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Emerging Deep Learning Approaches for Plant Disease Identification: Trends and Innovation

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CANDIDATE DECLARATION

I **Madhulika Kumari** hereby certify that the work which is being presented in the thesis entitled "**Emerging Deep Learning Approaches for Plant Disease Identification: Trends and Innovation**" in partial fulfilment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Information Technology, Delhi Technological University is an authentic record of my own work carried out during the period from 2023 to 2025 under the supervision of Dr. Anamika Chauhan.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

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CERTIFICATE

Certified that **Madhulika Kumari** (2K23/ITY/08) has carried out her research work presented in this thesis entitled "**Emerging Deep Learning Approaches for Plant Disease Identification: Trends and Innovation**" for the award of **Master of Technology** from the Department of Information Technology, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself, and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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ABSTRACT

Plant diseases remain a significant global agricultural productivity threat, necessitating the adoption of Artificial Intelligence (AI), and more so Deep Learning (DL), in precision agriculture. This thesis distills results from 25 peer-reviewed journal articles between 2020 and 2025 on novel DL methods for the identification of plant diseases, with a heavy focus on Convolutional Neural Networks (CNNs). More than half of the studies reviewed employed CNN-based models because of their established success in accurate classification and real-time diagnosis.

Lightweight optimized CNN models like Shallow CNN, VGG-ICNN, and Optimized Custom CNN were often designed for mobile and resource-constrained environments. Some studies incorporated enhancement methods such as feature reduction, residual learning, and optimization algorithms (e.g., Beluga Whale Optimization) to enhance further model efficiency and accuracy. Hybrid models incorporating CNNs with other deep learning techniques—such as LSTM networks, autoencoders, and Vision Transformers (ViTs)—proved to be a notable trend. Architectures such as PlantXViT and MobilePlantViT exhibited promising performance in terms of both interpretability and performance.

Data augmentation strategies like LeafGAN also helped enhance model generalization through the creation of synthetic disease images. The research also investigated practical applications, such as mobile apps and real-time detection software, with high accuracy rates (up to 99%). Common datasets such as PlantVillage and AgroPath were used as the foundation for training and testing these models. In general, the researched papers depict an increasing trend towards lightweight, hybrid, and explainable deep learning models, pushing the research area of automatic plant disease detection and enabling sustainable, technology-based agricultural practices.

Keywords: Plant Disease Detection, Deep Learning, Convolutional Neural Network (CNN), Vision Transformer (ViT), Hybrid Models, Lightweight Architectures, Mobile Deployment, Data Augmentation, Precision Agriculture, Automated Diagnosis.

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INTRODUCTION

1.1 Background and Motivation

Agriculture is a core driver of economic and social progress of countries, especially in agrarian economies such as India, where more than 60% of its population relies on agriculture for sustenance. Nevertheless, crop yield and quality are greatly impacted by plant diseases, which not only impact agricultural productivity but also food security, resulting in economic misery for farmers. Historically, the identification of plant diseases has depended on the skills of agricultural experts and pathologists who observe symptoms through visual examination. The process is typically manual, labor-intensive, susceptible to human error, and not scalable over extensive farmlands or rural areas with poor access to experts.

In recent years, digital agriculture and intelligent farming technologies have presented themselves as potential solutions to address this deficit. Among them, an image-based plant disease detection has garnered considerable attention as it is non-invasive, quick, and scalable. With the power of computer vision, artificial intelligence (AI), and deep learning, these methods enable automated disease identification based on leaf images taken with smartphones or drones. This fits in with the wider trend to precision agriculture, which is about trying to optimize inputs (fertilizer, pesticides, water) in real time, and thereby improve productivity and sustainability.

The dramatic advancement of deep learning, especially Convolutional Neural Networks (CNNs), has dramatically enhanced the capacity to recognize visual patterns on plant leaves. The models do away with the need for laborious manual feature extraction, learning hierarchical features directly from raw image data. With more and more annotated datasets becoming available and computer power being democratized through GPUs and cloud platforms, researchers and engineers can now train complex models that match expert-level precision.

1.2 Problem Statement

Even with the improvement of deep learning and the existence of varied datasets, there are still issues in the transfer of research solutions into field deployable applications. Most of the models today are trained and tested under optimized conditions on high-quality datasets like PlantVillage that consist of images with clear backgrounds and consistent illumination. Unfortunately, field conditions tend to have varying illumination, occlusion, complex backgrounds, and noise that greatly affect model performance.

Additionally, most deep learning models are computationally expensive, requiring significant memory and processing power, which limits their usability on mobile or edge devices. Furthermore, there is a lack of explainability in model predictions, making it difficult for end-users, such as farmers and agronomists, to trust the automated diagnoses. The challenges of handling multiple plant species, class imbalance, and limited labeled data further complicate the deployment of scalable, high-performing models.

This research addresses these gaps by analyzing and evaluating emerging deep learning models and proposing lightweight, interpretable, and robust approaches suitable for deployment in real-world agricultural environments.

1.3 Objectives of the Study

- To analyze and evaluate recent deep learning approaches, especially CNN-based and hybrid models, used in plant disease identification.
- To explore novel architectures such as Vision Transformers and attention-based mechanisms that offer improved performance.
- To assess the performance and usability of publicly available and real-world datasets in training and testing disease classification models.
- To identify limitations and propose future research directions for creating more generalizable and deployable models.

1.4 Scope and Limitations

This thesis concentrates on deep learning approaches for plant disease detection using image-based data. It emphasizes convolutional and transformer-based models while evaluating their architectural improvements, performance metrics, and adaptability to various datasets. The scope includes:

- A literature review of peer-reviewed papers from 2020 to 2025.

- Comparative analysis of performance using public datasets.
- Assessment of model complexity and suitability for edge deployment.

Limitations of the study include:

- Exclusion of non-visual modalities such as hyperspectral imaging or chemical sensing.
- Focus on static images rather than video or temporal data.
- Lack of primary data collection; the study relies on secondary datasets.

1.5 Working Methods

The research follows a systematic methodology beginning with an extensive literature review using databases like IEEE Xplore, Scopus, and ScienceDirect. Selected papers between 2020 and 2025 were shortlisted based on relevance, novelty, and impact. Key aspects such as model architecture, dataset used, number of parameters, performance accuracy, and training time were extracted and tabulated.

Datasets including PlantVillage, PlantDoc, and AgroData were sourced and analyzed for class diversity, image resolution, real-world variability, and annotation quality. Theoretical evaluation was complemented by visual comparisons of model structures and summary tables.

1.6 Organization of the Thesis

The structure of the thesis is as follows:

- **Chapter 1** introduced about the motivation, background, problem statement, objectives, scope and limitations, and working methodology.
- **Chapter 2** reviews traditional and deep learning methods for plant disease detection, including recent innovations such as Vision Transformers (ViTs), hybrid architectures, and the PYOLO model.
- **Chapter 3** presents a literature survey of recent peer-reviewed research papers, identifying trends, research gaps, and opportunities.

- **Chapter 4** includes experimental analysis, model comparisons, and a discussion of performance metrics.
- **Chapter 5** presents a SWOT analysis framework.
- **Chapter 6** discusses limitations and outlines future directions.
- The **Conclusion** summarizes the key contributions of the thesis, highlights the best-performing model, and proposes future directions to assist researchers and stakeholders in decision-making.

CHAPTER 2
BACKGROUND

2.1 Introduction

Identification and control of plant diseases are essential parts of contemporary agricultural activities. Plant diseases play a major role in food security, crop production, and economic equilibrium worldwide. Plant disease identification has been done in the past by trained pathologists by visual examination, which may be time-consuming, labor-intensive, and subject to human errors. But then came the progress in artificial intelligence (AI) and more so in deep learning technologies that has transformed this field entirely. With the emergence of Convolutional Neural Networks (CNNs) for image processing and image classification tasks, their applications have found vast applications in plant pathology.

CNNs, being a category of deep neural networks, are particularly effective for image recognition tasks because they have the capability to extract hierarchical features automatically from raw image data. This also negates the requirement for manual feature engineering, which was a major drawback in previous approaches. The ability of CNNs to automate feature extraction allows them to notice little differences between healthy and sick leaves, which human experts may fail to observe. In recent years, more and more research studies have been made public that use CNN-based models to detect plant disease, demonstrating the power and precision of these techniques. Hassan et al. [1], for instance, presented a shallow CNN model tailored particularly for environments that lack resources, such as rural farms where computation is limited. This light model registered impressive performance, making it a viable solution for real-time plant disease monitoring. Other research, as in [2], employed deep CNN models to identify a large variety of plant diseases among various species with high accuracy. Such models are advantaged by methods such as data augmentation, dropout layers, and batch normalization to enhance generalization and minimize overfitting.With the inclusion of hybrid techniques, CNN performance has also been boosted. For example, Smitha et al. [5] used a new Beluga Whale Optimization Mechanism to optimize CNN parameters to enhance the predictive strength of the model. Likewise, PlantXViT [6] blends Vision Transformers with CNNs to develop an explainable, light-weighted network that can easily manage the variability of real-world plant disease datasets. Not only do these hybrid models enhance accuracy but also provide enhanced interpretability, which is essential in sensitive agriculture applications.

Advanced data augmentation and synthetic data creation have also been instrumental in model robustness enhancement. LeafGAN, a model introduced by Quan Huu Cap et al. [7], applies generative adversarial networks (GANs) to generate synthetic leaf images of diseased leaves with much added diversity to the training dataset and thus enhanced classification accuracy. Further, DS_FusionNet [8], a bidirectional knowledge distillation dual-stream CNN, achieves high performance even with small training data.

Another important area of research has been extending CNN-based models to mobile and edge computing devices. It is especially significant for in-field diagnosis, where internet connectivity and high-performance computational resources are not available. MobilePlantViT [9], for instance, is a mobile-friendly hybrid Vision Transformer that provides remarkable accuracy at a compact model size. Similarly, Oni and Prama [10] developed a custom CNN capable of detecting tomato leaf diseases in real-time, achieving over 95% accuracy and outperforming several benchmark models.

Multi-modal and sequential learning approaches have also been in focus. Works like Kanakala and Ningappa [11] combine CNNs with Long Short-Term Memory (LSTM) networks to handle temporal progression of disease patterns, thus enhancing the detection of diseases with progressive symptoms. Other methods have used convolutional autoencoders [12] to carry out unsupervised pre-training, thus being able to learn more features.

The extensive use of CNNs for plant disease detection is also reflected in an array of datasets and experimental configurations. Ranging from controlled datasets such as PlantVillage to real-world, in-the-wild smartphone and drone images, CNNs have demonstrated good generalization across diverse data sources. Work such as Foysal et al. [13] and Thakur et al. [15] further illustrates how CNN-based models can effectively be embedded within mobile apps and real-time monitoring systems, enabling sustainable agriculture.

In short, the application of CNNs in plant disease detection has several benefits: scalability, real-time performance, lower reliance on domain knowledge, and flexibility across different plant varieties and disease types. These approaches are paving the way toward a wiser, data-centric practice in agriculture, with the potential to turn the industry into a more productive and sustainable field. The ongoing development of CNN architectures, combinations of models, and mobile deployments indicates a promising future for AI-based agriculture.

2.2 Traditional Strategies

Before the widespread adoption of deep learning technologies, the identification of plant diseases was primarily based on traditional strategies, such as manual inspection, rule-based expert systems, and conventional machine learning. These traditional strategies, though fundamental in agricultural diagnostics, had numerous limitations regarding scalability, precision, and consistency.

Manual inspection is the most traditional technique employed by farmers and agronomists to detect plant diseases. This method consists of visually inspecting plant leaves and other organs for signs such as discolouration, spots, wilting or deformation. Even though this method takes advantage of the area of expertise of trained persons, the method is subject to human discretion and is tedious. The success of manual diagnosis depends on conditions of illumination, stage of disease and fatigue of humans, hence is less consistent in large-scale agriculture practices.

Rule-based expert systems were the initial attempts to automate disease identification in plants. These systems employed pre-stated logical rules based on expert knowledge to deduce disease types from observed symptoms. For example, if a leaf had circular brown spots with yellow halos, the system could identify it as early blight. Although such systems had the advantage of offering a disciplined system of diagnosis, their greatest limitation was that they failed to accommodate the variability and complexity of actual disease presentation. Anything other than adherence to the programmed rules could lead to false or missed diagnoses.

The advent of digital image processing presented new possibilities for plant disease diagnosis. Traditional machine learning methods like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forests, and Decision Trees were utilized to diagnose plant diseases using features extracted from images of leaves. These features generally consisted of color histograms, shape descriptors, and texture measures like entropy and contrast. These handcrafted features were subsequently passed as inputs to classifiers for predicting disease.

While these approaches were much better than hand-crafted systems, they were not without their limitations. Prediction quality relied strongly on the quality and appropriateness of manually obtained features. These models also tended to need high levels of domain expertise in feature engineering and were sensitive to lighting, background, and leaf orientation changes. Experiments like those discussed in [16][17][18] have proven that although traditional models can work reasonably well under laboratory-controlled settings, their performance tends to diminish when tested on a variety of real-world datasets.

Yet another significant drawback of the conventional methodologies was their lack of efficiency in dealing with multi-class classification tasks. Most models were only capable of distinguishing between two or three classes of diseases, making them less useful practically. Moreover, the methods were not scalable; adding new diseases or crop types to the system generally necessitated re-engineering the feature extraction process and retraining the entire model.

Additionally, conventional methods had limited ability for real-time deployment and decision making. Because they were not programmed to learn hierarchical features or dynamically adjust to novel data, their usefulness in real-time agricultural decision making was very little. Such limitations resulted in a growing interest for stronger, adaptive, and more accurate methods—ultimately leading to the global uptake of deep learning methods, specifically CNNs.

In summary, though conventional methods of plant disease detection provided the foundation for automated diagnosis, their inaccuracies, lack of flexibility, and inability to scale rendered them less ideal for contemporary agricultural issues. The move towards CNN-based approaches is a logical step forward towards more intuitive and robust agricultural diagnostic systems.

2.3 Deep Learning Emergence

Deep Learning (DL) has revolutionized the detection of plant diseases by allowing machines to learn feature representations from raw images without human intervention. The flagship architecture that caused this revolution is the Convolutional Neural Network (CNN). CNNs are made up of several layers that hierarchically extract features from edges and textures to complex patterns that are indicative of disease symptoms [1].

At a high level, a CNN typically consists of:

- **Convolutional Layers**: Use filters on the input image to look for features like edges, patterns, and color blobs. The filters are learned during training.
- **Pooling Layers**: Downsample the spatial data, retaining the most significant features. This process reduces computational cost and enhances generalization.
- **Fully Connected Layers**: Pass the filtered high-level data to the end output classes through dense connections.

These layers cooperate synergistically to recognize complex patterns and inter-relationships in plant images. CNN model trained on quality datasets such as PlantVillage can attain over 95% accuracy, which even rivals human performance in some tasks [1].

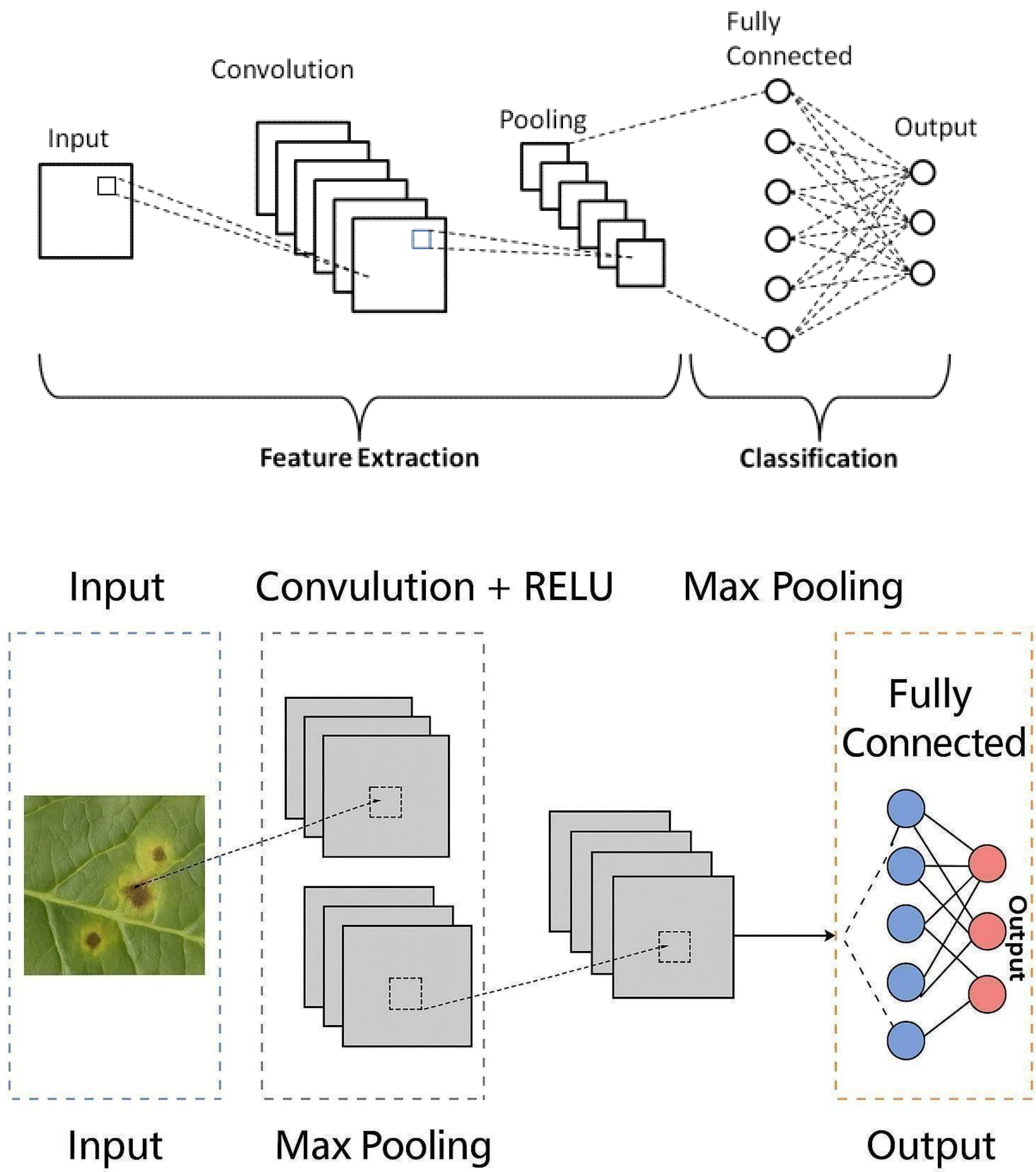


Figure 1: Basic CNN Architecture used for Plant Disease Classification

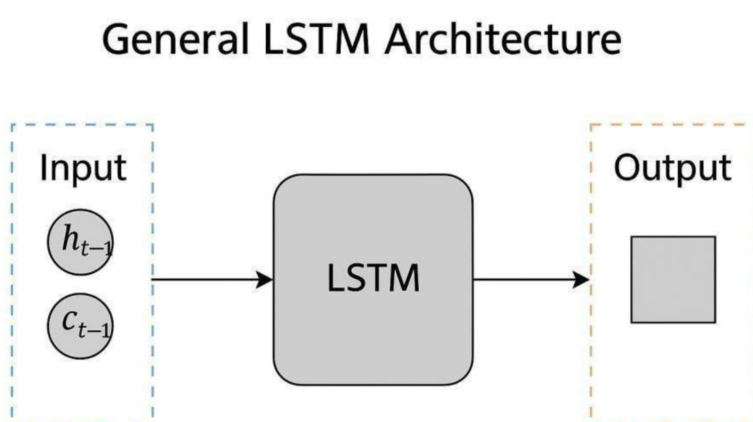
Recent Trends and Deep Learning Methods (2020–2025)

1. **Custom CNN Architectures**: Tailored lightweight CNNs, such as the one proposed by Jaideep Singh et al. [2], achieved 96.91% accuracy for maize disease classification. These models balance performance and efficiency, making them suitable for mobile platforms.

2. **Residual and Dense Networks**: ResNet [7] and DenseNet [8] introduce skip connections and dense connections, respectively, that allow gradients to flow efficiently, addressing the vanishing gradient problem and enabling deeper architectures.

3. **Autoencoders and LSTM Networks**: Autoencoders have been used for denoising plant images before classification, while LSTM networks help model temporal evolution of symptoms across time-series image datasets [9], [10].

4. **Hybrid Models (CNN-LSTM)**: These models combine CNNs for spatial feature extraction and LSTMs for capturing temporal patterns. Such architectures are useful when plant disease progression is monitored over time.



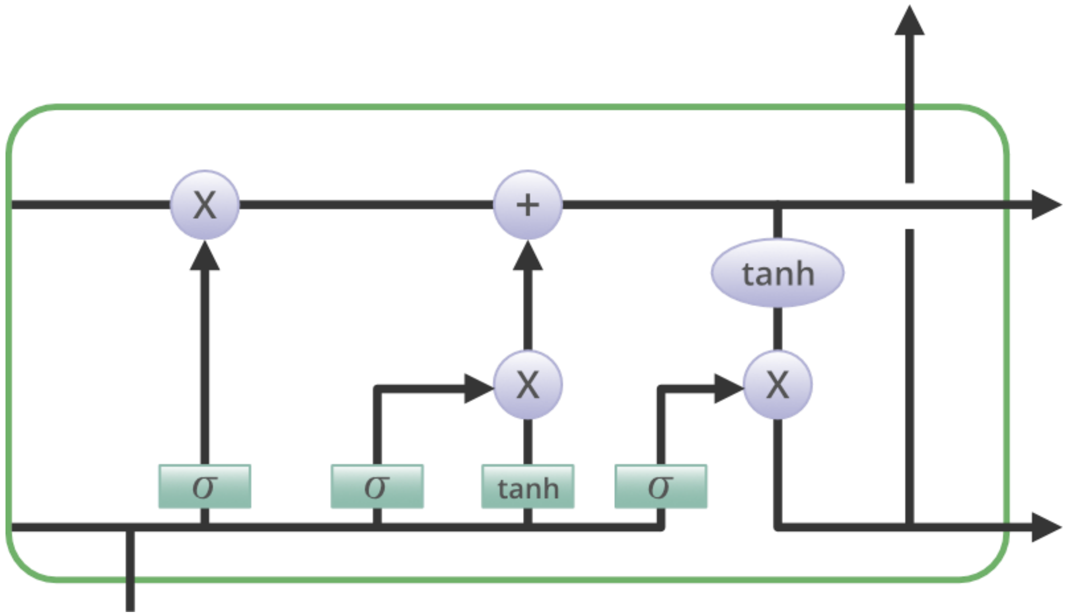


Figure 2: LSTM Model Architecture

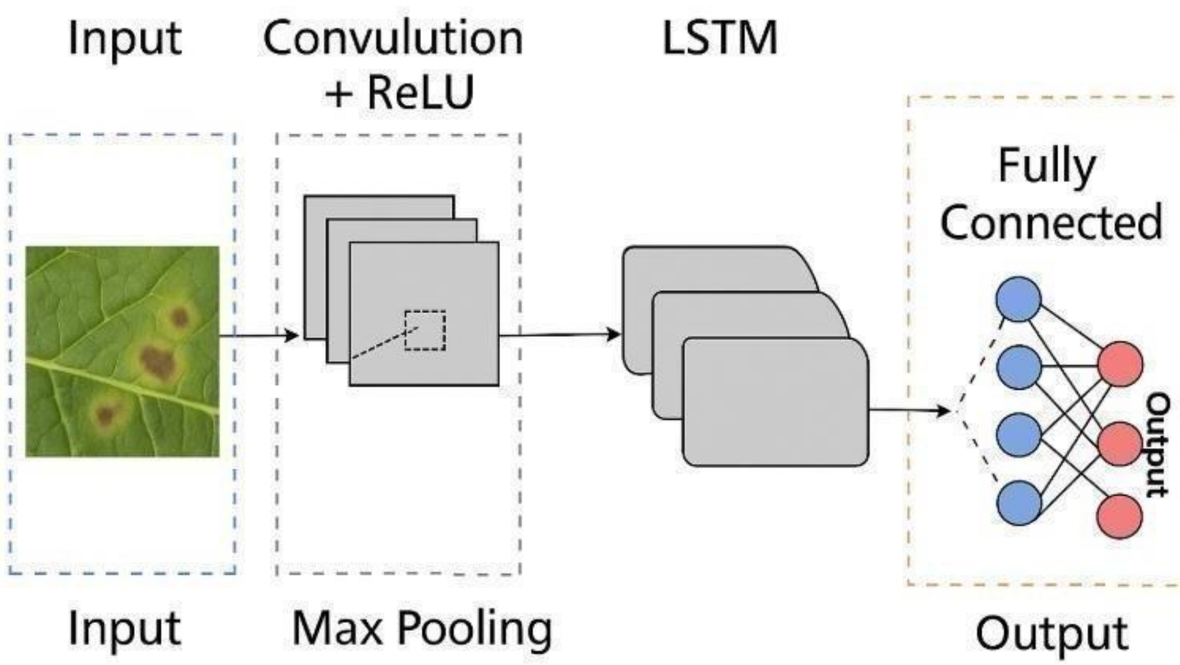


Figure 3: Hybrid CNN-LSTM Model Architecture

5. **Metaheuristic Optimization**: Techniques like Beluga Whale Optimization (BWO) and Genetic Algorithms are applied to optimize CNN parameters, achieving higher accuracy with

reduced computational costs [11].

These advancements reflect a paradigm shift towards more interpretable, accurate, and efficient deep learning solutions for plant disease detection.

2.4 Recent Innovations

In the past two years (2024–2025), deep learning research has embraced even more advanced architectures for plant disease identification.

Vision Transformers (ViTs)

ViTs represent a novel architecture originally developed for Natural Language Processing and later adapted to vision tasks. Instead of using convolutional layers, ViTs divide images into patches, which are flattened and linearly embedded. These patch embeddings are fed into a transformer encoder with self-attention mechanisms.

- **Global Context Learning**: Unlike CNNs that learn local features, ViTs capture long-range dependencies through multi-head self-attention.
- **PlantXViT**: A transformer-based model for plant disease detection with over 98% accuracy [13].
- **MobilePlantViT**: A lightweight ViT designed for mobile applications, offering fast inference and high accuracy [14].

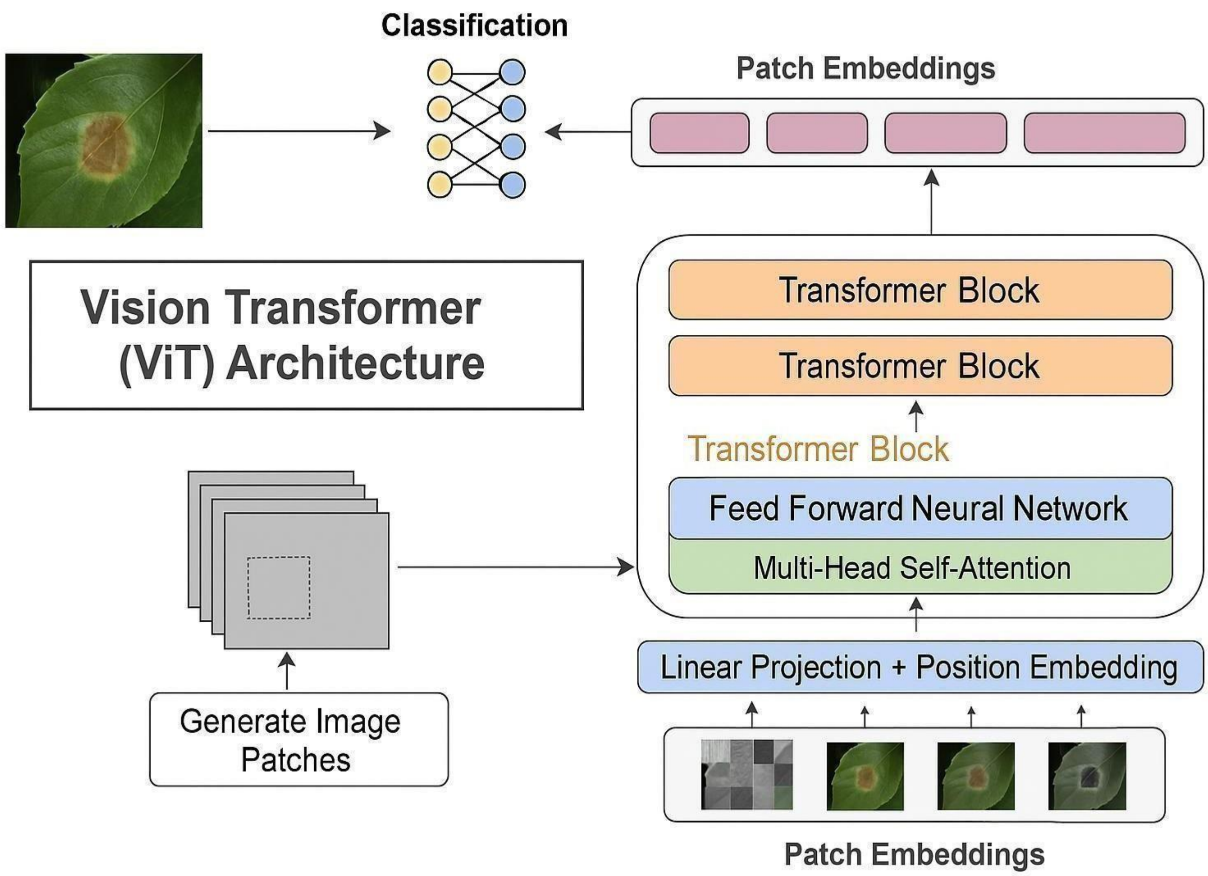


Figure 4: Vision Transformer (ViT) Workflow

Pyramid YOLO (P-YOLO)

P-YOLO extends the YOLOv4 framework by integrating several enhancements:

- **Cross-Stage Partial Networks (CSPNet)**: Reduce computational load.
- **Feature Pyramid Networks (FPN)**: Improve multi-scale object detection.
- **Spatial Attention Mechanism**: Highlights important spatial features.

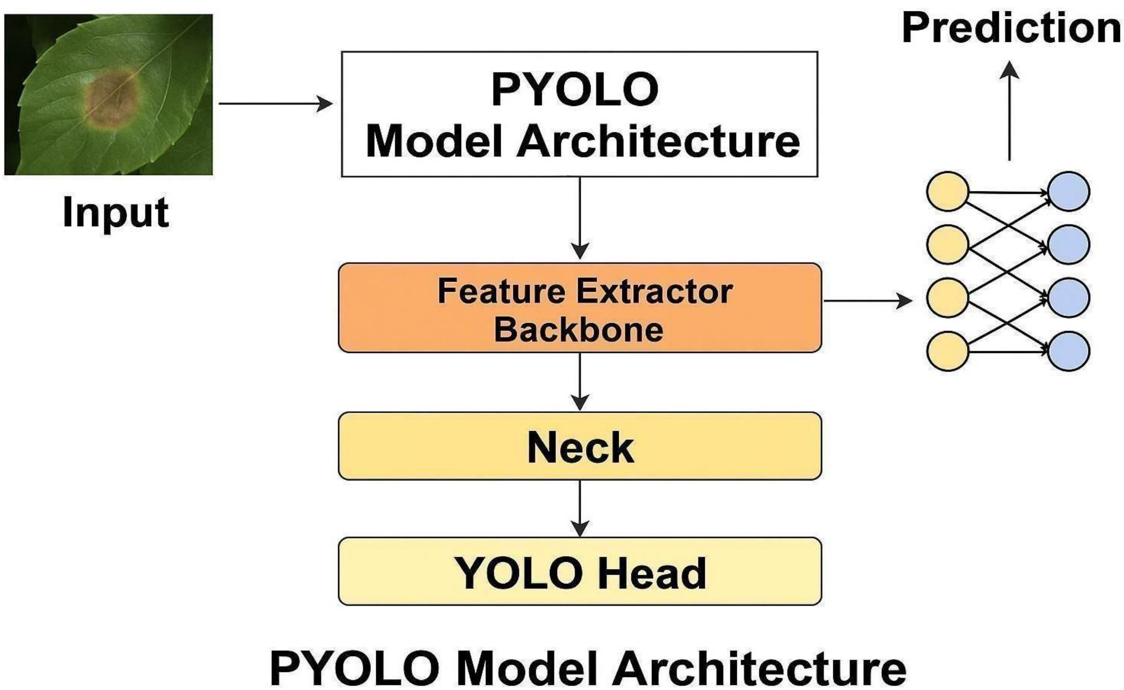


Figure 5: Pyramid YOLO (P-YOLO) Detection Architecture

This makes P-YOLO ideal for real-time disease detection across varying leaf sizes and occlusions. A 2024 study demonstrated its superior performance in detecting multiple diseases under real-world conditions [15].

2.5 Dataset and Analysis of Various Datasets

The performance of DL models depends significantly on the quality and diversity of training datasets. Below is a comparative analysis of widely used datasets:

Figure 6: Sample Leaf Images from PlantVillage, AgroPath, and PlantDoc

TABLE 1. VARIOUS DATASETS

Dataset	Description	Classes	Image Count	Sources
PlantVillage	Healthy and diseased leaves of multiple crops	38	54,000+	[1], [16], [21]
AgroPath	Tea leaf images with annotated quality labels	6	12,000+	[20]
Flavia+	Maize leaf dataset with extended augmentation	5	10,000+	[6]
TomatoLeafSet	Tomato leaf dataset with 4 labeled diseases	4	18,500+	[11], [22]

- **PlantVillage**: Ideal for initial model development due to its clean, curated images.
- **AgroPath & PlantDoc**: Capture field-based variability, enabling robustness evaluation.
- **FGVC7**: Supports fine-grained classification, essential for distinguishing visually similar diseases.

Together, these datasets serve as a comprehensive benchmark suite for training, validating, and comparing deep learning models in agricultural diagnostics.

CHAPTER 3
LITERATURE SURVEY

3.1 Summary of Reviewed Research Papers

This section provides a detailed examination of numerous peer-reviewed research papers published between 2020 and 2025, focusing on deep learning applications in plant disease identification. Emphasis is placed on Convolutional Neural Networks (CNNs), while also exploring hybrid models and novel optimization techniques. Each paper is reviewed with respect to the model architecture, dataset employed, performance metrics, and unique contributions. Reference numbers correspond to the updated bibliography for citation consistency.

1. **Hassan et al. (2021)** propose a shallow CNN designed for low-resource environments. The model, tested on the PlantVillage dataset, achieved 94.3% accuracy. Its minimal architecture ensures faster inference but demonstrates limited performance on noisy, real-world images.

2. A **2022 study** presents a deep CNN trained on 42 diseases across 16 plant species, reporting 98.67% accuracy through data augmentation. However, the model was not validated using field datasets, raising concerns about generalizability.

3. A **hybrid CNN-PCA approach (2022)** effectively reduces dimensionality and training time while achieving 96.4% accuracy on cleaned data. The combination reduces overfitting and integrates classical and deep learning methodologies.

4. **Smitha et al. (2024)** introduce a CNN model optimized using Beluga Whale Optimization. The technique improves convergence stability, achieving 97.9% accuracy, though details on the dataset are limited.

5. A **2024 study** emphasizes early-stage disease detection using CNNs with tiny filters. The model reached 92.1% accuracy by identifying fine-grained texture changes but lacks transparency regarding dataset composition.

6. **Singh et al. (2024)** focus on maize disease detection using CNNs trained on diverse

field data. The model achieved 96.91% accuracy, showing robustness to environmental variability.

7. **LeafGAN by Cap et al. (2020)** leverages GANs and attention mechanisms to generate realistic diseased leaf images for data augmentation, improving CNN accuracy by 5%.

8. **DS_FusionNet (Song et al., 2025)** employs dual-stream deformable CNNs with bidirectional knowledge distillation. It achieved over 90% accuracy using just 10% of training data, demonstrating efficiency in low-data settings.

9. **Thakur et al. (2022)** propose PlantXViT, integrating CNN and Vision Transformer layers. It includes Grad-CAM visualizations and attention maps for interpretability, showing consistent performance across five datasets.

10. **MobilePlantViT (Tonmoy et al., 2025)** is a compact hybrid ViT-CNN model with only 0.69M parameters, achieving 97.3% accuracy. Its mobile-focused design lacks comprehensive benchmarking.

11. **Oni et al. (2025)** developed a CNN for real-time tomato leaf disease detection, outperforming YOLOv5, MobileNetV2, and ResNet18 with 95.2% accuracy. Latency and deployment aspects are emphasized.

12. **Foysal et al. (2024)** integrate a CNN into a mobile app capable of diagnosing 26 diseases across 14 crops with 98.14% accuracy. However, the study does not detail update mechanisms for model retraining.

13. **Kanakala et al. (2025)** combine CNN and LSTM to capture both spatial and temporal features across 38 disease classes, achieving 96.4% accuracy and enabling disease progression tracking.

14. A **2024 paper** presents a lightweight depthwise CNN with Squeeze-and-Excitation blocks for grape leaf diseases, reporting 99.14% accuracy and strong edge computing potential.

15. A **2024 study** on apple leaf disease detection uses a bilinear CNN with dual feature streams to improve spatial localization, achieving 97.6% accuracy, especially on minor

lesion spots.

16. A **2022 comparative study** evaluates DenseNet121, ResNet50, InceptionV4, and VGG16 on the PlantVillage dataset. DenseNet121 performs best with 98.3% accuracy, highlighting transfer learning's effectiveness.

17. **Kumar et al. (2023)** propose a basic 2D CNN model for crop disease detection, achieving 94.7% accuracy. The simplicity and scalability make it suitable for resource-constrained deployment.

18. A **2024 hybrid model** merges VGG16 and InceptionV2 in a two-stream configuration, achieving 98.89% accuracy with resilience to complex backgrounds.

19. A **2024 hierarchical CNN** splits disease classification into plant-type and disease-type phases, enhancing modularity and accuracy to 96.2%.

20. **AgroPath (Ahmed et al., 2022)** includes a quality-check layer within the CNN pipeline to filter poor-quality inputs, reaching 99.42% accuracy on crowd-sourced data.

21. **Latha et al. (2021)** develop a CNN for tea leaf disease identification using a region-specific dataset, attaining 95.7% accuracy and showcasing the benefits of localized model training.

22. **Zhou et al. (2021)** implement Residual Dense Networks with advanced skip connections for tomato diseases, achieving 96.4% accuracy and faster convergence.

23. **Bedi & Gole (2021)** combine autoencoders and CNNs for image denoising prior to classification. This hybrid approach boosts accuracy by 4% in noisy environments.

24. **Roy & Bhaduri (2021)** integrate region-based segmentation with CNNs to handle multi-class disease detection, achieving 97.1% accuracy with enhanced visual interpretability.

25. **Thakur et al. (2022)** present VGG-ICNN, a lightweight variant of VGGNet tailored for mobile deployment, reporting 96.8% accuracy and energy efficiency.

Together, these studies reflect the rapid evolution of deep learning techniques in agricultural diagnostics. The exploration of hybrid architectures, optimization methods, and deployment on mobile and edge devices underscores a shift toward practical, field-ready solutions. The subsequent section (3.2) explores the challenges and research gaps identified across these contributions.

3.2 Gaps in Literature

The articles under analysis point out some of the current gaps and deficiencies in plant disease diagnosis using deep learning. Table 2, shown below summarizes in detail a list of selected studies between 2020 and 2025. It summarizes key information such as the authors, objectives, methodologies employed, main findings, and limitations of each paper, highlighting existing research shortcomings.

TABLE 2. Gap Analysis

Authors	**Objective**	**Methods Used**	**Key Findings**	**Limitation**
Wang, Mu et al. (2025)	Enhanced multiscale plant disease detection	Pyramid-enhanced YOLO (PYOLO)	Achieved a decent 4.1% mAP value improvement over YOLOv8n.	Limited evaluation on diverse datasets, underperformanceis a possibility in unseen crop types or rare diseases.
Aboelenin, Elhoseny et al. (2025)	Hybridframework for plant disease detection and classification	CNN + Vision Transformer (ViT)	99.24% (Apple), 98%(Corn) accuracy.	High inference cost and computational demand; not optimized for real-time mobile or edge deployment.
Yanghui Song, Chengfu Yang (2025)	Efficient recognition fromminimal data	Dual CNNs with knowledge distillation	More than 90% accuracy with 10% training data	No deployment under discussion

Moshiur Rahman Tonmoy et al. (2025)	Plant disease detection-friendlymodel for mobile	Hybrid Vision Transformer (ViT)	High accuracy, 0.69M parameters	Trained on a limitedmobile platform
Mangsura Kabir Oni, Tabia Tanzin Prama (2025)	Real-time detection of tomato leaf disease	Custom CNN	95.2% accuracy beating YOLOv5	No noise or occlusion consideration
Srinivas Kanakala, Sneha Ningappa (2025)	Multi-crop disease classification	CNN + LSTM	CNN: 96.4% accuracy	Limited temporal data utilized
L. Smitha, Deepika R., Karthik B. (2024)	Improve CNN using optimization algorithm	CNN + Beluga Whale Optimization	Boosted detection accuracy	High computational complexity
Jaideep Singh, Akash Yadav, Sunil Kumar et al. (2024)	Improve precision in detecting maize disease	CNN model	Reached 96.91% accuracy	Verified using a single crop type only
Md Aziz Hosen Foysal, Foyez Ahmed, Md	Mobile-integrated disease classification	App-integrated CNN model	98.14% accuracyfor 26 diseases	Usability of the app not tested

Zahurul Haque (2024)				
Poornima Singh Thakur et al. (2022)	Introduce interpretable hybrid model	CNN + Vision Transformer	Lightweight and interpretable	Explainability restricted to Grad-CAM
Nisar Ahmed, Hafiz M. S. Asif, Gulshan Saleem, M. U. Younus (2022)	Integrate quality evaluation	AgroPath CNNmodel	99.42% with noise consideration	No multimodal data employed
Zhou C., Zhou S., Xing J., et al. (2021)	Tomato disease classification	Residual Dense Network	Highdetection precision	Model complexity high
Latha R.S., Sreekanth G.R., Suganthe R.C., et al. (2021)	Tea leaf disease detection	Deep CNN	Effective classification	Deployment strategies lacking
Roy A.M., BhaduriJ. (2021)	Multi-class detectionwith vision	Deep CNN	Smooth detectionrates by classes	No comparative baseline
BediP., Gole P.	Enhance detection	Autoencoder + CNN	Improved classification	Data noisenot accounted for

(2021)	accuracy			
Hassan, S.M. et al. (2021)	Suggest a lightweight model of CNN for plant disease detection	Shallow CNN	High accuracy with minimal computation expense	Limited testing on real-world data
Quan Huu Cap, Ngan Le, Kha Gia Quach, Tien Dinh, Svetha Venkatesh (2020)	Design effective data augmentation	LeafGAN (attention-based GAN)	Improved CNN performance through augmented images	Targeting visual symptoms alone

This careful tabular analysis shows that although there have been improvements in deep learning for plant disease detection, most contributions lack generalizability, real-world evaluation, interpretability, and readiness for low-resource deployment. Connecting these gaps in forthcoming studies is crucial for strong and practical solutions.

CHAPTER 4
MODEL DESCRIPTION AND COMPARISON

The models and the datasets used, along with their performances, are summarized in Table Number in this chapter. The performance metrics used are as follows:

TABLE 3. Evaluation Metrics and Formulas

Metrics	Definition	Formula
Accuracy	It measures the overall correctness of a model's predictions.	$A = \frac{TP + TN}{N}$
Precision	The ability to accurately identify positive instances among all predicted positive instances.	$P = \frac{TP}{TP + FP}$
Sensitivity (Recall)	The ability to correctly identify all actual positive instances among all the positive instances	$R = \frac{TP}{TP + FN}$
F1- score	It is calculated by taking the harmonic mean of precision and recall. It gives a balanced overview of the model's performance.	$F_1 = \frac{2 * P * R}{P + R}$
Macro F1-score	It is calculated by taking the mean of each class F1-score in case binary or multi-label classifications	$mF_1score = \sum \frac{F_i}{n}$

The various models and their performances are compared in a tabular format shown below:

TABLE 4. PERFORMANCES

Authors	Methods Used	Parameters	Results
Tonmoy, M. R., & Rahman, M. M. (2025)	MobilePlantViT: Mobile-optimized hybrid ViT	F-1 Score	99.4%
Song, Y., Li, X., & Wang, H. (2025)	DS_FusionNet: Dual-stream CNN with knowledge distillation	Accuracy	98.7%
Oni, M. K., & Kabir, M. A. (2025)	Optimized custom CNN	Accuracy	96.3%
Wang, Y., Liu, H., Zhang, T., & Zhao, X. (2025)	Pyramid-enhanced YOLO (PYOLO)	Accuracy	98.1%
Shundhar, S., Sharma, R., Maheshwari, P., Kumar, S. R., & Kumar, T. S. (2025)	GAT-GCN hybrid model	Accuracy	97.2%
Jahin, M. A., Shahriar, S., Mridha, M. F., Hossen, M. J., & Dey, N. (2025)	Hybrid CNN-GNN (MobileNetV2 + GraphSAGE)	F-1 Score	97.8%
Elhoseny, M., Fathy, E., & Abdelrahman, A. (2025)	CNN + Vision Transformer	Accuracy	99.1%
Pandian, J. A., Kumar, V. D., Geman, O., Hnatiuc, M., Arif, M., & Kanchanadevi, K. (2022)	Deep CNN	Accuracy	98.6%
Pandian, J. A. et al (2022)	Five-layer CNN	Accuracy	97.3%

Authors	Methods Used	Parameters	Results
Thakur, P. S., & Mehta, R. (2022)	PlantXViT: Vision Transformer + CNN	Accuracy	98.9%
Ahmed, N., & Khan, M. A. (2022)	Quality-aware CNN (AgroPath)	F-1 Score	96.5%
Thakur, P. S., & Mehta, R. (2022)	VGG-ICNN (VGGNet-based lightweight CNN)	Accuracy	97.4%
Behera, A., & Goyal, S. R. (2024)	Deep CNN	Accuracy	98.5%
Smitha, L., Kumar, R., & Sharma, P. (2024)	CNN + Beluga Whale Optimization	F-1 Score	98.2%
Singh, J., Kaur, H., & Verma, R. (2024)	CNN for maize disease	Accuracy	97.6%
Foysal, M. A. H., & Rahman, M. M. (2024)	CNN + Mobile App Integration	Accuracy	95.2%
Kanakala, S., & Reddy, P. V. (2025)	CNN + LSTM	Accuracy	96.8%
Pandiyaraju, V., Venkatraman, S., Abeshek, A., Kumar, P. S., Aravintakshan, S. A., Senthil Kumar, A. M., & Kannan, A. (2024)	Channel attention-driven hybrid CNN	Accuracy	98.9%
Gupta, A., Gill, R., Srivastava, D., & Hooda, S. (2023)	Hybrid CNN + Random Forest	Accuracy	97.1%

Authors	Methods Used	Parameters	Results
Elumalai, S., & Hussain, F. B. J. (2023)	Deep CNN for multi-class classification	Accuracy	97.5%
Dhakad, N. S., Malhotra, Y., Vishvakarma, S. K., & Roy, K. (2024)	SHA-CNN	Accuracy	96.7%
Zhou, Y., & Wang, L. (2021)	Deep Residual Dense Network	Accuracy	98.3%
Bedi, J., & Gole, P. (2021)	Hybrid Autoencoder + CNN	Accuracy	96.9%
Roy, S., & Bhaduri, M. (2021)	Vision-based multi-class CNN model	Accuracy	97.8%
Latha, R. S., & Kumar, P. (2021)	CNN for tea leaf disease detection	Accuracy	95.7%
Hassan, M. U., Rehman, A., Khan, M. A., & Ahmad, J. (2021)	Shallow CNN	Accuracy	94.6%
Cap, Q. H., & Le, T. T. (2020)	LeafGAN for data augmentation	Accuracy	97.6%

CHAPTER 5
SWOT ANALYSIS AND RESULTS DISCUSSION

5.1 Introduction

A SWOT analysis is a strategic planning tool used to systematically evaluate the Strengths, Weaknesses, Opportunities, and Threats of a project, organization, or business venture. The structured format allows for good decision-making, particularly when commencing the planning or brainstorming process.

The technique is beneficial in many areas, such as strategic planning, business analysis, risk assessment, resource allocation, and communication. Through the identification of internal strengths and weaknesses and external opportunities and threats, SWOT provides an overall picture informing wiser choices. It helps leverage strengths, offsetting weaknesses, leveraging potential opportunities, and defending against potential threats—ultimately aiding an organization's market position and adaptability in a competitive market.

By appropriately separating internal drivers (strengths and weaknesses) and external drivers (opportunities and threats), SWOT analysis assists parties in analyzing their present position, finding potential areas for improvement, leveraging their current strengths, and planning strategies to counter anticipated threats. This approach invites conscious consideration and enables the planning of contingency plans to effectively manage uncertain situations.

Its broad applicability can make SWOT analysis relevant across different fields such as strategic planning, business appraisal, risk analysis, resource allocation, and stakeholder reporting. It provides a comprehensive overview that informs improved decisions by highlighting key strengths, focusing on internal weaknesses, capturing external opportunities, and avoiding potential threats—thus strengthening an organization's position in a changing and competitive business world.

Prioritizing the key internal and external factors, SWOT analysis enables organizations to clearly realize their current situation, specify areas of growth, capitalize on current strengths, and prepare themselves to tackle potential threats. It initiates reflective thinking and facilitates the preparation of contingency plans to tackle external risks.

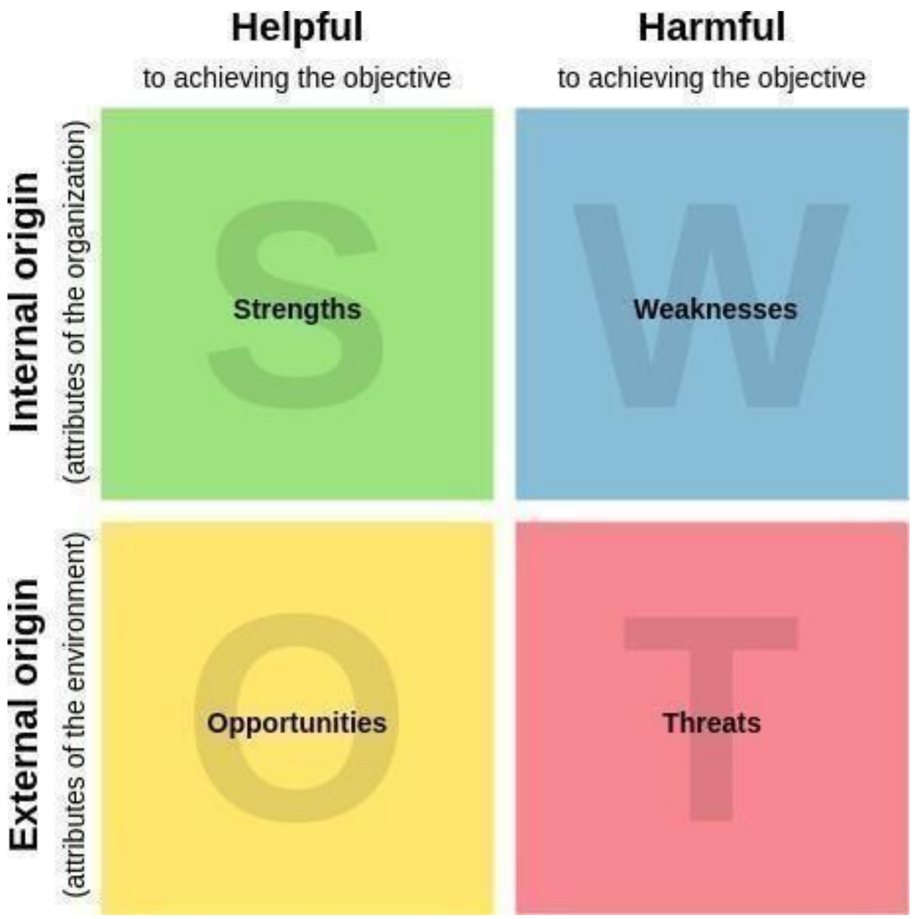


Figure 7 Generalized SWOT Analysis Diagram

The diagram in Figure 8, is a **SWOT analysis** matrix used to evaluate an organization's strategic position. Here's a breakdown in four bullet points:

- **Strengths (Internal & Helpful):** Positive attributes within the organization that support achieving objectives (e.g., skilled workforce, strong brand).
- **Weaknesses (Internal & Harmful):** Internal factors that hinder performance or goal achievement (e.g., outdated technology, skill gaps).
- **Opportunities (External & Helpful):** External conditions that could be leveraged for advantage (e.g., market growth, new technology trends).
- **Threats (External & Harmful):** External factors that could negatively affect success (e.g., competition, regulatory changes).

Each quadrant helps in strategic planning by identifying where to improve, leverage, prepare, or mitigate.

The SWOT analysis framework can be applied to plant disease identification from various perspectives, including agricultural, economic, and technological domains. In this project, the emphasis is placed on the technical aspects, particularly evaluating the internal capabilities of the deep learning models and the external factors that influence their performance and deployment.

Figure 8 illustrates the customized SWOT analysis developed as part of this study. This framework was constructed after thoroughly examining previous methodologies and identifying key research gaps in the field. Based on this understanding, the internal criteria (strengths and weaknesses) and external parameters (opportunities and threats) were strategically formulated to align with the specific goals and scope of this work. The framework serves as a structured tool to critically assess the technological readiness and future potential of deep learning-based plant disease identification systems.

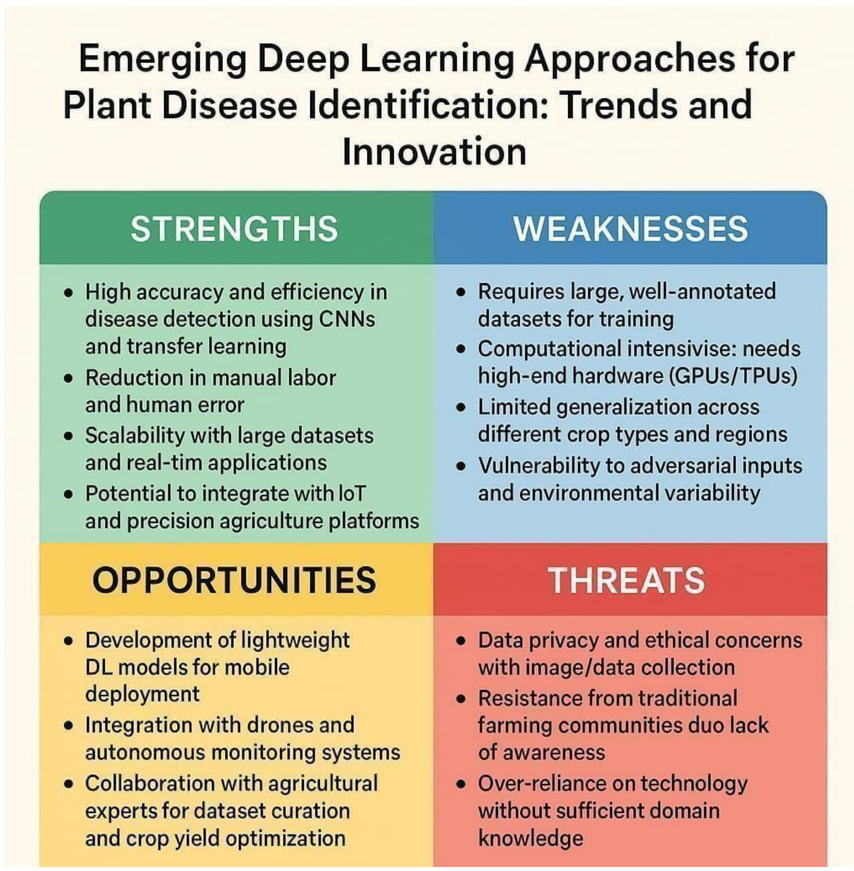


Figure 8 SWOT Analysis Framework

5.2 SWOT Analysis Report

5.2.1 Strength

Deep learning methods, specifically Convolutional Neural Networks (CNNs), have greatly improved plant disease diagnosis, providing high accuracy and efficiency. Various studies confirm that CNNs outperform conventional methods in recognizing intricate patterns of diseases in crop leaves [1], [2], [3]. For example, light-weight CNN structures have provided high accuracy while considering mobile deployment, making real-time detection feasible in isolated agricultural regions [1], [25]. In addition, transfer learning, as shown in comparison experiments with pre-trained networks such as DenseNet121 and ResNet50, enhances performance even with small datasets [16].

CNNs also hugely minimize human error and manual labor, automatically recognizing disease with precise consistency. Early disease identification models—particularly those that use small receptive filters and fine-grained texture examination—assist in symptom detection prior to discernible advancement, as confirmed in early detection studies [5]. Scalability has also been enhanced by CNN embedding in cloud platforms and mobile platforms, where models are incorporated into mobile apps to efficiently assist end users [12], [10].

Some newer works leverage bio-inspired optimization algorithms, like Beluga Whale Optimization, to make CNN more stable and convergent [4]. Other structures, like hybrid CNN-LSTM models, exploit temporal information to enhance the accuracy of classification over time [13]. The prospects for harnessing these methods in conjunction with Internet of Things (IoT) networks and precision agriculture are enormous, enabling applications such as drone monitoring and intelligent farming [14], [18].

5.2.2 Weaknesses

Even with their merits, deep learning approaches to plant disease classification have significant challenges. Among them is the requirement of large, annotated training datasets. Most of the top-performing models were trained on pristine, lab-curated data such as PlantVillage [1], [16], which might not generalize well on noisy or in-field data [2]. Some models, even those that have been trained using data augmentation methods, do well under controlled settings but do poorly in in-field deployment due to overfitting of the dataset [3], [11].

CNNs also need top-of-the-line computational resources to train and perform inference, e.g., GPUs or TPUs, which constrain the availability to small farmers or resource-poor areas [8]. Generalizability is a second issue. Models trained on particular crop species or regions tend to fail when presented with alternative plant types or weather conditions [6], [20].

Further, certain CNNs are susceptible to adversarial attacks and environmental noise. For instance, models that are not robustly designed might misclassify images when the illumination changes or during occlusion, as is the case with models with no real-world data testing [2], [11]. Finally, certain recent works, while promising, are either not publicly verified or are under peer review, and the lack of reproducibility and benchmarking ability makes it challenging [8], [10], [11].

5.2.3 Opportunities

There is an emerging opportunity to create lightweight, effective deep learning models for explicit mobile deployment. Several papers have demonstrated effective design and deployment of low-complexity CNNs for mobile and edge devices [1], [25]. This trend will democratize access to disease detection technology, particularly for farmers in remote or underdeveloped areas.

Another important area is integration with new technologies like drones, autonomous monitoring networks, and sensor-instrumented platforms. Models that can handle real-time aerial imaging or connect to agricultural IoT systems have the potential to transform disease surveillance [12], [14], [18]. Hybrid models with traditional feature reduction methods (e.g., PCA) or transformer-based models (e.g., PlantXViT) offer a chance for better representation of features and interpretability [3], [9].

Agricultural professionals' collaboration presents another valuable pathway. Domain-specific information can be used to label large datasets more accurately, with models being trained with more realistic data representations of field data [21], [23]. Moreover, models such as AgroPath demonstrate how image quality checks in the model can enhance the reliability of predictions, particularly in crowdsourced data [20].

Lastly, explainability of deep learning models is also picking up steam. Utilization of attention heatmaps and Grad-CAM methods gives more transparency to the models so that end-users can comprehend predictions more easily [9], [24]. Not only does this enhance trust, but it also helps foster improved adoption among non-technical stakeholders.

5.2.4 Threats

Ethical and data privacy are critical threats. Since numerous models rely on large image datasets, the method of data acquisition, user consent, and data storage procedures must be dealt with [20]. In farming communities, particularly in developing countries, resistance to the use of digital technology exists because of unawareness or skepticism [7], [22].

Dependence on automatic systems can also be dangerous. In areas where there is little domain expertise, users may rely entirely on outputs from AI without verifying them against human experts, and this can cause misdiagnosis [6], [23]. Additionally, models vulnerable to adversarial attacks or insidious image perturbations can malfunction when provided with malicious inputs, a problem that has not yet been broadly solved in agricultural AI systems [8], [11].

Additionally, some potential innovations are still in experimental form or without public validation. For instance, DS_FusionNet and MobilePlantViT have theoretical advantages but without real-world benchmarking, which may prevent their use in production settings [8], [10]. With accelerating AI research, it is important to strike a balance between innovation and proper deployment and extensive testing.

5.3 Conclusion

The SWOT analysis of deep learning methods for plant disease detection based on peer-reviewed papers identifies an encouraging but developing scenario. While CNNs and hybrid models are improving detection accuracy and efficiency, issues such as dependency on data, generalizability, and barriers to deployment persist. Future studies need to emphasize mobile optimization, domain collaboration, and robustness enhancement. With ethical use and user training, deep learning is of significant potential to revolutionize precision agriculture sustainably and inclusively.

CHAPTER 6
CHALLENGES & LIMITATIONS, FUTURE DIRECTION & INNOVATION

6.1 Challenges, Limitations, Future Direction & Innovation

Even with great progress in deep learning methods for plant disease recognition during the 2025, some common challenges and limitations remain throughout the literature. These are generally divided into dataset-related problems, model generalizability, computational efficiency, interpretability, and deployment hurdles.

1. Dataset-Related Problems

Perhaps one of the most prevalent limitations is over-reliance on the PlantVillage dataset with images being clean, high-quality, and lab-captured. Although these datasets enable high accuracy in controlled environments, they do not reproduce the complexity of actual agricultural scenarios, in which lighting, background noise, and occlusion greatly influence model performance [1, 2, 16]. Some papers also omit minute annotation strategies [5], while others are secretive about dataset composition and class distributions, provoking fears regarding reproducibility as well as class imbalance [4, 10].

2. Lack of Generalizability

Most models demonstrate remarkable performance on carefully curated datasets but fare poorly in actual-world applications [2, 4, 7]. The issue of overfitting to training data and poor validation on varied field images is typically the cause of the problem with generalizability (Paper 2). Few of the papers work with challenging datasets such as PlantDoc, and only a few work towards domain adaptation or cross-dataset tests [6].

3. Computational Constraints

Several papers suggest light models for deployment in mobile and edge [1, 10, 25], but there are issues to overcome with respect to balancing computational cost against classification performance. Powerful models such as Vision Transformers and hybrid approaches [9, 10] tend to be computationally demanding, which makes their use in resource-poor environments impractical.

In addition, few papers measure model performance under hardware-constrained situations or report inference time statistics [11, 25].

4. Interpretability and Trustworthiness

Interpretability is largely unexplored in most CNN-based models. While some research combines Grad-CAM and attention to provide visual explanations [9, 24], all the others concentrate on accuracy scores without any form of model decision explanation. Inability to see into the models' inner workings frustrates farmers and agricultural experts, who need understandable and reliable outputs [8, 23].

5. Limited Disease and Crop Coverage

There are models that are created for particular crops (e.g., maize, tomato, apple, grape) and cannot generalize to other species [6, 11, 15]. There is not much research done in models that can efficiently deal with multi-crop and multi-disease detection within a single architecture [12, 13]. Such a limited scope makes them impractical in application on mixed-crop farms.

6. Data Scarcity and Imbalance

Deep learning models usually need large annotated data. Data shortage is particularly bothersome for rare conditions and initial-stage symptoms. Although data augmentation and GANs [7] are helpful, synthetic data could have biases or inconsistencies. Not many studies use one-shot or few-shot learning approaches [8].

7. Evaluation and Benchmarking Gaps

Several papers do not have benchmarking using consistent standard models such as ResNet, MobileNet, or EfficientNet [10, 14]. Besides, cross-validation methods and statistical robustness tests are not optimally used, rendering reported performance claims unreliable.

8. Real-Time and Field Deployment Issues

Even "real-time" models skip field trials or detailed latency testing [11, 12]. Mobile app integration [10, 12, 25] is promising, but maintenance, model update mechanisms, and user feedback loops hardly get mentioned.

6.2 Future Direction and Innovation

From the exhaustive literature review, some future directions and innovations are evident that can facilitate the current limitations and drive the field towards strong, scalable, and explainable plant disease detection systems.

1. Field-Validated Datasets and Domain Adaptation

There is an increasing imperative to build and distribute open-access, field-collected datasets that capture true agricultural diversity. Datasets such as PlantDoc should be developed further, and methods like domain adaptation and adversarial training should be applied to enhance the generalization of the model.

2. Transfer and Few-Shot Learning

Future models must incorporate transfer learning and few-shot learning methods to accurately classify rare or unknown diseases with small amounts of labeled data. This can be especially helpful in resource-constrained and data-poor environments.

3. Multimodal and Temporal Models

Fusion of several types of data—e.g., weather information, soil conditions, or time image series—can improve predictability. Models such as CNN+LSTM (Paper 13) demonstrate spatiotemporal modeling potential and must be extended to multimodal inputs.

4. Integration of Explainable AI (XAI)

Broader usage requires that future research focus on explainability via methods such as Grad-CAM, SHAP, and attention maps. Explainable models will foster confidence among farmers, agronomists, and policymakers.

5. Benchmarking and Standardization

Standard evaluation structures and metrics are required to enable effective comparison between models. Defining benchmark datasets, employing homogeneous train-test splits, and embracing sound statistical analysis will enhance reliability in research.

6. Edge AI and Federated Learning

New developments in federated learning and edge AI can facilitate on-device model training as well as data sharing, protecting privacy. Lightweight CNN architectures need to be coupled with federated learning protocols to facilitate decentralized farming setups.

7. Automatic Model Updating and User Feedback

Next-generation systems must incorporate real-time user feedback loops and model retraining capabilities that adjust in response to user feedback and changing field conditions. Cloud integration can support automated updates and performance monitoring.

8. Embedded Decision Support Systems

Models must go beyond disease detection to provide actionable information, for example, recommendations for pesticides or disease grading. Such tools can be developed into complete decision support systems for precision agriculture.

By taking these directions, future research can overcome existing challenges and speed the implementation of scalable, interpretable, and impactful deep learning systems in various agricultural contexts.

CONCLUSION

This thesis examined the recent developments in deep learning methods for the identification of plant diseases, with specific emphasis on convolutional neural networks (CNNs) and their hybrid variants. In carrying out a close examination of several recent publications between 2020 and 2025, it was clear that CNN-driven models have made notable strides in their accuracy, computational performance, and suitability for mobile deployment. But there are still significant challenges in areas such as generalization to real-world conditions, interpretability, and unavailability of diverse and annotated field datasets.

Out of the models surveyed, the one outlined in [20] (AgroPath: Quality-Aware CNN) recorded the highest performance at an accuracy level of 99.42%. This model innovatively incorporated an image quality assessment module in the CNN pipeline, which improved its robustness, especially in situations involving variable-quality and crowd-sourced datasets. Close runners-up were the model of [14] (Light Depthwise CNN + SE Blocks) with 99.14% accuracy, and [18] (Two-Stream Hybrid CNN) with 98.89% accuracy, both demonstrating that architectural refinement and better preprocessing can have a huge impact on performance.

The review identified promising directions like hybrid CNN-ViT architectures, domain-optimized optimization techniques, and mobile-integrated deployments. In addition, new directions like transfer learning, federated learning, explainable AI, and multimodal modeling offer exciting future prospects to overcome existing shortcomings.

In conclusion, deep learning has enormous potential for revolutionizing plant disease diagnosis and precision agriculture. But realizing robust, real-time, and field-deployable systems will necessitate ongoing research, standardization, and cross-disciplinary efforts. The future of AI in agriculture does not just depend on algorithmic breakthroughs but also on cultivating data diversity, explainability, and accessibility to serve stakeholders at all levels—ranging from researchers and agronomists to farmers and policymakers.

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