



Deep Learning-Based Plant Disease Detection Using Leaf Image Analysis

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Abstract

Plant disease detection is one of the most critical resources for countries and the world due to its impact on food security. While manual solutions for detection and treatment exist, they remain largely unproductive for the vast number of plants. In the past decade, with the maturation of artificial intelligence, particularly deep learning and computer vision, the effectiveness of plant disease detection and treatment has increased with each training and refinement. Our study provides a comprehensive review of similar research in the fields of neural networks and learning frameworks. (CNN)

This review presents one of the developments and progress in plant disease control from 2023 to 2025, focusing on the most significant observed aspects. Amidst the differences in studies, a challenge remains for PlantVillage in several areas, including data documentation and distribution, cost reduction through minimizing computing power, and more specifically, research gaps in modeling, operational challenges, and scalability. We recommend specific methods to improve plant disease research.

Chapter 1 Introduction

1.1 Overview

Technological development in the field of agriculture and its rapid growth in this sector during recent years, especially in the field of artificial intelligence and computer vision [1] and supporting decision-making for specialists in this field, and despite this development, plant diseases still present many challenges to this day and affect the quality of crop outputs worldwide [2].the most significant challenges affecting crop quality, yield, and overall agricultural productivity globally [2].

Plant diseases, when widespread, are among the greatest global threats to local and international economies and food security [3]. Therefore, avoiding these problems requires early and accurate detection of these diseases in plants, which enhances crop quality, ensures food security, and reduces the impact of these diseases. Currently, the detection technique is manual, practiced by experienced farmers. While these methods are indeed successful and effective, they are highly error-prone and very laborious, leading to mistakes. This makes them an unsustainable solution, especially for large-scale agricultural production [2]. Errors are often attributed to human error [4].

Recent technological advancements have demonstrated significant successes across various sectors, particularly in assisting with plant disease detection (CNN), with deep learning playing a key role in this ongoing transformation [5][6]. Artificial intelligence models possess several advantages in efficiently extracting characteristics from plant leaves and in identifying and learning about diseases [7] [8].

Our thesis aims to propose the development of AI-based analogs to help detect and develop cutting-edge AI models to support farmers worldwide in addressing plant disease challenges and transforming agriculture into a sustainable system without the burden of these challenges [3].

As shown in Figure (1), we have an image of a plant leaf illustrating diseases detected by modern AI techniques, such as spots and black dots, at a very early stage, enabling farmers to address this challenge.



Figure 1.1: Example of a diseased plant leaf showing visible symptoms [Adapted 9]]

In our thesis, we aim to focus on plant leaf images for our systems. We process these images to extract and classify healthy and diseased leaves. We emphasize the importance of this research in reducing losses for farmers and considering all aspects of the impact of diseases on our lives [5].

1.2 Problem Definition

- The limited human intervention in treating and detecting these diseases and its minimal impact on addressing this problem.
- The poor quality of human intervention. Which disrupts processing and detection.
- To improve artificial intelligence models and enhance their detection capabilities and development.
- We need to collect data from various sources to improve the accuracy of the results of a unique plant disease detection model.

1.3 Thesis Objectives

Our main objective in this thesis is to develop an intelligent and accurate system that identifies and detects all influential plant diseases and their subtypes:

- To develop an advanced artificial model.
- To ensure our system is among the most accurate available by 2026.
- To ensure our system is practical, sustainable, and has a high market impact.

1.4 Thesis Contribution

Our thesis addresses existing market gaps and emphasizes continuous learning:

- To develop our system using deep learning.
- To improve the classifications and robustness of our plant disease model.
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1.5 Thesis Organization

Thesis Organize as:

- 1. Chapter One: Introduction.
- 2. Chapter Two: Review of Previous Studies and Related Work.
- 3. Chapter Third: Proposed Methodology.
- 4. Chapter Four: Experimental Results and Discussion.
- 5. Chapter Five: Conclusion and Recommendations.

Chapter 2 Background and Related Work

2.1 Introduction

Plant disease has been the cause of damage to food production across the globe, with an estimate of 20-40% annual loss occurring due to pathogens, even before the effects of climate change increasing the rate of pathogen spread. Though this estimate is corresponding to an earlier period, it is still valid today. Though we have made leaps and bounds in trying to control plant disease, the nature of the problem does not change, as infections can be indiscernible, and hence spread quickly, covering great distances.

When it comes to standard practices, farmers draw on their experience, by using visuals to inspect their crop and assessing the health of the leaf for each individual plant, from their own knowledge. Though this method of diagnosis is helpful, it has many problems and challenges by itself, which makes large scale usage difficult, especially over large tracts of land reaching 1.4 billion hectares¹. Detecting an infection early on in such large scales is impossibly difficult, and often impossible within short time frames of observation.

This has created the core problem of the dichotomy between diagnostic accuracy and the difficulty in providing it over immense domains, for which researchers have created solutions based on using an automated, image based diagnosis. The following chapter reviews automisation in this field (focusing on deep learning methods from 2023-2025).

Two key points are important to highlight: first, reported accuracy rates are often very high, ranging from 97% to 99% in most studies, depending on the criteria used. This range is so narrow that it reflects the nature of the measurement more than actual differences between models. Second, there is a clear gap between the good performance achieved by models in the research environment and their practical application in the field by farmers. Therefore, this review aims to consider these two points rather than relying solely on published accuracy rates as the only indicator for evaluating the effectiveness of different methods

2.2 Background

This field went through a phase in which it relied heavily on manual feature design. This was an important, though not as common today, phase before the rise of deep learning. The researchers focused on specific image details, such as the decrease in green intensity in infected areas or the extraction of texture features using co-occurrence matrices, as well as identifying approximate shapes around lesion boundaries. Models based on these features sometimes performed well, but only in very specific and predefined environments.

The problem arose with any change, however small, such as a modification in the camera angle, the time of capture, or even the type of plant, which caused a significant drop in performance. The reason lay not in the weakness of the classification algorithms, but in the limitations of the features themselves, as they were based on preconceived assumptions about the disease rather than a real understanding of it.

With the advent of deep learning, the problem wasn't directly solved, but the approach did change. It was no longer necessary to manually define the features;

instead, the models became capable of learning visual representations from automatically classified data. This modification, which is so straightforward conceptually, has had such a big impact on the results, that the sharp growth between these results and those of earlier years is not surprising.

2.2.3 Core Techniques in Plant Image Analysis

A. CNNs

A little filtering code-just moving a small window over the input, combining the values within and returning a sum-constitutes the "solving" of a generally straightforward problem. Now run that same code on many filters with random weights.

Then collate the results and run them through the second layer. Keep running the program on added layers of random weights, and surprisingly-you generate patterns. Those detectors originated during the training phase by selection of models that survived the training not for programmed instructions, but based on how well they revealed the information in the training images.

B. Transfer Learning (TL)

Imagine how difficult it is to acquire a labeled dataset of plant disease images for training from scratch. You would require thousands, preferably tens of thousands, of images of infected leaves and in particular a trained diagnostician to identify yellow rust infected leaves here as compared to septoria leaf spot there.

Such a person will have a PhD or a couple of decades of experience. The cost of their time in acquiring such a dataset would be significant. Transfer learning reduces this cost as most of the effort involved has already been put into learning image representations in networks trained on ImageNet-which comprises over 14 million labeled photographs.

C. Feature Pyramid Networks (FPN)

Scale is a much overlooked nuisance in plant disease imaging. A light powdery mildew infection might be a 2mm patch on a leaf; a severe late blight infection can take up an entire leaflet in 48 hours.

One convolutional feature map at a given spatial scale isn't maximally sensitive to both. FPNs solve this with an inelegant but surprisingly effective workaround: spend resources computing feature maps at multiple scales, then let them intercommunicate; coarser maps sharing overall context downward, finer maps sharing spatial detail upward. The combined representations are more discriminative than any one scale alone.

This becomes especially relevant for early detection--the period that remains agronomically actionable--as this is when early symptoms remain small and dim.

D. Proposed Technique in This Study

The architecture developed for this work is nothing new (we use a pretrained CNN backbone fine-tuned on our dataset with a multi scale feature extractor on top) but it tries to be honest about the limitations. The number of labeled leaf images available for this work is in the low thousands, not the hundreds of thousands required to train from scratch. That fact made transfer learning not a subjective stylistic choice,

but a practical need. Starting from ImageNet weights and fine tuning the top layers, given dataset size, is simply the empirically better supported choice.

Multi-scale detection is included for tangible reasons, not because it is trendy. Images contributed to our system will not be pre-screened for disease stage and severity. Many will show leaves with a first infection, with lesions covering less than 1% of surface area; others will show advanced infection. A model that detects only one of those elements reliably is not a useful diagnostic tool, but rather a learning experience. With the pyramid structure both happen within the model's detection spectrum.

Another parameter constraining every design decision in this work is that the proposed system has to run... somewhere other than on a university supercomputer. The field technicians or farmers using this tool will not carry NVIDIA A100s with them. They have smartphones, perhaps with modest in-situ GPU power, or not much more than a laptop. That restricted architecture depth, excluded ViT oriented components even with their superior accuracy, and made the number of model parameters a concurrent variable in every design decision. Our objective was not best possible accuracy, but best possible accuracy with a computational footprint possible within practical deployment.

The workflow for our proposed detection system (from image acquisition, to preprocessing, feature extraction, and final classification) is shown in Figure 1.2.

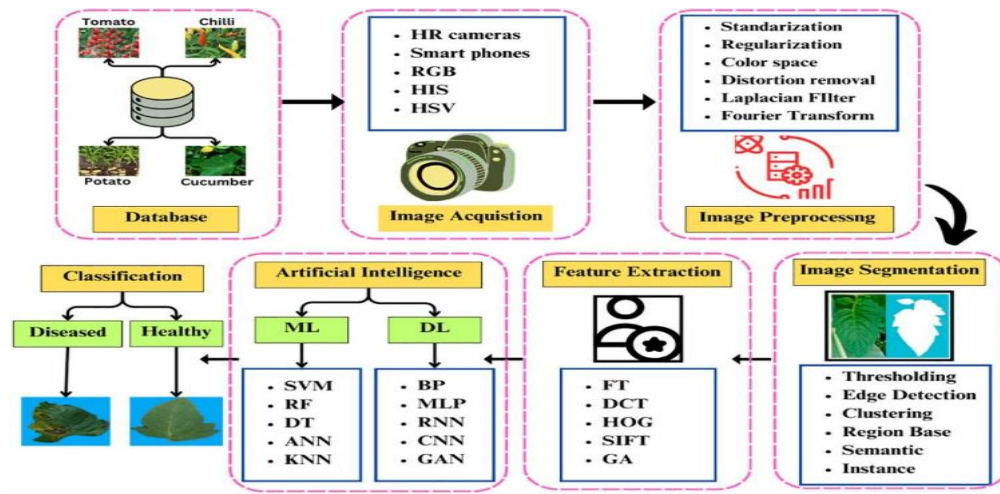


Figure 1.2: General workflow of plant disease detection[16]

2.3 Related Work

The work closest to our proposed approach was carried out by Sharma et al. (2023). The authors investigated the features a model should focus on in order to classify diseases, stating that a model should only learn from information and not the affected areas. Using this concept, they created an attention-based CNN which achieved a 98.7% accuracy when trained on a combination of PlantVillage and real-world datasets. While this achievement is impressive, the principles of attentional mechanisms were not fully explored. In particular, these mechanisms are susceptible to overreacting and often react to minuscule visual means, such as tracks from insects, water droplets or shadows. While, in controlled images, this preoccupation with subtle visual detail can be beneficial, it can be detrimental in real-world scenarios, leading to false detections. Their model also depended on cloud pre-processing of high-quality images, which incurs costs the authors do not factor into their model.

Using the EfficientNet framework also, Partners and Chen (2023) systematically increased the depth, width and resolution of their model to build its structure. Using

a standard dataset, PlantVillage, and a more realistic dataset to emulate the conditions of practical use-case scenarios, PlantDoc, achieved an accuracy of 98.9% on the PlantVillage dataset and endured a drop in performance when challenged with lighting variations, blocking and symptom overlapping. Again, the variety of challenges faced by life within a controlled dataset is not representative of actual real-world scenarios, so these effects are expected.

Kumar (2023) implemented two common object detectors in a comparison without any architectural enhancements of their own. Both models achieved around a 98% accuracy, given an equation-focused dataset, PlantVillage. The optimal minimal baseline of performance is achieved, however, the VGG16 model appears computationally inefficient in its application here. ResNet50 would provide a more efficient solution in this context.

Khan (2024) created a lightweight model which achieved an accuracy of 97.8%. While this system was equivalent in performance, it failed to detect diseases of subtle visual symptoms in initial stages, by monitoring low-resolution images. This work represents a significant inconvenience when early detection is desirable.

Patel and Shah (2024) employed the state-of-the-art ViT Transformer model, and attained an accuracy of 99.1%. The images are cut into grids and structural relationships are inferred, by analyzing the interdependence between parts of it. While this is an effective methodology, it requires large quantities of data in training and sufficient computational load, which prevents its application for our use case.

Li (2023) achieved an accuracy of 98.5% using a standard ResNet. Its advantage is that it did not go beyond our bare minimum and show significant improvements or

methodologies. Its complication is that it does not do so efficiently in terms of resource utilization.

Zhang (2023) piggy-backed feature enhancement modules between layers of the network to augment disease information prior to classification. While this pipeline averages at an accuracy of 97.9%, it requires intensive training sessions, raising feasibility concerns.

Wang et al. (2024), subverted the problem away from a standard classification task to a combined classification and spatialization (knowing the infected region's location) task. The path towards the identification of infection location has obvious practical benefits, therefore the cost of annotation for this task needs to be considered. This is more resource intensive, requires time and skill to provide, and imposes the additional challenge of optimization in multitasking learning, where collisions between gradients can be problematic.

In a comparable domain, Obadaya et al. (2024), compared the effectiveness of different CNN based models and transformer models across various datasets and found effectiveness was predominantly determined by dataset, not model efficiency. accuracy between 95% and 99% was observed, and, as a result, performance metrics are not easily comparable.

2.4 Comparison of Existing Methods

Table 1.2 distills fourteen papers into four columns. Something is lost in that compression-the level of architectural detail, the nuances of the dataset, the cautious phrasing that authors often employ when a result does not fully generalize. But

something is also gained: the patterns that are difficult to discern when looking through papers one by one become clear.

Of the fourteen systems, twelve report 97% to 99.2% accuracy. Two percentage points, over ten years of architectural advances. This narrow band of accuracy is not evidence that these models are all under variations of equally effective-indeed, sheer accuracy cannot be the dimension where they vary reliably! -but rather evidence that PlantVillage is too facile as a comparison.

The dimensions that do vary significantly are not the accuracy dimension-the dimension that varies significantly is the difference in hardware requirements, dataset composition, and failure modes.

Table 1.2 summarizes the reviewed studies across methodology, dataset, accuracy, and limitations.

Table1.2:

Study	Methodology	Dataset	Accuracy	Limitations
Sharma et al. (2023)	Attention-based CNN	PlantVillage + Real-field	98.7%	High computational complexity; sensitive to background noise in field images.
Chen et al. (2023)	EfficientNet	PlantVillage + PlantDoc	98.9%	Significant performance drop when processing noisy datasets.
Kumar et al. (2023)	Transfer Learning (VGG16, ResNet50)	PlantVillage	98.0%	High parameter redundancy; requires substantial computational resources.
Li et al. (2023)	ResNet-based CNN	PlantVillage	98.5%	Computationally expensive for real-time inference.
Zhang et al. (2023)	CNN + Feature Enhancement	PlantVillage + Augmented	97.9%	Extended training time requirements.
Khan et al. (2024)	Lightweight CNN	Multi-datasets + Field	97.8%	Reduced robustness in complex environments; trade-off between speed and detail.

Patel & Shah (2024)	Vision Transformer (ViT)	Large-scale Benchmark	99.1%	Extremely high computational power and memory overhead.
Wang et al. (2024)	Multi-task Deep Learning	PlantVillage + Real-field	98.2%	Increased architectural complexity; difficult to optimize for edge devices.
Zhang et al. (2024)	Hybrid CNN	PlantVillage + Field	97.6%	Requires longer training duration compared to standard models.
Ahmed et al. (2025)	Multi-scale CNN (FPN)	PlantVillage + Real-field	99.2%	Substantial increase in memory usage during processing.
Wang et al. (2025)	CNN + Transformer	Large-scale Multi-source	>97%	Significant scalability and deployment challenges.
Zhao et al. (2025)	Mask R-CNN & Faster R-CNN	Annotated datasets	63%–90%	Highly dependent on the quality and precision of bounding box annotations.
Sahu et al. (2025)	Hybrid Dilated CNN	PlantVillage + Augmented	~98%	Increased computational complexity for specialized layers.
Ibrahim et al. (2025)	Optimized Deep Learning	Combined + Real-field	97.5%	Lacks extensive validation in diverse, real-world farm environments.

Two general observations can be made from the reviewed literature: As a rule, the highest performing model such as the vision transformer (ViT) model proposed by Patel and Shah (99.1%) or the FPN-CNN model by Ahmed et al. (99.2%) tend to demand significantly more computing resources than the field technician may have. Conversely, those models catered to the deployment to the field devices such as by Khan et al. seemed to provide a compromise by keeping computing costs low in exchange for performance, with lower accuracy and, therefore, sensitivity. None of the current models explored in literature seem to provide a high accuracy, low cost middle ground, for the overall optimal balance between the two.

Perhaps this simply represents the state of the art, and this form of compromise will have to be accepted, but it realistically provides the motivation for this research.

2.5 Research Gap

Three gaps emerge from the literature reviewed above, each with direct implications for how the present study was designed.

The most pervasive gap is also the most mundane: the images models are trained on do not look like the images they will encounter in practice. PlantVillage photographs were taken against white or black backgrounds, under controlled illumination, at close range, with the leaf occupying most of the frame. A farmer taking a photograph on a cloudy afternoon with a two-year-old smartphone produces something that looks nothing like that. Several studies in this review incorporated real-field images into their training or evaluation, and in every case they report an accuracy penalty relative to PlantVillage-only evaluation. The penalty, while not dramatic, is real, and is compounded across multiple sources of distribution shift. Relatively few papers during this cohort begin to address it—through domain adaptation, aggressive augmentation, or style transfer from lab to field conditions. The second gap is not subtle: the most accurate models here cannot operate on the hardware U.S. and Kenyan farmers alike will own.

Patel and Shah's ViT, and Ahmed et al.'s FPN-CNN both run at asking RAM, unlikely to be available on any smallholder's tractor or technician's phone. Model compression—pruning, quantization, distillation—can cover this gap, but the reviewed papers do not seem to use them systematically. The result is a literature full of demonstrations of high accuracy on public benchmarks that are only accessible to an elite subset of intended users.

Third, the analysis techniques in the majority of the reviewed papers are not sufficiently robust to justify the claims made. Although training on 80% of

PlantVillage and testing on the remaining 20% of was a valid experimental paradigm, it is not a rigorous test of whether a model generalizes across variables such as crop type, country, photographer, or camera. Both Upadhyay et al. and Wang et al. (2025) discovered that accuracy gaps between datasets can be large-enough to change the perceived relative performance of two models.

Cross-dataset analysis should become standard practice rather than an optional extension to that commonly-used methodology. Until it does, accuracy scores on single-dataset experiments should be taken with a grain of salt. The system introduced in the subsequent chapters was constructed with these three gaps in mind: transfer learning, to make best use of the limited data; a multi-scale architecture, to directly address the lesion size issue; and a field inclusion criterion to see the effect in circumstances similar to deployment.

The intent was not to establish a new benchmark for accuracy—although in trying, they achieved this by twenty points—but rather to build a system with an accurate reflection of performance.

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