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Fast and Accurate Apple Scab Diagnosis via Dipper Throated Optimizer Enhanced CNNs

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Abstract.

Apple scab, caused by the fungal pathogen *Venturia inaequalis*, poses a significant threat to global apple production, leading to considerable yield and economic losses. Early diagnosis is essential for effective management; however, conventional identification methods are often labor-intensive, error-prone, and unreliable. Recent advancements in deep learning and optimization algorithms present promising solutions for automated, accurate, and efficient disease recognition. In this study, a filtered dataset of 297 apple leaf images—90 healthy and 207 scab-infected—was developed. Data preprocessing included handling missing values, feature scaling, and augmentation to address class imbalance. Various Convolutional Neural Network (CNN) models were trained and optimized using metaheuristic algorithms, including the Dipper Throated Optimizer (DTO), Grey Wolf Optimizer (GWO), Particle Swarm Optimizer (PSO), Whale Optimization Algorithm (WOA), and Genetic Algorithm (GA). Experimental results demonstrated that the proposed DTO-CNN model achieved superior performance, with an accuracy of 98.55%, sensitivity of 98.19%, specificity of 98.86%, and an F-score of 98.45%. The DTO-CNN model also exhibited faster convergence and greater stability compared to other optimizers. These outcomes indicate that optimized CNN architectures can provide scalable, real-time solutions for early apple disease detection, supporting precision agriculture through mobile, drone-based, or automated farming systems.

.Keywords. Apple Scab Detection, Convolutional Neural Networks (CNN), Metaheuristic Optimization, Precision Agriculture, Deep Learning.

1. INTRODUCTION

Venturia inaequalis is a fungal pathogen that causes apple scab, considered one of the most devastating diseases affecting apple orchards worldwide. It significantly reduces fruit production and marketability, as it leaves marks on leaves and fruits, ultimately resulting in financial losses for growers. Early detection of apple scab, though important, is difficult. The symptoms (dark lesions on leaves or fruit) are usually similar to those of several other diseases or abiotic stresses affecting apples, which can easily be confused and therefore require manual identification. Moreover, the presence of multiple diseases simultaneously may obscure the appearance of scab symptoms, exacerbating the diagnosis and delaying effective treatment [1]. CNNs and other optimization-based systems have demonstrated an impressive capacity to automatically detect detailed features directly off unprocessed leaf images with minimal image pre-processing required to achieve this feat of extraction [2]. Deep model optimization methods, including transfer learning and fine-tuning, are also employed to enhance the performance of deep models by reducing their computational requirements and facilitating generalization across datasets. These methods are also being

used in the detection of apple diseases, where they provide robust solutions for large-scale supervision and real-time health control of orchards [3-5].

The combination of CNNs and these optimizers enabled a powerful search for the best hyper parameters and weight changes, thereby enhancing the learning ability and classification accuracy of the models, ultimately improving their classification ability [6]. The contributions of this work can be summarized as follows:

- 1) Development of a comprehensive and well-structured dataset representing multiple apple diseases, ensuring the inclusion of diverse, high-quality annotated images suitable for deep learning tasks.
- 2) Design and implementation of CNN-based architectures combined with advanced optimizers (DTO, GWO, PSO, WOA, GA) to improve convergence stability, parameter tuning, and overall classification robustness.
- 3) Empirical demonstration of the proposed CNN-optimizer frameworks, where the best-performing model (DTO-CNN) achieved an accuracy of 98.55%, outperforming other optimizer-based models. These findings underscore the robustness and effectiveness of optimization-driven CNN approaches for apple disease classification, offering practical potential for real-world orchard applications, including automated early detection systems and decision-support tools for precision agriculture.

II. LITERATURE REVIEW

Apple production faces major challenges due to diseases and the need for reliable classification of varieties, which has led to significant advances in computer vision and deep learning approaches. Several studies have focused on building robust models for disease detection, apple variety recognition, and yield estimation.

Another comparative study explored series networks (AlexNet, VGG-19) and directed acyclic graph networks (ResNet-18, ResNet-50, ResNet-101) for classifying 13 apple classes from over 7,000 images. Results showed dataset configuration had a significant effect, with VGG-19 reaching up to 100% accuracy under optimal conditions. Visualization methods further improved interpretability, offering insights into the models' decision-making processes [6]. For more complex disease classification, a Multi-scale Dense classification network enhanced with Cycle-GAN for data augmentation was developed. By generating synthetic disease samples, the approach improved detection of multiple apple diseases, reaching state-of-the-art performance with accuracies above 94%.

3. MATERIAL AND METHODS

The dataset used in this study consists of 297 apple leaf images divided into two classes: 90 images of healthy leaves and 207 images of scab-infected leaves. This distribution indicates a class imbalance, with a larger proportion of scab samples compared to healthy ones, which was carefully considered during training and evaluation to ensure model robustness. The original class distribution is illustrated in Figure 1, which clearly shows the prevalence of Scab samples compared to Healthy ones.

Fig. 1. Bar plot showing the original dataset distribution across Healthy and Scab classes.

Before training, several pre-processing steps were applied to enhance data quality and model performance. Principal Component Analysis (PCA) was conducted to measure the effects of scaling in two experimental conditions: the presence and absence of scaling.

A. Deep Learning Models



1) Convolutional Neural Network (CNN): The early stage of the CNN's performance showed encouraging results, but additional optimization was needed to increase the accuracy of prediction and the model's ability to generalize.

5. DEEP LEARNING RESULTS

By integrating optimizers such as the Dipper Throated Opti- mizer (DTO), Grey Wolf Optimizer (GWO), Particle Swarm Optimizer (PSO), Whale Optimization Algorithm (WOA), and Genetic Algorithm (GA) with CNN architectures, the models achieved different levels of accuracy, sensitivity, specificity, and overall balance between precision and recall. All the tested models demonstrated the highest overall performance, with an accuracy rate of 98.55%, a sensitivity rate of 98.19%, a specificity rate of 98.86%, and an F-score of 98.45%.

In summary, two key takeaways emerge from these results:

- 1) Predictive accuracy improvements: The integration of CNN with advanced optimizers significantly enhanced classification performance, with DTO-CNN outperforming all competitors across accuracy, sensitivity, speci- ficity, precision, and F-score.
- 2) Computational efficiency: Optimizer-driven CNNs, particularly DTO-CNN, accelerated convergence and reduced computational cost, making them practical for deployment in real-time orchard monitoring and preci- sion agriculture systems.

Model	Accuracy	Sensitivity (TRP)	Specificity (TNP)	PPV	NPV	F-score
DTO-CNN	0.9855	0.9819	0.9886	0.9870	0.9841	0.9845
GWO-CNN	0.9599	0.9524	0.9665	0.9620	0.9580	0.9572
PSO-CNN	0.9496	0.9406	0.9595	0.9620	0.9367	0.9512
WOA-CNN	0.9411	0.9406	0.9416	0.9453	0.9367	0.9429
GA-CNN	0.9348	0.9406	0.9272	0.9453	0.9211	0.9429

As depicted in Figure 2, the DTO-CNN model consistently outperforms other variants across accuracy, sensitivity, specificity, PPV, NPV, and F-score, while also showing lower variability, indicating a more stable and reliable learning process.

Fig. 2. Line plots showing the mean and standard deviation of evaluation metrics (Accuracy, Sensitivity, Specificity, PPV, NPV, and F-score) for CNN models optimized with DTO, GWO, PSO, WOA, and GA. tive predictive value (NPV), and F-score. The results of the Figure 3 demonstrate that DTO-CNN is always at the top of the metrics, with the highest accuracy (98.6%), sensitiv- ity (98.2%), specificity (98.9%), and the balanced F-score (98.5%). To further explore the distributional

Fig. 3. Bar plots comparing the performance metrics (Accuracy, Sensitivity, Specificity, PPV, NPV, and F-score) of CNN models optimized with DTO, GWO, PSO, WOA, and GA.

These plots provide smooth approximations of the probability density functions for accuracy, sensitivity (TRP), specificity (TNP), precision (PPV), negative predictive value (NPV), and F-score. By visualizing the density curves, it becomes possible to identify the concentration of metric values and assess the stability of model performance. As shown in

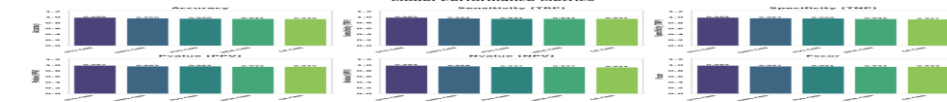


Figure 4, the KDE plots confirm that DTO-CNN consistently achieves higher density peaks near the upper range of the metrics, indicating reliable and robust performance compared to the other models.

6. CONCLUSION AND FUTURE WORK

TABLE I : PERFORMANCE COMPARISON OF CNN MODELS WITH DIFFERENT OPTIMIZERS. BEST VALUES ARE HIGHLIGHTED IN BOLD.

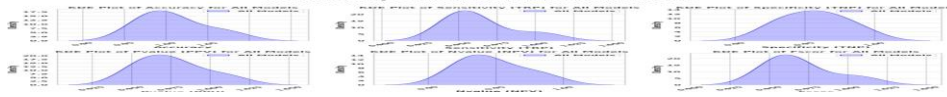


Fig. 4. Kernel Density Estimation (KDE) plots for evaluation metrics (Accuracy, Sensitivity, Specificity, PPV, NPV, and F-score) across all CNN-optimizer models.

REFERENCES

- [1] El-Sayed M El-Kenawy, Abdelhameed Ibrahim, Amel Ali Alhussan, Doaa Sami Khafaga, Ayman EM Ahmed, and Marwa M Eid. Smart city electricity load forecasting using greylag goose optimization-enhanced time series analysis. *Arabian Journal for Science and Engineering*, pages 1–19, 2025.
- [2] El-Sayed M Elkenawy, Amel Ali Alhussan, Doaa Sami Khafaga, Zahraa Tarek, and Ahmed M Elshewey. Greylag goose optimization and multilayer perceptron for enhancing lung cancer classification. *Scientific Reports*, 14(1):23784, 2024.
- [3] R. Kumar, Vevekanandam, and R. Dey, “IoT-enabled bioimpedance and thermal imaging system for non-destructive fruit maturity assessment,” *International Journal of Vegetable Science*, pp. 1–23, 2025, doi: 10.1080/19315260.2025.2574898.
- [4] Amel Ali Alhussan, El-Sayed M. El-kenawy, Doaa Sami Khafaga, Amal H. Alharbi, and Marwa M. Eid. Groundwater resource prediction and management using comment feedback optimization algorithm for deep learning. *IEEE Access*, pages 1–1, 2025.
- [5] Fanqianhui Yu, Tao Lu, and Changhu Xue. Deep learning-based intelligent apple variety classification system and model interpretability analysis. *Foods*, 12(4), 2023.
- [6] R. Kumar, A. B. Queyam, M. K. Singla, M. Louzazni, and D. K. Mishra, “Optimizing efficiency and performance in a Rankine cycle power plant analysis,” *Energy Engineering*, Mar. 2025, doi: 10.32604/ee.2025.058058.