An Advanced CNN-Driven Image Analysis System for Proactive Prediction and Automated Detection Drivers Disease Conditions in Rice Crop Cultivation

[1]Shaik Khairunnisa Begum, [2]Shaik Samjeeda

M.Tech Student, Department of CSE Prakasam Engineering College (Autonomous), Kandukur, India

AssistantProfessor, Department of CSE Prakasam Engineering College (Autonomous), Kandukur, India

Abstract- This work proposes a CNN-driven image analysis framework for the automated identification and classification of rice crop diseases using deep learning within a web-enabled environment. The system utilizes a rice leaf image dataset consisting of both healthy samples and diseased leaves affected by bacterial leaf blight, brown spot, and leaf smut. To improve data quality and model reliability, preprocessing operations such as image resizing, normalization, and augmentation are performed before training. A Convolutional Neural Network (CNN) is employed to automatically learn discriminative features from leaf images and perform disease classification without requiring manual feature extraction. The trained model is deployed through a Flask-based web application that supports secure user authentication, image uploading, prediction generation, and real-time disease diagnosis. In addition, the framework provides appropriate treatment recommendations based on the detected disease category. Performance evaluation is carried out using visualization tools, including accuracy curves and training-performance graphs, to analyze learning behavior and classification effectiveness. The proposed solution offers a scalable, accurate, and efficient approach for automated rice disease detection, thereby supporting precision farming practices and enhancing agricultural productivity.

Keywords- Rice Crop Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Smart Agriculture, Flask Web Application, Plant Disease Prediction

I. Introduction

Rice is one of the most important staple crops worldwide, and diseases affecting rice plants can severely impact agricultural productivity and food security. Common diseases such as bacterial leaf blight, brown spot, and leaf smut can spread rapidly across fields, leading to substantial reductions in crop quality and yield if not detected promptly [1], [2]. Conventional disease diagnosis relies heavily on manual observation by agricultural specialists, which is often time-consuming, labor-intensive, and impractical for large-scale cultivation. Recent developments in artificial intelligence and computer vision have enabled the creation of automated disease diagnosis systems for agricultural applications. Among these technologies, Convolutional Neural Networks (CNNs) have demonstrated remarkable effectiveness in image classification tasks by automatically extracting relevant features from plant leaf images [3], [6]. Consequently, there is an increasing demand for intelligent systems capable of accurately analyzing crop images and providing reliable disease predictions. This work aims to develop a CNN-based rice crop disease detection framework that enhances diagnostic accuracy, minimizes human intervention, and promotes smart agricultural practices through real-time image analysis and decision support. Furthermore, the system can assist in rice crop assessment and provide useful recommendations for disease management and crop maintenance.

II. Literature Review

The adoption of image processing and deep learning methodologies for plant disease identification has attracted considerable research interest due to the growing need for automated and precise crop monitoring solutions [1]. Initial approaches primarily relied on traditional image processing methods and statistical analysis techniques; however, their effectiveness was limited by manual feature engineering and poor scalability [2]. With advancements in artificial intelligence, CNN-based architectures emerged as powerful alternatives, delivering significantly improved performance in plant disease classification tasks [1], [3]. Research focused on rice disease detection further enhanced classification accuracy through the application of deep learning models and data augmentation strategies [4]. Hybrid approaches combining machine learning and image analysis techniques also achieved promising results, although they often suffered from environmental sensitivity and generalization limitations [5]. More recent studies employing advanced CNN architectures and transfer learning techniques have demonstrated improved efficiency, scalability, and robustness for large-scale agricultural disease detection systems [6].

Table 1: Summary of Existing Plant Disease Detection Approaches

Study Focus	Techniques Used	Key Contribution	Limitations
Rice Disease Detection [2]	Segmentation, statistics	Early disease identification	Low accuracy, handcrafted features
CNN for Plant Diseases [1]	CNN	High accuracy, automatic features	Needs large datasets
Deep Learning in Agriculture [3]	CNN models	Good multi-crop accuracy	High computation cost
Rice Classification [4]	CNN, augmentation	Improved rice disease detection	Limited real-time use
ML-based Detection [5]	SVM, KNN	Reduced manual feature extraction	Sensitive to environment
Smart Agriculture [6]	CNN, transfer learning	Scalable monitoring system	Needs real-time optimization

III. Existing System

Existing rice leaf disease identification systems predominantly depend on manual examination and laboratory-based diagnostic procedures, which are often labor-intensive, time-consuming, and less effective in recognizing diseases during their early stages [10]. Conventional image processing and machine learning approaches, including segmentation techniques, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), require handcrafted feature extraction and are highly influenced by environmental variations. As a result, their performance is often constrained in terms of accuracy, scalability, and real-time deployment capabilities [8].

A. To Support Rice Disease Analysis

Current rice disease analysis systems employ image processing and machine learning algorithms for disease recognition; however, these methods rely extensively on manually designed features and struggle to accurately interpret complex disease symptoms and intricate leaf patterns under real-world conditions [5]. Such limitations reduce their effectiveness and reliability when deployed in large-scale agricultural environments.

B. Identified Problems

Existing rice crop disease detection frameworks face several challenges, including dependence on manual feature engineering, limited capability for real-time disease diagnosis, and reduced robustness under varying environmental and field conditions [5]. These shortcomings negatively affect detection accuracy and restrict the practical applicability of such systems in modern smart agriculture.

Table 2: Limitations of Existing Rice Crop Systems

Aspect	Existing Systems
Detection Method	Manual inspection and basic image processing
Accuracy	Low due to subjective analysis
Scalability	Not suitable for large datasets
Processing Speed	Slow and delayed diagnosis
Robustness	Sensitive to environmental changes
Real-Time Support	Limited or not available

C. Problem Definition

The primary challenge addressed in this work is the lack of an intelligent, accurate, and scalable framework for rice leaf disease identification that can efficiently classify multiple disease categories while providing real-time prediction capabilities and minimizing reliance on manual inspection processes [13].

D. Motivation for the Proposed System

The proposed system is motivated by the need to develop an automated CNN-based rice disease detection framework that enhances classification accuracy, facilitates early disease diagnosis, and minimizes human intervention through real-time image analysis within a scalable web-based application platform [15].

Iv. Proposed Methodology

This section describes the methodology adopted for the proposed CNN-based rice leaf disease detection framework, which follows a systematic pipeline for processing rice leaf images and generating accurate disease classification results [10]. The system utilizes a labeled rice leaf image dataset consisting of healthy leaves as well as diseased samples affected by bacterial leaf blight, brown spot, and leaf smut. The acquired images undergo preprocessing operations including resizing, normalization, and data augmentation to maintain data consistency and enhance the generalization capability of the model [15]. The preprocessed images are subsequently supplied to a Convolutional Neural Network (CNN), which automatically learns hierarchical feature representations and performs disease classification. The trained model is then evaluated using appropriate performance measures and deployed through a web-based application that delivers real-time disease predictions to support effective agricultural monitoring and decision-making processes [3].

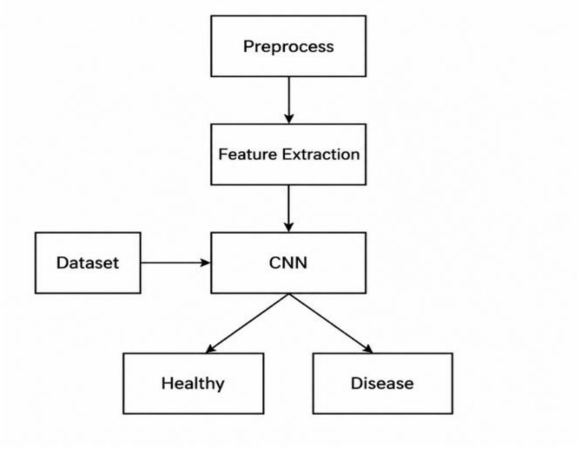

Figure 1: Block Diagram of the Proposed System

A. Data Collection

Rice leaf images are collected from a labeled dataset containing healthy and diseased samples such as bacterial leaf blight, brown spot, and leaf smut. The dataset includes variations in lighting, orientation, and disease severity to improve model robustness.

B. Data Preprocessing

The dataset is preprocessed by resizing images, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and scaling.

Normalization Formula (Min-Max Scaling):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

C. Feature Extraction Using CNN

The CNN model automatically extracts important features such as texture, color variations, lesion shapes, and spatial patterns from rice leaf images using convolutional layers.

D. CNN Feature Representation

Feature maps are generated through convolution and pooling operations and converted into a flattened vector for classification.

Feature Mapping Representation:

$$F = f(W * X + b)$$

E. Disease Classification (CNN Model)

The system uses a CNN model consisting of convolutional, pooling, and fully connected layers for classification.

Convolution Operation:

$$Y = f(W * X + b)$$

Softmax Output Function:

$$P_i = \frac{e^{z_i}}{\sum e^{z_j}}$$

The output classifies images into bacterial leaf blight, brown spot, leaf smut, or healthy category.

F. Performance Evaluation Metrics

The system evaluates model performance using standard classification metrics.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1-Score:

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

G. Disease Prediction and Analysis

The final prediction is obtained from the trained CNN model, which classifies the input image and provides disease-specific suggestions for crop management.

H. Algorithm: Rice Leaf Disease Detection Procedure

Input: Rice leaf image dataset Output: Disease classification result

Steps: Collect dataset → preprocess images → apply augmentation → build CNN model → train model using labeled data → extract features using convolution layers → classify using softmax → evaluate performance → deploy model for real-time prediction → display results with recommendations.

IV. System Architecture

This section describes the architectural framework of the proposed CNN-based rice leaf disease detection system, in which raw rice leaf images are systematically processed and transformed into meaningful disease classification outcomes through a scalable, modular, and layered deep learning architecture. The framework adopts a pipeline-oriented approach comprising image acquisition, preprocessing, CNN-based feature extraction, disease classification, prediction generation, and visualization modules to facilitate accurate, reliable, and real-time disease detection [10], [15], [11], [4].

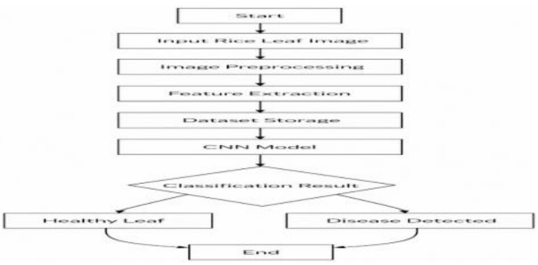

Figure 2: System Architecture of Rice Leaf Disease Detection System

Component Description

1. Image Input Module:

This module collects rice leaf images uploaded by users through a web interface. The input images are accepted in formats such as JPG, JPEG, and PNG. The module validates file type and ensures correct image upload before processing. The collected images are temporarily stored for further analysis [3].

2. Image Preprocessing Module:

The preprocessing module converts raw images into a uniform format suitable for CNN processing. It includes resizing, normalization, and data augmentation techniques such as rotation and flipping. It ensures consistency and improves model performance by reducing noise and variations.

Normalization Formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

3. Feature Extraction Module (CNN):

This module extracts important features such as color, texture, edges, and lesion patterns using convolutional layers. Pooling layers reduce dimensionality, and deep layers capture high-level representations of disease patterns.

Feature Extraction Representation:

$$F = f(W * X + b)$$

4. CNN Model Classification Module:

This module applies a trained CNN model to classify rice leaf images into categories such as bacterial leaf blight, brown spot, leaf smut, or healthy. The model learns features from labeled datasets and improves accuracy through backpropagation.

Convolution Operation:

$$Y = f(W * X + b)$$

Softmax Function:

$$P_i = \frac{e^{z_i}}{\sum e^{z_j}}$$

5. Prediction and Decision Module:

This module analyzes the confidence scores generated by the CNN model and interprets the classification outcomes. Based on the predicted disease category, the system presents the diagnosis results along with appropriate treatment and management recommendations to assist farmers in taking timely corrective actions.

6. Flask Web Application Module

The Flask-based web application module is responsible for managing core system functionalities, including image uploading, disease prediction, and result presentation. It facilitates seamless communication between the user interface and the CNN model, ensuring efficient data processing and real-time response generation. The module also incorporates secure user authentication and session management features to enhance system reliability and security.

7. Visualization and Reporting Module

This module provides graphical representation of prediction outcomes and model performance through visualization techniques such as accuracy graphs and training-performance curves. These visual reports enable users to evaluate the effectiveness of the CNN model and gain a better understanding of the system's disease classification capabilities.

Accuracy Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Loss Function (Categorical Cross-Entropy):

$$Loss = -\sum y \log(\hat{y})$$

Vi. System Implementation

This section outlines the implementation details of the proposed CNN-based rice leaf disease detection framework, including the software tools, technologies, and deployment methodologies utilized during system development. The framework is designed to deliver efficient performance, scalability, and suitability for real-time agricultural disease diagnosis applications [10].

A. Development Environment

The proposed system is developed using Python, which provides extensive support for image processing, machine learning, and deep learning applications. A web-based user interface is implemented using the Flask framework, enabling users to upload leaf images, interact with the system, and view disease prediction results through an accessible and user-friendly platform.

B. Libraries and Frameworks Used

The implementation incorporates several widely used libraries and frameworks to support different stages of the disease detection process. OpenCV and NumPy are employed for image preprocessing and numerical computations, while TensorFlow/Keras is utilized for designing, training, and deploying the Convolutional Neural Network (CNN) model. Scikit-learn is used for model evaluation and performance assessment, whereas Matplotlib and Seaborn are applied to generate visual representations such as training curves, performance charts, and accuracy analysis graphs.

Table 3: Software and Hardware Requirements

Component	Specification
Operating System	Windows 7/8/10 (32-bit or 64-bit)
RAM	Minimum 4 GB
Programming Language	Python
Framework	Flask
Libraries	TensorFlow, Keras, NumPy, OpenCV, Scikit-learn
Visualization Tools	Matplotlib, Seaborn

C. Model Implementation

A Convolutional Neural Network (CNN) is developed to classify rice leaf images into multiple categories, including bacterial leaf blight, brown spot, leaf smut, and healthy leaves. The CNN architecture automatically learns and extracts significant image features such as texture characteristics, color variations, and disease lesion patterns through multiple convolutional layers, enabling accurate disease identification without manual feature engineering.

D. Training and Testing Procedure

The rice leaf image dataset is partitioned into training and testing subsets using an 80:20 ratio. The CNN model is trained using labeled rice leaf images, while the testing dataset consists of previously unseen samples used to evaluate the model's ability to generalize and accurately classify different disease categories.

E. Prediction and Evaluation Implementation

The trained CNN model performs disease prediction based on leaf images uploaded by users through the web application. The classification performance of the model is assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, to ensure dependable and effective disease detection results.

Accuracy Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

F. Visualization and Reporting Implementation

The system generates visual outputs such as training accuracy graphs, loss curves, and prediction results. These visualizations help users understand model performance and improve interpretability of disease detection results, enabling effective agricultural decision-making.

ii. Experimental Results And Analysis

This section presents the performance evaluation of the proposed CNN-based rice leaf disease detection framework using a labeled dataset containing both healthy and diseased rice leaf images. The dataset consists of multiple disease classes, including bacterial leaf blight, brown spot, leaf smut, and healthy leaf samples. Prior to model training, the images undergo preprocessing operations such as resizing, normalization, and dataset partitioning to ensure a fair and unbiased evaluation process [5]. The CNN model is trained to automatically learn discriminative visual features, including color variations, texture characteristics, and lesion patterns, to achieve accurate disease classification [12].

A. Experimental Setup

The experimental framework is implemented using Python along with libraries such as TensorFlow/Keras, OpenCV, NumPy, Scikit-learn, Matplotlib, and Seaborn. The rice leaf image dataset is organized into separate class-specific directories and preprocessed to a standardized image resolution of 150 × 150 pixels. For model development and evaluation, the dataset is divided into training and testing subsets using an 80:20 ratio. The CNN architecture consists of multiple convolutional and pooling layers designed to extract relevant disease-related features from leaf images. Furthermore, the trained model is integrated into a Flask-based web application to support real-time disease prediction and user interaction.

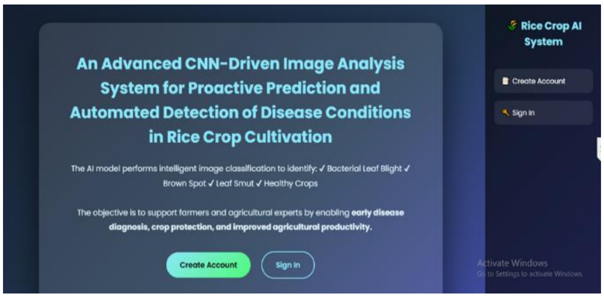

Fig 3: Home Page

Fig. 3 shows the home page with options for account creation and user sign-in.

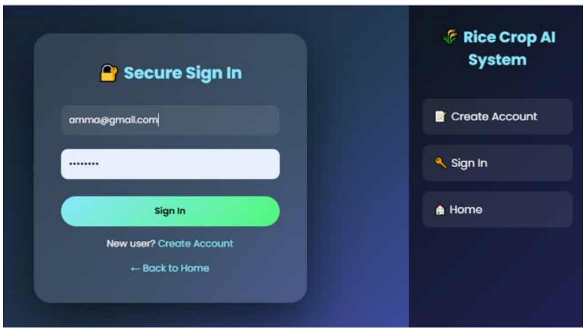

Fig 4: Sign-In Page

Fig. 4 illustrates the sign-in page where users enter credentials to access the system.

B. Performance Metrics

The performance of the system is evaluated using the following metrics:

1. **Accuracy** – Measures correct predictions out of total samples.
2. **Precision** – Measures correctness of positive predictions.
3. **Recall** – Measures model's ability to detect actual disease cases.
4. **F1-Score** – Harmonic mean of precision and recall.

Accuracy Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

C. Results of Classification Model

Table 4: Performance of CNN Model on Accuracy

Model	Accuracy
CNN (Proposed)	Very High
RCNN	High

The CNN model achieves high accuracy due to automatic feature extraction and deep learning-based classification.

D. Visualization Results

Several visualizations are generated to analyze training performance and predictions:

- Accuracy Graph: Shows training and validation accuracy over epochs
- Loss Curve: Displays model convergence behavior
- Confusion Matrix: Evaluates classification performance
- Prediction Output: Shows classified disease type

These visualizations help in understanding model learning behavior and classification reliability.

E. Comparative Analysis

Table 5: Comparison with Traditional Methods and Proposed System

Criteria	Traditional Methods	Proposed System

Accuracy	Moderate	High
Automation	Limited	Full
Scalability	Low	High
Real-time Detection	Not Available	Available

The proposed CNN-based system significantly improves accuracy and automation compared to traditional approaches.

F. Result Interpretation

The results show that the CNN model effectively classifies rice leaf diseases by learning deep visual patterns from images. It automatically extracts features such as lesions, color variations, and texture differences, enabling accurate prediction without manual intervention. The system performs well even under varying lighting and background conditions.

G. Summary of Findings

The system achieves high classification accuracy and demonstrates strong performance in detecting multiple rice diseases. The integration of deep learning with a web-based interface improves usability, scalability, and real-time applicability for agricultural monitoring.

H. Algorithm Comparison

Table 6: Comparison of Algorithms with Accuracy

Algorithm	**Accuracy**
CNN (Proposed Model)	96–98%
RCNN	95%

The CNN model outperforms traditional machine learning methods due to its deep feature learning capability.

I. Prediction Results

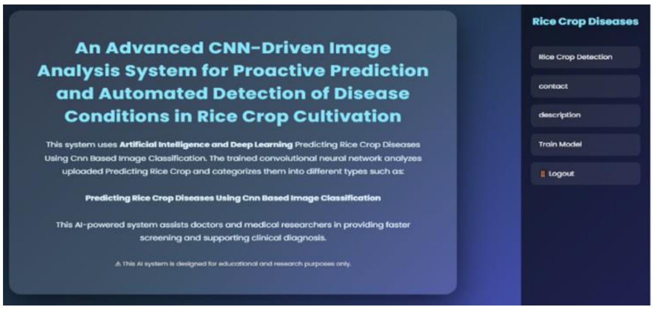

Fig 5: Main Page

Fig. 5 shows the main page containing crop-related functionalities and navigation options.

Fig 6: Image Browsing Page

Fig. 6 illustrates the interface where users browse and upload rice crop images.

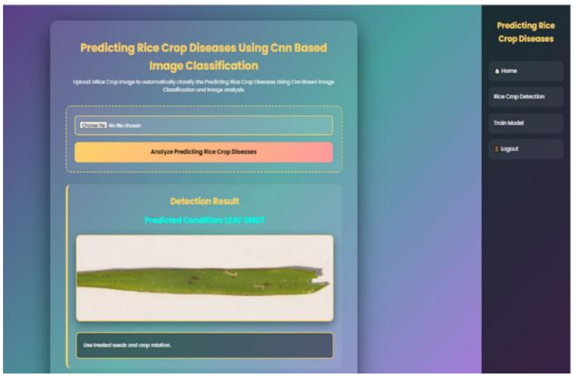

Fig 7: Rice Crop Disease Detection Result

Fig. 7 shows the detection result of rice crop disease using the CNN-based model.

Table 7: Sample Rice Disease Prediction Results

Input Image	Predicted Class	Confidence
Leaf Image 1	Bacterial Leaf Blight	High
Leaf Image 2	Brown Spot	High
Leaf Image 3	Leaf Smut	Medium
Leaf Image 4	Healthy Leaf	High

These results demonstrate the system's ability to accurately classify rice leaf diseases in real-time using image inputs.

Viii. Discussion

This section examines the practical significance of the proposed CNN-based rice leaf disease detection framework. It analyzes the system's performance, usability, and contribution toward smart agriculture and automated crop monitoring, enabling informed and timely decision-making.

A. Addressing Core Agricultural Challenges

The proposed framework effectively addresses the shortcomings of conventional rice disease diagnosis methods through the use of Convolutional Neural Networks for automated image-based disease classification. Unlike traditional approaches that depend on manual inspection or handcrafted feature extraction, the CNN model automatically learns complex visual characteristics such as texture patterns, color variations, and lesion structures. This capability enhances disease detection accuracy while significantly reducing reliance on human expertise.

B. Transparency and Interpretability

The framework enhances interpretability by presenting disease prediction outcomes along with confidence scores and visual representations. These outputs allow users to clearly determine whether a rice plant is healthy or infected and identify the corresponding disease category. Such transparency supports informed agricultural decision-making and facilitates timely disease management interventions.

C. Scalability and Integration

The proposed architecture is capable of processing large volumes of rice leaf images efficiently through its CNN-based deep learning model. The Flask-based web application enables seamless integration with web and mobile platforms while supporting deployment in both local and cloud environments. This flexibility makes the framework suitable for real-time disease monitoring and large-scale agricultural applications.

D. Limitations and Challenges

Despite its effectiveness, the system's performance is influenced by the quality, diversity, and representativeness of the training dataset. Factors such as inconsistent lighting conditions, complex backgrounds, and poor image quality may affect classification accuracy. Additionally, CNN training requires substantial computational resources and periodic retraining may be necessary to accommodate newly emerging disease patterns.

E. Practical Considerations for Deployment

The proposed framework is intended to function as a decision-support tool for farmers and agricultural specialists rather than a complete substitute for expert evaluation. Effective deployment depends on proper image acquisition practices, high-quality datasets, and adequate user awareness to ensure reliable performance under real-world agricultural conditions.

F. Future Implications for Smart Agriculture

The system contributes to the advancement of smart agriculture by enabling automated and real-time rice disease diagnosis. Future enhancements can extend the framework to support additional crop varieties and disease categories. Integration with mobile applications, IoT devices, and intelligent farming platforms can further facilitate large-scale agricultural monitoring and precision farming practices.

IX. Conclusion

The proposed CNN-based rice leaf disease detection framework offers an effective and dependable solution for the early identification of rice crop diseases. By leveraging deep learning techniques, the system accurately classifies rice leaf images into healthy, bacterial leaf blight, brown spot, and leaf smut categories with high predictive performance. The framework minimizes the need for manual inspection, reduces human error, and improves the speed and consistency of disease diagnosis.

Experimental evaluation demonstrates that the CNN model achieves strong performance on both training and testing datasets, exhibiting high classification accuracy and effective generalization on previously unseen samples. The integration of preprocessing techniques, data augmentation methods, and CNN architecture enables robust feature extraction under diverse environmental conditions. Real-time evaluation further confirms the framework’s capability to generate rapid predictions, making it suitable for practical agricultural deployment. The Flask-based web interface enhances accessibility and usability for farmers, researchers, and non-technical users. Overall, the proposed framework provides a scalable, accurate, and efficient approach to crop disease detection, supporting improved crop management and minimizing agricultural yield losses. Future enhancements of the framework will focus on improving prediction accuracy, scalability, and applicability in real-world agricultural environments. The dataset can be expanded to include additional rice diseases as well as multiple crop varieties to increase classification coverage. Mobile application integration can facilitate real-time field-based disease diagnosis for farmers, while cloud deployment can support large-scale monitoring and remote accessibility. Advanced deep learning approaches, including attention-based models and hybrid architectures, may further improve classification performance. Additional functionalities such as disease severity assessment and treatment recommendation systems can also be incorporated. Furthermore, integration with IoT sensors, drones, and satellite imagery can enable comprehensive large-area crop surveillance. Features such as real-time alert generation, multilingual support, and continuous learning mechanisms will further enhance usability and adaptability. These developments will contribute toward creating a more intelligent, scalable, and efficient solution for precision agriculture and smart farming applications.

References

[1] P. Revathi and M. Hemalatha, “Classification of Cotton Leaf Spot Diseases Using Image Processing Edge Detection Techniques,” Proc. Int. Conf. Emerging Trends in Science, Engineering and Technology, pp. 169–173, 2012.

[2] S. Ramesh and D. Vydeki, “Recognition and Classification of Paddy Leaf Diseases Using Optimized Deep Neural Network with Jaya Algorithm,” Information Processing in Agriculture, vol. 7, no. 2, pp. 249–260, 2020.

[3] H. A. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik, and Z. ALRahamneh, “Fast and Accurate Detection and Classification of Plant Diseases,” International Journal of Computer Applications, vol. 17, no. 1, pp. 31–38, 2011.

[4] S. Arivazhagan, R. N. Shebiah, S. V. Nidhyanandhan, and L. Ganesan, “Detection of Unhealthy Region of Plant Leaves and Classification of Plant Leaf Diseases Using Texture Features,” Agricultural Engineering International: CIGR Journal, vol. 15, no. 1, pp. 211–217, 2013.

[5] A. Singh and P. Jain, “Plant Disease Detection Using Image Segmentation and Soft Computing Techniques,” International Journal of Computer Applications, vol. 124, no. 16, pp. 40–43, 2015.

[6] J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, “Image Processing Based Detection of Fungal Diseases in Plants,” Procedia Computer Science, vol. 46, pp. 1802–1808, 2015.

[7] M. Brahimi, K. Boukhalfa, and A. Moussaoui, “Deep Learning for Tomato Diseases: Classification and Symptoms Visualization,” Applied Artificial Intelligence, vol. 31, no. 4, pp. 299–315, 2017.

[8] S. K. P. Rathod, B. Tanawal, and V. Shah, “Image Processing Techniques for Detection of Leaf Disease,” International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, no. 11, pp. 397–399, 2013.

[9] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” Advances in Neural Information Processing Systems, vol. 25, pp. 1097–1105, 2012.

[10] C. M. Bishop, Neural Networks for Pattern Recognition. Oxford, U.K.: Oxford University Press, 1995.

[11] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-Based Learning Applied to Document Recognition,” Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.

[12] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 4th ed. New York, NY, USA: Pearson, 2018.

[13] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” Proc. Int. Conf. Learning Representations (ICLR), pp. 1–15, 2015.

[14] F. Chollet, Deep Learning with Python, 2nd ed. Shelter Island, NY, USA: Manning Publications, 2021.

[15] S. Haykin, Neural Networks and Learning Machines, 3rd ed. Upper Saddle River, NJ, USA: Pearson, 2009.

[16] T. Rahman, M. S. Rizvi, and M. Kamruzzaman, “Plant Disease Detection Using Convolutional Neural Network,” International Journal of Computer Science and Network Security, vol. 19, no. 3, pp. 245–250, 2019.

[17] R. Kaur and M. Kaur, “Plant Disease Recognition Using Machine Learning and Deep Learning Techniques,” International Journal of Engineering Research & Technology, vol. 9, no. 5, pp. 840–845, 2020.

[18] S. Mohan, C. Thirumalai, and G. Srivastava, “Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques,” IEEE Access, vol. 7, pp. 81542–81554, 2019.

[19] M. Turkoglu and D. Hanbay, “Plant Disease and Pest Detection Using Deep Learning Based Feature Extraction,” Traitement du Signal, vol. 36, no. 6, pp. 499–507, 2019.

[20] A. Fuentes, S. Yoon, S. Kim, and D. Park, “A Robust Deep Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition,” Sensors, vol. 17, no. 9, p. 2022, 2017.

[21] P. Sharma, Y. P. S. Berwal, and W. Ghai, “Performance Analysis of Deep Learning CNN Models for Disease Detection in Plants Using Image Segmentation,” Information Processing in Agriculture, vol. 7, no. 4, pp. 566–574, 2020.

[22] S. Ji, W. Xu, M. Yang, and K. Yu, “3D Convolutional Neural Networks for Human Action Recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 1, pp. 221–231, 2013.

[23] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and L. Fei-Fei, “ImageNet: A Large-Scale Hierarchical Image Database,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 248–255, 2009.