RICE LEAF DISEASE DETECTION USING DEEP LEARNING

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Abstract— Rice is one of the most important food crops in the world and serves as a staple diet for millions of people, especially in countries such as India and China. However, rice production is frequently affected by several plant diseases including bacterial leaf blight, brown spot, leaf smut, and rice blast. These diseases significantly reduce crop yield and quality when they are not detected at an early stage. Therefore, timely identification of plant diseases is essential for effective crop management. This study presents an automated approach for detecting rice leaf diseases using a deep learning technique based on the MobileNet architecture. MobileNet is a lightweight convolutional neural network that is designed to perform efficient image classification while requiring fewer computational resources. The proposed model processes leaf images through preprocessing and feature extraction stages and classifies them into five categories, including healthy leaves and four disease classes. Compared with traditional deep learning models such as VGG and ResNet, MobileNet provides comparable classification accuracy while using fewer parameters and lower computational power. Experimental results show that the system can accurately detect different types of rice leaf diseases and can be implemented on mobile or embedded devices to assist farmers in real-time disease diagnosis.

KEYWORDS: Rice disease detection, Deep Learning, CNN, Mobile Net, Agriculture, Image Classification

Introduction

Agriculture plays a crucial role in supporting the global economy and ensuring food security. Among the various agricultural crops, rice is one of the most widely cultivated cereals and serves as a primary food source for a large portion of the world's population. The productivity of rice crops is highly dependent on environmental conditions, farming practices, and plant health. One of the major challenges faced by farmers is the occurrence of plant diseases that affect crop growth and reduce yield.

Rice plants are vulnerable to several types of diseases caused by fungi, bacteria, and viruses. Some of the most common diseases include bacterial leaf blight, brown spot, leaf smut, and rice blast. These infections damage the leaves of the plant, which directly affects the photosynthesis process and ultimately lowers the productivity of the crop. If these diseases are not identified and treated at an early stage, they can spread rapidly across large agricultural fields.

Traditionally, disease detection relies on visual inspection by farmers or agricultural experts. Although this method is widely used, it has several limitations. Manual inspection is time-consuming, requires expert knowledge, and may not always provide accurate results. Additionally, farmers in remote areas may not have easy access to agricultural specialists who can help identify plant diseases.

Recent advances in artificial intelligence and deep learning have made it possible to develop automated systems capable of recognizing plant diseases from images. Deep learning models, particularly convolutional neural networks (CNNs), have shown excellent performance in image classification tasks. These models can learn complex patterns and visual features directly from data without requiring manual feature engineering.

This research focuses on developing an automated system for detecting rice leaf diseases using the MobileNet deep learning architecture. The proposed system analyzes images of rice leaves and classifies them into different disease categories. Because MobileNet is computationally efficient, it can potentially be deployed on smartphones or portable devices, making it useful for farmers and agricultural professionals.

Problem Statement

Conventional methods for detecting rice diseases mainly depend on manual field observation by agricultural experts. While this approach can provide accurate assessments, it is often labor-intensive, time-consuming, and prone to human subjectivity. Additionally, farmers in remote or rural regions frequently lack immediate access to professional guidance, which can delay disease identification and result in significant crop damage. Earlier machine learning–based detection techniques attempted to address this issue; however, these methods typically relied on manual feature extraction and handcrafted image descriptors. Such approaches often struggle to handle variations in lighting conditions, backgrounds, and environmental factors, thereby limiting their effectiveness in real-world agricultural environments.

In recent years, deep learning models, particularly Convolutional Neural Networks (CNNs), have significantly improved the accuracy of image-based plant disease classification. Architectures such as VGG and ResNet are widely recognized for their high predictive performance. Nevertheless, these models contain a large number of parameters and demand substantial computational resources, which restricts their practical deployment on mobile devices or edge-based agricultural systems.

To address these challenges, this research focuses on the use of MobileNet, a lightweight deep learning architecture specifically designed for efficient image classification on mobile and embedded platforms. MobileNet employs depthwise separable convolutions, which reduce computational complexity and model size while preserving strong classification capabilities. This efficient design makes it highly suitable for real-time applications in resource-constrained environments.

Dataset Description

The Rice Leaf Bacterial and Fungal Disease Dataset available on is a curated image dataset developed to support research in automated rice disease detection using computer vision and deep learning techniques. The images were collected directly from real paddy fields in Bangladesh, ensuring practical field-level variability such as differences in lighting conditions, background clutter, leaf orientation, growth stages, and disease severity. This real-world diversity makes the dataset suitable for training robust deep learning models capable of generalizing beyond laboratory conditions.

The dataset contains both original and augmented images. The original images were captured using standard digital cameras and smartphones, preserving natural variations in resolution and environmental context. To improve dataset balance and increase training diversity, augmentation techniques such as rotation, flipping, scaling, translation, and brightness adjustment were applied. These augmented samples help reduce overfitting and improve model generalization, particularly for convolutional neural network (CNN) architectures.

The dataset is organized into eight labeled classes representing major rice diseases and healthy leaves. These include Bacterial Leaf Blight, Brown Spot, Leaf Scald, Narrow Brown Leaf Spot, Rice Hispa, Sheath Blight, Leaf Blast, and Healthy leaves. Each class is stored in separate folders, making it convenient for supervised learning tasks. The clear annotation and structured organization enable easy integration with deep learning frameworks such as TensorFlow and PyTorch.

This dataset is particularly valuable for evaluating lightweight architectures like MobileNet because it provides sufficient variability for training while remaining manageable in size. It supports research in plant pathology, precision agriculture, and AI-based crop monitoring systems. Overall, the dataset serves as a reliable benchmark for developing, training, and validating automated rice leaf disease classification models aimed at real-time agricultural deployment.

System Architecture

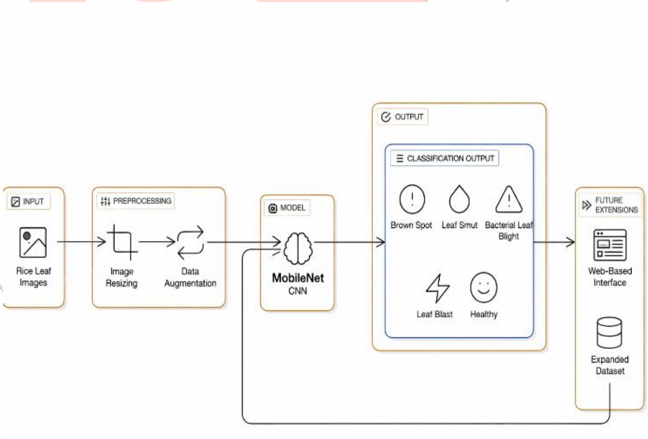

Fig – 1System Architecture Diagram

A suitable rice leaf image dataset containing samples of both healthy and diseased leaves is first identified and selected for model development. The dataset consists of images representing several common rice diseases and is prepared for training through systematic preprocessing steps. These steps include resizing all images to a fixed input dimension compatible with the neural network, normalizing pixel values to ensure stable learning, and applying data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment. These augmentation strategies increase dataset diversity and help reduce overfitting during training. After preprocessing, the dataset is divided into training and testing subsets to evaluate the model's ability to generalize to unseen data.

For disease classification, the **MobileNet architecture** is employed due to its lightweight design and computational efficiency. MobileNet uses depthwise separable convolutions, which significantly reduce the number of parameters and computational cost while maintaining strong feature extraction capabilities. Because of these advantages, MobileNet is particularly suitable for real-time agricultural applications and deployment on resource-constrained devices such as smartphones or edge systems. The model is trained using the prepared dataset, and its performance is evaluated using the testing subset. Once training is completed, the optimized model is saved for deployment. The trained model is then integrated into a Streamlit-based web application, enabling users to upload rice leaf images and receive immediate predictions regarding the detected disease.

The operational workflow of the rice leaf disease detection system involves multiple stages, beginning with the acquisition of rice leaf images from field environments. These images may represent healthy leaves or those affected by diseases such as Brown Spot, Leaf Smut, Bacterial Leaf Blight, and Leaf Blast. After collection, the images undergo preprocessing to standardize their format and improve classification performance. Each image is resized according to the input requirements of the MobileNet model, and augmentation techniques—including flipping, rotation, and brightness variation—are applied to simulate real-world environmental conditions. This structured preprocessing pipeline ensures consistent data preparation and improves the model's ability to accurately recognize disease patterns under diverse agricultural conditions.

Working Mechanism

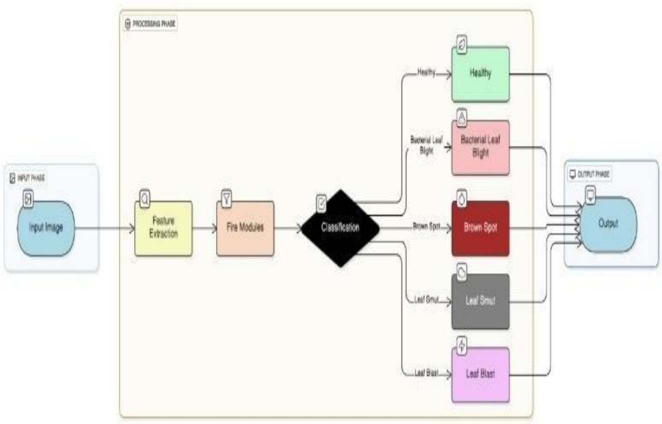

Fig – 2 Workflow of detection

Input Image – A rice leaf image (healthy or diseased) is given to the model.
1. Feature Extraction – MobileNet applies multiple convolution layers that automatically extract features such as spots, streaks, and color changes on the leaf.
2. Fire Modules – Instead of using many large filters, MobileNet uses special blocks called "fire modules", which "squeeze" the data into fewer filters and then "expand" it efficiently. This reduces model size but keeps accuracy.
3. Classification – After learning the features, the model predicts whether the leaf is:
1. Healthy
2. Bacterial Leaf Blight
3. Brown Spot
4. Leaf Smut
5. Leaf Blast

6. Output – The result is displayed with the disease name and can also show its causes/effects.

The figure illustrates the working process of a rice leaf disease classification system based on a Convolutional Neural Network (CNN) using the MobileNet architecture, which operates through three main phases: Input Phase, Processing Phase, and Output Phase. In the Input Phase, a rice leaf image is captured or uploaded to the system, which may represent either a healthy leaf or a leaf affected by disease. In the Processing Phase, the image undergoes feature extraction where significant visual characteristics such as color, texture, and shape patterns are automatically identified. These features are then processed through the depthwise separable convolution layers of the MobileNet architecture, which efficiently extract meaningful patterns while reducing computational complexity and the number of parameters in the model. This lightweight structure enables the system to maintain high classification accuracy while remaining suitable for real-time applications. The extracted features are then passed to the classification layer, where the model analyzes them and categorizes the rice leaf into one of five classes: Healthy, Bacterial Leaf Blight, Brown Spot, Leaf Smut, or Leaf Blast. Finally, in the Output Phase, the predicted disease category is displayed to the user, enabling quick identification of rice leaf diseases and supporting timely decision-making for effective crop management.

Proposed Methodology

The methodology designed for the Rice Leaf Disease Detection System focuses on developing an accurate and computationally efficient deep learning solution using the MobileNet convolutional neural network architecture. The primary objective is to build a lightweight yet powerful model capable of operating effectively in resource-constrained environments such as rural agricultural areas or mobile platforms. To accomplish this objective, the system follows a structured workflow consisting of dataset acquisition, data preprocessing, model design, training strategy, performance evaluation, and deployment through a web-based interface.

1. Data Acquisition

The first stage involves collecting a comprehensive dataset of rice leaf images representing five categories: Bacterial Leaf Blight, Brown Spot, Leaf Smut, Leaf Blast, and Healthy leaves. The images are obtained from publicly available agricultural datasets and research repositories. Efforts are made to include variations in lighting conditions, disease intensity, leaf orientation, and background environment to improve the model's ability to generalize to real-world agricultural conditions.

2. Data Preparation

Since raw images often vary in resolution, size, and quality, 1images are resized to 224 × 224 pixels to match the input requirements of the MobileNet architecture. Pixel values are normalized to ensure stable model training and faster convergence. In addition, all images are maintained in RGB format for consistent processing. To increase the diversity of training samples and minimize overfitting, data augmentation techniques such as rotation, horizontal and vertical flipping, scaling, and brightness adjustment are applied.

3. MobileNet Model Design

The classification model is developed using the MobileNet architecture, which is widely known for its lightweight structure and high computational efficiency. MobileNet utilizes depthwise separable convolutions, which divide the standard convolution operation into two steps: depthwise convolution and pointwise convolution. This design significantly reduces the number of parameters and computational cost while maintaining strong feature extraction capability. The network extracts meaningful patterns from rice leaf images and passes them through multiple convolutional layers followed by global average pooling and a softmax classification layer, which assigns the input image to one of the five disease categories.

4. Model Training Strategy

The processed dataset is divided into training, validation, and testing sets using a 70:15:15 ratio. The MobileNet model is trained using the Adam optimizer with a learning rate of 0.001, while categorical cross-entropy is used as the loss function for multi-class classification. Training is performed for multiple epochs, and early stopping techniques are implemented to prevent overfitting and improve model generalization. GPU acceleration is utilized during training to enhance computational efficiency and reduce training time.

5. Performance Evaluation

After completing the training process, the model's performance is evaluated using several classification metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis. Additionally, graphical plots of training and validation accuracy and loss are analyzed to understand the learning behavior and convergence of the model. The testing dataset is used to validate the system's ability to correctly classify unseen rice leaf images, ensuring reliability and practical applicability.

6. Web-Based Implementation

Once the model achieves satisfactory performance, the trained MobileNet model is integrated into a web-based application developed using Streamlit. The interface allows users to upload rice leaf images directly through a web browser on a computer or smartphone. The uploaded image is processed by the trained model, which predicts the corresponding disease class and displays the result along with a confidence score. The application is designed to be simple, accessible, and user-friendly, making it suitable for farmers and agricultural practitioners.

Result and Discussion

After training the MobileNet model, its performance was evaluated using the testing dataset. The system successfully classified rice leaf images into their respective categories with high accuracy.

The experimental results demonstrate that MobileNet can effectively detect various rice leaf diseases while maintaining efficient computational performance. Compared to heavier CNN architectures like VGG and ResNet, MobileNet requires fewer parameters and less memory, making it more suitable for deployment on mobile platforms.

The classification accuracy achieved by the model indicates that deep learning techniques can significantly improve the process of plant disease detection. By using automated image analysis, farmers can identify diseases earlier and take appropriate preventive measures to reduce crop losses.

Furthermore, integrating this system with mobile applications could allow farmers to capture leaf images using their smartphones and receive immediate diagnostic feedback. This would improve accessibility to agricultural expertise and support better crop management practices.

Output Interfaces

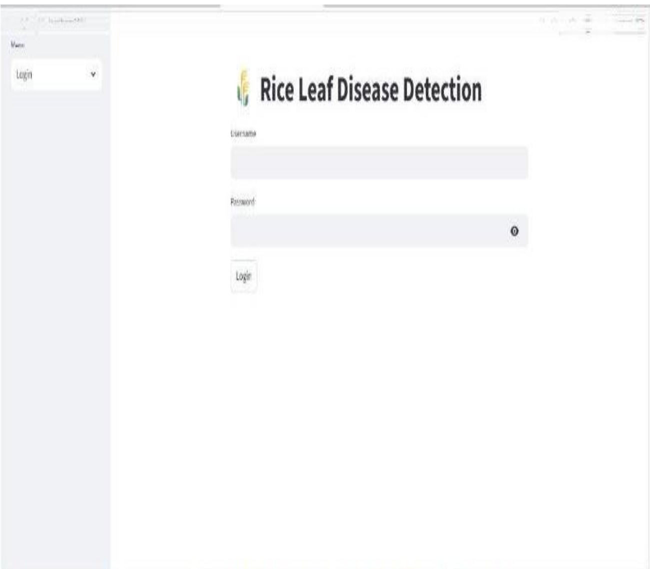

Fig – 3 login interface

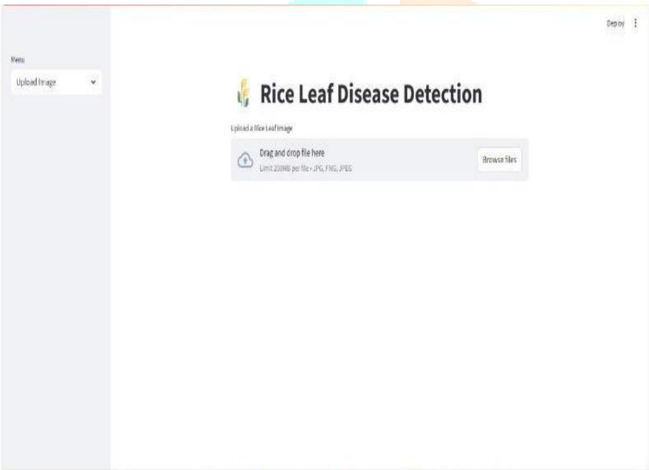

Fig – 4 Detection Interface

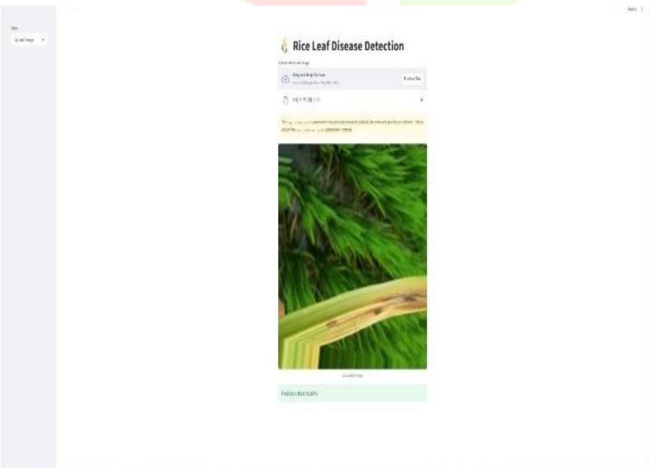

Fig – 5 Output Interface

Conclusion

The developed rice leaf disease detection system demonstrates that a lightweight deep learning architecture such as MobileNet can effectively achieve a balance between classification accuracy and computational efficiency. By utilizing depthwise separable convolution layers, the model significantly reduces the number of parameters and computational complexity while still maintaining strong feature extraction and reliable disease classification performance. This efficiency makes the system suitable for deployment on smartphones, embedded systems, and other low-resource agricultural platforms where computational capacity and memory are limited. Careful preprocessing and data augmentation techniques further improved the model's robustness by enabling it to handle variations in real-world conditions such as differences in lighting, background noise, and leaf orientation. The model's performance was evaluated using multiple metrics including classification accuracy, precision, recall, F1-score, confusion matrix analysis, and ROC curves, which confirmed its capability to effectively distinguish between major rice leaf diseases and healthy leaves. Overall, the proposed framework offers a practical, scalable, and user-friendly solution that can support precision agriculture and early disease detection, ultimately helping farmers take timely action to reduce crop losses and improve productivity.

Future work

Further improvements can be achieved by continuously enriching the dataset with additional disease categories, varied crop growth stages, and images captured from different geographical regions and climatic conditions. Expanding the dataset to include more rice infections, including less common or emerging diseases, will enhance the model's adaptability and practical relevance.

From a technical standpoint, future research may involve experimenting with alternative lightweight architectures such as MobileNet, EfficientNet, or transformer-based vision models, as well as hybrid and ensemble approaches. Comparative evaluation of these architectures could help identify the most optimal balance between model size, speed, and predictive accuracy.

Moreover, integrating the system with IoT-based crop monitoring tools and deploying it through a dedicated mobile application can enable real-time, on-field diagnosis. Incorporating explainable AI mechanisms to highlight infected regions within leaf images would also improve transparency and user trust. These advancements will contribute to improved crop management, reduced chemical overuse, and more sustainable agricultural production systems.

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