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Deep Learning Approaches for Multiclass Plant Disease Detection: A Comparative Study of Custom and Pretrained Models

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Abstract.

This study evaluates the performance of three models: Here we present a Tiny VGG model trained from scratch for our targeted object classes, and another two pre-trained models: EfficientNet-B0 and Inception V3 in PyTorch. The carefully trained, customized Tiny VGG model from the onset that had even basic preprocessing of the images such as resizing and converting to tensor was evidenced to perform dismally with an accuracy of only 3.78% which was interpreted to mean that the model was too simple to deal with the variation in the dataset. The high performance of EfficientNet-B0 indicates that it avails itself to generalize well across multiple plant types and diseases as further presented by its accuracy of 96.98% of F1 Score of 0.9697, a precision of 0.9699, and a recall of 0.9698. Inception V3 came next with an 80.97% accuracy, an F1 Score of 0.8165, reasonable precision at 0.8656, but slightly lower recall at 0.8097.

Keywords. Plant disease detection; deep learning; multi- class classification; transfer learning; pretrained models; efficientnet

1. INTRODUCTION

Plant diseases pose a significant threat to global agricultural productivity, leading to substantial crop losses and severe economic repercussions. Optimization plays a fundamental role in computational intelligence, as it focuses on identifying the best possible solution within a defined search space by maximizing or minimizing an objective function. Within the context of deep learning, optimization is crucial for efficient model training, parameter tuning, and performance enhancement. Traditional optimization methods, such as gradient descent, while effective for convex and differentiable problems, often struggle with the nonlinear, multimodal, and high-dimensional nature of real-world challenges—such as those encountered in complex agricultural image classification tasks [1] [2].

To address these limitations, metaheuristic algorithms have emerged as powerful, adaptive, and flexible optimization techniques. Inspired by natural and biological processes including evolution, animal foraging behavior, and collective intelligence metaheuristics are designed to explore vast and complex search spaces efficiently. Well-known examples include the Genetic Algorithm (GA), inspired by natural selection; Particle Swarm Optimization (PSO), modeled after the social dynamics of bird flocks; Grey Wolf Optimizer (GWO), based on the leadership hierarchy and cooperative hunting of grey wolves; and the Whale Optimization Algorithm (WOA), which emulates the bubble-net feeding behavior of humpback whales. These algorithms effectively balance exploration and exploitation, reducing the likelihood of premature convergence and increasing the probability of identifying global optima [3].

In deep learning-based plant disease detection, metaheuristic optimization techniques have proven increasingly valuable for tasks such as hyperparameter tuning, feature selection, and neural network weight optimization. Their capacity to navigate complex, nonlinear, and multimodal search landscapes enables the development of more accurate, stable, and generalizable models. Furthermore, hybrid metaheuristic strategies combining the strengths of algorithms such as PSO, GA, and WOA have demonstrated enhanced convergence speed and improved generalization in agricultural image analysis. Consequently, the integration of metaheuristic optimization with deep learning architectures represents a promising frontier in precision agriculture, facilitating the creation of intelligent and adaptive systems for automated plant disease diagnosis [4] [5].

2. LITERATURE REVIEW

Recent developments in plant disease identification and diagnosis have witnessed a new shift towards the use of deep learning approaches, as they provide excellent solutions for plant disease diagnosis. The Convolutional neuron network CNN models have been developed particularly to enhance the classification accuracy from simple images of the leaves of healthy or diseased plants. For example, particular research carried out illustrated that a CNN model having a substantial training data set comprised of 87,848 images experienced an accuracy of 99.53% in recognizing particular plant disease combinations [6].

These models hold lots of potential as decision support for early disease identification in real-world agriculture. While methods such as DNA identification and visual inspection are used frequently, they have a host of drawbacks, including an inability to deliver early results in asymptomatic stages of diseases. The newest technologies for real-time disease surveillance include biosensors and remote sensing methods as efficient instruments in

disease identification. These novel approaches can detect early infections directly in the field and function as an additional diagnostic tool to existing ones – promoting a more sustainable agriculture [7] [8]. Due to the dynamic state of plant pathogens, it becomes cumbersome to detect them early and methods of detection have to be advanced. For example, a lightweight deep CNN model incorporates hand-crafted feature descriptors for the enhancement classification of leaf diseases [9].

3. PROPOSED METHODOLOGY

The proposed methodology for plant disease detection and classification is structured around two primary phases: the transfer learning phase and the localization and classification phase. This framework is aimed at maximizing the opportunity of deep learning methodologies to improve the efficiency of plant disease diagnosis. The first module, known as dataset preparation, entails the careful collection of images that constitute the plant disease image dataset which contains images from different countries to enhance universal usage. With over 125,000 images of plant leaves belonging to 10 different plant species and 37 health and disease groups, this dataset comprises images of plant leaves. Test set: It consists of images for model testing and has hidden images to determine its accuracy. Examples of the dataset are shown in Figure 1 to reveal the range of plant diseases and variability of the image conditions that are major difficulties in the detection of plant diseases.



Fig. 1. Samples of the Dataset

4. RESULTS

The findings of this study confirm the usability of the deep learning models utilized for plant disease identification and classification. These statewide performance metrics are provided for each model, to fully evaluate their capacity and capability: For Tiny VGG, its accuracy is determined to be 3.78%, F1 Score of 0.0075, precision of 0.0048, and recall of 0.0378. Tiny VGG failed and even in this simple structure, it was evident that its concept does not have the adequate capability to extract every detail in the datasets.

TABLE I: Performance Metrics of Classification Models

Model	Accuracy	F1 Score	Precision	Recall
Tiny VGG	0.038	0.008	0.005	0.038
EfficientNet-B0	0.970	0.970	0.970	0.970
Inception V3	0.810	0.817	0.866	0.810

However, on the same platform, the EfficientNet-B0 model presented a better performance, the accuracy was 96.98%, the F1 Score was 0.9697, the precision was 0.9699, and the recall of 0.9698. They said that this model shows that it can generalize well across different plants and different classes of diseases. High accuracy and equilibrium F1 Score demonstrating the stability of the model's performance and the ability to measure the difference in the similarity of healthy and diseased leaves. Lastly, using the Inception V3 we got an accuracy of 80.97%, an F1 Score of 0.8165, a precision of 0.8656, and a recall of 0.8097.. Table I.

The confusion matrices give information on the classification capabilities of the models and reveal how cleanly the models can separate one disease from the others.

5. CONCLUSION

The present work can provide a proof of concept of deep learning models for the identification and diagnosis of plant diseases, making use of a dataset that includes more than 125,000 images involving 10 plant species and 37 diseases. Comparing the Tiny VGG, EfficientNet-B0, and Inception V3 models, we found meaningful disparities concerning performance indicators such as accuracy, F1 Score, precision, and recall. Tiny VGG also had negligible ability to classify plant diseases appropriately with a maximum accuracy of 3.78%; The second-best performer was EfficientNet-B0 with a total accuracy of 96.98% and good precision and recall. This implies that EfficientNet-B0 is quite robust in generalizing across several plant species and categories of diseases, which makes it ideal for use in deployment in agricultural applications.

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