38 healthy/diseased crop categories. WWPA-CNN achieved superior performance: 97.89% accuracy, 97.53% sensitivity, 98.20% specificity, 97.79% F-score—outperforming GWO-CNN (95.33%), PSO-CNN (94.30%), WOA-CNN (93.45%), and GA-CNN (92.82%). Histograms, KDE, and CDF plots confirmed WWPA-CNN's stability. Metaheuristic-optimized CNNs enable reliable, scalable plant disease detection for real-world agriculture.

Index Terms—Plant Disease Detection, Convolutional Neural Networks (CNNs), Metaheuristic Optimization, Waterwheel Plant Algorithm (WWPA), Precision Agriculture

I. INTRODUCTION

Agriculture has long been recognized as the foundation of human civilization and remains central to global food security, rural livelihoods, and economic growth. With the global population projected to approach 10 billion by 2050, the Food and Agriculture Organization (FAO) estimates that food production must increase by at least 70% to sustain future demand. However, plant diseases represent one of the most significant challenges to achieving this target, accounting for up to one-third of annual agricultural production losses. These losses not only threaten food supply but also contribute to economic in-stability, Plant diseases threaten crop yields, exacerbating farmer vulnerability and food prices; effective detection is essential for sustainability. Deep Learning (CNNs) automatically discovers subtle disease features invisible to the naked eye, enabled by datasets like PlantVillage/PlantDoc and enhanced by metaheuristics (WWPA, GWO, PSO, WOA, GA) for field generalization. However, and impose high computational barriers for smallholder farmers. This systematic review analyzes CNN-metaheuristic architectures for plant disease prediction, highlighting contributions/limitations and practical research directions to bridge lab success and field deployment:

- 1) **Extensive testing of hybrid CNN models:** We test CNN-based architectures using metaheuristic algorithms, including WWPA-CNN, GWO-CNN, PSO-CNN, WOA-CNN, and GA-CNN. These models represent the new generation of models, aiming to enhance plant disease classification performance by providing improved parameter tuning and optimization.
- 2) **Quantitative insights into performance:** Experimental evidence demonstrates that **WWPA-CNN consistently outperforms competing models**, achieving an accuracy of 97.89%, sensitivity of 97.53%, and specificity of 98.20%. By comparison, GWO-CNN and PSO-CNN recorded accuracies of 95.33% and 94.30%, respectively, while WOA-CNN (93.45%) and GA-CNN (92.82%) delivered competitive but slightly lower outcomes. These results confirm the superior generalization capacity of WWPA-CNN across multiple metrics.
- 3) **Robustness through predictive metrics:** Beyond accuracy, this study evaluates predictive reliability using sensitivity (True Positive Rate), specificity (True Negative Rate), positive predictive value (PPV), negative predictive value (NPV), and F-score. The consistently high values observed for WWPA-CNN across these metrics underscore its robustness in minimizing both false positives and false negatives.

In summary, this work contributes to the broader body of research by bridging theoretical advances in DL-based plant disease detection with practical considerations for agricultural deployment. By critically examining recent contributions and providing comparative evidence, this review offers both re-researchers and practitioners a clear perspective on the current state of the field and the pathways toward scalable, field-ready solutions.

II. LITERATURE REVIEW

FAO estimates global food supply must increase 70% by 2050 to meet population needs, yet plant diseases cause ~2/3 of food losses, driving automated detection strategies. **Datasets:** PlantVillage (lab, poor field performance), PlantDoc (field, annotation errors), FieldPlant (5,170 images/8,629 leaves, 27 expert-verified classes—outperforms PlantDoc). ML/DL advances include YOLOv5 (object detection), ResNet50/MobileNetv2 (classification efficiency) []. EfficientNet transfer learning on PlantVillage achieved 99.91-99.97% accuracy [6]; thermal CNN+XAI hit 98.55% on 4,720 images, 90.04% on paddy [7]. Xception+Adam led validation (99.81% accuracy, 0.9978 F1) [8]; crop-specific CNNs scored 98.3% (potato), 98.5% (pepper), 95% (tomato) [9]. Hybrid CNN-ViT balances ViT's accuracy gains with real-time inference speed [10].

Rice, a staple crop in India, suffers from significant yield losses due to fungal and bacterial infections. A CNN-based detection method was developed to classify three major rice diseases—leaf smut, brown spot, and bacterial leaf blight. Using Otsu's thresholding for background removal, the model trained on 8,000 leaf images achieved 99.7% accuracy, out-performing prior rice disease recognition methods [11].

III. MATERIALS AND METHODS

The dataset, downloaded from Kaggle (augmented recreation of GitHub original), contains ~87,000 RGB images of healthy/diseased crop leaves across 38 classes. Split 80:20 (training: validation), it retains original directory structure plus a separate test set of 33 unseen images for generalization testing. Figure 1 shows balanced class distribution (~1,800-2,000 images each) across categories like Apple healthy, Apple Cedar apple rust, Apple Black rot, and Apple scab—essential for unbiased deep learning training.

To train the model, a preprocessing sequence was employed on all images to make sure they were consistent and suitable as inputs to deep learning models:

- 1) **Image loading:** All images were read from the dataset directories and loaded into memory in their raw format.

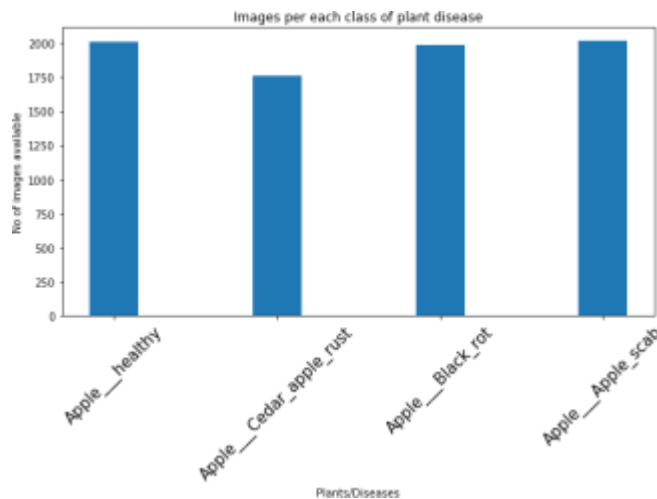


Fig. 1. Distribution of images across different classes of apple diseases in the dataset.

- 2) **Resizing:** All images were resized to a common resolution that the CNN input layers could accept, ensuring a uniform image size regardless of the original image.
- 3) **RGB conversion:** To maintain the color information, which is crucial in the disease identification process, the images were converted into a three-channel RGB format.
- 4) **Normalization:** Normalization of pixel values was performed to the range [0, 1] to improve model stability during training and accelerate convergence.
- 5) **Tensor conversion:** Finally, the preprocessed images were converted into tensors to serve as inputs for the deep learning models during training and evaluation.

These preprocessing steps ensured that the dataset-maintained consistency in size, scale, and format, thereby improving the efficiency and performance of the deep learning models trained in subsequent stages.

Convolutional Neural Network (CNN) CNNs automatically extract spatial/hierarchical features from raw plant disease images. This study's baseline architecture used convolutional/pooling layers for feature extraction, ReLU activations, batch normalization for training stability, dropout regularization in fully connected layers, and softmax for 38-class probability outputs. While baseline CNNs yielded satisfactory results, metaheuristic optimization (learning rates, dropout, filter sizes) maximized accuracy, sensitivity, and specificity under adverse conditions. WWPA produced the largest gains; WWPA-CNN outperformed unoptimized models across all metrics, validating metaheuristic-enhanced CNNs for real-world plant disease detection.

IV. HYPERPARAMETER OPTIMIZATION RESULTS

Five CNNs optimized with WWPA, GWO, PSO, WOA, and GA were evaluated across Accuracy, Sensitivity (TPR), Specificity (TNR), PPV, NPV, and F-score. WWPA-CNN led with 97.89% accuracy, 97.53% sensitivity, 98.20% specificity, 98.04% PPV, 97.75% NPV, and 97.79% F-score. GWO-CNN followed (95.33% accuracy), PSO-CNN emphasized specificity/PPV (94.30% accuracy, 93.40% sensitivity), while WOA-CNN (93.45%) and GA-CNN (92.82%, lowest specificity) trailed. Metaheuristics universally improved performance: Figure 2's histograms+KDE visualize metric distributions, central tendencies, and consistency across models.

TABLE I
PERFORMANCE COMPARISON OF CNN MODELS OPTIMIZED WITH DIFFERENT METAHEURISTIC ALGORITHMS.

Model	Accuracy	TPR	TNR	PPV	NPV	F-score
WWPA-CNN	0.9789	0.9753	0.9820	0.9804	0.9775	0.9779
GWO-CNN	0.9533	0.9458	0.9599	0.9554	0.9514	0.9506
PSO-CNN	0.9430	0.9340	0.9529	0.9554	0.9301	0.9446
WOA-CNN	0.9345	0.9340	0.9350	0.9387	0.9301	0.9363
GA-CNN	0.9282	0.9340	0.9206	0.9387	0.9145	0.9363

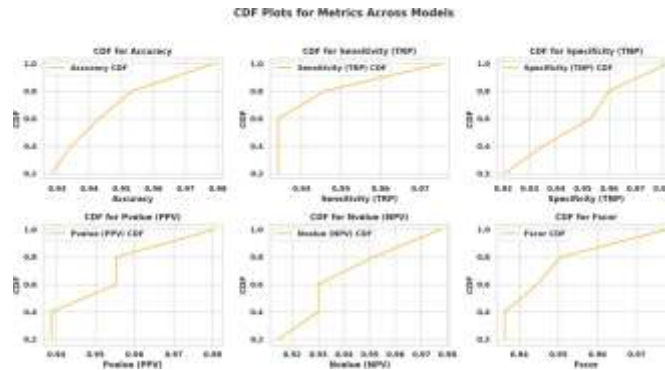


Fig. 2. Histogram and KDE plots for the evaluation metrics across optimized CNN models.

Cumulative Distribution Function (CDF) plots in Figure 3 examine optimized CNN performance distributions across Accuracy, Sensitivity (TPR), Specificity (TNR), PPV, NPV, and F-score. Unlike histograms/KDE, CDFs show the percentage of models achieving specific performance levels, enabling clear detection of significant inter-model differences and relative comparisons.

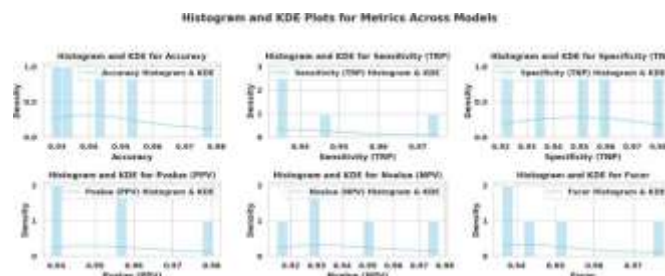


Fig. 3. CDF plots for evaluation metrics across optimized CNN models.

Figure 4's line plots with mean/standard deviation examine model consistency across Accuracy, Sensitivity (TPR), Specificity (TNR), PPV, NPV, and F-score for metaheuristic-optimized CNNs. Solid blue lines show individual model performance; red dashed lines indicate means; green dotted lines mark ± 1 SD from means—enabling direct optimizer comparison relative to overall variability..

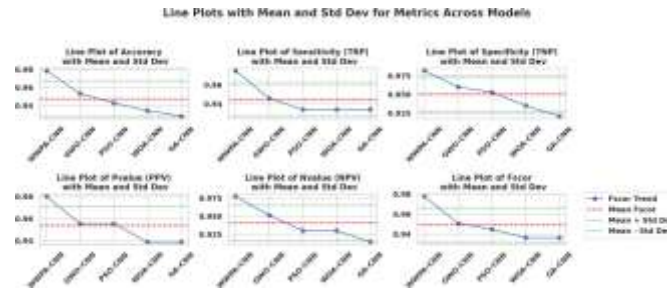


Fig. 4. Line plots with mean and standard deviation for evaluation metrics across optimized CNN models.

V. CONCLUSION AND FUTURE WORK

This study demonstrates CNN-metaheuristic integration (WWPA, GWO, PSO, WOA, GA) for plant disease detection, with WWPA-CNN achieving top performance: 97.89% accuracy, excelling across accuracy, sensitivity, specificity, PPV, NPV, and F-score. KDE/CDF visualizations confirm its robustness. Limitations include controlled dataset bias and computational complexity for resource-constrained farmers. Future work targets diverse field datasets (pathologist-verified), lightweight edge-deployable CNNs, multimodal data (thermal/hyperspectral), explainable AI, hybrid optimization, and adaptive frameworks to enable scalable precision agriculture for food security.

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