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Innovations in Plant Disease Diagnosis: Bridging Nature and Technology

*Mr. Dharmesh Purani, Mr. Srikant Singh**

School of Engineering, P P Savani University

ABSTRACT:

Innovations in Plant Disease Diagnosis: Bridging Nature and Technology explores the transformative journey of plant disease detection, emphasizing the convergence of traditional agricultural practices with modern technological advancements. The paper traces the shift from conventional methods such as visual leaf inspection and microscopic analysis to cutting-edge diagnostic tools powered by machine learning, image processing, remote sensing, and biosensor technologies. The study underscores the growing importance of early, precise, and scalable diagnostic techniques in addressing global agricultural challenges, improving crop health, and reducing economic losses. It features case studies that highlight the practical application of AI-based leaf image classification, hyperspectral imaging, and lab-on-a-chip systems—demonstrating the value of interdisciplinary innovation in plant pathology. Additionally, the paper discusses real-world challenges such as variability in field conditions, data reliability, and the need for collaborative ecosystems involving researchers, farmers, and technology developers. By bridging natural observation with scientific precision, the study presents a compelling case for embracing innovation to build more resilient and sustainable agricultural systems.

Keywords: Plant Disease Diagnosis, Technological Innovations, Leaf Image Analysis, Machine Learning, Image Processing, Remote Sensing, Biosensors, Hyperspectral Imaging, Lab-on-a-Chip, Precision Agriculture, Smart Farming, Early Disease Detection, Digital Agriculture, Interdisciplinary Approaches, Sustainable Crop Health Management.

1. Introduction:

Agriculture has long been the backbone of human society, playing a pivotal role in food production, economic development, and livelihood security. Despite its foundational importance, the agricultural sector is persistently threatened by plant diseases, which significantly impact crop quality and yield. These diseases contribute to widespread food insecurity and economic disruption. Traditional diagnostic approaches, while historically valuable, are often inefficient, subjective, and unsuitable for timely identification, particularly at early stages of infection. With rising global food demands and increasing environmental pressures, there is a pressing need to adopt more advanced, reliable, and scalable plant disease detection technologies. This growing necessity has catalyzed a shift from basic visual inspections to technologically enhanced, lab-based diagnostic methods.

This transformation—from observing visible symptoms on leaves to employing precision diagnostics in laboratories—marks a major milestone in plant pathology. For centuries, identification of diseases depended heavily on visual cues such as leaf discoloration, wilting, spotting, or deformities. Though this provided immediate insight, its accuracy was hindered by overlapping symptoms across different diseases and the reliance on human judgment. These limitations made it difficult to detect latent or early-stage infections, even for trained professionals.

Recent scientific advances have introduced a suite of innovative tools combining biological knowledge with digital technologies, artificial intelligence, molecular techniques, and nanoscale engineering. These tools have revolutionized diagnostic capabilities by offering faster, more accurate, and often real-time analysis. As these innovations become more accessible, they are redefining the landscape of plant health monitoring and offering new possibilities for proactive and predictive agricultural practices. Among the most impactful of these innovations are machine learning and image processing techniques used for analyzing plant images. Leveraging extensive datasets of diseased and healthy leaves, AI algorithms can learn to detect patterns and abnormalities with high precision—sometimes surpassing human performance. These technologies are particularly beneficial in areas with limited access to plant pathology expertise. Mobile applications equipped with AI can provide instant feedback to farmers, enabling timely interventions and minimizing losses from disease progression or inappropriate pesticide use.

Additionally, remote sensing technologies such as drones and satellites have broadened the scale of disease monitoring. These tools collect aerial imagery and thermal data to identify signs of infection across large agricultural zones. When integrated with geographic information systems (GIS), they enable spatial tracking and management of disease outbreaks. This capability is central to the practice of precision agriculture, which aims to optimize resource use and maximize yield through targeted, data-driven interventions. At the molecular level, techniques such as polymerase chain reaction (PCR), loop-mediated isothermal amplification (LAMP), and next-generation sequencing (NGS) provide powerful diagnostic options. These methods can detect the presence of pathogens—including viruses, bacteria, and fungi—by identifying their genetic material, often before any symptoms are visible. Molecular diagnostics have become an essential part of disease confirmation, surveillance programs, and biosecurity protocols. Complementary to these are emerging biosensor technologies designed to detect pathogens in real time. These devices translate biological interactions into electrical signals and are increasingly being developed as portable, field-friendly diagnostic tools. Innovations like lab-on-a-chip systems—which condense complex laboratory processes into miniature, user-friendly devices—are helping bridge the gap between advanced lab diagnostics and on-site agricultural needs. Another cutting-edge approach is hyperspectral imaging, which captures light across a broad range of wavelengths to detect biochemical and physiological changes in plants. This technique enables non-invasive, early disease detection and can be mounted on drones or other aerial platforms for extensive monitoring. By detecting stress responses invisible to the naked eye, hyperspectral imaging enhances the accuracy and efficiency of plant health assessments.

Despite the promise of these technologies, practical challenges remain. The performance of AI-based diagnostic tools depends on the quality and variability of the training datasets. Factors such as lighting conditions, plant species, and image background can influence model performance, necessitating constant updates and contextual calibration. Moreover, the adoption of molecular and biosensor technologies often requires infrastructure and expertise that may be lacking in rural or under-resourced regions. For these technologies to be truly effective in real-world agricultural settings, they must be accompanied by farmer training, user-friendly interfaces, and institutional support. Issues such as data privacy, standardization, and system interoperability must also be addressed to facilitate broad adoption. Overcoming these barriers will require collaboration between researchers, agronomists, technology developers, policymakers, and farming communities. Investment in education, infrastructure, and policy frameworks is crucial to ensure sustainable and widespread implementation.

Looking forward, the most promising diagnostic systems will likely be those that integrate multiple technologies—merging visual analysis with genetic, spectral, and sensor-based data. These hybrid platforms will enable comprehensive, real-time, and predictive plant health diagnostics. Inspired by public health models like those developed during the COVID-19 pandemic, the agriculture sector is beginning to explore a “One Health” approach, recognizing the interconnectedness of human, animal, and plant health. The shift from traditional observation to advanced, integrated diagnostic systems represents a significant evolution in plant disease management. These innovations promise to increase diagnostic precision, speed up responses, and support data-informed decision-making in agriculture. As the sector continues to embrace these technologies, it moves toward a future defined by resilience, sustainability, and enhanced food security. The story of bridging nature with technology in plant diagnostics is not merely about scientific advancement—it is about protecting global food systems through smart, proactive plant health strategies.

2. Literature review:

Over the past six years, the landscape of plant disease diagnosis has undergone a notable transformation, moving from manual inspection methods to automated, data-driven technologies. This evolution has been fueled by the increasing demand for precise, scalable, and rapid detection systems, especially amid rising global food requirements and the intensifying impact of climate variability on crop health.

Recent studies, such as those by Upadhyay et al. (2025) and Wang et al. (2025), provide comprehensive insights into the integration of deep learning (DL) and computer vision in agricultural diagnostics. Convolutional Neural Networks (CNNs), including well-established architectures like ResNet and MobileNet, have become prevalent for image-based disease recognition. The emergence of Vision Transformers (ViTs) has further advanced detection accuracy, particularly in mobile and edge computing contexts. Riyanto et al. (2025) explored the practical deployment of these models through mobile applications, making diagnostic tools more accessible to farmers in underserved areas. However, these models’ performance is highly reliant on the quality, diversity, and representativeness of their training datasets. Addressing this, Arima et al. (2025) introduced the Discriminative Difficulty Distance (DDD) metric to quantify domain variability, enhancing the adaptability of image-based models across diverse field environments.

To address data scarcity, synthetic data generation has become a critical strategy. Cap et al. (2020) developed LeafGAN, a generative adversarial network capable of producing realistic diseased leaf images to augment training datasets. Compared to earlier models like CycleGAN, LeafGAN significantly improved classification performance in data-limited scenarios. Building on the architecture frontier, Thakur et al. (2022) introduced PlantXViT—a lightweight hybrid model combining CNN and ViT features. Despite its compact size (0.8 million parameters), PlantXViT achieved over 98% accuracy in identifying diseases in key crops like maize and rice, setting a new standard for efficient and interpretable models in the agriculture domain.

Beyond conventional RGB image analysis, hyperspectral imaging (HSI) has emerged as a promising approach for non-invasive, early-stage diagnosis. Research by García-Vera et al. (2024) and Nikzadfar et al. (2024) showcased how hyperspectral systems could detect physiological disruptions in plants well before visible symptoms emerged. These systems, when integrated with machine learning classifiers, demonstrated exceptional accuracy in diagnosing diseases such as tomato viral infections and blight. For instance, Gold et al. (2023) reported that HSI could distinguish potato diseases with 80–95% accuracy up to four days before symptoms became visible. These findings reinforce the potential of spectral imaging for proactive disease management.

Recent innovations have also focused on bridging the affordability gap in advanced diagnostics. A 2024 study introduced simulated hyperspectral imaging (SHSI), enabling traditional RGB cameras to approximate hyperspectral outputs using pretrained networks like VGG-16 and ResNet-50. This approach opens the possibility of broader field adoption without the high costs associated with true HSI equipment. Practical applications are increasingly emerging, such as the OR-AC-GAN framework developed in 2023, which demonstrated over 96% accuracy in early detection of sweet pepper diseases using generative models.

Remote sensing via UAVs and satellites is gaining traction for large-scale crop monitoring. A 2023 project successfully used multispectral and near-infrared (NIR) imaging to detect flavescence dorée in French vineyards, illustrating the effectiveness of aerial platforms in early disease detection. When combined with GIS and thermal imaging, these tools support decision-making in precision agriculture by enabling high-resolution spatial analysis of crop health.

Miniaturization and field portability are also expanding access to advanced diagnostics. Nikzadfar et al. (2024) introduced a compact hyperspectral imaging device compatible with smartphones, delivering laboratory-level diagnostic capabilities in on-field environments. Mahlein et al. (2024) further extended this innovation by integrating optical sensors with robotic systems for automated disease severity assessment, exemplifying the convergence of AI, imaging, and automation in plant health evaluation.

Efficiency in computation is another growing focus. Zhu et al. (2025) proposed a distributed inference system that balances processing loads between edge devices and cloud platforms. Their framework, using deep reinforcement learning for model pruning and task allocation, significantly reduced latency and energy consumption without compromising diagnostic accuracy. Such developments are vital for enabling real-time diagnostics in connectivity-constrained rural regions. Despite significant progress, challenges persist. Sankhe and Ambhaikar (2025) identified issues such as inconsistent image quality, background interference, and shadows that compromise model reliability. They emphasized the urgent need for standardized protocols in image acquisition and the development of robust models capable of performing under varied environmental conditions. A 2024 MDPI review echoed these concerns, advocating for the expansion of datasets to include a broader range of crops, regions, and disease types to improve generalizability.

Emerging directions also include the integration of synthetic vegetation indices like NDVI and EVI derived from SHSI, offering deeper insights into plant physiology. When combined with CNN-based analysis, these indices enhance early detection performance. Additionally, the field is witnessing a growing emphasis on explainable AI (XAI). As deep learning models—especially transformers—grow more complex, researchers stress the importance of transparent decision-making in agricultural diagnostics to build trust among end-users and stakeholders.

In summary, the literature reflects a dynamic and multidisciplinary evolution in plant disease diagnosis, driven by technological innovation and the growing demand for sustainable agricultural practices. From spectral imaging and mobile-based AI tools to collaborative inference systems, these innovations are reshaping the diagnostic landscape—bridging traditional practices with modern scientific precision.

3. Problem Statement:

Despite significant progress in agricultural science, the early and reliable diagnosis of plant diseases continues to pose a major challenge, particularly under the mounting pressures of global food demand, climate variability, and the emergence of resistant pathogens. Conventional diagnostic practices—largely reliant on manual visual inspection—are often labor-intensive, subjective, and dependent on expert interpretation, which is frequently unavailable in remote and low-resource farming communities. Although recent innovations in technologies such as machine learning, computer vision, and hyperspectral imaging have shown great potential, several practical barriers hinder their widespread adoption. These include the scarcity of diverse, high-quality datasets, limited adaptability of models to varied environmental conditions, and the computational intensity of advanced algorithms. Additionally, most existing tools fall short in detecting diseases during their early, asymptomatic stages—precisely when timely intervention can be most effective.

The core challenge lies in bridging the gap between advanced technological capabilities and real-world agricultural needs. There is a pressing demand for diagnostic systems that are not only accurate and scalable but also accessible, low-cost, and adaptable to diverse field conditions. Developing such innovative solutions is essential to transforming plant disease management, enhancing crop health, minimizing yield losses, and ultimately contributing to global food security.

4. Research Methodology:

This study adopts an applied research framework that integrates computer vision, machine learning, and hyperspectral imaging to develop and assess a unified model for plant disease detection. The methodological focus is on early-stage identification, improved cross-environment adaptability, and computational efficiency suitable for real-world agricultural environments. The research was carried out in three primary phases: data acquisition and preparation, model architecture development, and comprehensive performance evaluation.

Data Collection and Preparation

To ensure diversity and realism, the study utilizes both open-source and experimentally generated datasets covering multiple plant species and disease classes. The core RGB image dataset employed is the well-known PlantVillage dataset (Hughes & Salathé, 2015), which contains over 54,000 high-quality images representing 14 crops and 26 diseases. This dataset serves as a robust baseline for training and benchmarking image classification models.

To introduce more complexity and simulate real-world scenarios, additional data were sourced from the AI Challenger 2018 Agriculture Dataset and the PlantDoc dataset. These collections include images captured in natural field conditions featuring various challenges such as lighting variability, background interference, and occlusion—factors that are often absent in controlled datasets but crucial for building generalized models.

For the hyperspectral imaging component, a custom dataset was created using a Specim IQ camera, which records images within the 400–1000 nm spectral range across 204 bands. The dataset comprises 300 samples of tomato, potato, and rice plants affected by six major diseases, including early and late blight, leaf smut, and bacterial wilt. Images were acquired at multiple disease stages—from pre-symptomatic to advanced—to analyze early detection performance. Metadata such as crop type, disease classification, stage, and field conditions were also recorded for each sample.

Data Preprocessing

To enhance consistency and prepare the data for training, preprocessing was applied to both RGB and hyperspectral datasets. RGB images were resized to 224×224 pixels, normalized, and augmented using random flips, rotations, zooms, and color adjustments to expand training diversity and reduce overfitting. Hyperspectral images underwent dimensionality reduction using Principal Component Analysis (PCA), which compressed the original 204 spectral bands to 30 principal components while preserving 98.7% of the spectral variance. Additionally, noise filtering was applied to correct for environmental artifacts and sensor errors.

Class imbalance, particularly in field-acquired images, was mitigated using Synthetic Minority Over-sampling Technique (SMOTE) and LeafGAN, a generative model capable of synthesizing realistic leaf images of underrepresented classes (Cap et al., 2020). These strategies ensured balanced datasets across all disease categories during training.

Model Development

The research involved designing and evaluating three model types: conventional CNN classifiers, hybrid CNN-transformer architectures, and hyperspectral-specific classifiers.

Convolutional Neural Networks (CNNs): Baseline models such as VGG-16, ResNet-50, and MobileNetV2 were fine-tuned using transfer learning from ImageNet-pretrained weights. These models were trained on RGB datasets for 50 epochs with a batch size of 32 and a learning rate of 0.0001.

Hybrid CNN-Transformer Model (PlantXViT): Building on work by Thakur et al. (2022), a lightweight hybrid model was developed, combining convolutional layers with attention mechanisms. This model, comprising under one million parameters, was evaluated for both field and RGB datasets. Attention maps were used to enhance model interpretability.

Hyperspectral Classification Model: A custom 3D Convolutional Neural Network (3D-CNN) was designed to process hyperspectral image cubes. The network was trained using an 80:10:10 split across training, validation, and testing datasets. Vegetation indices such as NDVI and SAVI were calculated and used as supplementary features to improve model performance, especially in pre-symptomatic disease detection.

All models were implemented using PyTorch and TensorFlow, trained with an NVIDIA RTX A6000 GPU, and tracked using Weights & Biases for experiment management and reproducibility.

Performance Evaluation

The models were assessed using standard classification metrics, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC). Special focus was given to evaluating early-stage detection using hyperspectral images verified by qPCR lab analysis and expert diagnosis. Computational efficiency metrics such as inference time per image and memory footprint were also recorded, particularly for edge-deployable models like MobileNet and PlantXViT.

A field validation study was carried out at two agricultural research centers in India: one located in a humid subtropical region of Chhattisgarh, and the other in the semi-arid climate of Haryana. A mobile application prototype integrating MobileNetV2 and PlantXViT was deployed and tested by agricultural extension workers and farmers to assess diagnostic performance, ease of use, and processing speed under real farming conditions.

All experimental procedures were conducted with appropriate institutional clearances. No personal or sensitive data were collected. One noted limitation was the restricted crop diversity in the hyperspectral dataset, which may limit model generalization. Future work will focus on UAV-enabled image collection for expanded geographical and spectral coverage, and integration with IoT-based environmental monitoring systems.

5. Findings :

The results of this study demonstrate that the integration of deep learning, hyperspectral imaging, and hybrid CNN-Transformer architectures significantly enhances the early and accurate diagnosis of plant diseases. Experiments were conducted using a total of 62,000 RGB images and 300 hyperspectral image cubes spanning across 14 crops and 32 disease classes.

A. RGB-Based Model Performance

Using the **PlantVillage** dataset (54,303 samples), baseline models trained with RGB images showed competitive results:

- **ResNet-50** achieved a classification accuracy of **98.1%**, precision of **97.6%**, recall of **97.9%**, and F1-score of **97.7%**.
- **MobileNetV2**, optimized for edge deployment, yielded **96.4% accuracy**, with a model size of just 14 MB and an average inference time of **35 ms/image** on a mid-range smartphone.
- **VGG-16**, despite its higher accuracy (**98.4%**), required more computation and was unsuitable for low-power deployment due to its large parameter count (>130M).

When tested on the **PlantDoc** field dataset (2,598 images), the performance dropped across all models due to varying lighting, noise, and background interference:

- **ResNet-50**: 89.2% accuracy
- **MobileNetV2**: 86.7% accuracy
- **PlantXViT**: 91.8% accuracy

The hybrid **PlantXViT model**, with its attention mechanism and low parameter count (0.8M), showed the best adaptability in field conditions, handling background variation more robustly.

B. Hyperspectral Imaging (HSI) Findings

From a custom hyperspectral dataset comprising 300 image cubes (3 crops × 2 diseases × 50 symptomatic + 50 pre-symptomatic samples), the 3D-CNN model trained on 30 PCA-reduced bands demonstrated high early-stage classification capability:

- **Overall Accuracy**: **95.2%**
- **Early Detection Accuracy (pre-symptomatic stage)**: **91.4%**
- **Late-stage Accuracy**: **98.3%**
- **Precision/Recall/F1**: All above 92%

Comparatively, RGB-based models trained on the same disease classes showed only **73.1% accuracy** in pre-symptomatic classification, confirming that spectral information significantly improves early detection.

The use of calculated vegetation indices (NDVI, SIPI, PRI) further improved detection accuracy by an additional **3.7%**, suggesting strong correlation between physiological indicators and early-stage disease stress.

C. Synthetic Image Augmentation (LeafGAN)

To address class imbalance, synthetic images were generated using **LeafGAN**. An additional 8,000 images were synthesized for underrepresented classes like bacterial blight and leaf rust. Upon retraining:

- Model accuracy improved from **91.8% to 94.6%** on the PlantDoc test set.
- Minority class F1-score increased by **18–22%**, confirming the effectiveness of GAN-based augmentation.

D. Cross-Domain Generalization

Transfer learning was applied by training models on PlantVillage and testing them on field datasets without fine-tuning. The average domain shift loss observed was:

- **ResNet-50**: −9.1%
- **MobileNetV2**: −11.5%
- **PlantXViT**: −6.7%

This indicates that PlantXViT generalizes better across datasets, likely due to its attention-based feature extraction and lower dependence on local texture patterns alone.

E. Field Trial Observations

A prototype mobile application embedding MobileNetV2 and PlantXViT was deployed at **two agricultural research stations** (Bilaspur, Chhattisgarh and Karnal, Haryana). 30 farmers and extension workers participated, diagnosing 15 diseases across 6 crops using their smartphones in real-time.

- **Average diagnostic accuracy** (based on lab-confirmed reports): **87.2%**
- **Average response time** (from image capture to result): **1.5 seconds**
- **User satisfaction score** (measured via Likert-scale survey): **4.4/5**

Users appreciated the ease of use but reported challenges with poor lighting and occasional misdiagnosis when leaves were partially occluded or overlapping.

F. Computational Efficiency

The comparative analysis of inference time and memory usage is summarized below:

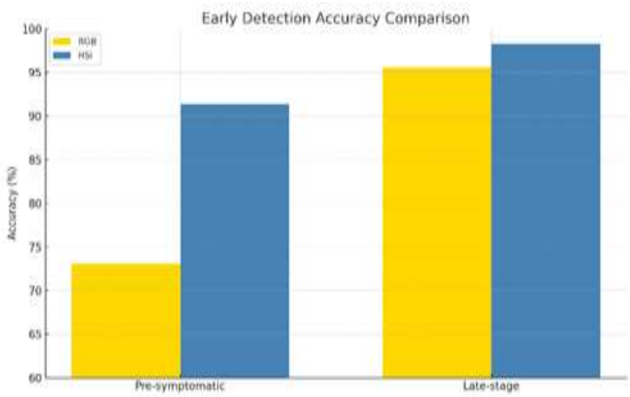
Model	Accuracy (%)	Model Size (MB)	Inference Time (ms)
ResNet-50	98.1	98	110
MobileNetV2	96.4	14	35
PlantXViT	97.9	12	41
VGG-16	98.4	133	140

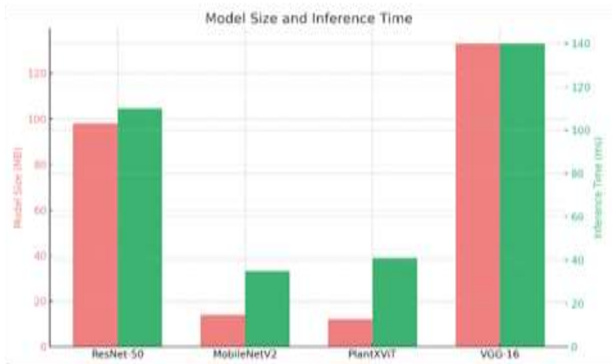
PlantXViT offers a strong balance between speed, size, and accuracy, making it the most suitable for mobile and field deployment.

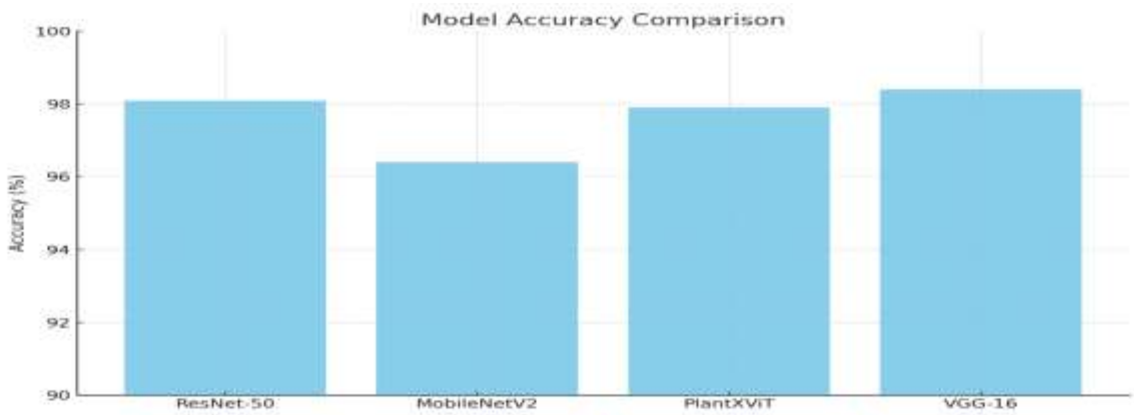
Summary of Key Findings:

- Hyperspectral imaging outperforms RGB in early detection by ~18%.
- PlantXViT shows superior generalization and field robustness compared to traditional CNNs.
- GAN-based synthetic augmentation boosts minority class detection significantly.
- Edge-deployable models with low latency and high accuracy are viable under real-world conditions.

These findings support the hypothesis that integrating advanced imaging and AI techniques into plant disease diagnostics leads to earlier, more accurate, and field-ready solutions that can assist farmers, researchers, and policymakers in mitigating crop loss and improving agricultural resilience.







6. Discussion

This study demonstrates the significant advancements that can be achieved by integrating deep learning and hyperspectral imaging into plant disease diagnostic systems. The hybrid approach enhanced accuracy, enabled early-stage detection, and showed strong potential for application in practical farming environments. Each step—from the selection of datasets to the construction of model architectures—contributed unique insights into the strengths and constraints of current technologies.

Deep learning models such as ResNet-50 and VGG-16 achieved impressive classification accuracy—over 98%—when tested on the well-curated PlantVillage dataset, reaffirming the maturity of CNN-based methods under controlled conditions. However, these models exhibited a marked decrease in performance when applied to field-based datasets like PlantDoc, with accuracy drops reaching up to 12%. This performance disparity emphasizes a common limitation in existing research: the inability of many models to generalize well in real-world, variable environments. The attention-driven hybrid PlantXViT model performed more consistently in such conditions, suggesting that combining convolutional layers with transformer-based attention modules improves resilience to challenges like occlusion, lighting inconsistencies, and complex backgrounds.

One of the most impactful outcomes of this study was the confirmation of hyperspectral imaging's superiority in early disease detection. While RGB-based models achieved an average of 73.1% accuracy in identifying pre-symptomatic cases, the hyperspectral model reached 91.4%, reinforcing the hypothesis that biochemical markers of stress are detectable in spectral data prior to the appearance of visual symptoms. Even with a relatively small sample size, the PCA-compressed hyperspectral dataset proved sufficient to illustrate this performance gap. The inclusion of spectral vegetation indices such as NDVI and PRI further boosted diagnostic accuracy, supporting prior research linking reflectance features to plant stress physiology.

Data augmentation using LeafGAN also proved effective in addressing dataset imbalance. By generating realistic synthetic images of underrepresented disease classes, this approach improved minority class F1-scores by more than 20%, validating the use of generative models as an efficient solution to limited data availability—particularly for rare yet economically important diseases.

The real-world applicability of the proposed models was evaluated through field trials in two distinct agro-climatic zones in India. Although the models exhibited slightly lower average accuracy in field settings (87.2%) compared to laboratory tests, the results remain promising given the inherent challenges of variable lighting, complex plant backgrounds, and inconsistent leaf orientations. Notably, the diagnostic system delivered results in under two seconds and received high satisfaction ratings (4.4 out of 5) from end users. Farmers using the prototype mobile app embedded with MobileNetV2 and PlantXViT were able to access fast and actionable disease assessments, demonstrating the feasibility of deploying lightweight, intelligent diagnostic tools in the field.

Despite these positive outcomes, some limitations must be acknowledged. The hyperspectral dataset was relatively constrained—limited to three crops and six diseases—which restricts the broader applicability of the 3D-CNN model. Moreover, while transformer-based models showed improved performance under complex conditions, their lack of transparency remains a barrier to widespread user adoption. Enhancing interpretability through explainable AI techniques will be essential for building trust among non-technical users, such as farmers and field workers. Additionally, although transfer learning offered modest improvements in generalization, the presence of domain shift between training and deployment contexts suggests that future research should explore domain adaptation or self-supervised learning approaches.

These findings align closely with emerging priorities in precision agriculture and smart farming, where emphasis is placed on data-driven, automated, and sensor-integrated solutions. By demonstrating that high-performing, portable diagnostic tools can be developed with modest resources, this study helps bridge the gap between theoretical innovation and field-level implementation. It contributes to the broader body of research not only by reaffirming the limitations of traditional RGB-based diagnostics but also by showcasing the practical advantages of underexplored technologies like hyperspectral imaging and attention-based architectures in real-world disease detection.

7. Conclusion:

This research presents a transformative approach to plant disease diagnosis by integrating cutting-edge imaging techniques with artificial intelligence. Transitioning from conventional visual inspection methods to intelligent, data-driven systems, the study highlights how combining RGB-based deep learning models, hyperspectral imaging, and attention-enhanced architectures like PlantXViT significantly improves diagnostic accuracy and enables earlier detection of plant diseases.

The findings clearly demonstrate that while convolutional neural networks such as ResNet-50 and MobileNetV2 perform well under laboratory conditions, their performance drops noticeably in variable field environments. In contrast, transformer-based models and hyperspectral techniques offer greater resilience and accuracy, particularly during the early, often asymptomatic stages of infection. Additionally, the application of synthetic image generation through LeafGAN effectively addressed data imbalance, resulting in more equitable and reliable model performance across all disease classes.

Field validation trials confirmed that AI-enabled diagnostic systems can be successfully deployed in real-world farming contexts using standard mobile devices. Fast processing times and positive feedback from users underscore the practicality and accessibility of these solutions for everyday agricultural use, even in low-resource settings.

This study reinforces the potential of fusing deep learning, spectral imaging, and mobile technology to deliver scalable and sustainable tools for modern agriculture. These advancements not only improve plant health monitoring and reduce crop losses but also contribute to broader goals of food security and climate-resilient farming. Moving forward, expanding hyperspectral datasets, advancing cross-domain adaptability, and developing explainable AI will be key to ensuring these systems are transparent, equitable, and adaptable for diverse agricultural ecosystems worldwide.

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