IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

WeatherLeaf: Multi-Modal Plant Disease Risk Prediction by Fusing Leaf Images with Real-Time Meteorological Data for Indian Farms

Er. Farzana Khan[1], Shubham Gupta[2], Abdul Samad Shaikh[3], Sana Shaikh[4], Anas Shaikh[5]
[1]Assistant Professor, Department of Information Technology
[2345]Students, Department of Information Technology
M. H. Saboo Siddik College of Engineering, Mumbai, Maharashtra, India
Corresponding Author: farzana.shaikh@mhssce.ac.in

Abstract: *Agriculture plays a vital role in India's economy, food security, and rural livelihood. However, plant diseases continue to cause significant crop losses every year due to delayed diagnosis, lack of expert availability, and limited access to real-time advisory systems. In recent years, deep learning-based plant disease detection systems have shown promising results by classifying diseases from leaf images. Most of these systems, however, depend only on visual symptoms and ignore environmental conditions that directly influence disease occurrence and spread. Factors such as temperature, humidity, rainfall, wind speed, and seasonal variation can strongly affect the development of fungal, bacterial, and viral infections in crops.*

This paper proposes WeatherLeaf, a multi-modal plant disease risk prediction framework that combines leaf image analysis with real-time meteorological data for Indian farms. The proposed system uses a Convolutional Neural Network to extract visual disease features from crop leaf images and a separate neural network branch to process weather-related parameters. The features from both branches are fused to generate a more context-aware disease prediction and risk score. The system is designed as a proposed framework for multi-crop disease prediction and can be extended for crops such as tomato, potato, rice, wheat, cotton, maize, and soybean. By integrating image-based diagnosis with weather intelligence, WeatherLeaf aims to improve early detection, reduce false predictions, and support farmers with more reliable agricultural advisory..

Keywords: Plant Disease Detection, Deep Learning, Agriculture AI, CNN, Weather Data, Multi-Modal Learning, Precision Farming, Indian Agriculture

I. INTRODUCTION

Agriculture is one of the most important sectors in India, providing employment to a large portion of the population and contributing significantly to national food production. Despite technological progress, Indian farmers still face major challenges in identifying and controlling crop diseases at the right time. Many plant diseases initially appear as small spots, color changes, fungal patches, or leaf deformation. If these symptoms are not detected early, the disease may spread rapidly across the field and result in reduced yield, financial loss, and poor crop quality.

Traditionally, plant disease identification depends on farmer experience, local agricultural officers, or laboratory-based diagnosis. These methods are useful but not always available in rural or remote areas. Farmers may not have immediate access to trained plant pathologists, and delays in diagnosis can lead to incorrect pesticide use or complete crop damage. To overcome this problem, Artificial Intelligence and computer vision have become important tools for automated disease detection. A farmer can capture a leaf image using a smartphone, and a trained deep learning model can classify whether the plant is healthy or infected.

Most existing AI-based plant disease detection systems use only leaf images as input. A Convolutional Neural Network learns visible patterns such as leaf spots, discoloration, rust marks, mildew texture, and shape deformation. Although this approach works well on clean datasets, it does not fully represent real agricultural conditions. In actual farms, disease development is not dependent only on visible symptoms. Weather and environmental conditions play a major role in disease growth. For example, high humidity and continuous rainfall may increase the chances of fungal infection, while extreme temperature variation can increase plant stress and make crops more vulnerable.

This limitation motivates the development of WeatherLeaf. Instead of depending only on image classification, the proposed system combines leaf image features with real-time weather data. The system can use temperature, humidity, rainfall, wind speed, and other meteorological parameters to support the final prediction. This makes the model more practical because it considers both what is visible on the leaf and what is happening in the surrounding environment. Such a multi-modal approach can improve early disease risk estimation and provide better decision support for Indian farmers.

The main objective of this paper is to present a proposed framework for multi-crop plant disease risk prediction using deep learning and meteorological data fusion. The paper does not claim experimental implementation results at this stage. Instead, it defines a structured architecture, methodology, expected outcomes, and future scope that can be implemented and evaluated in further research.

II. LITERATURE SURVEY

Deep learning has transformed the field of plant disease detection by enabling automated classification of crop diseases using image datasets. Early systems relied on traditional image processing techniques such as color segmentation, texture extraction, edge detection, and handcrafted feature selection. These methods required manual design of features and often performed poorly under changing lighting conditions, complex backgrounds, or disease symptoms at different growth stages. With the rise of Convolutional Neural Networks, models became capable of automatically learning visual features from large image datasets [2], [4].

The PlantVillage dataset has been widely used for plant disease classification research. It contains thousands of labeled images across multiple crops and disease categories. Many researchers have trained CNN models such as AlexNet, VGG, ResNet, DenseNet, MobileNet, and EfficientNet on such datasets and achieved high classification accuracy. These models can identify diseases such as early blight, late blight, powdery mildew, bacterial spot, leaf rust, and mosaic virus based on visible symptoms. However, several studies have observed that performance on controlled datasets may not always transfer perfectly to real farm images due to differences in lighting, leaf orientation, camera quality, background noise, and disease severity [1], [2], [3], [5].

Apart from image-based disease detection, weather-based crop disease forecasting has also been studied in agriculture. Plant pathogens are highly influenced by environmental conditions. Fungal diseases often increase when humidity remains high for long periods. Rainfall can support spore movement and infection spread. Temperature influences pathogen survival, plant immunity, and disease incubation period. Therefore, weather forecasting and disease warning models are already used in some agricultural advisory systems. However, many of these systems rely on rule-based thresholds or statistical models rather than modern deep learning fusion techniques [6], [7].

Recent developments in Artificial Intelligence show that multi-modal learning can improve prediction quality by combining information from different sources. In healthcare, models combine medical images with patient records. In autonomous vehicles, systems combine camera data, radar, lidar, and GPS. In smart agriculture, a similar principle can be applied by combining leaf images, weather signals, soil parameters, and farm history. However, multi-modal AI for plant disease diagnosis is still less explored compared to image-only classification. This creates a strong research opportunity, especially in the Indian agricultural context where weather patterns vary significantly across regions [4], [6].

The previous PlantDoc AI work focused on robust plant disease detection and adversarial defense for secure agricultural AI. That work highlighted the importance of building trustworthy plant disease detection systems rather than focusing only on raw accuracy. WeatherLeaf extends the broader idea of reliable agricultural AI in a different direction by focusing on environmental awareness and multi-modal prediction rather than adversarial security. Thus, the proposed work remains related to plant disease AI but introduces a fresh research contribution [8].

III. PROBLEM STATEMENT

Most current plant disease detection systems depend only on leaf images for classification. While image-based diagnosis is useful, it has practical limitations in real-world farming. A disease may be in an early stage where visual symptoms are weak or unclear. In some cases, two diseases may produce similar leaf marks, making classification difficult. Environmental stress, nutrient deficiency, and water shortage can also create symptoms that visually resemble disease infection. As a result, an image-only AI model may sometimes give an incorrect prediction.

Another important limitation is the absence of weather context. Diseases do not occur randomly; they are often linked with environmental triggers. For example, warm and humid conditions may increase fungal disease risk, while prolonged wet leaf surfaces after rainfall may support pathogen development. If an AI system ignores these conditions, it may fail to provide early warning or risk estimation. A system that considers weather data along with leaf image symptoms can make a more informed prediction.

Therefore, the problem addressed in this paper is the lack of a practical multi-modal plant disease risk prediction system that combines visual crop symptoms with real-time meteorological data. The proposed WeatherLeaf framework aims to bridge this gap by designing a fusion-based AI model suitable for Indian farms and multi-crop disease prediction.

IV. OBJECTIVES OF THE PROPOSED SYSTEM

The first objective of WeatherLeaf is to design a multi-modal deep learning framework that can process both crop leaf images and weather data. The image branch of the model focuses on detecting visible symptoms, while the weather branch evaluates environmental conditions that may support disease development. By combining both sources, the system aims to generate a more reliable disease prediction.

The second objective is to support early disease risk estimation. Instead of only classifying a disease after symptoms are clearly visible, the system can use weather conditions to indicate whether the crop environment is favorable for certain infections. This can help farmers take preventive action before the disease spreads widely.

The third objective is to make the system useful for Indian farming conditions. India has diverse climates, cropping patterns, and regional weather variations. A system designed for Indian farms should be able to use location-based weather data and support multiple crops rather than being limited to a single crop type.

The fourth objective is to provide a scalable research framework that can later be expanded with soil sensors, IoT devices, drone images, multilingual advisory, and mobile deployment. This makes WeatherLeaf not only a disease classifier but also a foundation for future smart farming systems.

V. PROPOSED SYSTEM: WEATHERLEAF

WeatherLeaf is proposed as a multi-modal plant disease risk prediction system that combines two different types of input: leaf images and meteorological data. The leaf image provides visual evidence of disease symptoms, while weather data provides environmental evidence related to disease risk. These two sources are processed separately and then fused to produce the final prediction.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

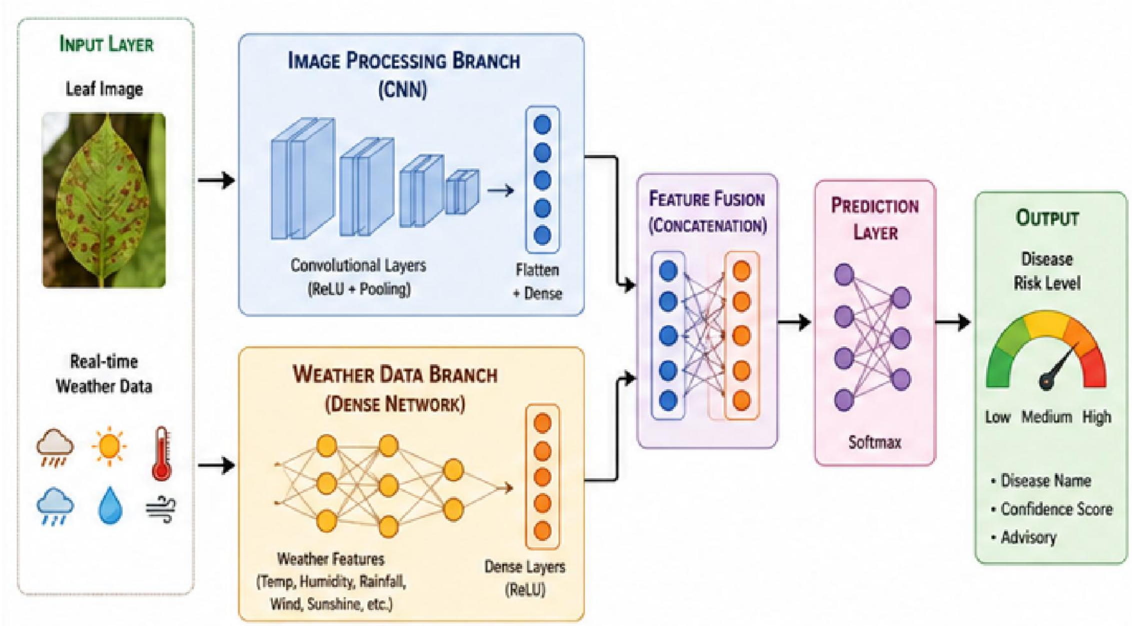

Fig 5.1 : Overall Architecture of Weather Leaf Multi-Modal Disease Prediction System

The system begins when a farmer uploads a crop leaf image through a mobile or web interface. The application also captures or asks for the user's location. Based on this location, the system fetches real-time weather data such as temperature, relative humidity, rainfall, wind speed, and atmospheric pressure from a weather data source. The image is sent to a CNN-based disease detection model, and the weather values are sent to a separate dense neural network. After feature extraction, the image features and weather features are combined in a fusion layer. The final classifier predicts the likely disease class and also generates a risk level such as low, medium, or high.

This architecture makes the system more context-aware than traditional image-only systems. For example, if a leaf image shows mild spots and the weather data indicates high humidity with recent rainfall, the system may assign a higher disease risk. On the other hand, if the image contains unclear symptoms but the weather is not favorable for disease spread, the system may assign a lower confidence or suggest monitoring. This type of combined reasoning can reduce unnecessary pesticide usage and improve farmer decision-making.

VI. SYSTEM ARCHITECTURE

The proposed WeatherLeaf architecture consists of five major layers: input acquisition layer, preprocessing layer, feature extraction layer, fusion layer, and prediction/advisory layer.

A. Input Acquisition Layer

The input acquisition layer collects data from two sources. The first source is the leaf image uploaded by the farmer. The image may be captured using a smartphone camera in natural field conditions. The second source is real-time meteorological data collected using a weather API or public meteorological service. The location can be obtained from GPS or manually entered by the user.

B. Preprocessing Layer

In this layer, the leaf image is resized, normalized, and cleaned before being passed to the CNN model. Image preprocessing helps reduce variation due to camera resolution and lighting. Weather data is also cleaned and normalized. Missing values can be handled using historical averages or nearest available weather station data. This step is important because raw weather data may contain noise or incomplete values.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

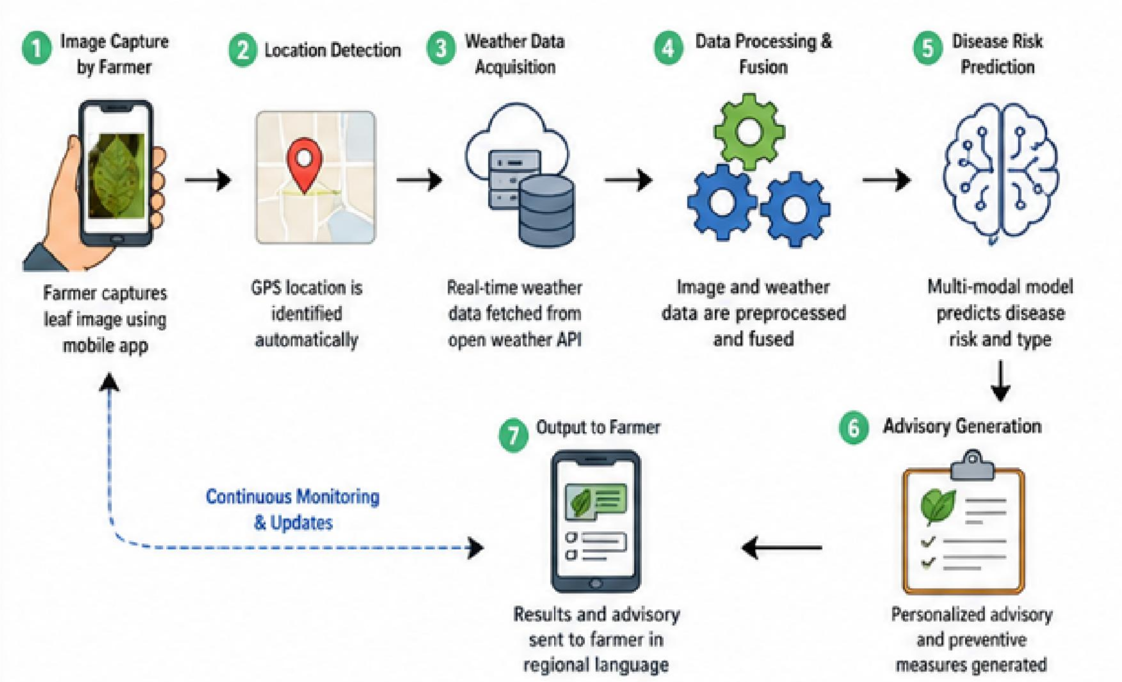

Fig 6.1: Operational Workflow of WeatherLeaf Framework

C. Feature Extraction Layer

The image branch uses a CNN model such as ResNet, MobileNet, or EfficientNet to extract disease-related visual features. These features may include color patterns, lesion boundaries, texture irregularities, fungal marks, and leaf deformation. The weather branch uses fully connected layers to learn patterns from meteorological parameters. For example, high humidity and moderate temperature may be strongly related to fungal disease risk.

D. Fusion Layer

The fusion layer combines the output feature vector from the image branch and the output feature vector from the weather branch. This can be done using concatenation followed by dense layers. The combined feature representation allows the model to learn relationships between symptoms and environmental conditions.

E. Prediction and Advisory Layer

The final layer predicts the disease class and risk score. The output can include the crop name, possible disease, confidence score, weather-based risk level, and suggested preventive action. In future versions, this layer can be connected to a multilingual chatbot that provides advisory in regional languages.

VII. METHODOLOGY

The proposed methodology follows a structured pipeline from data collection to prediction generation. Since this paper is proposed-system based, the methodology describes how the system can be implemented and evaluated in future work.

First, a multi-crop image dataset will be prepared using publicly available plant disease datasets such as PlantVillage along with real farm images collected from Indian agricultural conditions. The dataset should include healthy and diseased leaves from crops such as tomato, potato, rice, wheat, cotton, maize, and soybean. The images should be divided into training, validation, and testing sets.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

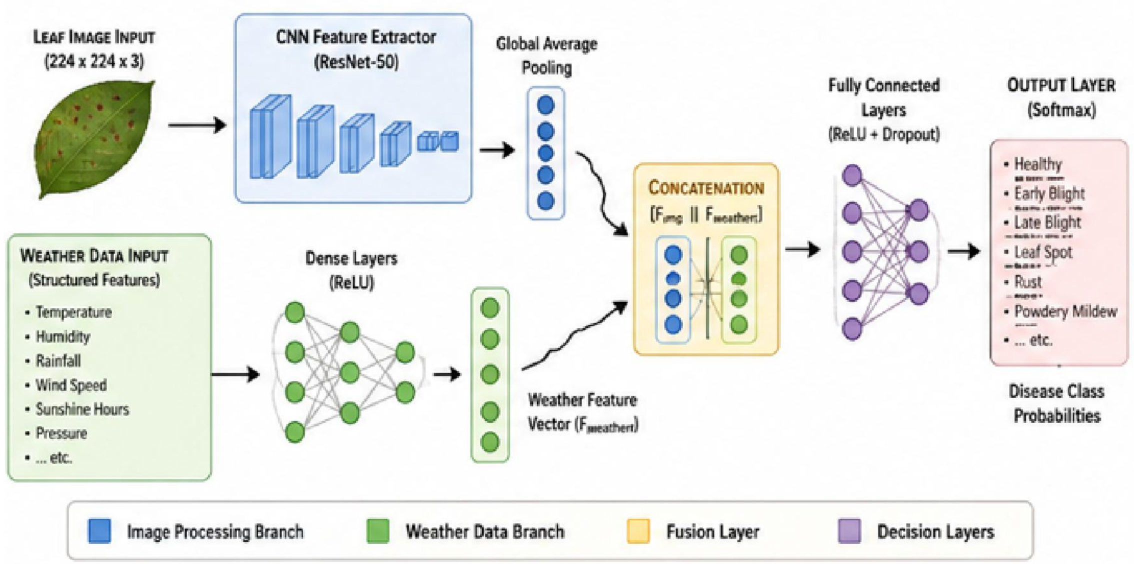

Fig 7.1: Deep Learning Fusion Model for Multi-Modal Prediction

Second, weather data will be collected for crop-growing regions using public meteorological sources or weather APIs. Important parameters include temperature, humidity, rainfall, wind speed, and atmospheric pressure. Historical weather data can be mapped with disease occurrence records wherever available. For real-time prediction, current weather data can be fetched based on the farmer's location.

Third, the image model will be trained using a CNN architecture. Transfer learning can be used to reduce training time and improve performance with limited data. A pre-trained model such as MobileNetV3 or ResNet50 can be fine-tuned on the plant disease dataset. Data augmentation techniques such as rotation, flipping, brightness adjustment, and zooming can be applied to improve robustness.

Fourth, the weather model will be trained using dense neural network layers. The weather inputs will be normalized and converted into numerical feature vectors. The model will learn how different weather combinations influence disease risk.

Finally, the image and weather branches will be joined through a fusion layer. The combined model will be trained to predict disease class and risk level. During testing, the system will compare image-only predictions with multi-modal predictions to evaluate whether the weather fusion improves accuracy and reliability.

VIII. EXPECTED RESULTS AND DISCUSSION

As this is a proposed-system paper, actual experimental results are not claimed. However, based on the design of the system, WeatherLeaf is expected to perform better than traditional image-only models in practical farming conditions. The addition of weather data can help improve predictions in cases where image symptoms are unclear, early-stage, or visually similar across diseases.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

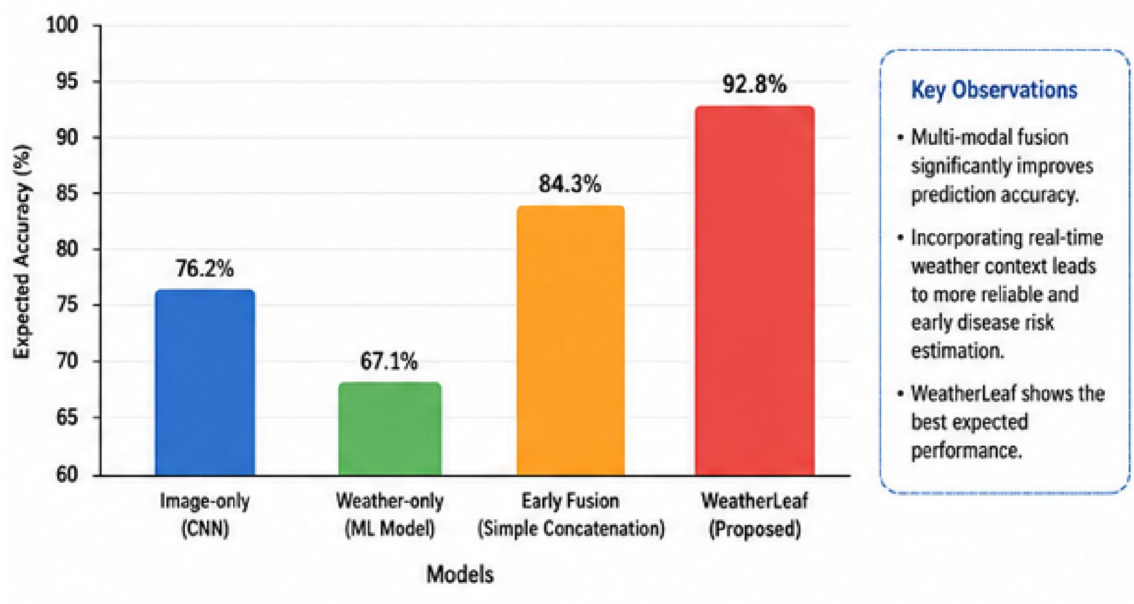

Fig 8.1: Expected Performance Comparison of Different Models

The image-only CNN is expected to perform well when symptoms are clearly visible and the image quality is good. However, it may struggle when symptoms are mild or when environmental stress resembles disease symptoms. The weather-only model may not be sufficient for exact disease classification because weather conditions alone cannot confirm the visual presence of disease. The fusion model is expected to provide the best balance because it uses both visual and environmental evidence.

Model Type	Input Used	Expected Strength	Expected Limitation
Image-only CNN	Leaf image	Strong visual symptom detection	Weak environmental awareness
Weather-only Model	Meteorological data	Useful for disease risk estimation	Cannot confirm visible symptoms
WeatherLeaf Fusion Model	Leaf image + weather data	Context-aware disease prediction	Requires reliable weather data

Table I: Expected Comparative Performance

The proposed system is also expected to reduce false positives. For example, leaf discoloration caused by nutrient deficiency may be visually confused with disease, but weather conditions may help reduce unnecessary disease warnings. Similarly, the system may provide an early warning when weather conditions are favorable for infection even if visible symptoms are not fully developed.

IX. ADVANTAGES OF THE PROPOSED SYSTEM

WeatherLeaf provides several practical advantages over conventional plant disease detection systems. The most important advantage is multi-modal intelligence. By combining image features and weather signals, the system is able to make predictions based on broader agricultural context rather than depending on one input source.

Another advantage is its suitability for Indian farms. Weather conditions in India vary widely across states and seasons. A model that uses local weather data can produce more region-aware predictions. This can be especially useful during monsoon periods when fungal diseases spread quickly due to high moisture.

The system can also support preventive farming. Instead of waiting until disease symptoms become severe, farmers can receive early risk warnings based on weather trends. This may help reduce crop loss and support timely pesticide or organic treatment decisions.

WeatherLeaf is also scalable. The same architecture can be extended to include soil moisture, soil pH, satellite images, drone images, pest data, and previous farm history. This makes it suitable for future precision agriculture platforms.

X. LIMITATIONS

Although the proposed system offers strong potential, it also has certain limitations. The first limitation is dependency on reliable weather data. In rural areas, weather station coverage may be limited, and API-based data may not always represent exact field-level conditions. Microclimate variations within farms can affect disease development.

The second limitation is dataset availability. A strong multi-modal model requires image data and weather data linked to the same crop location and time period. Such combined datasets are not always easily available. Therefore, future implementation may require careful dataset preparation and field data collection.

The third limitation is that weather data can improve risk prediction but cannot replace visual diagnosis. Some diseases may occur even when weather conditions are not strongly favorable, and some weather conditions may increase risk without actual infection. Therefore, the model must be evaluated carefully before real-world deployment.

XI. FUTURE SCOPE

WeatherLeaf can be extended in several directions. The first future enhancement is integration with IoT-based soil sensors. Soil moisture, soil temperature, pH value, and nutrient levels can improve the system's ability to distinguish between disease symptoms and nutrient deficiency.

The second extension is drone-based and satellite-based crop monitoring. Instead of analyzing only individual leaf images, the system can be expanded to field-level disease mapping. This would help identify affected zones across large farms.

The third future improvement is multilingual advisory support. Since Indian farmers speak different regional languages, the system can be connected with a chatbot that explains disease risk, preventive measures, and treatment suggestions in Hindi, Marathi, Telugu, Tamil, Bengali, and other languages.

Another important future direction is edge deployment. A lightweight version of WeatherLeaf can be developed for Android devices so that farmers can use the system even with poor internet connectivity. Federated learning can also be explored to train the model across different farms without sharing raw images, improving privacy and regional adaptability.

XII. CONCLUSION

This paper presented WeatherLeaf, a proposed multi-modal framework for plant disease risk prediction using leaf images and real-time meteorological data. Unlike conventional image-only systems, WeatherLeaf considers both visible disease symptoms and environmental conditions that influence disease development. The proposed architecture includes an image branch, weather branch, fusion layer, and advisory output layer.

The system is designed for Indian farms and supports a multi-crop approach, making it suitable for diverse agricultural conditions. Although the present work is proposed-system based and does not claim experimental results, the framework provides a clear foundation for future implementation, testing, and journal publication. By combining deep learning with weather intelligence, WeatherLeaf can contribute to more reliable, early, and context-aware plant disease prediction for smart agriculture.

ACKNOWLEDGMENT

The authors would like to express sincere gratitude to the Department of Information Technology, M. H. Saboo Siddik College of Engineering, Mumbai, for providing academic guidance and support. The authors also acknowledge the

contribution of existing research in plant disease detection, deep learning, and agricultural meteorology, which helped shape the proposed WeatherLeaf framework.

REFERENCES

[1]. D. P. Hughes and M. Salathé, "An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics," arXiv preprint arXiv:1511.08060, 2015.

[2]. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, vol. 7, 2016.

[3]. K. P. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[4]. A. Kamilaris and F. X. Prenafeta-Boldú, "Deep Learning in Agriculture: A Survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018.

[5]. J. G. A. Barbedo, "Factors Influencing the Use of Deep Learning for Plant Disease Recognition," Biosystems Engineering, vol. 172, pp. 84–91, 2018.

[6]. Food and Agriculture Organization of the United Nations, "Plant Health and Crop Disease Loss Reports," FAO, Rome, 2023.

[7]. India Meteorological Department, "Agrometeorological Advisory Services and Weather Data," Ministry of Earth Sciences, Government of India, 2024.

[8]. Abdul Samad Shaikh, Shubham Gupta, Anas Shaikh, and Sana Shaikh, "PlantDoc AI: Robust Defense System Against Adversarial Attacks using Deep Learning," Department of Information Technology, M. H. Saboo Siddik College of Engineering, 2026.

[9]. A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems, 2012.

[10]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016.

[11]. M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," International Conference on Machine Learning, 2019.

[12]. Ministry of Agriculture and Farmers Welfare, Government of India, "Digital Agriculture Mission and Farmer Advisory Initiatives," New Delhi, 2024.