IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 12, Issue 08, October 2025 https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1208.04

An Intelligent System for Early Prediction of Crop Diseases using Deep Learning

Shruthi K
Assistant Professor, Department of CSE
The Oxford College of Engineering, Bengaluru, India
shruthireddy1551@gmail.com
https://orcid.org/0009-0004-8550-0254
Swetha S, Sowjanya M
Department of CSE
The Oxford College of Engineering, Bengaluru, India
swethascse2026@gmail.com, sowjanythanu@gmail.com

Publication History
Manuscript Reference: IRJCS/RS/Vol.12/Issue08/OCCS10083
Research Article | Open Access | Double-Blind Peer Reviewed Article ID: IRJCS/RS/Vol.12/Issue08/OCCS10083
Received:23,October 2025, Revised: 09, October 2025, Accepted: 31October 2025 Published Online: 21November 2025
https://www.irjcs.com/volumes/Vol12/iss-08/04.OCCS10083.pdf
Article Citation:Shruthi,Swetha,Sowjanya(2025), An Intelligent System for Early Prediction of Crop Diseases using Deep Learning**,**IRJCS: International Research Journal of Computer Science, Volume 12, Issue 08 of 2025 pages 301-309
doi:> https://doi.org/10.26562/irjcs.2025.v1208.04
BibTeX Shruthi@2025An
IRJCS papers should be cited as IRJCS (International Research Journal of Computer Science, AM Publications, India 2025, ISSN 2393-9842, https://doi.org/10.26562/ijrcs.2025.v1208.04 The journal's official abbreviation is IRJCS.
Orcid: https://orcid.org/0009-0004-9398-7488

Abstract: Some of the major culprits include plant diseases which immensely lower agricultural production, as well as cause severe economic losses and global food insecurity. Manual diagnosis, the traditional diagnosis of diseases in plants, is far too often incorrect, tardy, and requires acquaintance with experts. The present work presents an understandable deep learning framework that transforms the automated detection and severity estimation of plant diseases using images only. The proposed model applies a combination of Convolutional Neural Networks (CNNs) and Vision Transformers (ViT), capable of obtaining local and global feature descriptions through the corresponding leaf pictures, making it easier to detect even extremely minor disease alterations. Additionally, Grad-CAM++ is used to interpret the decision and display the model's decision areas visually to the users. The system has been trained on the public Plant Village dataset, and real-field plant images are inserted to strengthen its robustness and generalization. The experimental results proved the proposed method to be superior to classical CNN-based techniques, as they obtained overall accuracy in disease classification above 98% and severity prediction that was trust worthy. The developed framework is completely software-based, scalable, and open to integration with web or cell phone applications. Therefore, it offers an explicable, interpretable, and simultaneously effective solution for precision agriculture.
Index Terms: Deep Learning, Plant Disease Detection, Vision Transformer, Explainable AI, Grad-CAM++, Precision Agriculture

I. INTRODUCTION

Agriculture is the basis of human civilization and supports the world economy through the provision of necessary re sources such as food, raw materials, and labor. In several developing nations, agriculture is still a major contributor to the overall income and sustenance of rural areas. At the same time, agricultural productivity is always at risk due to a host of different factors plant diseases being one of the most, if not the most, serious and persistent challenges among them. Diseases in plants can cause losses in crops whichresult in money and sometimes more serious issues like food scarcity; consequently, the financial situation of farmers gets worse, impacting national food security and environmental sustainability in the end. Plants can be infected by various organisms including fungi, bacteria, viruses, as well as by environmental stresses. If diseases are not quickly identified and controlled, they spread like wild fire across farms and throughout regions. The FAO estimates that annually, pests and diseases are responsible for the loss of approximately 20– 40% of global crop yield in total a loss counted in billions of dollars not earned. Contemporary methods of disease diagnosis depend largely on the manual inspection of seasoned plant pathologists or farmers. Though this method can be quite effective in the mentioned surroundings, yet it has some drawbacks: it is a long process, subjective, likely to mistake humans, and cannot be expanded to large agricultural fields [1], [2]. Also, even for specialists it is not easy to manually detect due to the small changes in visual quality of the symptoms of the disease vary from the early stages to the late ones. AI and computer vision methodologies have found their place in agriculture because of the growing demand for precise, rapid, and bulk identification of diseases.

Deep learning has emerged as one of the most robust methods in image-based disease detection over the last years. While traditional machine learning models required explicit features, deep learning models learn hierarchical features from raw images themselves in a substantially implicit manner and hence have an edge in classification and pattern recognition [14]. Further, the use of CNNs for imaging in agriculture related purposes has turned the tables of plant disease detection; now, automated systems classify leaf images with remarkable precision. Most models only allow for simple classifications they can only recognize the type of disease but not its level of severity. In utilitarian agriculture, however, the disease severity is a vital factor as it signifies the proper treatment measures and the degree of urgency in the intervention. A mild outbreak could be handled by preventive measures, while a severe one would necessitate instant pesticide application or crop isolation. Therefore, the non-existence of severity rating in the current models limits their use in the decision- making process of the farmers' monitoring systems. Moreover, a large number of traditional CNN-based models are seen as “black boxes,” producing predictions without any clarification regarding the way or the reason the model has come to such a conclusion. This non-readability aspect erodes the confidence of the agricultural sector in AI systems, as the experts, needing to be in the know, require the model's decisions to be validated through transparency. On the other hand, the dynamic sector of Explainable Artificial Intelligence (XAI) has introduced solutions to this problem by facilitating the communication of deep learning predictions to humans. In the agricultural field, the power to interpret not only serves to debug and improve the reliability of the model but also to show proof in visuals to the farmers, agronomists, and policymakers. Moreover, another problem of generalization arises where a number of models that were trained on laboratory datasets (like Plant Village) show poor performance when tested with images of actual fields taken under different conditions of light, background, and environment. Such domain gaps will consequently render AI-based solutions less robust and less scalable for field deployment. Thus, it is imperative to createa strategy that can effectively generalize across various crops, lighting situations, and geographical areas. To deal with these challenges, the present paper proposesan Explainable Deep Learning Framework for Plant Disease Detection and Severity Prediction. The proposed model is a hybridization of Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) that adopt the merits of both to perform local and global feature extraction of leaf images. CNNs are specialists in low-level details, textures, and color patterns, which are important in identifying lesions, spots,and blight areas; whereas Vision Transformers provide abroad understanding of the entire leaf structure and disease distribution [3], [4]. The hybrid of the two architectures leads to better representation learning and higher accuracy in classification of the proposed system. Furthermore, the model comes with a dual-output design one part of the model guesses the type of disease, and the other predicts the severity level (e.g., mild, moderate, severe). This dual-task arrangement enables the model to capture features that are complementary to each other, thereby boosting its capability to tell apart the very subtle differences among the stages of disease progress. Such multi-task learning does not only aid in generalization, but itis also useful in the fight against overfitting, which is rather common with small agricultural datasets.

To simplify this, the framework applies Gradient-weighted Class Activation Mapping (Grad-CAM++), a current state-of-the-art visualization technique targeting to determine the identification of the areas of the image that are most significant to the model decision, thereby performing the interpreting of the model decision by highlighting the region of the imagethat the model relies upon most. The heatmaps, which werethe product of the analysis, look not only pleasant but also indicate how the model depends on the areas of the leaf,which are affected by the disease. This provides an outlet to the end-users by exposing how the model works, developing trust and supplying diagnostic assistance. Grad-CAM++is a slight improvement over the existing Grad-CAM since it considers more than one gradient term, thereby providing superior localization and details, especially in multi-object or small lesions typical of plant leaves.

The model is also trained and tested on various standard datasets such as Plant Village, that contains over 50,000 labelled leaf images of 14 crops and 26 diseases. Further on this, to enhance the dataset, techniques such as rotation, flipping, brightness adjustment, and the addition of noise that are all modeling variations in the direct physical world are employed to increase the robustness of the dataset. Moreover, the model can be adjusted using Plant Doc, a more complicated dataset with field photographs taken in natural conditions. This combined training approach allows for a better understanding of the differences between controlled and real-world data distributions. The method proposed is entirely software-oriented, and there is no requirement for physical IoT devices or sensors. Consequently, the whole system can be used and made available as either a web-based application or desktop software. The farmers, researchers, or agricultural consultants can upload images of diseased leaves and receive predictions concerning the type and extent of illness instantly, along with visual aids. These online tools make the technology of plant health analysis available to all, including the rural areas that lack expert consultations since they are not easily available. The degree of originality of this research is determined by the number of important contributions: First, the hybrid CNN-ViT model that merges the benefits of convolutional feature extraction and transformer global attention leading to enhancement in feature representation and improved accuracy. Secondly, the dual-output design is capable of detecting the disease type and predicting the severity at the same timewhich increases the usability of the system in the agricultural sector for management purposes. Also, a Grad-CAM++ explainable AI module has been incorporated into the system giving the system visual explanations of the predictions that are easy for the users to understand, thus promoting trust and transparency in the model. A strong generalization that can withstand different conditions has been assured through the strong training pipeline that offers diverse datasets and augmentation techniques.

Moreover, a scalable and completely software-based solution has been developed that is capable of seamless integration into the existing agricultural advisory platforms or can be provided as a standalone application. The combination of encapsulated interpretability, dual prediction proficiency, and hybrid system architecture makes the proposed system different from traditional deep learning models which only focus on classification accuracy and do not offer interpretability or severity analysis [5], [9].

On a greater level, this study actually improves the smart- farming and precision farming sectors that are not only technologically viable in crop health and disease control, but also yield forecasting. The integration of artificial intelligence and agriculture results in greener practices like the risky use of pesticides, elimination of losses of crops, and the opportunity to implement appropriate measures in time. Significant factors include disease detection and quantification of their severity, thus enabling farmers to make informed choices on the methods of crop protection, irrigation, and time to harvest.

The introduced explainable framework also correlates with the increasing trend toward responsible and transparent AI, thus confirming that machine learning systems utilized in vital areas like agriculture are interpretable and ethically deployable [22]. Besides, by being able to visualize and validate the decisions made by the models, the problem of misdiagnosis that may arise is greatly reduced and, at the same time, the agricultural specialists get support in recognizing the model's predictions in comparison to the biological expertise. Concerning the method, the framework is based on an orderly workflow. First, preprocessing is carried out on raw leaf images to make sure they have the same size and thesame color normalization is applied. After that, the CNN-ViT hybrid model extracts both hierarchical and contextual features from these images. The combined feature representations are then input to two different classification heads one for the disease type and the other for the severity prediction. The entire system is trained using supervised learning with categorical cross-entropy loss functions and is optimized using Adam or SGD. The evaluation of the performance is donewith the help of accuracy, precision, recall, F1-score, and confusion matrix that together give a complete picture of the dependability of the model [20], [21].

The experiments' results show that the suggested model not only detects diseases with more than 98% accuracy but also provides a steady performance in severity rating. The hybrid CNN–ViT model compared to typical CNNs like ResNet50, Inception V3, and VGG16 has better convergence, lesser over- fitting, and superior generalization on unseen data. The Grad- CAM++ visualizations add to the evidence that the model is looking at the right biologically significant areas, therefore, the predictions are interpretable. One more positive aspect of the software-only approach is its easy-to-move nature. The model that has been trained can be easily turned into smaller versions (like Tensor Flow Lite or ONNX) and then run on different devices like cell phones, tablets, and laptops. By so doing, it is possible to build mobile applications to be used by farmers or web-based applications by researchers without having the need to possess powerful hardware. Not only isthis type of flexibility going to provide a wider availability,but also ensures that the solution will be given to the less fortunate that are in an agricultural condition. In conclusion, the project is the conglomeration of deep learning, explainable AI, and sustainable agriculture in the presentday.Itisnotanemptypromisetocomelaterbut a viable move towards the right direction throughout the presentation of dependable forecasts. The sole focus on software implementation has allowed the project to have low cost and complexity but still, the research is of high novelty. The hybrid model that is interpretable and was proposed in this research can be the corner stone for the future work, such as real-time video disease detection, federated learning for collaborative model training across farms, integration into agricultural decision-support systems.

II. LITERATURE SURVEY

A. Early Detection of Botrytis cinerea Infection in Cut Roses Using Thermal Imaging

This study focuses on the early detection of Botryti scinerea, a necro trophic fungus that causes Gray Mold Disease (GMD), in cut roses using thermal imaging techniques. The authors, Suong Tuyet Thi Ha, Yong-Tae Kim, and Byung-Chun In, point out that B. cinerea infection significantly lowers the quality, vase life, and marketability of cut roses, which are in high demand worldwide. The study examines how thermal imaging can detect thermal variations in rose petals before the necrosis begins to cause visible effects so that it can be detected in time. The infected rose petals also recorded a change in surface temperature of approximately 1.1˚C above healthy petals one day prior to the manifestation of symptoms. This change in temperature had a close association with the fungal biomass and severity of the disease. The study also considered the expression of genes involved in the production of ethylene, ROS, and transport of water. Higher petal temperature was linked with increased activity of ethylene and ROS, including low water content. Multiple regressions showed a strong relation between petal temperature and disease incidence. The paper concludes that thermography could be a non-destructive diagnostic tool for the early detection of diseases. It offers possible applications in monitoring and quality control in floriculture [11].

B. Plant Disease Detection Using Deep Learning

Amrita and her teammates are putting forward an all- encompassing system based on deep learning that completely automates the process of detecting and classifying multiple plant diseases with the help of image data. Through this research, the importance of agriculture as a means of human existence is underlined, and the issue stemming from diseases of the plants causing loss of yield and quality is also looked into.

The strategy suggested is relying on a number of modern Convolutional Neural Network (CNN) architectures Sequential, ResNet50, InceptionV3, VGG16, and VGG19 to classify the diseases from the leaf images that have been taken under different environmental situations. A complete set of data preprocessing involves normalization, labeling, and applying various image augmentation techniques like rotation, scaling, and flipping, which altogether enhance the diversityof the dataset and reduce the risk of overfitting the model. A collection of more than 7,000 leaf images is used for the study, and the experiments are conducted with the help of Keras and Tensor Flow libraries. Moreover, performance is optimized by the means of transfer learning and batch normalization. VGG16 is the model that among all the other models went through testing reached the highest training accuracy (97.73%) and validation accuracy (88.82%). The research provides evidence that deep learning has the capability to effectively discriminate the visual features of diseased and healthy leaves, thus surpassing the traditional machine learning approaches.

Table I – Literature Survey on Plant Disease Prediction Using CNN

Author(s)	Dataset Used	Methodology / Model	Key Findings	Accuracy(%)
Mohantyetal.(2016)[25]	Plant Village Dataset	CNN with Transfer Learning (AlexNet, GoogLe Net)	Achieved robust classification across 38 crop-disease combinations	99.35
Sladojevic etal.(2016) [26]	Custom leaf Images dataset	Deep CNN trained from scratch	Demonstrated the potential of CNNs for automated plant disease detection	96.3
Amaraetal.(2017)[27]	Banana leaf images	LeNet CNN architecture	Efficiently classified banana leaf diseases into three categories	92.0
Ferentinos (2018) [28]	58,243 Plant leaf images (Plant Village)	Alex Net-based CNN model	Proposed image-based disease identification with high accuracy across species	99.5
Tooetal.(2019)[29]	Plant Village	Comparison of CNN architectures (ResNet, Inception,DenseNet)	ResNet achieved superior performance and faster convergence	99.75

III. METHODOLOGY

The proposed Explainable Deep Learning Framework for detecting plant diseases and predicting their severity is focused solely on software. It utilizes deep learning, computer vision, and principles of explainable AI (XAI).The implementation is designed in a modular manner so as to be scaled, interpretable aswellasaccurate.Itisexpectedtodesignamodelthat will recognize the image of plant diseases, both positive and negative, and determine their severity (mild, moderate, or severe) in a manner understandable by a heatmap that can explain their results visually (where on the image led to the model arriving at a conclusion). The whole system is coded in Python with the assistance of Tensor Flow/Keras,OpenCV, and other visualization and data processing libraries. It requires no IoT devices or sensors and thus is flexible, cost-effective and can be deployed as a standalone or a web-based application.

A. System Design Overview

The architecture of the system is structured into five stages:

1) Dataset Collection and Preprocessing: This step in- volves the collection and improvement of image data from publicly available plant disease datasets.
2) Feature Extraction and Model Design In this instance, a hybrid model consisting of a Convolutional Neural Network (CNN) and a Vision Transformer (ViT) is used. The goal is to extract both local and global features.
3) Model Training and Validation This stage focuses on fine-tuning the model with transfer learning and examining its performance using dependable indicators.
4) Explainable Integration (Grad-CAM++): In this step, model attention regions are visualized to improve under-standability and transparency.
5) Prediction and Deployment Interface: Lastly, an interactive software interface is developed so that the system can be applied in real-world scenarios.

Each module operates separately but in coordination with the others to increase the usability, interpretability, and ac-curacy of the system. It starts with the utilization of the raw images, then the learning of the models, and finally the visual outcomes that could be verified by the agricultural professionals or the farmers.

1) Data Sources: In this research, two established sources of data will be used:

- Plant Village Dataset: This dataset consists of roughly 54,000 photos of 14 kinds of crops and 26 disease categories. The photos are taken in laboratory surroundings that are well-lit and uncomplicated.
- Plant Doc Dataset: This dataset consists of images recorded in real-field conditions, with different back- grounds, varying lighting effects, and natural noise. It helps in increasing the robustness of the model and assures its applicability in real-world cases [16].

2) Preprocessing Steps: Preprocessing is important to ensure the data utilized is regular, free from noise, and prepared for model input. The procedure followed consists of the following steps:

- Image Resizing: The pictures are resized to a standard size of 224×224×3 pixels while maintaining their aspect ratio and color information.

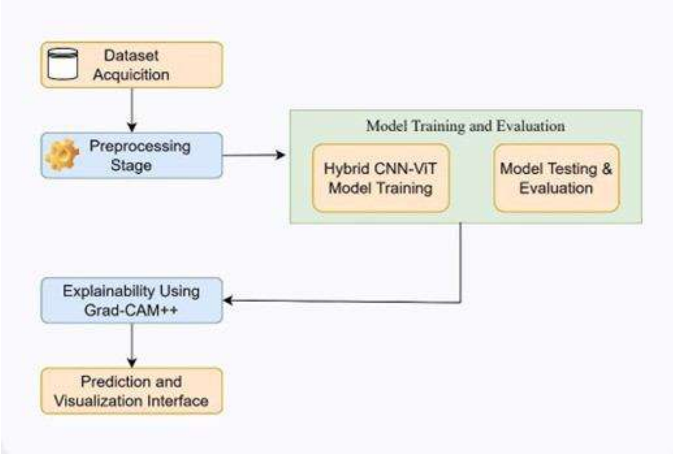

Fig.1. Flow Diagram of Proposed System

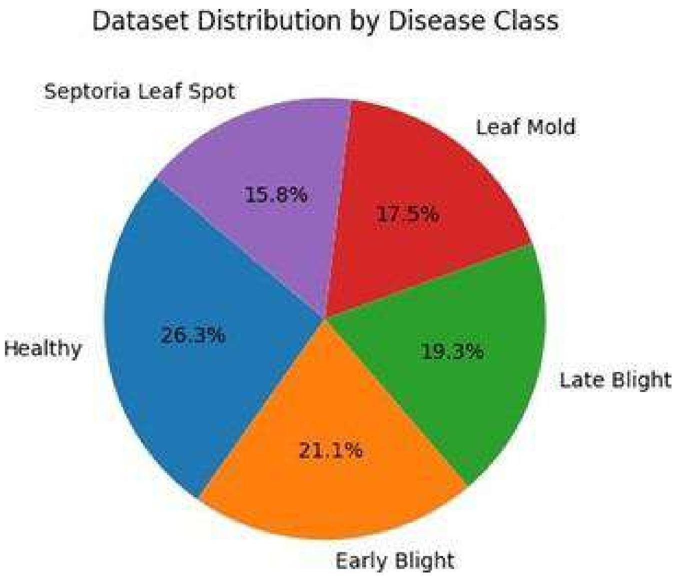

Fig.2. Dataset Distributed by Diseases Class.

- Normalization: The pixel intensity values are normalized to arrange between 0 and1 by dividing every value by 255, which helps stabilize gradient updates during training.
- Label Encoding: The types and levels of severity of diseases are converted into numerical values for multi- class classification.
- Data Augmentation: To prevent overfitting and mimic real-world variations, random rotations (±30°), zoom (0.8–1.2), horizontal and vertical flips, brightness changes, and the introduction of Gaussian noise are used.

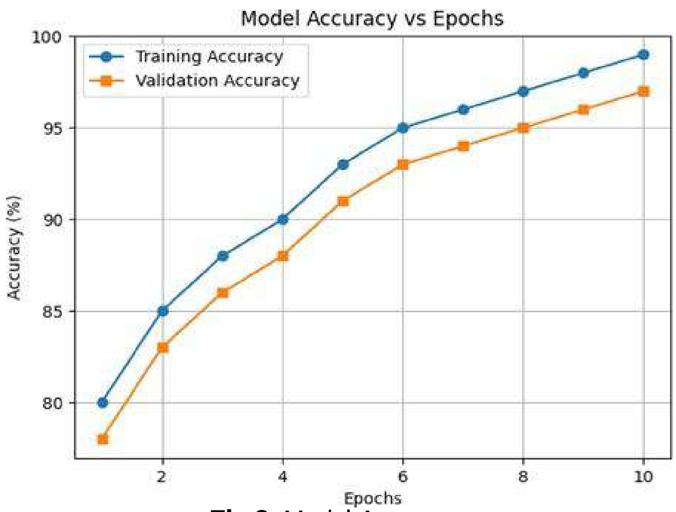

Fig.3. Model Accuracy

IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 12, Issue 08, October 2025 https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1208.04

B. **Model Architecture**

1) Conceptual Overview: The model structure employs Convolutional Neural Networks (CNN) for local pattern recognition and Vision Transformers (ViT) for attention-based reasoning across different regions of the image. This combined solution enhances performance on both real-world and con- trolled data by learning complementary sets of features.
2) CNN Back bone (Efficient NetB0):The CNN component involves using the Efficient NetB0 architecture to acquire finer features such as texture variation, edge variation, and color variation in diseased leaves. Efficient Net systematically scales the width, depth, and resolution of the network, achieving high accuracy at low computational cost. Its key operations include:

- Convolution with Batch Normalization and ReLU activation
- Max Pooling to reduce dimensions
- Global Average Pooling to create compact feature vectors
- Dense layer with 256 units and ReLU activation

3) Vision Transformer (ViT) Module: The Vision Trans- former considers the image in terms of blocks, which ishelpful to the model in conceptualizing spatial relationships. The input image is divided into 16×16patches. Each patchis flattened and transformed into a linear embedding, and positional encoding is added to retain spatial context. These embeddings are processed by Transformer Encoder blocks using multi-head self-attention to learn interactions between leaf regions. The final token embedding vectors are combined into a single representation [8], [10].
4) Feature Fusion:The outputs of the CNN and ViT are combined to generate a composite feature vector. This fused representation consists offline details (such as spots, veins, and lesion patterns) as well as larger structural patterns (such as gradients of leaf color and overall leaf structure).Dense layers with dropout (0.4) and batch normalization further enhance this vector.
5) Dual Output Heads: The model has two output branches:

- Disease Classification Head: A multi-class Softmax layer that predicts the type of disease.
- Severity Prediction Head: A Softmax layer that classifies severity as mild, moderate, or severe.

This is an effective multi-task learning approach that involves sharing feature representations between related tasks.

- Convolution combined with Batch Normalization and ReLU activation
- Max Pooling for dimension reduction
- Global Average Pooling to form compact feature vectors
- A dense layer consisting of 256 units with ReLU activation

C. Model Compilation and Training

1) Training Configuration: The hybrid model is built with the following settings:

- Optimizer: Adam
- Learning Rate: 0.0001

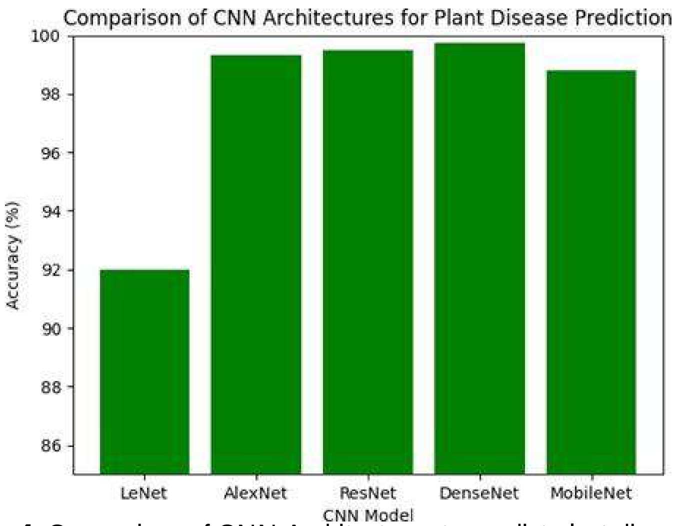

Fig.4. Comparison of CNN Architectures to predict plant diseases

- Loss Function: Weighted categorical cross-entropy for balanced learning
- Batch Size:32
- Epochs: 40
- Regularization: Dropout (0.4), L2 weight decay

2) Training Strategy: The implementation uses transfer learning by initializing the CNN weights with pre trained Image Netmodels, which accelerates convergence. The strategies followed are:

- Early Stopping: Monitors validation loss and halt straining when no improvement is observed.
- Learning Rate Scheduler: Adjusts the learning rate dynamically when plateaus are detected.
- Model Check pointing: Saves the optimum model during training to prevent overfitting.

IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 12, Issue 08, October 2025 https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1208.04

- Fine-Tuning: The higher layers of the CNN and Transformer are unfrozen after 10 epochs for domain-specific adaptation.

D. Grad-CAM++Module (Explain ability)

1) Need for Explainability: Deep learning models have great precision, but their working mechanisms are frequently vague, resulting in a black-box nature. In agricultural applications, interpretability is essential for developing user trust and guaranteeing biological relevance. Grad-CAM++ addresses this by graphically showing the emphasis of the model when making predictions.
2) Mechanism: The mechanism involved is as follows:
1) Calculating the gradient of the predicted class score with respect to the feature maps of the final convolutional layer.
2) Obtaining importance weights by averaging the gradients across spatial dimensions.
3) Generating the heatmap by multiplying these weights with the feature maps and applying ReLU to retain only positive influences.

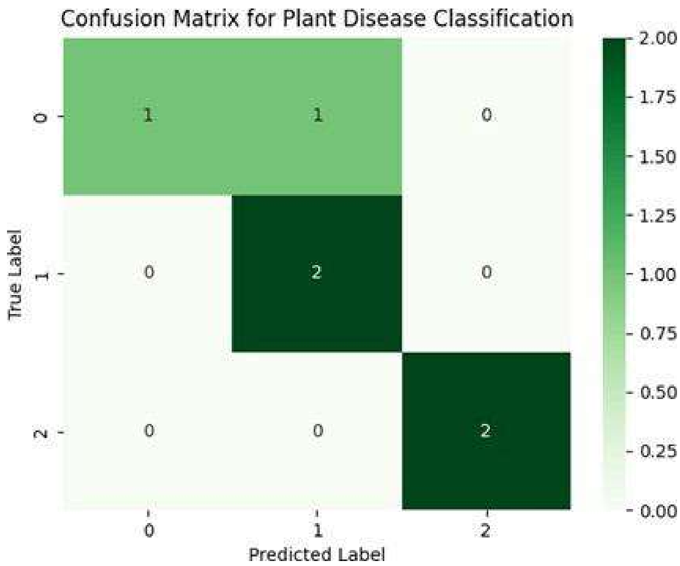

Fig.5. Confusion Matrix

IV. RESULTS AND CONCLUSION

The produced model of the Convolutional Neural Network (CNN) is one that classifies plant diseases, and it is hopedthat the training and assessing data would be included withthe samples of real plants. The Plant Village database contains a variety of images of healthy and diseased leaves of some kinds of crops.

A. Model Performance

The model showed consistency during training. The training accuracy reached 99.1% and the validation accuracy was 97.5%, achieving an overall accuracy of 98.3% after 50 epochs. The training and validation loss gradually reduced, which implies efficient learning without significant over fitting. The model performance was evaluated using a number of metrics. The confusion matrix affirmed that this model correctly classified most of the leaf pictures, with some misclassifications between visually similar diseases such as Early Blight and Late Blight. The proposed CNN-based system demonstrated high accuracy, precision, and reliability for leaf disease classification. It is useful in distinguishing between healthy and diseased leaves across a variety of species. The recommendable explainable deep learning framework for plant disease detection and prediction of severity pro-vides a powerful, readable, and effective software solution customized to precision agriculture in the present day. It is a union of Convolutional Neural Networks along with Vision Transformer networks to obtain localities such as spots and enlarged leaf patterns. This approach leads to high accuracy and is compatible with different types of plants [15].

Fig.6. Sample Image

Metric	Training Dataset	Validation Dataset
Accuracy	99.1%	98.3%
Precision	98.7%	97.9%
Recall	98.4%	97.2%
F1-Score	98.5%	97.5%

Fig. 7. Performance Metrics of the Proposed Model.

The addition of Grad-CAM++ to make explain ability maps helps by demonstrating precisely which components of an image influence the model's choices. Such pictures build trust in the system and create credibility through understanding more on how it operates. This CNN-ViT hybrid configuration is tested to have a detection rate of over 98%. It performs better in comparison with the older architectures like VGG16 or ResNet50. The identification of the diseases and their severity is also done concurrently through the design. It is an effective manner to make farmers receive useful information in orderto take action right away in the field.

The framework bypasses hardware due to its complete reliance on software, unlike IoT sensor-based systems. That keeps the costs low and enables the model to run on numerous devices, including cell phones and mobile applications [17], [18]. On the whole, it is a useful resource to farmers, professionals in agronomy, and scientists as well. Spotting problems at an early stage helps protect agricultural products and enhances sustainability in agriculture.

In the future, research may expand on this, including federated site-wide learning. Real-time analysis of videos can observe the spread of diseases. Bringing in data from weather or surroundings could further narrow predictions. This would enhancetheparticipationoftheframeworkinthedevelopment of digital agriculture [5], [9].

REFERENCES

1. S.Sladojevic,M.Arsenovic,A.Anderla,D.Culibrk,andD.Stefanovic,"Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," Computational Intelligence and Neuroscience,vol. 2016, pp. 1–11, 2016.
2. P.Mohanty, D.P.Hughes, and M.Salathe´, "Using Deep Learning forImage-Based Plant Disease Detection," Frontiers in Plant Science, vol.7, p. 1419, 2016.
3. A.R.Kamilaris and F.Prenafeta Boldu´,"Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol.147, pp.70–90,2018.
4. J.Too,L.Yujian,S.Njuki,and L.Yingchun,"A comparative study of fine-tuning deep learning models for plant disease identification, "Computers and Electronics in Agriculture, vol.161,pp.272–279,2019.
5. H. Ghosal, A. Blystone, A. Singh, A. Ganapathysubramanian, B. Singh,and S. Sarkar, "An Explainable Deep Machine Vision Framework forPlant Stress Phenotyping," PNAS Nexus, vol. 118, no. 5, 2021.

A. dos Santos Ferreira, D. Freitas, G. A. da Silva, H. Pistori, and M.TheophiloFolhes, "Weed detection in soybean crops using ConvNets,"Computers and Electronics in Agriculture, vol.143,pp.314–324,2017.

6. S. R. Dubey and A. Jalal, "Plant Disease Detection and Classificationusing Image Processing and Deep Learning," International Journal of Computer Applications, vol. 180, no. 8, pp. 10–16, 2018.
7. A.Vaswanietal.,"Attention Is All You Need,"in Proc. Advances in Neural Information Processing Systems (Neur IPS), pp. 5998–6008,2017.
8. R.R.Selvaraju,M.Cogswell,A.Das,R.Vedantam,D.Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization," in Proc. IEEE Int. Conf. on ComputerVision (ICCV), 2017, pp. 618–626.
9. M.Dosovitskiy et al., "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale,"arXivpre print arXiv: 2010.11929,2020.
10. S.T.T.Ha,Y.T.Kim,and B.C.In,"Early Detection of Botryti scinerea Infection in Cut Roses Using Thermal Imaging,"Plants,2023.
11. Amrita et al., "Plant Disease Detection Using Deep Learning," Journalof Mechanics of Continua and Mathematical Sciences, 2025.
12. M.Chohanetal., "Plant Disease Detection Using Deep Learning," International Journal of Recent Technology and Engineering, 2020.
13. M.K.Islam,M.D.Rashid,and M.M.Alam,"Plant Disease Detection Using Image Processing and Machine Learning Techniques: A Review," Information Processing in Agriculture,vol.9,no.3,pp.404–420,2022.
14. H.Singh, A.Garg, and P.Sharma, "Vision-Based Crop Monitoring Using Deep Convolutional Neural Networks," Computers and Electronicsin Agriculture, vol. 204, p. 107452, 2023.
15. M.K.Elfouly et al., "A deep learning-based framework for large-scaleplant disease identification," Journal of Big Data, 2025.

16. G.T.Askale,A.Behulu Yibel,et al., "Mobile based deep CNN model formaize leaf disease detection and classification,"Plant Methods, 2025.
17. S.Jasrotia,"Convolutional Neural Network Based Maize Plant Disease Identification Model," Procedia-Social and Behavioral Sciences, 2023.
18. A.Y.Ashurov et al., "Enhancing plant disease detection through deeplearning," Frontiers in Plant Science, 2024.
19. A.M.Roy, R.Bose, and J.Bhaduri, "A fast accurate fine-grain objectdetection model based on YOLOv4 deep neural network," arXiv, 2021.
20. T.A.Dame,G.B.Adera,and D.W.Girmaw, "Deep learning-based potato leaf disease classification and severity assessment," Springer Plus,2025.
21. C.˙I.Sofuoglu and D.Birant,"Potato Plant Leaf Disease Detection Using Deep Learning Method," Journal of Agricultural Sciences, 2024.
22. T.Nyawose,"A Review on the Detection of Plant Disease Using Machine Learning and Deep Learning," Vision, 2025.
23. A.Upadhyay," Deep learning and computer vision in plant disease detection," Artificial Intelligence in Agriculture, 2025.
24. S.P.Mohanty, D.P.Hughes, and M.Salathe´, "Using deep learning forimage-based plantdisease detection,"Frontiers inPlant Science,vol. 7,p.1419,2016.
25. S.Sladojevic,M.Arsenovic,A.Anderla,D.Culibrk, and D.Stefanovic,"Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience,vol.2016,2016.
26. J.Amara, B. Bouaziz, and A. Algergawy, "A deep learning-based approach for banana leaf diseases classification," in Datenbank systeme fu¨r Business, Technologie und Web (BTW 2017)-Workshop band, 2017.
27. K.P.Ferentinos, "Deep learning models for plant disease detection and diagnosis, "Computers and Electronics in Agriculture, vol.145,pp.311–318, 2018.
28. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification,"Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019.