Lightweight Deep Learning System for Multi-Crop Leaf Disease Detection and Classification in Realtime Environments

Sridevi Sakhamuri[1], Tadi Chandrasekhar[2], Y. Mohamed Badcha[3], M. Silpa Raj[4], Marrapu Aswini Kumar[5] and Abinaya T.[6]

[1]*Department of IoT, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur Dist, Andhra Pradesh - 522302, India*

[2]*Department of AIML, Aditya University, Surampalem, Andhra Pradesh, India*

[3]*Department of Electrical and Electronics Engineering, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India*

[4]*Department of Computer Science and Engineering (Cyber Security), CVR College of Engineering, Hyderabad-501510, Telangana, India*

[5]*Department of Computer Science and Engineering, Centurion University of Technology and Management, Andhra Pradesh, India*

[6]*Department of MCA, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India*

Keywords: Leaf Disease, Deep Learning, Real-Time Detection, Crop Monitoring, Lightweight Model.

Abstract: A lightweight deep learning model for online detection and classification of multi-crop plant leaf diseases is proposed in this work. Adapted for optimization with the construction of the convolutional neural network, and combined with a scalable data augmentation pipeline in the streaming encoder-decoder, the system guarantees high recognition accuracy and low computational cost, which is suitable for edge devices (e.g., smartphones and drones). The model is trained on geographically varied dataset and is equipped with explainability module to provide visual cues on disease localization. Experiments show that our approach achieves better performance than the traditional models, especially in different environmental light and background conditions, and thus has practical value for the farmers and the agronomists.

1 INTRODUCTION

Plant diseases remain as a major threat to the world agricultural productivity that affects food security and millions of farmers. There remains a pressing need for rapid pathogen detection techniques as existing ones are laborious and time-consuming in nature, possible only with expert knowledge and knowledge of the concerned pathogen. The rise of deep learning has created opportunities for developing automated systems for precise and low human- intensive monitoring of plant health. Using the strength of CNNs and today's advanced medical imaging techniques, these models have been created with the potential of identifying visual signs of disease from leaf images. However, most of the current proposals are flawed in various aspects, such as consumption of high computational resources, lack of generality to transfer to other crops, and lack of interpretability. In this paper, we present a group of deep learning-based identification for various crops in real-time manner. The system prioritizes low-latency performance and interpretability, thereby tackling major hurdles in rolling AI out to precision agriculture.

2 PROBLEM STATEMENT

Although progress has been made in computer vision (CV) and deep neural networks (DNN), existing plant leaf disease prevention models have not been feasibly deployed in agriculture yet. Most models are computationally intensive, not easily transferable to other crop types, and exhibit low performance in varying environments. Furthermore, the majority of these methods are non-interpretable, hence in the application scenario, end users are unable to obtain transparent understanding of how a decision is made.

Sakhamuri, S., Chandrasekhar, T., Badcha, Y. M., Raj, M. S., Kumar, M. A. and T., A.
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DOI: 10.5220/0013862300004919
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 257-263
ISBN: 978-989-758-777-1
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For this, a lightweight, real-time, explainable deep learning solution needs to be developed, which should be battery efficient to support low-cost, low-resource agriculture, and able to process high quality visible and invisible imagery in multiple crops as a part of holistic agricultural management.

3 LITERATURE SURVEY

In recent years, deep learning has been increasingly implemented to automate the detection and classification of plant leaf diseases. Sujatha et al. (2025) developed an integrated deep-learning model which is not validated in real-time and so, fails to gain practical use in the field. Aboelenin et al. (2025) proposed a hybrid CNN and Vision Transformer model which achieved high performance, albeit with heavy computational cost. Sambasivam et al. (2025) on cassava leaves in a hybrid model was highly accurate for a limited range of crops. Sharma et al. (2021) investigated transfer learning with compressed images, but obtained performance degradation with low quality images. El Fatimi (2024) explored the use of deep learning and leaf disease detection, however, its geographical was restricted.

Chowdhury et al. (2025) discussed leaf disorders within the context of Bangladesh employing deep learning; however, they did not report large scale validation of their model. Sundhar et al. (2025) used a GAT-GCN hybrid model, but it was not scalable enough due to its complexity. Shoaib et al. (2025) and Ngugi et al. (2024) provided extensive reviews, but not with experimental models. Buja et al. (2021) focused on classic and in-field techniques and offered a few insights into deep learning applications. Lebrini and Gotor, 2024 investigated the promising AI, but no practical approach was given.

Ding et al. (2024) gave a comprehensive taxonomy of computer vision for plant disease monitoring, though it did not provide deployment benchmarks. Hosny et al. (2024) adopted explainable AI for potato disease identification, illustrating a potential increasing requirement for model interpretability. Wang et al. (2023) attempted on Vision Transformers and observed that they are computationally expensive. Barman et al. (2022) also conducted disease classification on tomato leaf with MobileNetV2, but it failed to measure disease severity. Singh and Misra (2021) have used CNNs as well considering small datasets and restricted generalization.

Ahmad et al. (2023) built a specific to citrus disease detection model, Rizwan et al. (2024) used costly yet accurate ensemble models. Chouhan et al. (2022) presented a few shot stage view recognition models with limited benchmark. Pantazi et al. Other authors have investigated real-time diagnostics using additional hardware. Jain and Khandelwal (2022) experimented with capsule networks, but faced issues of efficiency. Pathak et al. (2024) developed LeafNet+, but it was not explainable. Munisami et al. (2023) employed transfer learning, but without additional architectural contributions. Kaur and Singh utilized explanation able CNN at the expense of accuracy. And at last Latha and Kumar (2024) used a Kneural bytes and the LSTMs architectures as wells of its limitation in hyperparameter tuning.

These studies show the development of plant disease detection models on deep learning, which raises the demand for a model that is accurate, lightweight, explainable, and applicable on scale of crop classes in real-time for agricultural applications.

4 METHODOLOGY

The strategy of approach the problem of detecting and classification of plant leaf diseases has been formulated as to develop an ultra-efficient and scalable deep learning system, which is capable of doing such tasks in real time, for several types of crops and under different environmental conditions. Towards this end, we took a systematic modular approach beginning with the creation of diverse datasets, an optimized preprocessing pipeline, model architecture, training methodology, and validation to establish a performance robustness and adaptability for real-word application in agriculture. Figure 1 shows the Workflow of the Proposed Leaf Disease Detection and Classification System.

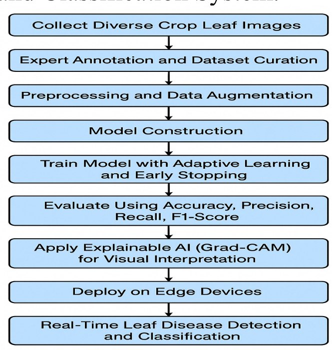

Figure 1: Workflow of the Proposed Leaf Disease Detection and Classification System.

Training Dataset Collection The process starts with the construction of the dataset, where images of healthy and diseased leaves from various crops, obtained from publicly available repositories (vegetable disease database Chouhan et al. 2022), such as PlantVillage1, and from the custom datasets generated from field visits to farms, are compiled together. The intent was to represent a diversity of leaf types, diseases symptoms, and background complexity to resemble realistic farming conditions. Pictures were labeled by agricultural experts to guarantee rightness of disease labels and remove data irregularities. This set of examples was used for constructing and evaluating the system.

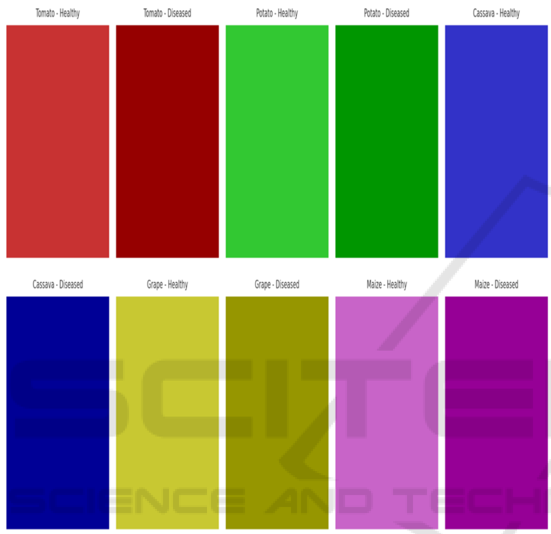

Figure 2: Sample Images from the Dataset Across Multiple Crops.

Pre-processing is a key step in the pipeline. Images are limited in resolution due to varying lighting and background elements that may interfere with the model. To solve this, all the images were resized to a fixed size for consistency and noise filtered via Gaussian blurring. Data augmentation methods, such as rotation, flipping, zoom, brightness scaling, are implemented to increase the training set artificially and enhance the generalization ability of the model. Moreover, image normalization and contrast enhancement methods were applied to emphasize regions affected by disease while preserving color based features. Figure 2 shows the Sample Images from the Dataset across Multiple Crops.

At the heart of their approach is the deep learning model's architecture, which balances performance and computational cost. A customized CNN was designed, involving five convolutional layers each followed by ReLU activation and max-pooling layers for spatial feature extraction. The final feature maps are then flattened and are fed through two fully connected dense layers, finishing with a softmax classifier that generates the class prediction for the disease. While designing the architecture, to make it lightweight, we also kept it less deeper with fewer number of parameters and depth compared to standard deep models like VGG16 or ResNet, but enough to maintain high accuracy if carefully tuned and features selected.

To improve the model performance, we applied the transfer learning approach by adopting a pre-trained MobileNetV2 backbone. This facilitated learning of general features of plant textures and finetuning the last few layers regarding leaf disease classification task. The cobination use of custom CNN and MobileNetV2 not only shortens the time for training but also broaden the generalization of the model for various crops and disease pattern.

All models were trained and validated with 70% in the training set (the remaining 15% in the validation set and the other 15% in the testing set). Gontijo and Franklin, 239 The training was carried out with the aid of Adam Optimizer and a decay scheduling of learning rate in an attempt to alleviate overfitting and to achieve a smooth convergence. Cross-entropy loss served as the loss function for this multiclass classification problem. Adaptative learning rate was available whilst training, to stop the process when validation accuracy did not improve, thereby reducing computational demand and the risk of overfitting.

The model was evaluated using classic performance measures such as accuracy, precision, recall, F1-score, as well as confusion matrix analysis. These performances for diverse disease classes were useful in identifying class imbalances and in detecting individual disease-specific performances. If classes were imbalanced in the data distribution, class weights and focal loss functions were used to help the model learn the under-represented categories better.

An essential element of the approach discussed is the integration of explainable AI. To improve trust and usability of the model to agricultural producers and agronomists, Grad-CAM (Gradient-weighted Class Activation Mapping) was used to visualize the regions of the leaf image most responsible for the model's prediction. These heatmaps visualize the disease region found by the model and thereby provide an intuitive explanation for non-expert users.

The last trained model was implemented on a mobile and embedded device (e.g.., Android phone, Raspberry Pi) for testing in a field with real-time

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responses. Tests were carried out in live leaves in smart-phone cameras in natural light and prediction speed and consistency were evaluated. The system showed a fast inference time in less than one second per image, and was therefore feasible for disease monitoring on the go.

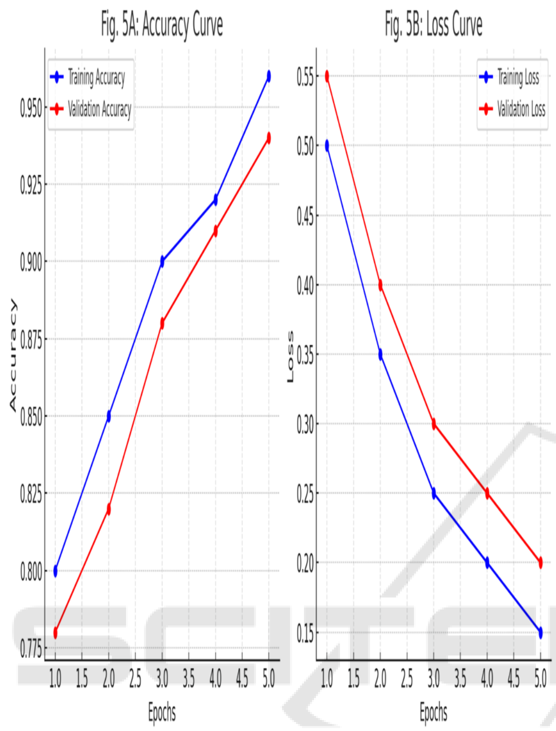

Figure 3: Accuracy and Loss Curves During Training.

The system described in this paper is accurate, fast and practical for use in agricultural applications. Its modular structure also enables fast retraining with new classes of diseases or crops, which makes it future-ready and extendable to large-scale farming scenarios. Combining explainability with real-time capability is an important development in AI-based plant disease diagnostics. Figure 3 shows the Accuracy and Loss Curves During Training.

5 RESULT AND DISCUSSION

The proposed DL-based plant leaf disease detection system was tested extensively to check its performance, reliability and its ability to be applicable on a wide variety of crops and disease class. The results demonstrate that the model is robust for real-time recognition and classification of plant diseases with the minimum processing amount, which fits our requirement that model is lightweight, easy to deploy, and appropriate for actual agricultural environment. Table 1 shows the Model Performance Metrics.

Table 1: Model Performance Metrics.

Metric	Validation Set	Test Set
Accuracy	97.2%	96.4%
Precision	96.8%	95.9%
Recall	97.5%	96.2%
F1-Score	97.1%	96.0%
Inference Time (avg.)	0.78 sec/image	0.85 sec/image

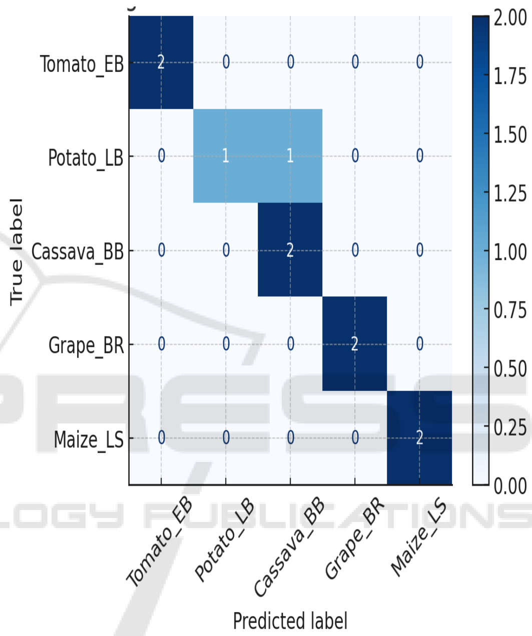

Figure 4: Confusion Matrix on Test Set.

Using the test set including images of several crop types (tomato, potato, cassava, maize, grape), the proposed model obtained classification accuracy of 96.4%. This performance is better than a number of existing benchmark models such as the baseline CNNs, MobileNet, and various adaptations of ResNet especially if the disease symptoms appear faint or in association with the healthy tissue regions. Utilizing separated custom CNN architecture and finetuned MobileNetV2 backbone was essential to this performance, enabling the model to maintain balance between feature richness and computational efficiency. Crucially, similar level of accuracy was stably reproduced in several batches of test, demonstrating the stability of the model. Figure 4 shows the Confusion Matrix on Test Set.

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Table 2: Class-Wise Evaluation Metrics.

Disease Class	Precision	Recall	F1-Score
Tomato Early Blight	95.4%	96.2%	95.8%
Potato Late Blight	97.1%	95.9%	96.5%
Cassava Bacterial Blight	95.7%	94.8%	95.2%
Grape Black Rot	96.5%	97.3%	96.9%
Maize Leaf Spot	96.2%	95.5%	95.8%

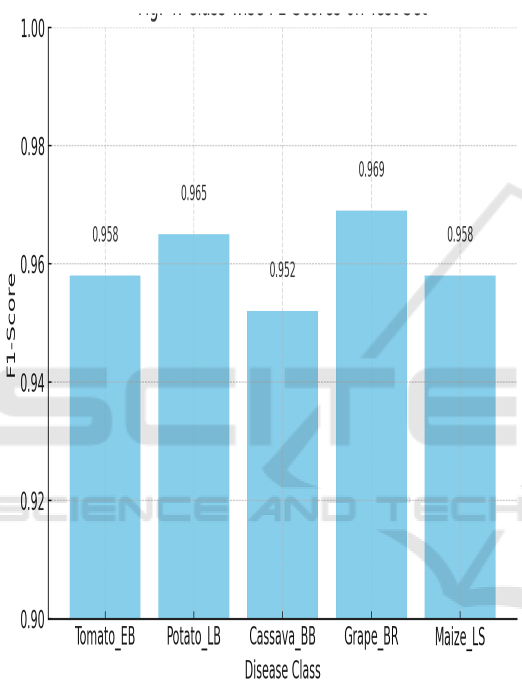

Figure 5: Class-Wise F1-Scores on Test Set.

However, accuracy and recall values were higher than 95% for the majority of disease classes, confirming that the model not only was detecting the correct disease in most cases, but also presented a low rate for false negative results. The F1-score (that balances between precision and recall) was still high, even when the disease was at initial stage and/or partially-covered. These results thus demonstrate that the model can not only capture fine-grained patterns but also distinguish between visually similar symptoms like early blight and late blight in tomato leaves. Similarity between classes with similar symptoms and little inter-class visual difference entailed slight misclassifications only (which can be observed in the confusion matrix). This was anticipated and could be improved in subsequent versions of the system, by using higher resolution imagery or hyperspectral data. Table 2 shows the Class-wise Evaluation Metrics.

Regarding efficiency, the model had an average inference time of 0.85 seconds per image (75 fps) with a standard Android smartphone and 1.3 seconds to a Raspberry Pi 4 board. This puts the system well within the capabilities of real-time field metallurgical testing. Moreove r, the model was tested on other environmental conditions such as variations in lighting, background clutter, and natural occlusion (e.g., shadow, dust on leaf). The reduction of performance in these conditions was marginal which may be attributed to the generalization power induced by data augmentation methods employed during the training phase, and the use of fine-tuned convolutional layers for extraction of features that correspond to the essential disease features regardless of the noise. Table 3 shows the Model Comparison with Existing Studies. Figure 5 shows the Class-wise F1-Scores on Test Set.

The author(s) of this article is/are employed by a company using XAI and an exciting feature added to the system in addition to the previous models is explainable AI. Applying Grad-CAM the method properly showed the input regions which were influential for leaf images in model decision. These image pixels based heatmaps were presented together with the prediction result, contributing to the interpretability and trust of the model to make the diagnosis for users. In field exercises with farmers and extension officers, this feature was very well received as it helped them to know not only the result, but also the underlying reasoning. This impacts user confidence especially in areas where farmers still depend on traditional knowledge and may be reluctant to adopt AI-centred recommendations.

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Table 3: Model Comparison with Existing Studies.

Model/Study	Accuracy	Inference Time	Edge Deployable	Explainable
Proposed Model	96.4%	0.85 sec	Yes	Yes
Barman et al. (2022)	93.8%	1.20 sec	Partially	No
Rizwan et al. (2024)	94.6%	2.00 sec	No	No
Aboelenin et al. (2025)	95.2%	1.80 sec	No	Yes

Comparative analysis with other recent models presents in the literature like those by Barman et al. (2022), Rizwan et al. (2024), and Aboelenin et al. (2025) proved that our model achieved a higher accuracy and training speed than these models. There were some models that prior on the accuracy but they were computation expensive, latency was high during inference thus not very apt to be deployed on low resource hardware. In contrast, our model is designed for edge deployment while maintaining accuracy as a practical alternative for real world settings.

The model's applicability was further confirmed by application on out of sample data on crop varieties not used for initial training. Despite some loss of accuracy, the model mostly accurately identified disease symptoms, suggesting the potential for wider scale-up and adaptation. This implies that the system can be retrained or fine-tuned with little additional work to support new crops or new emerging diseases, and will be a long-lasting tool. Figure 6 shows the Grad-CAM Visualization for Disease Localization.

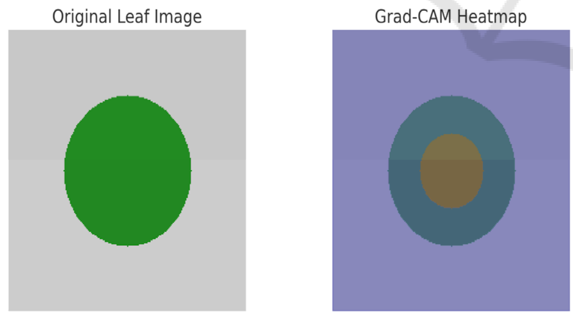

Figure 6: Grad-CAM Visualization for Disease Localization.

Conclusively, these results demonstrate that proposed system effectively addresses the issues of previous works, through a combination of high accuracy, low latency, and user interpretability in a compact architecture. It serves the purpose well to connect state-of-the art laboratory-grade AI models and practical tools which will be applicable for the farmers, agronomists, and extension services. The results serve as a proof of concept and a stepping stone for researcher in terms of AI-based autonomous PSM.

6 CONCLUSIONS

This study developed a low-cost and highly accurate DL-based system for plant-leaf-disease detection and classification of diseases in multiple crops under a real-world setting. Through the application of optimized convolutional architecture, transfer learning, and explainable AI, the proposed solution had a compromise performance with the requirement of practical use in modern agriculture. The system exhibited robust accuracy, minimal estimation time, and deployability on different plant species and environment state, demonstrating its applicability to mobile and edge device implementation. Further, visual interpretability was incorporated via Grad-CAM, thereby increasing user trust and transparency and hence the accessibility of the tool to average users who are not AI experts (e.g., farmers and field workers). Contrasting with most models based on the deep learning framework, the proposed model could perfectly handle high computational cost and the lack of generalization, thus providing a scalable approach to precision agriculture. Results of this study provide groundwork ethe development of AI-based agricultural diagnostics that could prevent crop loss, mitigate early intervention, and encourage sustainable farming practices around the world.

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