Intelligent Plant Disease Diagnosis with Explainable AI Methods and Lightweight Model

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Keywords: Plant Disease Detection, Artificial Intelligence (AI), Deep Learning, Explainable AI (XAI), Sustainable Agriculture.

Abstract: Agriculture is a most important contributor to a country economy and especially in India, as majority of rural people, its only source of livelihood. Plant diseases are among the most significant challenges to agriculture, which can be caused by pathogen, synthetic fertilizers, outdated farming practices, and environmental conditions. The yield for crops can be greatly reduced by these diseases that lead to substantial coronavirus economic impact. AI and Machine Learning techniques for outbreak detection have become widely used by researchers to tackle this issue. This survey examines prevalent plant leaf diseases, explores traditional and deep learning methods for disease detection, and reviews available datasets. It also addresses the use of Explainable AI (XAI) applied to deep learning to enhance the transparency of the models, leading to understandable decisions for the user. Drawing on this expertise, the survey provides insights for researchers, practitioners, and other stakeholders, informative the creation of effective and transparent biosolutions to plant diseases, resulting in sustainable agricultural systems.

1 INTRODUCTION

Even with the advancement of agricultural technology, plant disease continues to be a pressing challenge, leading to increasing annual crop losses globally and posing a significant threat to food security (Shirahatti et al.; Ko Ko Zaw et al.; Owomugisha et al.). Conventional methods for detecting plant diseases heavily depend on expert knowledge, which may introduce errors, biases, and inefficiencies, especially in large-scale agricultural practices (Hasib et al.; Singh et al.). These limitations often delay treatment, allowing diseases to spread further and reduce yields. The growing field of machine learning and computer vision offers a solution through automated systems for disease detection (Cap et al.; Amin et al.). However, many existing models' function as black-box systems, offering little to no insight into their decision-making processes (Baehrens et al.; Lundberg and Lee). This lack of transparency can reduce trust and hinder adoption among farmers and agronomists who require clear and verifiable recommendations (Wei et al.; Daglarli). Additionally, such models may perform poorly in varying visual environments (Rajeena et al.; Sapura et al.). This underscores the need for intelligent plant disease diagnosis systems that not only achieve high accuracy but also incorporate explainability through Explainable AI (XAI) methods (Arvind et al.; Tabbakh and Barpanda). These systems must provide interpretable outputs to empower users in making informed decisions about disease management (Wei et al.; Baehrens et al.). Furthermore, the solutions should be robust, scalable, and adaptable to different agricultural contexts to ensure widespread usability (Cap et al.; Amin et al.). Therefore, this survey paper presents a comprehensive overview of common leaf-based plant diseases, available datasets, and state-of-the-art detection techniques (Shirahatti et al.; Singh et al.; Ko Ko Zaw et al.). It also highlights the application of XAI techniques, especially in CNN and Transformer models, to enhance interpretability and model transparency in disease classification tasks (Tabbakh and Barpanda; Arvind et al.; Lundberg and Lee; Wei et al.). The paper emphasizes the importance of XAI in this domain and outlines potential directions for future research (Daglarli; Baehrens et al.; Amin et al.).

Joshi, I., Mardia, N. and Vidhya, R.
Intelligent Plant Disease Diagnosis with Explainable AI Methods and Lightweight Model.
DOI: 10.5220/0013904700004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 3*, pages 739-744
ISBN: 978-989-758-777-1

2 OVERVIEWS ON LEAF BASED PLANT DISEASE DETECTION

All living organisms, including plants, animals, and humans, are vulnerable to diseases. Researchers and professionals in agricultural science and management are actively searching for advanced solutions to mitigate plant disease outbreaks, which can cause significant damage to agricultural productivity (Shirahatti et al.; Owomugisha et al.). To address this, various scientific disciplines collaborate to control the spread of plant leaf diseases and ensure a stable food supply for the world's growing population (Ko Ko Zaw et al.; Sapura et al.; Rajeena et al.).

Plant diseases can manifest through various symptoms that affect a plant's structural components such as leaves, stems, and roots, ultimately influencing its growth and yield (Singh et al.; Cap et al.). The occurrence of these diseases varies seasonally, influenced by changes in weather conditions and the presence of specific pathogens (Amin et al.; Tabbakh and Barpanda). Recent approaches using convolutional neural networks and vision transformers show promising results in improving detection rates (Arvind et al.; Wei et al.).

The integration of Explainable AI (XAI) further enhances these models by offering transparent insights into classification decisions, promoting trust among end-users like farmers and agronomists (Baehrens et al.; Lundberg and Lee; Daglarli). Furthermore, research demonstrates that XAI models such as SHAP, LIME, and attention-based techniques are helping interpret deep learning decisions in agriculture and beyond (Hasib et al.; Wei et al.). This section thus surveys common leaf diseases, key datasets, and notable contributions in the area of leaf-based plant disease detection.

2.1 Common Leaf Diseases in Plants

Plant diseases predominantly affect the leaves, but can also impact the roots, stems, and fruits.

Among these, leaf diseases are the most prevalent and are typically managed using fungicides, bactericides, or resistant plant varieties. Below are some of the most common leaf diseases:

- **Blight:** One of the most destructive plant diseases, Blight has historically caused significant damage, such as during the 1840s potato famine. This fungal disease spreads in warm, humid conditions through wind-borne spores.
- **Scab:** This fungal disease is host-specific and can infect individual plants. It is prevalent in apple trees, where it initially causes olive green spots on the leaves, which eventually turn yellow before the leaves fall off.
- **Powdery Mildew:** Common in shaded areas, Powdery Mildew is easily recognizable by the white powdery coating on the upper surface of the leaves. This disease spreads in humid conditions with low soil moisture.
- **Mosaic Virus:** The mosaic virus affects plants at a molecular level, commonly infecting tomatoes, tobacco, and other horticultural plants. Infected leaves develop yellowish and whitish stripes.
- **Marssonina Blotch:** Caused by the fungus
- Marsonina Caronaria, this disease occurs in high rainfall areas. Infected leaves develop circular dark green patches that can turn dark brown in severe cases.
- **Black Spot:** Another fungal disease, Black Spot, creates round black spots on the upper surface of leaves. It thrives in prolonged wet conditions or when leaves remain moist for extended periods.
- **Frogeye Spot:** Caused by the fungus Cercospora Sojina, Frogeye Spot manifests as purple spots on leaves during early spring, which later develop into brownish rings resembling a frog's eye.
- **Rust:** This easily identifiable fungal disease causes brownish rusty spots on leaves and is commonly found on apples, roses, and tomatoes, especially during wet weather in early spring.

Plant leaf diseases are one of the growing challenges in agricultural productivity due to a wide range of pathogens such as fungus, bacteria, viruses, etc. These pathogens have different lifecycles and environmental triggers, making disease management a potentially complex and multi-factors challenge.

Exploring the conditions specific to diseases such as Blight and Rust for example to focus methods of intervention. For example, these diseases can cause significant changes in plant physiology, and impede photosynthesis and nutrient uptake, resulting in reduced growth and yield, or even death in some cases if not properly managed.

The dataset includes various plant diseases, such as Apple Scab (Figure 1), Rose Black Spot (Figure 2), Powdery Mildew (Figure 3), Blight (Figure 4), Mosaic Virus (Figure 5), Marssonina Blotch (Figure 6), Frogeye Spot (Figure 7), and Rust (Figure 8), each of which presents unique visual characteristics aiding in accurate classification.

Figure 1: Apple scab.

Figure 2: Rose black spot.

Figure 3: Powdery mildew.

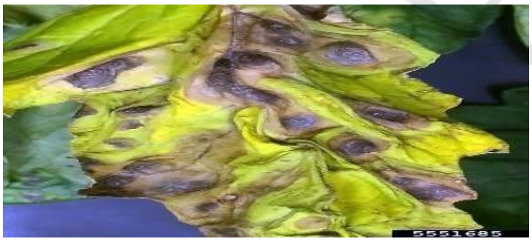

Figure 4: Blight.

Figure 5: Mosaic virus.

Figure 6: Marssonina blotch.

Figure 7: Frogeye spot.

Figure 8: Rust.

3 OVERVIEWS ON EXPLAINABLE AI (XAI)

AI (Artificial Intelligence) is the talk of the town, and with good reason, for almost every subtype of research is either moving towards AI or refactor their already existing rule-based system to AI systems. But many of today's AI systems, such as those that employ deep learning and machine learning, are very opaque, meaning that users cannot tell what is happening inside the system or what drives important decisions. This lack of source transparency creates mistrust and discourages users from adopting your final product.

Certain AI researchers claim that explanations do not need to be an area of focus in AI research as it is either not necessary or too ambitious, whereas others have stated that rather than hinder human intelligence, explanations accompanying AI outputs can facilitate it and can build trust in these systems. In this way, closing this gap would enhance trust on

AI systems and unleash opportunities for AI led products & services.

AI systems need to explain things to users in critical areas such as law, medicine, agriculture, finance and defence so that they can apply them safely and confidently. Explanations provide a useful layer of human-computer interaction, enabling users to get more value from AI-based services. AI has been advancing rapidly, made possible in no small part by machine learning methods ranging from Support Vector Machines (SVMs) and Random Forests (RF) to probabilistic models to Deep Learning (DL) neural networks, all of which work as blackbox models. These models require little to no human input in order to run, and can be employed right away in multiple environments with little tailoring.

But according to the tradition we have been trading off the performance of machine learning models such as predictive accuracy with model interpretability. For example, deep learning is often highly accurate models, but not very explainable, while decision trees are very explainable, but not very accurate. A hypothetical graph (Figure 2) illustrates this performance-explainability trade-off, demonstrating that explainability typically decreases while model performance increases. Figure 9 Shows Comparative Analysis of Machine Learning Algorithms: Explainability vs Learning Performance.

To address this challenge and make AI solutions more transparent and trustworthy, a research domain called Explainable Artificial Intelligence (XAI) has emerged. XAI aims to enhance the interpretability of AI systems, making them easier for users to understand and trust. A. What is XAI?

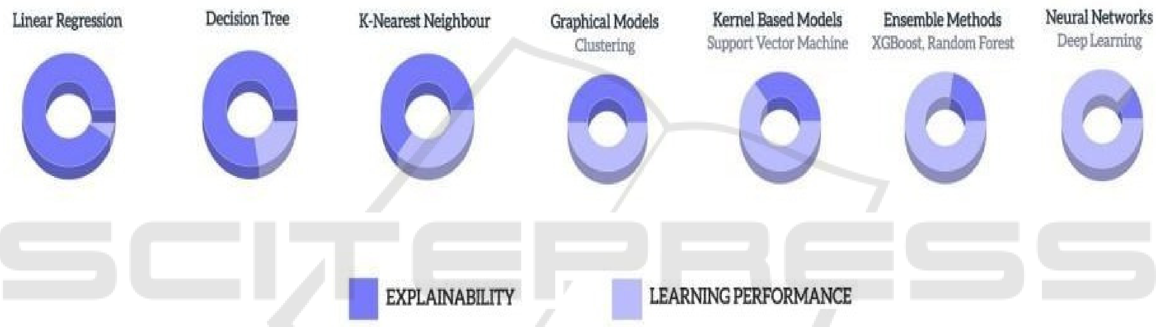

Figure 9: Comparative analysis of machine learning.

That said, artificial intelligence (AI) has become a hot new commodity, bringing about a considerable change in numerous environments, from automatic vehicles to medical diagnostics. Yet users who are not technical often do not understand the systems on which they depend, and therefore, trust in AI-generated decisions cannot be taken for granted. In industries as sensitive as defences, healthcare, and safety, this issue is being cast in an even graver light, given the extent of AI's integration into these domains. As AI becomes more prevalent in supporting or even replacing human supervisors in these domains, it is imperative to do more than show how the AI reached a given decision; it is a prerequisite of any responsible AI system to ensure the users can verify how the system works and how the AI works.

Concerns like these are why Explainable Artificial Intelligence (XAI), a sub field of machine learning, was created. These XAI techniques are finding applications for improving the transparency and reliability of AI systems by exposing their inner workings in a manner that users can appreciate and also be confident in the model's decisions. By implementing ethical considerations, XAI minimizes the chances of unintentional bias while boosting confidence in the system's results. XAI is mainly focused on providing humans a set of rules for XAI decisions and making AI systems more user and efficient friendly according to some similar principles.

For example, consider a healthcare scenario where a patient with breathing issues is placed on a ventilator. A doctor monitors the patient's heart rate through an AIenabled system, which displays fluctuating heart rates on the screen.

The AI algorithm is designed to predict the patient's heart rate for the next 15 seconds based on previous and current data. However, this system, like many "black-box" models, provides highly accurate predictions without explaining the factors influencing these heart rate variations. In this case, the doctor is relying on an AI system that offers no insight into its decision-making process, making it risky to trust such a system without understanding the internal factors driving the predictions.

This hypothetical example highlights the need for explainable AI systems in high-stakes environments, where users must be able to trust and understand the decisions made by AI in order to use them effectively and safely. By making AI more transparent, XAI can bridge this gap.

4 MODEL ARCHITECTURE

In this work, we used the LAAMA (Lightweight Attention-
Augmented Mobile-friendly Architecture), alongside EfficientNetV2L, MobileNetV2, and ResNet152V2 for comparison, to detect 38 diseases across 14 plant species. LAAMA incorporates lightweight attention modules to improve feature extraction and focus on important regions in the images while keeping the model suitable for deployment on mobile and edge devices.

The LAAMA architecture is designed with depth wise separable convolutions and attention mechanisms that reduce computational complexity and make it mobile-friendly.

We pertained LAAMA on the ImageNet dataset, fine-tuned it for plant disease detection, and followed the same steps for the other models to ensure a fair comparison.

We used the Adam optimizer with a learning rate of 0.0001, categorical cross-entropy as the loss function, and a softmax activation function in the output layer, which has 38 neurons due to the multiclass classification nature of this task. All models, including LAAMA, were trained for 50 epochs, using a dropout function to mitigate overfitting.

Table 1: Performance Metrics Comparison of Deep Learning Models for Classification Tasks.

Model	LAAMA	EfficientNetV2L	MobileNetV2	ResNet152V2
Accuracy	99.25%	99.63%	98.86%	98.44%
Precision	99.13%	99.63%	98.68%	98.19%
Recall	98.94%	99.63%	98.03%	97.53%
F1 Score	99.03%	99.63%	98.29%	97.82%

5 RESULT ANALYSIS

We have tested our models on quantitative performance evaluation metrics: accuracy (1), precision (2), recall (3), and f1 score (4) by their predictions on our test set. Figure 10 Shows the Training and Validation Accuracy.

$$Accuracy = \frac{TN + TP}{TP+FP+TN+FN} \quad (1)$$

Here, TN = True negative, TP = True positive, FN = False negative, FP = False positive.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Here, TP = True positive, FP = False positive.

$$Recall = \frac{2*Precision*Recall}{Precision + Recall} \quad (3)$$

Here, TP = True positive, FN = False negative.

$$F1Score = \frac{2*Precision*Recall}{Precision + Recall} \quad (4)$$

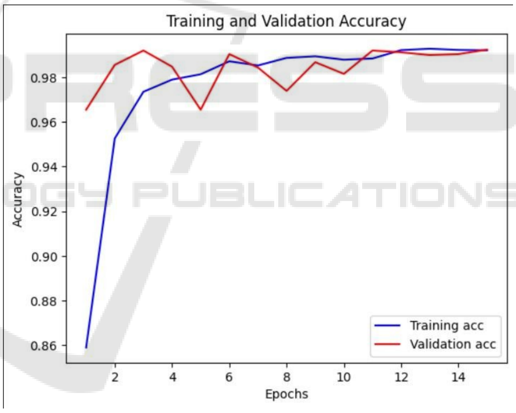

Figure 10: Training and Validation Accuracy.

From Table 1, we observe that EfficientNetV2L achieved the highest performance across all metrics, but LAAMA provided competitive results while maintaining a lightweight architecture suitable for mobile deployment:

- Accuracy: LAAMA scored 99.25%, which is 0.38% lower than EfficientNetV2L but higher than both MobileNetV2 and ResNet152V2.
- Precision: LAAMA achieved 99.13% precision, 0.5% lower than EfficientNetV2L but higher than MobileNetV2 and ResNet152V2.
- Recall: LAAMA had a 98.94% recall, 0.69% lower than EfficientNetV2L but still higher

than MobileNetV2 and ResNet152V2.

- F1 Score: LAAMA's F1 score was 99.03%**,** just 0.60% lower than EfficientNetV2L and higher than the other two models.
- Thus, while EfficientNetV2L outperformed in raw accuracy and precision, LAAMA provides a strong trade-off between performance and mobile-friendliness, making it highly suitable for applications requiring real-time processing on edge devices.

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