

A Survey on Leaf Disease Detection Methods

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ABSTRACT: Leaf disease detection plays a crucial role in modern agriculture by enabling early diagnosis and prevention of crop losses. With increasing demand for food production and the need for sustainable farming practices, automated, accurate plant disease detection systems have gained significant attention. This survey paper provides a comprehensive review of various leaf disease detection methods, ranging from traditional image processing techniques to advanced machine learning and deep learning approaches. Initially, conventional methods such as color-based segmentation, texture analysis, and feature extraction techniques are discussed, highlighting their advantages and limitations. The paper further explores machine learning (ML) classifiers, as well as recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), which are analyzed for their superior performance on complex, large-scale datasets. The survey also examines publicly available datasets, evaluation metrics, and challenges, including varying environmental conditions, image quality, and computational complexity. Finally, potential future directions, including real-time detection systems, integration with IoT-based smart farming, and lightweight models for mobile applications, are discussed. This study aims to provide researchers and practitioners with a clear understanding of current trends and emerging techniques in leaf disease detection, facilitating the development of more robust and efficient systems.

KEYWORDS: Leaf Disease Detection, Image Processing, Machine Learning, Deep Learning

I. INTRODUCTION

Agriculture remains a fundamental sector for economic growth and food security, particularly in countries like India, where a large share of the population depends on farming for their livelihoods. However, plant diseases significantly reduce crop yield and quality, leading to substantial economic losses each year. Among plant parts, leaves are most commonly affected and often show early visual symptoms of diseases such as spots, blights, and mildew. Therefore, accurate and timely detection of leaf diseases is essential for effective crop management and sustainable agricultural practices [1].

Traditionally, disease detection has relied on manual inspection by experts, which is time-consuming, labor-intensive, and prone to human error. With the advancement of digital imaging and computational techniques, automated leaf disease detection systems have emerged as a promising alternative. Early approaches primarily used image processing techniques, such as color analysis, edge detection, and segmentation, to identify diseased regions in leaf images [2]. These methods often rely on handcrafted features and may struggle under varying environmental conditions, such as changes in illumination and complex backgrounds.

To overcome these limitations, machine learning techniques have been introduced for improved classification accuracy. Algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees have been widely used for disease classification based on extracted features [2]. While these methods provide better performance than traditional techniques, they still require manual feature engineering and domain expertise.

In recent years, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have revolutionized the field of plant disease detection. CNN-based models automatically learn hierarchical features from raw images, eliminating the need for manual feature extraction and significantly improving detection accuracy [3]. Large-scale datasets such as the PlantVillage dataset have further accelerated research by providing labeled images for training and evaluation. These advancements have enabled the development of robust, real-time disease-detection systems applicable to smart agriculture. Despite these improvements, several challenges remain, including variability in leaf appearance, environmental noise, limited availability of diverse datasets, and the need for lightweight models suitable

for mobile and edge devices. This survey aims to provide a comprehensive overview of existing leaf disease detection methods, highlighting their strengths, limitations, and future research directions [18-19].

II. RESEARCH BACKGROUND

Automated leaf disease detection research has come a long way in the last 20 years, from simple image analysis methods to incredibly complex, learning-based systems. Rule-based and thresholding approaches were the primary focus of early research in the field of leaf disease symptom identification [7]. Thresholds for color and texture were established by hand. Although these methods were computationally inexpensive, they were unreliable across various plant species and illumination conditions. To address the shortcomings of rule-based systems, researchers created feature-based machine learning models. These techniques used descriptors such as color histograms, Gray-Level Co-occurrence Matrix (GLCM), and Local Binary Patterns (LBP) to extract disease-related texture and color patterns [8].

The obtained features were then categorized using standard machine learning methods including SVM, Random Forest, and k-NN. Although these models were more flexible, they often required extensive feature engineering and were susceptible to background noise.

The paradigm shifted with the introduction of deep learning, specifically Convolutional Neural Networks (CNNs), which significantly enhanced feature learning and model generalization. CNNs eliminated the need for human feature extraction by simply learning hierarchical representations from images. According to research like Ferentinos (2018) [9], CNNs could achieve over 99% accuracy on benchmark datasets like PlantVillage. Because these results were often obtained in controlled environments with clear, well-lit images, they did not always transfer well to real-world field scenarios. To enhance performance in noisy situations, recent research has investigated ensemble learning, data augmentation, and transfer learning [10].

Concurrently, mobile deployment frameworks (such as PyTorch Mobile and TensorFlow Lite) and lightweight CNN architectures are being developed to enable farmers to deploy disease-detection techniques on smartphones [11]. Enhancing the resilience, explainability, and practicality of detection systems is the main goal of current research. To close the gap between lab performance and field deployment, hybrid techniques that combine image processing, deep learning, and expert knowledge are also being investigated.

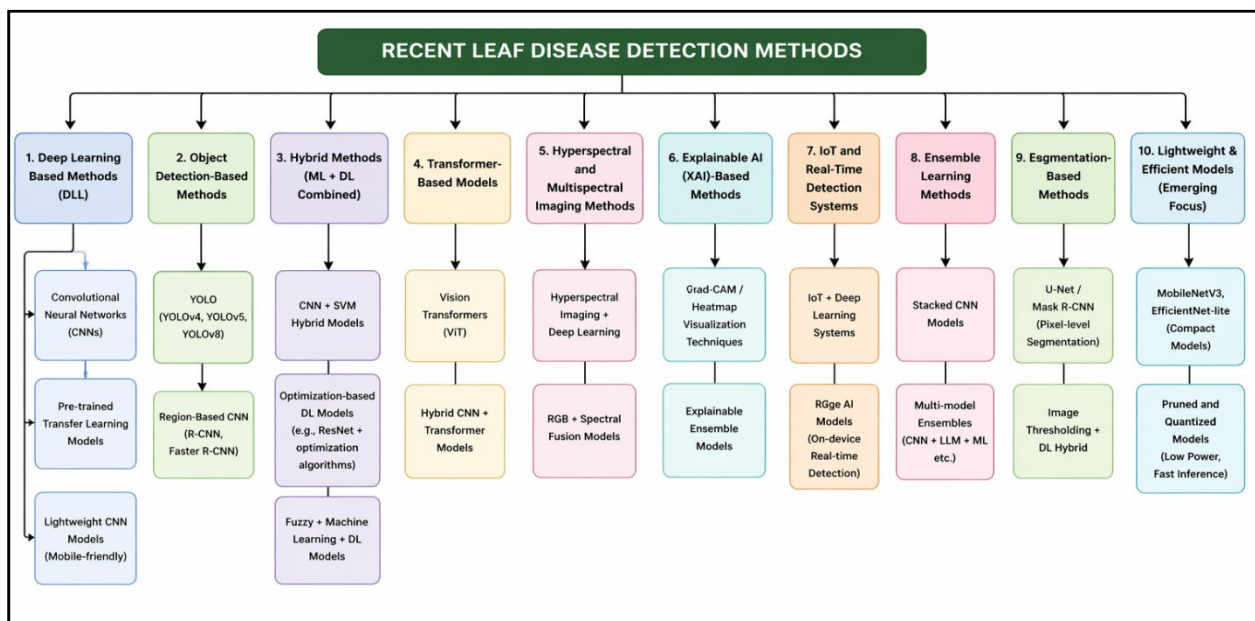


Figure 1: Recent Leaf Disease Detection Methods

III. CLASSIFICATION OF ML-BASED LEAF DISEASE DETECTION METHODS

Since deep learning (DL) can automatically identify intricate patterns from unprocessed visual data, it has taken the lead in the identification of leaf diseases. In contrast to conventional machine learning techniques, deep learning greatly increases detection accuracy across a variety of environmental settings and eliminates the need for manual feature extraction. Convolutional Neural Networks (CNNs), transfer learning models, and lightweight CNN architectures are the most popular deep learning methods in recent studies.

1. DL Based Methods: Convolutional Neural Networks (CNNs) are the backbone of most modern plant disease detection systems. CNNs consist of multiple layers, such as convolutional layers, pooling layers, and fully connected layers, that automatically extract hierarchical features from input images. In the context of leaf disease detection, CNNs can learn low-level features such as edges and textures, as well as high-level features like disease patterns, spots, and discoloration. The main advantage of CNNs is their ability to perform end-to-end learning, using raw leaf images as input without requiring handcrafted feature extraction. This makes CNNs highly robust against variations in lighting, background, and leaf orientation. Several studies have demonstrated that CNN-based models can achieve accuracy levels exceeding 95% when trained on benchmark datasets such as PlantVillage dataset. Additionally, CNNs are widely used in real-time applications due to their fast inference capabilities when deployed on GPUs or optimized hardware. However, CNNs require large amounts of labeled data and significant computational resources for training. Despite this limitation, they remain the most reliable and widely adopted method for leaf disease classification [13].

2. Pre-trained Transfer Learning Models: Transfer learning has emerged as a powerful technique to address the limitations of training deep learning models from scratch. In this approach, models pre-trained on large datasets such as the ImageNet dataset are fine-tuned for leaf disease detection tasks. Popular architectures include **ResNet**, **VGG**, and **EfficientNet**, which have already learned general visual features that can be adapted to agricultural images.

The key advantage of transfer learning is that it significantly **reduces training time and data requirements**, making it suitable for scenarios where only a limited number of labelled leaf images are available. These models also tend to achieve higher accuracy compared to traditional CNNs trained from scratch, as they benefit from previously learned representations.

For example, ResNet-based models utilize residual connections to overcome the vanishing gradient problem, enabling the training of very deep networks. Similarly, EfficientNet introduces a compound scaling method that balances network depth, width, and resolution for optimal performance. Transfer learning models have been successfully applied in real-world agricultural systems, achieving high classification accuracy even with small datasets. Despite their advantages, transfer learning models can be computationally intensive and may require fine-tuning to adapt to domain-specific features of plant diseases.

3. Lightweight CNN Models

Lightweight CNN models are specifically designed for deployment on resource-constrained devices such as smartphones, drones, and edge computing platforms. These models aim to balance accuracy and computational efficiency, making them ideal for real-time disease detection in field conditions. One of the most popular lightweight architectures is MobileNet, which uses depthwise separable convolutions to significantly reduce the number of parameters and computational cost. These models enable farmers to capture leaf images using mobile devices and obtain instant disease predictions without requiring high-end hardware or cloud processing.

Lightweight CNNs are particularly important in developing regions where access to advanced computational infrastructure is limited. They support on-device processing, reduce latency, and eliminate the need for continuous internet connectivity. Recent studies show that MobileNet-based models can achieve competitive accuracy (above 90%) while maintaining low power consumption and fast inference speed. However, lightweight models may sometimes compromise accuracy compared to deeper CNN architectures, especially when dealing with highly complex disease patterns. Ongoing research focuses on improving their performance through model optimization techniques such as pruning, quantization, and knowledge distillation.

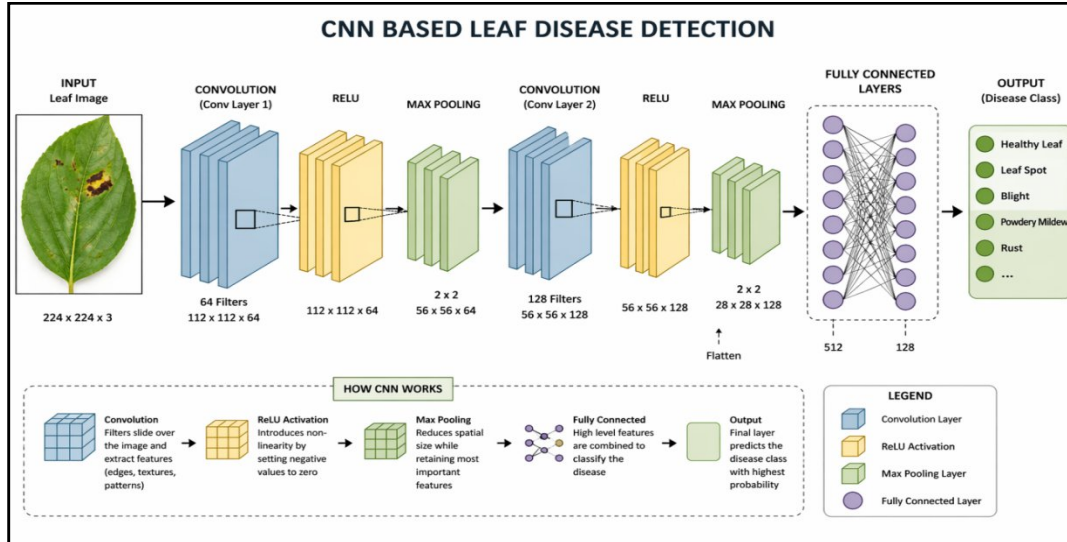


Figure 2: CNN Based Leaf Disease Detection

IV. CLASSIFICATION OF OBJECT DETECTION-BASED METHODS

Object detection-based methods are designed not only to classify whether a leaf is diseased but also to identify the exact location of the disease on the leaf. Unlike simple classification models, these methods provide bounding boxes or region-level outputs, making them highly useful for precision agriculture and real-time monitoring systems. The two most widely used approaches in this category are YOLO (You Only Look Once) and Region-Based CNN (R-CNN family).

1. **YOLO Methods:** These models are advanced object detection algorithms widely used in leaf disease detection for their speed and efficiency. Unlike traditional multi-stage methods, YOLO performs detection and classification in a single pass through the neural network, making it suitable for real-time applications. It divides an input leaf image into grids and simultaneously predicts bounding boxes, confidence scores, and disease classes, allowing it to identify both the type and location of infections. Modern versions such as YOLOv4, YOLOv5, and YOLOv8 offer high accuracy and fast processing, making them ideal for deployment in smart agriculture systems, including mobile apps and drone-based monitoring. However, their performance may slightly decrease when detecting very small or overlapping disease regions [16].

2.

3. **Region-Based CNN:** Region-Based Convolutional Neural Networks (R-CNN and Faster R-CNN) are multi-stage object detection methods that provide highly accurate localization and classification of leaf diseases. These models first generate region proposals likely to contain diseased areas and then apply a CNN to extract features and classify each region. The improved version, Faster R-CNN, introduces a Region Proposal Network (RPN) that significantly speeds up detection while maintaining high accuracy. Due to their ability to precisely identify small and complex disease patterns on leaves, these models are widely used in research and detailed agricultural analysis. However, they are computationally intensive and less suitable for real-time applications than single-stage detectors such as YOLO [16] [17].

V. CLASSIFICATION OF TRANSFORMER-BASED MODELS

Transformer-based models represent a recent and powerful trend in leaf disease detection, inspired by advances in Natural Language Processing (NLP). Unlike traditional CNNs, which focus mainly on local feature extraction, these models are capable of capturing global relationships across the entire leaf image.

1. **Vision Transformers (ViT):** These are a deep learning model that adapts the transformer architecture—originally introduced by Ashish Vaswani et al.—for image analysis tasks such as leaf disease detection. Instead of using

convolution operations like CNNs, ViT divides an input leaf image into small patches (e.g., 16×16), flattens them, and processes them as a sequence using self-attention mechanisms. This self-attention enables the model to analyze how different regions of the image relate to one another, regardless of their spatial distance.

Because of this mechanism, ViT can capture global features more effectively than CNNs, which mainly focus on local patterns through sliding filters. In leaf disease detection, this means ViT can better understand disease patterns across the entire leaf surface, rather than just localized spots. As a result, Vision Transformers are particularly useful for identifying complex, distributed infections, though they generally require larger datasets and greater computational resources for optimal performance [20].

2. Hybrid CNN + Transformer models: Hybrid CNN/ Transformer models combine the strengths of CNNs and transformer architectures to improve leaf disease detection. In these models, CNN layers first extract local features, such as edges, textures, and small disease spots, from leaf images. These features are then passed to transformer layers, which use self-attention mechanisms to capture global relationships across the entire image. This combination allows the model to understand both fine-grained details and overall disease patterns simultaneously. As a result, hybrid models often achieve higher accuracy and robustness than CNNs or transformers alone, making them increasingly popular in recent plant disease detection research [21].

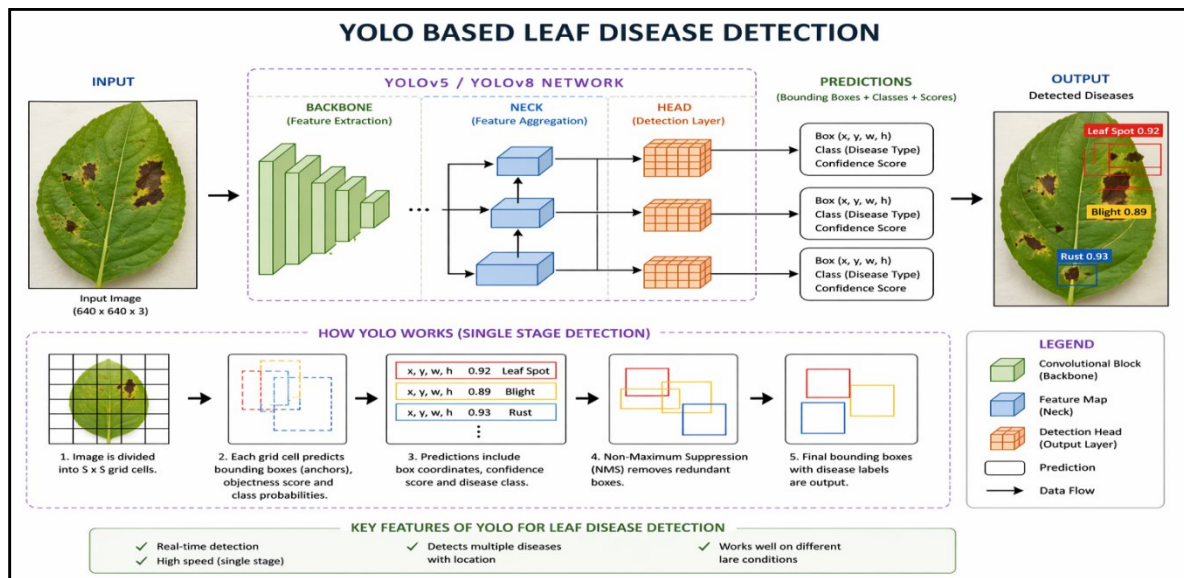


Figure 3: YOLO Based Leaf Disease Detection

VI. HYPERSPECTRAL AND MULTISPECTRAL IMAGING METHODS

Hyperspectral and multispectral imaging methods are advanced techniques used in leaf disease detection to identify infections before visible symptoms appear. Unlike standard RGB images, these methods capture information across multiple wavelengths of light, enabling the detection of subtle physiological and biochemical changes in plant leaves.

1. Hyperspectral Imaging Using Deep Learning: Hyperspectral imaging combined with deep learning is a powerful approach for early disease detection at the molecular and cellular level. Hyperspectral sensors capture hundreds of narrow spectral bands, providing detailed information on the chemical composition of plant tissues, including chlorophyll content, water stress, and pigment variations. These subtle changes often occur before visible disease symptoms appear on the leaf surface. Deep learning models, particularly CNNs, are then used to automatically analyze this high-dimensional spectral data and identify disease patterns. This combination enables highly accurate, early-stage disease detection, making it valuable for precision agriculture and research applications. However, hyperspectral systems are expensive, require specialized equipment, and are computationally intensive due to large data volumes [22].

2. Spectral Fusion Models: Spectral fusion models combine traditional RGB images with multispectral or hyperspectral data to improve disease detection performance. In this approach, RGB images provide visual features such as color, texture, and shape, while spectral data contributes hidden biochemical information about the plant’s condition. Fusion techniques—such as feature-level fusion or decision-level fusion—integrate both data types to create a more comprehensive representation of the leaf. This leads to improved accuracy and robustness compared to using either RGB or spectral data alone. These models are particularly useful in real-world agricultural systems where combining affordable RGB cameras with limited spectral sensors can balance cost and performance.

VII. EXPLAINABLE AI (XAI)-BASED METHODS

Explainable AI (XAI)-based methods are designed to make deep learning models more transparent and interpretable, which is especially important in applications like agriculture, where farmers and experts need to trust the model’s decisions. Instead of acting as a “black box,” XAI techniques help explain why a model predicts a particular leaf disease, improving reliability, adoption, and decision-making.

1. Grad-CAM / Heatmap Visualization Techniques: In leaf disease detection, Grad-CAM produces a color-coded map over the leaf image, clearly showing which areas of the leaf are considered diseased by the model. This helps verify whether the model is focusing on actual infected regions rather than irrelevant background features. As a result, Grad-CAM improves model transparency and is widely used in research and real-world applications for validation and debugging [23].

2. Explainable ensemble models: Explainable ensemble models combine multiple machine learning or deep learning models (e.g., CNNs, transformers, or classifiers) to improve prediction accuracy while incorporating an interpretation layer to explain their outputs. In such systems, different models may analyze various aspects of the leaf image, and their predictions are combined (e.g., via voting or weighted averaging) to produce a final decision [24].

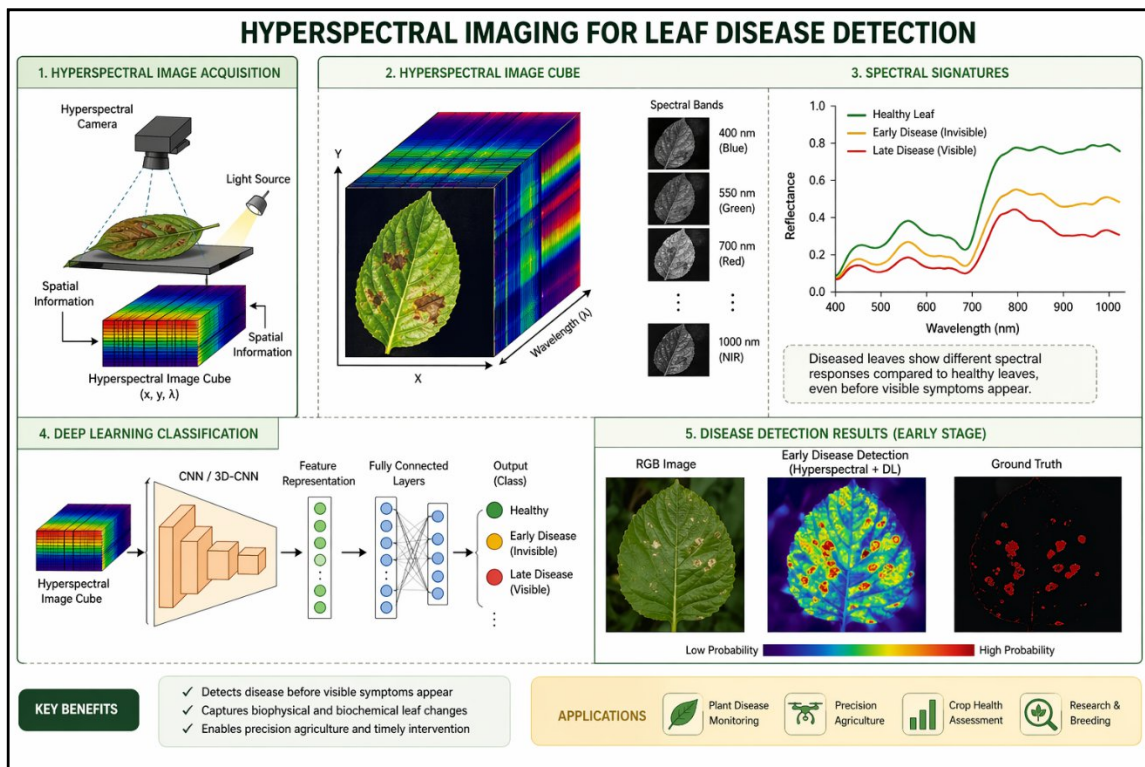


Figure 4: Hyperspectral Imaging-Based Leaf Disease Detection

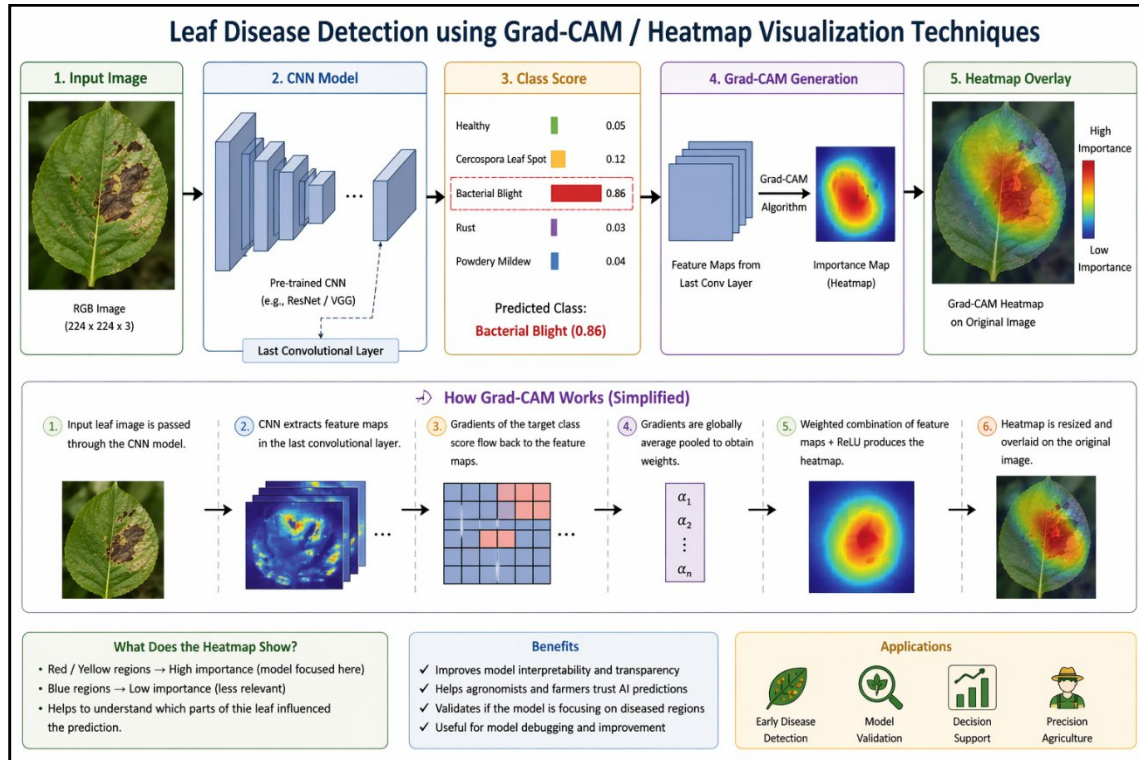


Figure 5: GRAD-CAM-Based Leaf Disease Detection

VIII. IOT AND REAL-TIME DETECTION SYSTEMS

IoT and real-time detection systems play a vital role in modern smart agriculture by enabling continuous monitoring of crop health and early detection of leaf diseases. These systems integrate sensors, cameras, and intelligent algorithms to deliver automated, timely insights, reducing the need for manual inspection.

1. IoT-Based System: These systems can either send data to cloud servers for analysis or process it locally, depending on the architecture. By combining environmental data with image-based analysis, IoT systems provide a more comprehensive understanding of plant conditions. This enables early disease detection, automated alerts, and better decision-making for irrigation, fertilization, and pesticide use. However, these systems may depend on internet connectivity and can involve higher setup costs. In this approach, sensors (such as temperature, humidity, and soil moisture sensors) and cameras are deployed in the field to continuously collect environmental and visual data. The captured leaf images are then processed using deep learning models, such as CNNs or YOLO, to detect diseases [25].

2. Edge AI Models: These models perform disease detection directly on local devices such as smartphones, drones, or embedded systems without relying on cloud computing. In this approach, trained deep learning models (e.g., lightweight CNNs like MobileNet) are deployed on edge devices to analyze leaf images in real time. The main advantage of Edge AI is that it provides fast, low-latency predictions and works even in areas with limited or no internet connectivity. This makes it highly suitable for rural and remote farming environments. Additionally, Edge AI reduces data transmission costs and enhances data privacy. However, these models must be optimized for low computational resources, which can sometimes lead to a trade-off between accuracy and efficiency[26].

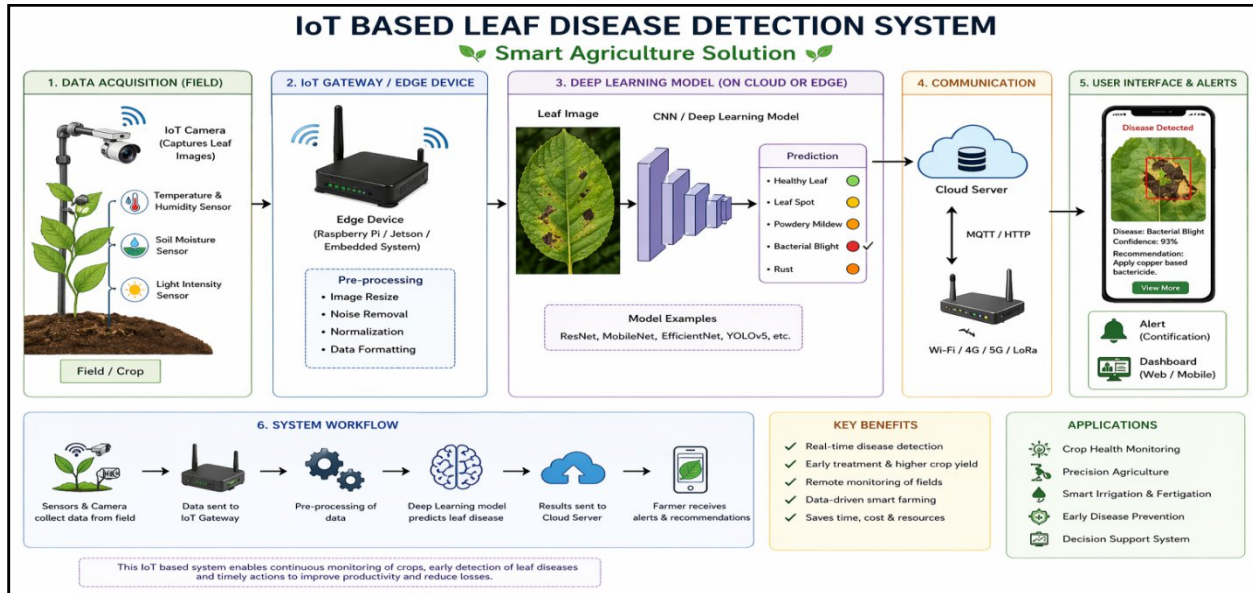


Figure 6: IoT-Based Leaf Disease Detection Method

IX. CONCLUSION

This survey highlights the rapid advances in leaf disease detection methods driven by developments in image processing, machine learning, and deep learning. Traditional approaches, while useful, are increasingly being replaced by more powerful models such as Convolutional Neural Networks (CNNs), object detection frameworks like YOLO and R-CNN, and emerging transformer-based architectures. Additionally, advanced techniques, including hyperspectral imaging, Explainable AI (XAI), and IoT-based real-time systems, have significantly enhanced the accuracy, interpretability, and practical applicability of disease detection systems.

Despite these advancements, challenges such as limited datasets, variability in environmental conditions, high computational requirements, and deployment constraints in real-world agricultural settings still persist. Future research should focus on developing lightweight, cost-effective, and robust models that can operate efficiently on edge devices while maintaining high accuracy. Integrating multiple approaches—such as hybrid models, IoT systems, and explainable frameworks—can further improve reliability and usability. Overall, the continued evolution of intelligent leaf disease detection systems holds great potential to improve crop productivity, support precision agriculture, and ensure global food security.

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