International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 02 | Feb 2026 www.irjet.net p-ISSN: 2395-0072

Rice Leaf Disease Detection and Solution Recommendation System

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Abstract - *Agriculture plays a major role in India's economy, and rice is one of the most important staple food crops. However, rice cultivation is severely affected by leaf diseases such as Brown Spot, Leaf Smut, and Bacterial Leaf Blight, which reduce crop yield and quality. Early and accurate identification of these diseases is essential to prevent large-scale crop loss. This paper presents a Rice Leaf Disease Detection and Solution Recommendation System using image processing and deep learning techniques. The proposed system uses a Convolutional Neural Network (CNN) and transfer learning models to classify rice leaf images into healthy or diseased categories. The input images are collected and preprocessed through resizing, normalization, and augmentation to improve model accuracy and robustness. The trained model automatically extracts features such as texture, color, and lesion patterns to predict the disease class. The system is implemented using Python and TensorFlow/Keras and is integrated with a Django-based web application that allows users to upload rice leaf images and receive instant disease predictions along with recommended treatments and preventive measures. This approach reduces dependency on manual inspection, provides fast and accurate diagnosis, and supports farmers in taking timely actions to improve crop productivity and promote sustainable agriculture.*

KEY WORDS : Rice Leaf Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Transfer Learning, Image Classification

1. INTRODUCTION

Agriculture is one of the most important sectors in India, and it plays a major role in supporting the national economy and ensuring food security. Rice is one of the primary staple crops cultivated across India and many other Asian countries. However, rice production is highly affected by various plant diseases that reduce both yield and grain quality. Diseases such as Brown Spot, Leaf Smut, and Bacterial Leaf Blight can damage rice leaves, reduce photosynthesis, and ultimately lead to significant crop loss. Traditionally, rice leaf disease detection is performed manually by farmers or agricultural experts through visual inspection. This manual method is time-consuming, subjective, and often inaccurate, especially when multiple diseases exhibit similar symptoms at early stages.

In recent years, deep learning and computer vision techniques have shown strong performance in agricultural disease detection by analysing leaf images and extracting complex patterns automatically. Convolutional Neural Networks (CNNs) have become one of the most widely used deep learning models for plant disease classification due to their ability to learn important features such as color variations, lesion shape, texture patterns, and infected regions. Similar research has been carried out in leaf disease detection for different crops using CNN-based architectures and deep learning strategies. Subbotin et al. demonstrated the effectiveness of CNN models for detecting apple leaf diseases, showing that automated classification improves accuracy compared to traditional approaches [1]. Bairwa et al. highlighted recent improvements in mango leaf disease detection using deep neural networks and emphasized the importance of robust training for handling image variations [2]. Revathi and Hemalatha presented image processing-based approaches for detecting cotton leaf spot disease and proved that automated detection can assist in early-stage identification [3]. Kottath and Bharathi reviewed preprocessing methods in deep learning-based disease prediction and concluded that resizing, normalization, and augmentation significantly enhance model performance [4]. Walia et al. proposed an optimized VGG16 model for cotton leaf disease classification and reported improved classification accuracy using transfer learning techniques [5].

Motivated by these advancements, this project proposes a Rice Leaf Disease Detection and Solution Recommendation System that not only detects rice leaf diseases but also provides recommended treatments and preventive measures. The system is developed using deep learning models and is integrated into a Django-based web application, allowing users to upload leaf images and instantly receive disease predictions. This system reduces dependency on experts, improves decision-making speed, and supports farmers by offering actionable guidance for disease control.

1.1 Objectives

The primary objective of this project is to develop an intelligent and automated rice leaf disease detection system using deep learning. The system aims to analyse rice leaf image datasets and understand the variations in healthy and diseased leaf patterns. It focuses on identifying and recommending suitable deep learning models such as CNN and transfer learning architectures including VGG16 and ResNet based on dataset characteristics. Another objective is to train and evaluate multiple models using standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix in order to determine the best-performing algorithm. The system also aims to automate the selection of the most accurate model, ensuring that the final deployed model provides reliable and consistent results. Finally, the project aims to extend the detection system by integrating a solution recommendation module that provides disease-specific treatments and preventive measures to assist farmers in timely decision-making.

1.2 Problem Statement

Rice leaf diseases such as Brown Spot, Leaf Smut, and Bacterial Leaf Blight cause serious damage to rice production and directly affect crop yield and quality. Traditional disease detection relies on manual inspection, which is slow, subjective, and often inaccurate. The challenge becomes more severe because several rice diseases share similar visual symptoms, particularly during early stages, leading to misclassification and delayed treatment. With the increasing availability of mobile devices and field survey images, manual analysis of large numbers of rice leaf images becomes impractical. Although deep learning models can identify disease patterns effectively, selecting the best model for accurate classification is difficult because different CNN architectures perform differently depending on dataset size, image quality, and disease characteristics. Therefore, there is a strong need for an automated system that can classify rice leaf diseases accurately and provide solution recommendations to reduce crop loss and support farmers in effective disease management.

2. PROPOSED SYSTEM

The proposed system presents an intelligent Rice Leaf Disease Detection and Solution Recommendation System using deep learning techniques. The main aim of the system is to automatically detect rice leaf diseases from uploaded images and provide suitable solution recommendations for the identified disease. The system eliminates the need for manual inspection by agricultural experts and provides fast and accurate results to farmers. The complete workflow includes image acquisition, preprocessing, disease classification using a trained CNN model, and solution recommendation through a predefined knowledge base. The system is developed using Python and Tensor Flow/Keras for deep learning implementation and is integrated into a Django-based web application to provide an easy-to-use interface for users.

The proposed model is designed to classify rice leaf images into different categories such as Healthy, Brown Spot, Leaf Smut, and Bacterial Leaf Blight. After classification, the system provides disease-specific treatment suggestions such as chemical control methods, preventive measures, and general farming practices. The proposed approach ensures high accuracy, consistency, and scalability, making it suitable for real-time agricultural applications.

2.1 System Architecture

The architecture of the proposed system consists of multiple modules that work sequentially to detect rice leaf diseases and recommend suitable solutions. The process begins with the user uploading a rice leaf image through the web interface. The uploaded image is validated and forwarded to the preprocessing module. In the preprocessing stage, the image is resized to a fixed dimension and normalized to improve model performance. After preprocessing, the image is passed into the trained deep learning model, where feature extraction and classification are performed automatically. The model predicts the disease type along with a confidence score. Once the disease is identified, the system uses a recommendation module to retrieve the appropriate solution from the knowledge base. Finally, the predicted disease name, confidence score, and recommended treatment are displayed to the user through the result page.

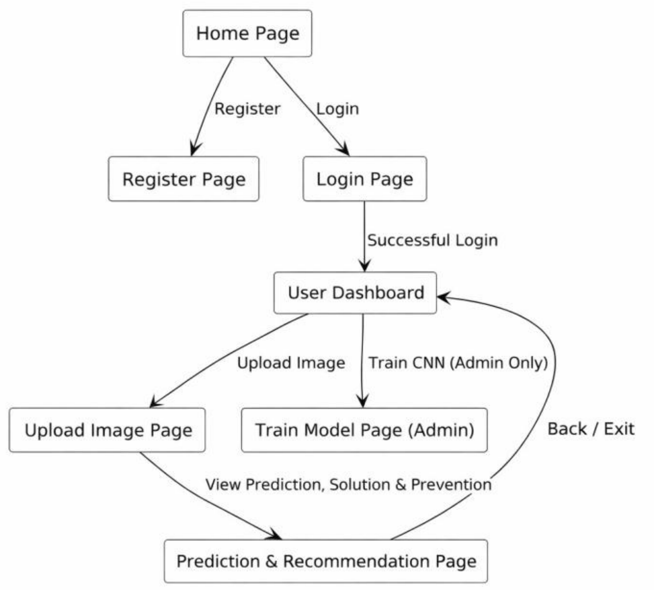

Fig -1 : Rice Leaf Disease Detection and Solution Recommendation System

2.2 Working of the Proposed System

The working of the proposed system follows a structured pipeline that ensures accurate detection and efficient recommendation generation. Initially, the system accepts a rice leaf image as input through the Django-based interface. The input image is pre-processed using resizing and normalization techniques to match the deep learning model input requirements. During training, data augmentation is applied to improve model robustness against variations in lighting, angle, and background conditions. After preprocessing, the image is passed into the trained CNN model or transfer learning model, which extracts deep features such as texture, lesion patterns, and colour differences. Based on these extracted features, the model classifies the image into one of the predefined classes. Once the disease is predicted, the system automatically generates solution recommendations such as pesticide suggestions, dosage guidance, and preventive farming measures. This ensures that the user not only receives disease identification but also receives actionable treatment guidance.

2.3 Advantages of the Proposed System

The proposed system provides an efficient and automated solution for rice leaf disease detection, which improves the speed and reliability of diagnosis compared to manual inspection. Since the model is trained using deep learning techniques, it provides high accuracy even when disease symptoms are complex and appear similar. The web-based interface allows users to access the system easily and upload leaf images from anywhere, enabling real-time diagnosis. The system ensures consistent results without human bias, and it can be scaled for larger agricultural monitoring applications. Additionally, the inclusion of a solution recommendation module makes the system more practical, as it provides disease-specific treatments and preventive measures immediately after prediction, helping farmers take timely action to reduce crop loss.

3. METHODOLOGY

The methodology of the proposed Rice Leaf Disease Detection and Solution Recommendation System is designed to provide an end-to-end automated workflow starting from image input to disease prediction and solution generation. The implementation combines image preprocessing, deep learning-based classification, and a recommendation module to assist users with appropriate treatments. The complete system is implemented using Python and Tensor Flow/Keras for model training and Django for web application integration. The methodology ensures that the system performs efficiently under different image conditions and provides accurate classification results for real-world agricultural usage.

3.1 Dataset Collection and Image Preprocessing

The first step of the methodology involves collecting rice leaf images containing both healthy and diseased samples. The dataset includes multiple rice leaf disease classes such as Brown Spot, Leaf Smut, and Bacterial Leaf Blight. Since images collected from different sources may contain variations in lighting, background, resolution, and noise, preprocessing is applied to standardize the input data before training and prediction.

In the preprocessing stage, all rice leaf images are resized into a fixed dimension such as 224×224 pixels to match the input requirement of CNN and transfer learning models. Pixel values are normalized by scaling them between 0 and 1, which improves model convergence and reduces computational instability. During training, data augmentation techniques are applied to increase dataset diversity and reduce overfitting. Augmentation improves the model's ability to generalize by exposing it to different image transformations such as rotation, flipping, zooming, and brightness variations. These preprocessing steps ensure that the model learns robust features and performs well on unseen rice leaf images.

3.2 Model Training and Disease Classification

After preprocessing, the dataset is divided into training and testing sets to evaluate model performance and avoid overfitting. Generally, 80% of the dataset is used for training and 20% is used for testing. The training dataset is used to learn disease patterns, while the testing dataset evaluates the model's generalization capability on unseen images.

For disease classification, the system supports both a custom CNN model and transfer learning-based CNN architectures. The custom CNN model is developed using multiple convolution layers, pooling layers, and dense layers to extract features and classify rice leaf diseases. Transfer learning models such as VGG16 and Res Net are also used, as they provide strong performance due to pretrained weights learned from large-scale image datasets. These models extract deep visual features such as texture patterns, lesion boundaries, and colour variations, which are essential for differentiating rice leaf diseases.

During training, the model learns by minimizing loss through backpropagation and optimization techniques. Validation accuracy is monitored after each epoch, and the best-performing model is saved for deployment. Once training is completed, the model is used to predict disease classes for uploaded rice leaf images. The predicted output includes the disease name and a confidence score, which indicates the reliability of the classification.

3.3 Solution Recommendation and Web Application Integration

Once the disease classification is completed, the system generates solution recommendations based on the predicted disease label. A predefined knowledge base is created that stores disease-specific recommendations such as chemical treatment methods, dosage guidance, preventive measures, and general farming practices. When the model predicts a disease, the system retrieves the corresponding solution from the knowledge base and displays it to the user.

To make the system accessible and user-friendly, the trained model is integrated into a Django-based web application. The web interface allows users to upload rice leaf images in standard formats such as JPG and PNG. After uploading, the system performs preprocessing, runs the deep learning model for prediction, and generates recommendations automatically. The final output is displayed on the result page, including the uploaded image, predicted disease name, confidence score, and suggested treatment measures. This integration ensures that the system can be used easily by farmers and agricultural users without requiring technical knowledge, enabling real-time disease detection and timely solution guidance.

4. RESULTS AND PERFORMANCE ANALYSIS

This section discusses the experimental results obtained from the proposed Rice Leaf Disease Detection and Solution Recommendation System. The performance of the system is evaluated based on its ability to accurately classify rice leaf images into different disease categories such as Brown Spot, Leaf Smut, Bacterial Leaf Blight, and Healthy leaves. The system was trained using deep learning-based Convolutional Neural Networks (CNN) and transfer learning architectures. The trained model was tested on unseen rice leaf images to verify its generalization ability.

The evaluation of the system is carried out using standard performance metrics such as accuracy, loss, precision, recall, F1-score, and confusion matrix. The results confirm that the model is capable of detecting rice leaf diseases effectively with high reliability. In addition to disease classification, the system also generates solution recommendations such as chemical treatments, water suggestions, and preventive advice. This improves the usefulness of the system in real agricultural environments.

4.1 Accuracy and Loss Analysis

During training, both training and validation accuracy were monitored for each epoch to evaluate learning efficiency. The experimental results show that the accuracy increases steadily with each epoch, indicating that the model successfully learns the visual patterns of rice leaf diseases. Similarly, the loss values decrease gradually, showing improved prediction capability and stable convergence. The validation accuracy remained close to the training accuracy, confirming that the model achieved good generalization without severe over fitting.

Transfer learning models such as VGG16 and Res Net achieved better accuracy compared to a custom CNN model due to their pretrained feature extraction ability. The best-performing model was selected based on maximum validation accuracy and minimum validation loss. This final selected model was deployed in the Django web application for real-time prediction.

4.2 Confusion Matrix and Classification Performance

To evaluate the class-wise performance of the system, a confusion matrix was generated using the testing dataset. The confusion matrix provides detailed information about correctly classified samples and misclassified samples across different disease categories. The results show that most test images were classified correctly, and only a small number of misclassifications occurred. Misclassification mainly occurred between diseases with similar symptoms, such as early-stage Brown Spot and Leaf Smut, where the infected patterns appear visually close.
A classification report was also generated to compute precision, recall, and F1-score for each class. The results show high precision and recall values for most disease categories, confirming that the model effectively detects diseased leaves and reduces false predictions. The high F1-score indicates balanced performance between precision and recall, making the system reliable for real-world disease diagnosis.

4.3 Web Application Output and Recommendation Results

The trained deep learning model was successfully integrated into a Django-based web application to provide an interactive user interface. The web interface allows users to upload a rice leaf image, after which the system performs preprocessing, prediction, and recommendation generation automatically. The output page displays the uploaded image, predicted disease name, disease stage, and solution recommendations including chemical treatment, water suggestions, and farming advice.
The output results confirm that the system provides real-time disease detection along with actionable recommendations. This makes the proposed system more practical compared to traditional models that only classify diseases without suggesting treatments. The integrated recommendation module helps farmers immediately understand what steps should be taken after disease detection, reducing decision-making time and minimizing crop loss.

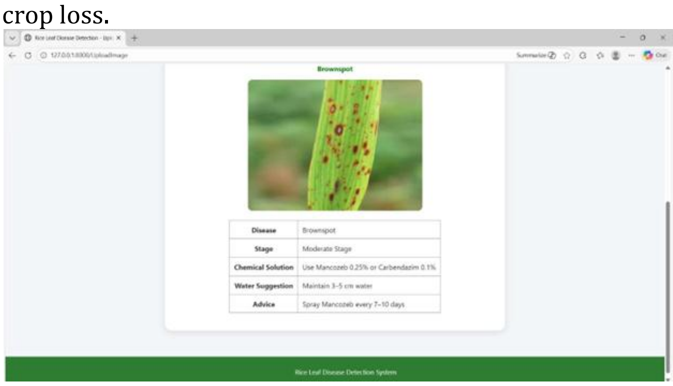

Fig- 4.1: Web Application Output Showing Brown Spot Prediction and Recommended Solutions

5. CONCLUSION

This project successfully developed an intelligent Rice Leaf Disease Detection and Solution Recommendation System using deep learning techniques. The proposed system effectively classifies rice leaf images into healthy and diseased categories such as Brown Spot, Leaf Smut, and Bacterial Leaf Blight by using a trained Convolutional Neural Network (CNN) and transfer learning models. Image preprocessing techniques such as resizing, normalization, and augmentation improved the robustness and accuracy of the model.In addition to disease detection, the system provides solution recommendations including chemical treatment guidance, water management suggestions, and preventive farming advice. The integration of the trained model into a Django-based web application enables users to upload rice leaf images and obtain real-time predictions with confidence scores. This reduces dependency on manual inspection, minimizes human error, and supports farmers in taking timely actions to prevent crop loss. Overall, the proposed system demonstrates that deep learning can be effectively applied in precision agriculture to improve disease diagnosis, enhance crop yield, and promote sustainable farming practices. With future enhancements such as mobile application deployment, support for more rice diseases, and larger real-world datasets, the system can be extended into a practical decision-support tool for farmers and agricultural organizations.

6. FUTURE ENHANCEMENT

The proposed Rice Leaf Disease Detection and Solution Recommendation System can be further enhanced to improve accuracy, usability, and real-world applicability. In future, the system can be trained using a larger and more diverse dataset collected from real agricultural fields under different lighting, background, and seasonal conditions. This will improve the model's ability to generalize and detect diseases more reliably in practical environments.

The system can also be extended to support additional rice diseases and multiple stages of infection, enabling early-stage detection and severity estimation. Future development can include integration of a mobile application so that farmers can capture leaf images directly using smartphones and receive instant predictions in remote areas. The recommendation module can be improved by adding localized treatment guidance based on region-specific agricultural practices, weather conditions, and soil characteristics.

Further enhancements may include real-time monitoring using IoT devices, automatic leaf segmentation for improved classification, and multilingual support to make the system more accessible to farmers. These improvements will transform the proposed system into a more advanced decision-support tool for precision agriculture.

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