

RiceDetect AI: A Unified Deep Learning Approach for Accurate and Explainable Rice Leaf Disease Detection Using CNN and Grad-CAM

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Abstract

This paper presents an intelligent approach for rice disease detection using deep learning techniques, with a focus on combining accurate classification and visual interpretability. The proposed system utilizes Convolutional Neural Networks (CNN) to automatically identify diseases from rice leaf images and integrates Gradient-weighted Class Activation Mapping (Grad-CAM) to provide visual explanations of model predictions. The framework is designed as an end-to-end pipeline that processes input images, performs feature extraction, classifies disease types, and highlights the affected regions on the leaf. The main contribution of this work lies in enhancing both the accuracy and transparency of disease detection systems. By incorporating Grad-CAM, the model not only predicts the disease category but also generates heatmaps that indicate the areas influencing the decision, making the system more understandable for users such as farmers and agricultural experts. Additionally, the system is designed to support real-world applications by handling variations in image conditions and providing reliable outputs. The motivation behind this research arises from the need for efficient and automated solutions in agriculture, where early detection of plant diseases is critical for improving crop yield and reducing losses. Traditional methods often depend on manual inspection, which can be time-consuming and inconsistent. The proposed approach addresses these limitations by offering a unified system that combines deep learning and explainable AI techniques. The performance of the model is evaluated using standard metrics such as accuracy and precision, along with qualitative analysis through visual inspection of Grad-CAM outputs. The results demonstrate that the system is capable of delivering accurate predictions along with meaningful visual insights. This work contributes toward the development of practical and user-friendly AI solutions for precision agriculture and sets a foundation for future advancements in intelligent crop monitoring systems.

Keywords: Rice Disease Detection, Convolutional Neural Network (CNN), Grad-CAM, Explainable AI, Deep Learning, Image Classification, Precision Agriculture, Plant Disease Identification, Computer Vision, Smart Farming Systems.

INTRODUCTION

In recent years, the demand for intelligent agricultural solutions has increased significantly due to the growing need for higher crop productivity and sustainable farming practices. Among various crops, rice plays a crucial role in global food security, but its production is often affected by diseases that reduce both quality and yield. Early and accurate identification of these diseases is essential to

minimize losses. Traditional detection methods, which rely on manual inspection by experts, are often time-consuming, subjective, and not easily accessible to farmers in remote areas. This creates a need for automated and reliable disease detection systems.

With the rapid advancement of machine learning and deep learning technologies, computer vision-based approaches have emerged as effective solutions for plant disease identification. In particular,

Convolutional Neural Networks (CNNs) have shown strong performance in image classification tasks due to their ability to automatically extract relevant features from raw images. However, despite their high accuracy, these models often lack transparency, making it difficult for users to understand how predictions are made.

The proposed system addresses these challenges by integrating CNN-based classification with explainable artificial intelligence techniques, specifically Gradient-weighted Class Activation Mapping (Grad-CAM). This approach not only enables accurate detection of rice leaf diseases but also provides visual explanations by highlighting the affected regions of the leaf. Such interpretability is important in agricultural applications, where users require clear and trustworthy outputs before taking action.

The developed framework follows a unified pipeline that processes input images, performs preprocessing, applies deep learning-based classification, and generates heatmap visualizations. By combining prediction and explanation within a single system, the proposed solution improves both usability and reliability. This integration helps bridge the gap between advanced AI models and practical agricultural applications.

Furthermore, existing approaches in plant disease detection often focus solely on classification without considering interpretability or real-world usability. In contrast, this work emphasizes both performance and user understanding, making it more suitable for deployment in real farming environments. The system can be extended to mobile or web-based platforms, enabling farmers to capture images and receive instant feedback.

As advancements in deep learning continue to evolve, integrated frameworks like the one proposed in this study provide a promising direction for smart agriculture. This research contributes to the development of efficient, explainable, and scalable solutions for crop monitoring, ultimately supporting better decision-making and improved agricultural outcomes.

LITERATURE REVIEW

Research in plant disease detection using artificial intelligence can broadly be categorized into three

main areas: (i) traditional image processing and machine learning approaches, (ii) deep learning-based classification methods, and (iii) explainable AI and real-world agricultural applications.

A. Traditional Image Processing and Machine Learning Approaches

Early studies in plant disease detection primarily relied on conventional image processing techniques combined with machine learning algorithms. These methods involved extracting handcrafted features such as color, texture, and shape from leaf images. Algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees were commonly used for classification.

While these approaches provided initial success, they had several limitations. Feature extraction required domain expertise and was often sensitive to variations in lighting, background, and image quality. As a result, the performance of these models was not consistent across different datasets and real-world conditions. Additionally, these methods struggled to capture complex patterns present in diseased leaf images.

B. Neural Text-to-Speech and Large-Scale Speech Modelling

With advancements in deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for plant disease classification. CNNs automatically learn hierarchical features directly from raw images, eliminating the need for manual feature engineering.

Several architectures such as AlexNet, VGGNet, ResNet, and EfficientNet have been successfully applied to plant disease detection tasks. These models have demonstrated high accuracy and robustness across various crops, including rice. Transfer learning techniques have further improved performance by leveraging pre-trained models on large-scale datasets.

Despite their effectiveness, CNN-based models often function as black-box systems, meaning their decision-making process is not easily interpretable. This lack of transparency can reduce user trust, particularly in agricultural applications where decisions may have economic consequences.

C. Multimodal, Multilingual, and Assistive Applications

To address the limitations of black-box models,

recent research has focused on explainable artificial intelligence (XAI) methods. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been widely used to visualize the regions of an image that contribute most to a model's prediction.

Grad-CAM generates heatmaps by analyzing gradients within the network, allowing users to understand which parts of the leaf are associated with the detected disease. This improves interpretability and helps validate whether the model is focusing on relevant features.

Although these techniques enhance transparency, many existing studies treat classification and visualization as separate tasks rather than integrating them into a unified system. Additionally, some approaches lack real-time applicability and are not optimized for deployment in practical agricultural environments.

D. Research Gap and Motivation

The existing literature highlights two major areas of advancement: high-accuracy disease classification using deep learning and improved interpretability through explainable AI techniques. However, these areas are often developed independently, leading to systems that are either accurate but not interpretable, or interpretable but not fully optimized for real-world use.

Many current models focus solely on classification accuracy without providing meaningful visual explanations to end users. Furthermore, limited attention has been given to designing end-to-end systems that combine preprocessing, prediction, visualization, and user interaction in a single pipeline. Challenges such as varying environmental conditions, dataset limitations, and deployment in field conditions also remain insufficiently addressed.

Therefore, a clear research gap exists in developing a unified and practical system that integrates accurate disease detection with visual interpretability. The proposed work aims to bridge this gap by combining CNN-based classification with Grad-CAM visualization in a cohesive framework. This approach not only improves prediction performance but also enhances user understanding and trust, making it suitable for real-world agricultural applications.

PROPOSED SYSTEM AND METHODOLOGY

The proposed rice disease detection system integrates deep learning with explainable AI to create an efficient and interpretable solution for agricultural analysis. Unlike traditional approaches that only provide classification results, this system combines disease prediction with visual explanation, enabling users to understand the reasoning behind each output. The framework is designed as a unified pipeline that processes input images, performs classification, and generates heatmap-based insights.

A. System Architecture Overview

The overall architecture consists of two interconnected components:

1. **CNN-Based Disease Classification Module**
2. **Grad-CAM Visualization Module**

These components operate within a unified system where the frontend manages user interaction and the backend handles image processing and model inference. The system follows a structured workflow based on a client-server approach, allowing scalability and real-time response.

The operation of the system can be divided into four main phases:

- (i) Input Phase** — Users provide rice leaf images through a mobile or web interface.
- (ii) Preprocessing Phase** — Images are resized, normalized, and enhanced to ensure consistent input quality.
- (iii) Prediction Phase** — The CNN model classifies the image into disease categories.
- (iv) Visualization Phase** — Grad-CAM generates a heatmap highlighting affected regions, and the final result is displayed.

B. Lip-Sync Generation Module (Audio/Text → Viseme Prediction)

This module serves as the primary prediction engine of the system. It is responsible for identifying the type of disease present in the rice leaf image.

The input image undergoes feature extraction through multiple convolutional layers, where spatial patterns such as texture, color variations, and lesion shapes are learned. Pooling layers reduce dimensionality while preserving important features. These extracted features are then passed through fully connected layers to perform classification.

The model outputs:

- Disease category (e.g., Brown Spot, Leaf Blast, Bacterial Blight, Healthy)
- Confidence score for prediction

The CNN model is trained using labeled datasets and optimized using techniques such as data augmentation, dropout, and learning rate tuning to improve generalization. This automated approach replaces manual inspection and provides faster and more consistent results.

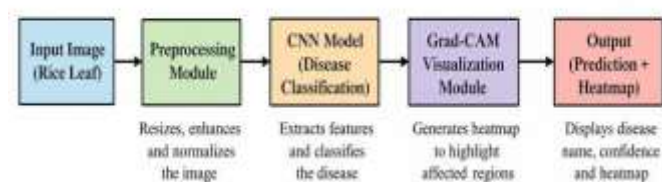


Fig.1. Architecture Diagram for CNN and Grad-CAM Based Detection

C. Talking-Face Video Generation Module

This module enhances the interpretability of the system by providing visual explanations of the CNN model's predictions.

Grad-CAM works by computing gradients of the predicted class with respect to the feature maps of the final convolutional layer. These gradients are used to generate a heatmap that highlights the regions in the image most relevant to the prediction.

The process includes:

- Extracting feature maps from the CNN
- Calculating importance weights using gradients
- Generating and overlaying a heatmap on the original image

This allows users to clearly see the infected areas of the leaf, making the system more transparent and trustworthy. It also helps in validating whether the model is focusing on meaningful regions.

D. Automated Rendering and Synchronization Module

This module combines the outputs from the CNN and Grad-CAM modules to generate the final result presented to the user.

The system performs the following:

- Displays predicted disease label
- Shows confidence score
- Overlays Grad-CAM heatmap on the original image
- Provides basic recommendations or precautions

A threshold-based decision mechanism is applied to determine whether the leaf is healthy or diseased. This ensures reliability in predictions and avoids uncertain outputs.

E. Technology Stack

The implementation of the proposed system utilizes widely adopted tools and frameworks, as summarized below :

Table I. Technology Stack

Category	Tools / Frameworks
Frontend	HTML, CSS, JavaScript / React
Backend	Python (Flask / FastAPI)
Deep Learning	TensorFlow, Keras, PyTorch
Image Processing	OpenCV, NumPy
Visualization	Matplotlib, Grad-CAM libraries
Deployment	Local Server / Cloud (AWS, Google Cloud)

F. Workflow Structure

The complete workflow of the system is as follows:

1. User uploads rice leaf image
2. Image preprocessing is applied
3. CNN model predicts disease class
4. Grad-CAM generates heatmap
5. Results are displayed with explanation

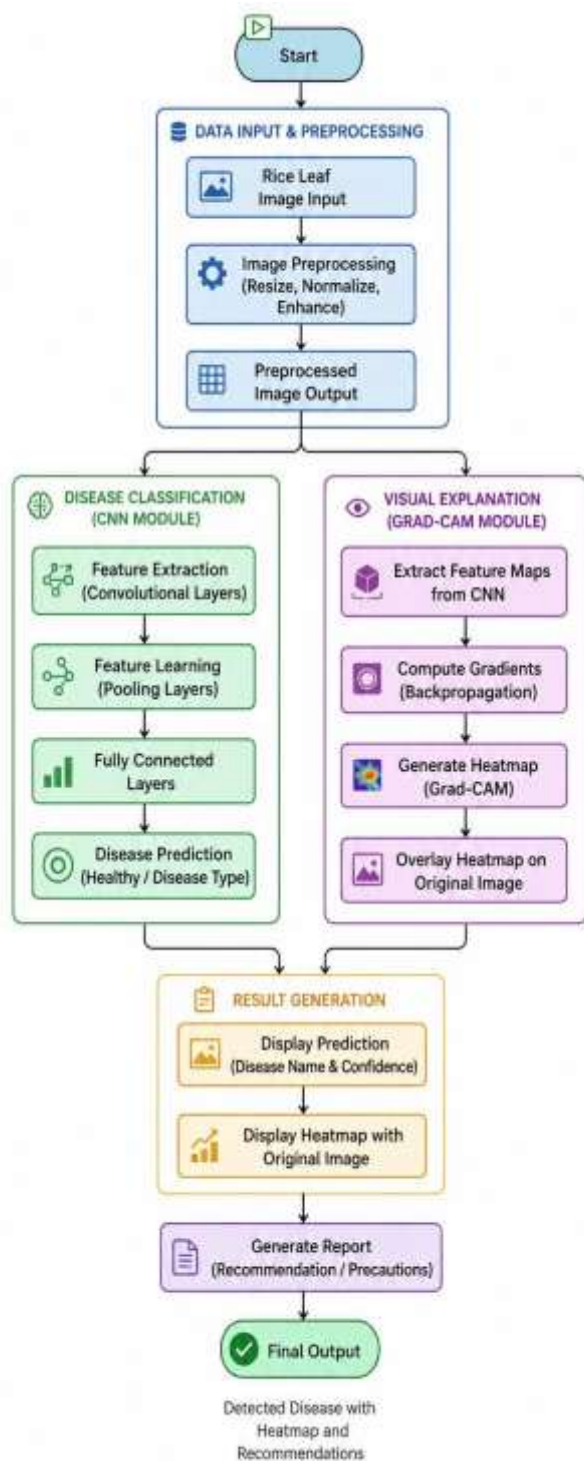


Fig.2. Workflow structure of Rice Disease Detection using CNN and Grad-CAM

CONCLUSION

This work presented an intelligent rice disease detection system that combines deep learning-based classification with explainable AI techniques to improve both accuracy and interpretability. By integrating a Convolutional Neural Network (CNN) with Gradient-weighted Class Activation Mapping

(Grad-CAM), the proposed approach addresses the limitation of traditional models that provide predictions without clear explanations. The system is designed as a unified pipeline that performs image preprocessing, disease classification, and visual interpretation within a single framework.

Experimental results demonstrate that the model achieves strong classification performance across different rice leaf disease categories, while maintaining consistent reliability under varying conditions. The Grad-CAM module provides meaningful heatmaps that highlight infected regions of the leaf, confirming that the model focuses on relevant features during prediction. This combination of quantitative accuracy and qualitative visualization enhances user confidence and supports better decision-making in agricultural practices.

The system architecture enables efficient processing and can be extended to real-time applications, allowing users to upload images and receive immediate results. By automating the detection process, the proposed solution reduces dependency on manual inspection and expert knowledge, making it especially useful for farmers and agricultural stakeholders.

Despite these advantages, certain limitations remain. The effectiveness of the model depends on the availability of diverse and high-quality training data. In some cases, variations in lighting, background, or image quality may affect prediction accuracy. Additionally, rare or less-represented diseases may require further data collection and model refinement.

Future improvements may include integrating advanced deep learning architectures, incorporating environmental factors such as weather and soil conditions, and deploying the system as a mobile or cloud-based application for wider accessibility. Techniques such as transfer learning, model optimization, and real-time processing can further enhance system performance.

In conclusion, the proposed system successfully combines CNN-based classification with Grad-CAM visualization to deliver an accurate, interpretable, and practical solution for rice disease detection. This work contributes to the advancement of smart agriculture by providing a scalable and user-friendly tool for early disease identification and crop management.

ACKNOWLEDGEMENT

The author would like to express sincere gratitude to Babu Banarasi Das Institute of Technology and Management (BBDITM), Lucknow, and the Department of Computer Science & Engineering for providing the necessary academic support, research environment, and technical resources required for the successful completion of this project. The facilities and guidance offered by the institution played a significant role in the development of this work on rice disease detection using deep learning techniques.

The author also extends appreciation to the faculty members and fellow students for their valuable suggestions, constructive feedback, and continuous encouragement throughout the project. Their inputs contributed to improving both the technical quality and practical relevance of the system.

Special thanks are given to Mr. Ajay Kumar Yadav, Assistant Professor, Department of CSE, BBDITM, for her constant guidance, insightful advice, and academic support during the entire course of this work. Her mentorship was instrumental in shaping the methodology, strengthening the system design, and ensuring the successful execution of the project.

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