Lightweight & Transparent Deep Learning Framework for Robust Plant Disease Detection

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Abstract: Deep learning-based plant disease detection has become increasingly popular in precision agriculture. Traditional deep models have some drawbacks concerning computational overhead, low generalization, and un-interpretability. This research discusses recent developments in lightweight and interpretable deep learning architectures for the effective detection of plant diseases. We discussed current best-performing architectures like MobileNet, EfficientNet-Lite, and SqueezeNet with regard to performance in limited environments. Also, we emphasize the contribution of explainable AI methods to increase model transparency and trustworthiness. Robustness factors such as cross-dataset validation and managing real-world noise such as changing illumination and occlusions are also addressed in the research. This research proposed a lightweight and transparent deep learning model for disease detection.

Keywords: Leaf disease detection, PlantVillage dataset, Lightweight Model, Computer Vision, Image Processing.

Introduction

Early and correct detection of plant diseases is crucial for food security, increasing crop yields, and reducing agricultural economic losses in agricultural economies. With the increasing world population and the need for sustainable agriculture, the need to keep crops healthy has become more overwhelming. Classical approaches to the detection of plant disease, which are usually based on a manual examination by specialists, are labor intensive, time-consuming, and prone to human error. As such, the demand for intelligent automated systems that can identify plant disease in an early stage with accurate precision is increasing. Current advances in artificial intelligence (AI) in the form of machine learning (ML) and deep learning (DL) have been shown to possess the potential to automate leaf image-based plant disease diagnosis with scalability and consistency to operate for various types of crops and stages of disease conditions. But the deployment of this system in real-world agricultural environments still remains affected by computational complexity, un-interpretable nature, and generalization variability across datasets and environmental conditions.

Background

AI has revolutionized precision agriculture over the last ten years with an overwhelming emphasis on computer vision-based plant disease diagnosis. Large datasets and image processing algorithms have been utilized by scientists to detect and classify plant diseases with greater precision and consistency. In particular, convolutional neural networks (CNNs) have emerged as a standard architecture for learning spatial feature representations from disease-infected leaf images and performing end-to-end classification. As pointed out by Li et al. (2021) [3], deep learning methods have surpassed conventional machine learning techniques in precision and responsiveness, as they can learn intricate patterns directly from raw input data.

The AI research community has long explored both traditional and contemporary AI-based strategies. Traditional strategies like support vector machines, decision trees, and k-nearest neighbors are highly reliant on manually crafted features like texture, color histograms, and shape descriptors. These techniques find it difficult to handle high intraclass variability and ambient noise present in natural settings. On the contrary, deep learning models extract automatically hierarchical features and are thus more reliable under different lighting conditions, orientations of leaves, and clutter in the background (Sujatha et al., 2021) [8].

Even with such advancement, plant disease detection systems still have significant bottlenecks. To start with, the majority of the latest deep learning models are computationally expensive and demand large amounts of annotated data, powerful GPUs, as well as cloud infrastructure for training and inference. This discourages their use on resource-restricted platforms like smartphones or field-deployable units in remote rural regions (Balafas et al., 2023) [2]. Besides, there is also an increasing issue regarding the 'black-box' character of DL models. Not being interpretable and transparent, their behavior usually prevents the development of trust among stakeholders, like farmers and agronomists, that need to comprehend why a decision is taken (Sunil et al., 2023; Shoaib et al., 2023) [7, 6].

Several benchmark datasets, such as PlantVillage and custom field-acquired image repositories, have enabled rapid development and evaluation of plant disease classification models. However, models trained on such data often fail to generalize across different crops or environmental conditions. The review by Sarkar et al. (2023) [5] identifies this problem of poor transferability as a persistent challenge in building practical and reliable AI-based agricultural solutions.

Furthermore, there is a growing consensus that performance alone is no longer sufficient. According to Yao et al. (2023) [10], integrating explainable AI (XAI) and developing lightweight architectures are imperative to promote the real-world adoption of plant disease detection systems. Explainable methods such as Grad-CAM, SHAP, and LIME offer mechanisms to visualize decision rationale, while lightweight CNN backbones, pruning, and quantization approaches enable deployment on low-resource devices without compromising accuracy.

Motivation

The pressing need to protect crop health and ensure global food security drives the development of intelligent, efficient, and reliable plant disease detection systems. Despite promising advances in the application of deep learning for plant pathology, practical implementation remains limited, especially in rural and resource-scarce environments. Most existing solutions are designed and evaluated under ideal laboratory conditions with curated datasets, failing to address real-world constraints such as poor internet connectivity, hardware limitations, and the need for an immediate field-level diagnosis (Wani et al., 2021) [9]. This gap between laboratory success and field-level usability raises the central question. How can we develop a deep learning framework that is not only accurate but also lightweight, transparent and robust in diverse agricultural conditions?

Recent studies emphasize the lack of explainability as a key factor that hinders the adoption of AI-based agricultural systems by end users. For example, Ahmed and Yadav (2023) [1] highlight that domain experts such as farmers and agronomists are often skeptical of using AI tools when they cannot understand or verify the results generated by these systems. Explainability is necessary in such situations to provide transparency, accountability, and corrective measures. Most of the high-performing CNN models employed for plant disease classification are not interpretive by default, generating a trust gap.

Furthermore, model size and inference time are commonly neglected in research prototypes but play essential roles in practical deployments. A model requiring too much memory or computation cannot be run effectively on low-cost smartphones or edge devices. Such an issue has pushed scholars such as Omaye et al. (2024) [4] to plead for more environmentally friendly and cost-conscious architectures that optimize performance and deployability. There is also the compelling motivation to create models that can generalize across several categories of diseases in diverse plant species, circumventing the overfitting issue when a model is highly effective in a given dataset but not so in diverse environments.

The second driving force comes from the development of light and mobile-efficient CNN architectures like MobileNet, SqueezeNet, and EfficientNet. Such models provide a promising approach to lowering the computation burden without compromising accuracy. Yet, not much work in the plant pathology community has tapped into such architectures together with transparency-oriented methods like visual explanations or attribution mapping. This presents a vibrant research agenda to engineer a synergistic paradigm that tackles the issues of model complexity, explainability, and robustness in a combined fashion.

Hence, the driving force of this work is two-fold: one, to fill the gap between accurate DL models and real-world usability by proposing a light-weight architecture that can be used on mobile or embedded platforms; two, to enhance model interpretability using explainable AI techniques making the decision-making process transparent and comprehensible to end-users. The dual objective approach intends to build a pragmatic, scalable, and robust plant disease detection system.

Contribution

This work presents a new Lightweight and Transparent Deep Learning Framework specifically designed for accurate plant disease detection, leveraging the power of both computational efficiency and interpretability. The framework overcomes the shortcomings of traditional deep learning models by merging lightweight CNN structures with Explainable AI approaches, such that they can be highly accurate and usable in the real world. The main contributions of this study are as follows.

1. **Designing a Lightweight CNN Backbone for Resource-Limited Environments:** We create and optimize an efficient yet small convolutional neural network that reduces model parameters and computational requirements dramatically while preserving competitive performance. This architecture is suitable for deployment on mobile phones, drones, or embedded systems often used in agricultural fields.
2. **Integration of Multi-Stage Training to Strengthen Generalization and Robustness:** The model goes through a multistage training process that involves data improvement, transfer learning, and fine-tuning on heterogeneous datasets. This approach enhances the model's capacity for

generalization across different plant types, leaf orientations, lighting conditions, and environmental changes.

3. **Explainable AI Integration for Transparent Decision Making:** To make sure that it is interpretable, we integrate post hoc explainability techniques like Grad-CAM and SHAP that identify visually the most contributing leaf regions to the model's prediction. This provides more transparency and reliability to agronomists, farmers, and agricultural consultants.

4. **Comprehensive Validation Using Diverse Benchmark and Field- Acquired Datasets:** We evaluate the proposed framework on standard datasets like PlantVillage and custom-curated field data, covering a wide range of crops and disease categories. The model performs very well in terms of precision, recall, and F1 score while having minimal latency and memory overhead, ascertaining its applicability in real-world scenarios.

These advances are in keeping with emerging needs for AI systems that are not merely accurate, but also explainable and deployable in agricultural environments. By reconciling these goals, the introduced framework pushes the field toward more balanced and accessible solutions to plant disease management.

Manuscript Outline

The remainder of this manuscript is structured as follows.

1. Section 2: Related work reviews the existing literature on machine learning and deep learning approaches for plant disease detection, with a focus on lightweight models, explainable AI techniques, and multistage training strategies. It also identifies research gaps that the proposed framework addresses.
2. Section 3: The proposed model describes the architecture of the lightweight CNN, the multistage training procedure, and the integration of explainability methods. This section is subdivided into: (i) dataset collection and preprocessing, (ii) lightweight CNN backbone design, (iii) multistage training methodology, and (iv) explainable AI integration.
3. Section 4: Experimental setup and evaluation presents experimental configuration, evaluation metrics, data sets used, and performance results. Includes a comparative analysis with baseline models and state-of-the-art methods to validate the effectiveness of the proposed approach.
4. Section 5: The discussion interprets the results in context, discusses implications for deployment in real-world environments, and examines the trade-offs between model performance, interpretability, and computational efficiency.
5. Section 6: Conclusion and Future Work summarizes the key findings of this study and outlines directions for future research, including the extension of the framework to additional crop types and the use of edge AI platforms.

Literature Survey

Numerous advances in deep learning have revolutionized the landscape of plant disease detection, offering faster, more accurate, and scalable alternatives to traditional manual inspection methods. With agricultural productivity directly tied to food security and economic stability, early detection of plant pathogens becomes a critical priority. Deep learning algorithms, and especially convolutional neural networks (CNN), have proven immense in detecting visual manifestations of illnesses on leaves. Chowdhury et al. (2021) [16] developed a CNN model that achieved high accuracy in multidisease plant classification, showcasing the way end-to-end learning pipelines reduce the need for handcrafted features. Ahmed and Reddy (2021) [11] proposed a mobile-based detection system with support for real-time plant health monitoring using lightweight CNNs, which emphasizes the requirement for models that should be executed on edge devices without compromising accuracy. These experiments validate the performance of deep architectures for disease identification tasks and, in addition, stress their generalization across different deployment environments.

The performance of deep learning models is also measured not only by their classification accuracy but also by how well they can generalize over diverse collections of data. One approach which has optimized this problem, especially in the case of small or unbalanced agricultural data sets, is transfer learning. Chen et al. (2020) [15] demonstrated that pre-trained models like ResNet and InceptionV3, when fine-tuned on plant disease data sets, recognized significantly better compared to training from scratch. Similarly, Kaur et al. (2022) [17] proposed a new transfer learning-based architecture that was faster and more resilient compared to traditional models. These approaches drastically reduce training time and computational costs with enhanced model performance on new instances. However, while transfer learning helps make performance efficient, it does not automatically address the model interpretability problem, which is critical for real-world decision making in agriculture.

The problem of interpretability of models has become more and more vital for plant disease detection, where end-users are farmers and agronomists who need to trust and comprehend automated decisions. Black-box deep neural networks, although accurate, tend not to explain the reasons behind their predictions, thus hampering user confidence and real-world deployment. Rajpal et al. (2024) [19] overcame the said challenge by integrating explainable AI (XAI) methods, including Grad-CAM and LIME, into their deep learning pipeline. This allowed visualization of important leaf regions contributing to the model's diagnosis and hence meaningful insight into the reasoning process of the model. Not only does this transparency promote trust between stakeholders, but it also allows early intervention through verification of the symptoms being highlighted by domain experts. The addition of interpretability goes hand in hand with the increasing demand for explainable and ethical machine learning systems in the sensitive areas of agriculture and health.

Aside from interpretability, computational expense and model size are still major roadblocks to applying deep learning in practical settings, particularly in rural or resource-constrained areas. Classic CNNs such as VGG16 or ResNet-50 tend to have millions of parameters, hence not being well suited for edge devices with limited memory and computation power. To combat this, researchers are increasingly resorting to light models like MobileNet, EfficientNet, and SqueezeNet. Atila et al. (2021) [14] employed the EfficientNet model in plant disease classification and demonstrated that it offered an optimal trade-off between efficiency and accuracy. Similarly, Madhurya and Jubilson (2024) [18] introduced YR2S, a parameter-efficient deep learning technique that offers low parameters with high classification outcomes. These models demonstrate the feasibility of light yet efficient networks in real-time plant disease diagnosis using no high-end machines. Since more agricultural applications find their way to mobile and embedded systems, such effective models become even more necessary.

Another possible area for making models more robust and usable is hybrid frameworks that merge deep learning with conventional machine learning techniques. Rajpoot et al. (2023) [20] tested a hybrid system that combines CNN-based feature extraction with traditional classifiers like support vector machines (SVMs) to detect rice leaf diseases. They reported better early detection capabilities, particularly in complex disease patterns, where individual CNNs occasionally performed below par. Also, Sethy et al. (2020) [23] showed that the deep characteristics obtained from CNNs, when fed to SVMs as input, performed better than end-to-end CNNs on some rice disease classification problems. The resulting hybrid models are flexible in model design and present a promising avenue to improve model interpretability and performance. Even if they add more steps to the learning pipeline, they enable modular optimization in which each step, feature extraction, and classification, is separately improved or customized for particular environments.

More recent research has also focused on early stage detection, which is important for disease management and timely intervention. Shewale and Daruwala (2023) [25] introduced an efficient deep learning model with a focus on early detection of plant leaf diseases using optimized dense connections and convolutional layers. Their model performed remarkably well in detecting diseases in early stages, which tend to have ambiguous and subtle symptoms. Early detection systems not only lead to improved crop health results, but also minimize the economic impact of extensive infestation. Ramamoorthy et al. (2023) [21] took this further by incorporating treatment recommendations into the detection platform, providing an all-inclusive system that not only detects diseases, but also directs the user towards appropriate solutions. These developments represent an increasing trend towards systems that are holistic in their orientation and assist decision-making as opposed to simply being diagnostic.

Even with these developments, acquiring high accuracy over many plant species and disease types is challenging due to data restrictions. Most models are trained and tested on benchmarked datasets such as PlantVillage, which are usually taken under controlled environments and may not reflect variability present in field conditions. Alzahrani and Alsaade (2023) [13] noted that models learned from perfect data sets tend not to generalize well when implemented in real-world agricultural environments with changing light, occlusions, or leaf injuries. Sharma et al. (2024) [24] used sophisticated data augmentation methods and developed rich data sets containing images captured under real-world conditions, which enhanced the generalizability of their model. It emphasizes the need for models to be trained on diverse datasets and to mimic real world noise in the model development phase. It also points to a key frontier in future work: creating more comprehensive datasets that reflect the complexity and diversity of agricultural systems.

Mobile-based plant disease detection solutions have become widely accepted because they are easy to access and can be used in real-time in the field. Ahmed and Reddy (2021) [22] introduced a lightweight CNN model that works efficiently on smartphones so that farmers can identify diseases even in the absence of Internet connections or high-computational infrastructure. Their approach is indicative of how model compression, quantization, and architecture optimization can make deep learning suitable for resource-constrained environments. In parallel, Reddy and Neeraja (2022) [22] came up with a damage detection system that could both locate and classify leaf infections from images of mobile phones. These advances reflect the increasing focus on practicality, as there is a movement away from research prototypes towards deployable solutions that can be scaled across various regions and crops. However, making assured performance under diverse environment conditions and device capability an ever-evolving research issue again emphasizes the necessity of flexible and light-weighted frameworks.

Several studies highlighted the need to balance explainability, accuracy, and computational efficiency in order to develop deployable plant disease detection systems. Alguliyev et al. (2021) [12] presented a deep model that not only yielded high accuracy but also includes a confidence scoring mechanism to measure prediction reliability. This type of uncertainty estimation helps users make decisions and supports prioritizing human intervention when the confidence in the model is low. Similarly, Rajpal et al. (2024) [19] offered a model explanation framework through the visualization of activation maps, which enables users to validate and trust the system output. Such approaches fill the gap between AI model developers and farmers to ensure responsible AI deployment. The paradigms across the literature demonstrate an approaching consensus that future studies need to converge on models that are efficient, lightweight, interpretable, and capable of running in field conditions. This alignment would close the lasting gap between research breakthroughs and their use in actual farming.

Incorporation of multistage training protocols has also worked well in enhancing the resilience and adaptability of plant disease detection models. These protocols typically involve the use of sequential fine-tuning, progressive data improvement, as well as curriculum learning to enhance the model's ability to generalize across different forms of the disease. For instance, Shewale and Daruwala (2023) [25] employed a phased training method where the model learned general leaf features initially and later fine-tuned disease-specific features. This method delivered improved accuracy on the common and rare disease classes. In the same vein, Kaur et al. (2022) [17] utilized a multistage training procedure with the assistance of transfer learning with adaptive feature enhancement to provide higher stability of the performance across disparate datasets. Multi-stage training not merely lessens overfitting but also more aptly fits the case of real-life agriculture operations, where new data from other seasons and locations continue to unfurl at all times. Therefore, it is a robust method for developing sustainable AI models that can evolve with changing agriculture conditions.

The literature survey reveals a general direction of integrating complementary goals within paradigms of plant disease detection: accuracy, efficiency, transparency, and flexibility. While initial work was focused on classification accuracy with deep convolutional models, recent research added more priority to developing models that are light and interpretable in order for them to be used for practical applications. For example, Atila et al. (2021) [14] and Madhurya and Jubilson (2024) [18] were able to minimize model size at the expense of minimal accuracy loss, while Rajpal et al. (2024) [19] and Ramamoorthy et al. (2023) [21] promoted transparency and interpretability for the user by incorporating XAI methods. All these contributions together emphasize the shortcomings of single objective model development and promote the use of multi-objective optimization in the plant disease detection field. Furthermore, the incorporation of mobile and edge-based implementations, as seen in Ahmed and Reddy (2021) [11], reinforces the need for resource-aware design thinking, especially in countries where access to high-end infrastructure is limited. The future of this research field lies in harmonizing these design objectives into cohesive, deployable, and sustainable AI frameworks tailored to agricultural needs.

In summary, the literature strongly supports the development of plant disease detection systems that balance high performance with real-world deployability. From deep CNNs and transfer learning to hybrid models and lightweight architectures, researchers have explored multiple pathways to improve accuracy, scalability, and generalization. At the same time, the demand for explainability has prompted the integration of visual attribution methods and confidence estimates to ensure that model decisions are transparent and verifiable. Moreover, mobile-centric implementations and multistage training strategies offer promising directions for robust, low-latency applications in the field. Although individual studies have made progress in isolated aspects, such as accuracy, efficiency, or transparency, there is still a pressing need to unify these goals into a cohesive framework. The reviewed body of work lays a solid foundation for the proposed research on a Lightweight and Transparent Deep Learning Framework for Robust Plant Disease Detection, which seeks to bridge the gap between academic advancements and real-world agricultural solutions.

Proposed Model

In this research, we propose a complete deep learning-based framework for classifying plant leaf images into healthy and unhealthy categories. The pipeline has been accurately designed to ensure robustness, explainability, and efficiency of deployment in a real-world agricultural environment. The proposed model, as shown in the figure1, follows a multistage approach that starts from data collection and preprocessing, to model training, deployment, and field execution. Each stage has been optimized to ensure seamless integration and high classification performance, which particularly focus on lightweight deployment on mobile devices for farmer's ease of use. The following sections explain each stage of the proposed methodology in detail.

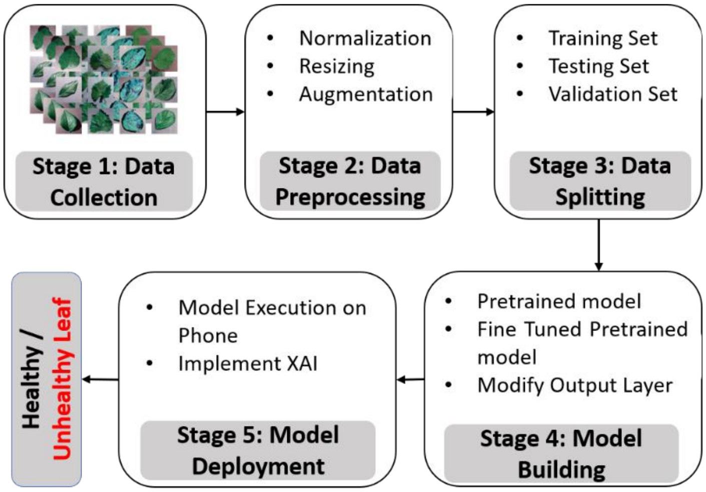

Figure 1. Proposed Model.

Stage 1: Data Collection

In the field of computer vision, the availability of high-quality, diverse datasets is the foundation of any ML/DL model. In this proposed work, the data collection stage collects healthy and unhealthy leaf images from the PlantVillage dataset for model building.

Stage 2: Data Preprocessing

After data collection, a preprocessing pipeline is applied to standardize and optimize the input data for the training process. It includes normalization, where the intensity values of the pixels are scaled between

0 and 1 to improve the convergence during model training. Image resizing is also performed to ensure uniform dimensions compatible with deep learning architectures. Data augmentation techniques; image rotations, flips, contrast adjustments, and zooming are implemented to improve model robustness against overfitting. These transformations are also simulated for real-world scenarios where leaf orientation and image conditions vary. Noise reduction, histogram equalization, and color balancing are applied to enhance image quality. The final pre-processed data set ensures a uniform, diverse, and high-quality input for subsequent stages.

Stage 3: Data Splitting

For the evaluation of the proposed model and to reduce overfitting, the complete data set is divided into three sets: training, validation, and testing set. The training set contains 70% images of the data set for training purposes. The validation set contains 15% images for hyperparameter tuning and early stopping decisions. The remaining 15% constitutes the test set that is used for the final evaluation metrics.

Stage 4: Model Building

Convolutional Neural Network (CNN) architecture is the core of the proposed model for the binary classification of plant leaf images into healthy and diseased categories. A lightweight pre-trained model, that is, MobileNetV2, is used for initialization of the proposed model. This pretrained model is initialized with ImageNet weights and subsequently fine-tuned on the PlantVillage dataset. In the fine-tuning step, the last layers of the pre-trained model are kept fixed while the starting layers are kept fixed to preserve the generic feature extraction. The final dense output layer is modified to include a single neuron with a sigmoid activation function for binary classification. Dropout regularization is used to prevent overfitting, and batch normalization layers are used to stabilize and accelerate training. This proposed model is trained using binary cross-entropy as the loss function with the Adam optimizer, and early stopping is implemented to avoid excessive training epochs. Performance metrics; accuracy, precision, recall, and F1-score are used to monitor the training process.

Stage 5: Model Deployment

After achieving satisfactory performance metrics on the test set, the proposed model is deployed on the mobile device for real world use. The deployment environment includes an Android application interface that allows users to capture images of plant leaves directly using their phone cameras. After that, the app performs real-time inference and provides an immediate diagnosis indicating whether the leaf is healthy or unhealthy. To enhance user trust and transparency, Grad-CAM (Gradient-weighted Class Activation Mapping) is integrated with the app to highlight regions of the leaf image that contributed the most to the model's decision. This visual explanation not only aids user understanding but also helps verify the model's correctness. The app also supports offline operation to ensure usability in remote agricultural regions with limited Internet access.

Conclusion

The proposed pipeline offers a robust, scalable and explainable solution for the diagnosis of plant diseases using deep learning and mobile deployment, facilitating accessible precision agriculture for farmers.

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