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Early Detection of Rice Plant Diseases Using Advanced Image Processing Techniques

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Abstract

Rice, a primary food source for more than half of the global population, faces significant threats from diseases such as brownspot, hispa, and blastleaf. These diseases compromise food security and reduce crop yields, especially in major rice-producing regions. Timely and precise disease diagnosis is crucial for sustainable agriculture and effective disease management. This research explores the application of deep learning techniques for classifying rice diseases, with a focus on rice leaves. Leveraging the MobileNet architecture for transfer learning, the study applies advanced computer vision and machine learning methods to improve disease diagnosis and control. By utilizing a pre-trained MobileNet model, the approach overcomes data limitations and enhances model robustness, achieving an impressive overall accuracy of 78%. This advancement signifies a notable enhancement in early-stage disease detection and differentiation.

Keywords: Sustainable Agriculture, Transfer Learning, Convolutional Neural Network, Deep Learning.

1. Introduction

Rice (Oryza sativa) is a vital staple that supports over half of the global population, making it essential for both economic stability and food security globally. It functions as a primary source of carbohydrates and critical nutrients, particularly in Asia, where it is central to daily diets and cultural traditions, symbolizing prosperity and communal identity [1]. Economically, rice cultivation and trade underpin numerous livelihoods and contribute significantly to global economies [2].

Nevertheless, the cultivation of rice is increasingly threatened by biotic stresses from pathogens such as viruses, fungi, and bacteria. These pathogens can cause devastating diseases like rice tungro virus, bacterial leaf blight, sheath blight, and blast, potentially reducing yields by over 30% and impacting both food security and the livelihoods of farmers. For instance, blast, caused by the fungus Magnaporthe oryzae, can decimate entire harvests under favorable conditions, while bacterial leaf blight, triggered by Xanthomonas oryzae pv. oryzae, rapidly spreads and damages rice crops [3]. These diseases not only directly affect rice production but also increase farmers' reliance on pesticides, leading to environmental degradation and health risks. Furthermore, the emergence of new pathogen strains and resistance exacerbates the challenges in disease management.

Effective disease control is imperative to mitigate these impacts and safeguard global food security. Traditional detection methods often lack the speed and precision needed for early intervention, leading to substantial crop damage [4]. This study seeks to address this gap by employing advanced image processing techniques to develop a rapid and accurate disease detection system. By enabling early identification and management of rice diseases, this approach aims to enhance farmers' ability to protect their crops and contribute to global food security.

2. Related works

Rice is fundamental to Bangladesh's rural economy and is crucial to its agricultural GDP. Maintaining healthy rice crops is vital for the country's economic growth, as rice serves as a staple for billions worldwide. However, rice production is threatened by various biotic stresses, including fungi, bacteria, and viruses, leading to potential yield losses of 30% or more, which can have serious consequences for food security and livelihoods [5]. Diseases like blast (caused by Magnaporthe oryzae), bacterial leaf blight (Xanthomonas oryzae pv. oryzae), and sheath blight (Rhizoctonia solani) can drastically reduce crop yields and grain quality if not managed effectively. Blast disease, for example, can inflict severe damage on leaves, panicles, and stems, potentially reducing global yields by 30-40%. Bacterial leaf blight affects both vegetative and reproductive stages, causing lesions that lower grain yield, while sheath blight leads to lodging and crop failure when severe infestations occur. These diseases not only diminish rice productivity but also increase the reliance on pesticides, raising environmental concerns and

production costs [6]. To mitigate the harmful impact of rice diseases and support global rice production, implementing effective management strategies is essential. These include using resistant cultivars, adopting cultural practices, and employing early detection technologies. Various studies have explored accelerated methods for detecting and classifying rice diseases using image processing techniques. One approach analyzed the RGB value percentage in the damaged areas of leaves, focusing on smaller samples rather than whole leaves [7]. Research in Sri Lanka employed mathematical morphological methods for segmenting images to detect diseases like rice blast, sheath blight, and brown spot [8]. Other studies utilized grayscale conversion and histogram extraction techniques via MATLAB to facilitate disease detection in rice [8]. A study in West Bengal, India, proposed a Convolutional Neural Network (CNN)-based model for disease categorization and prediction in rice crops [9]. Recent work employed CNNs and image processing to develop applications that help farmers detect pest insects and diseases in rice fields [5]. A study proposes a deep learning approach using a CNN to detect rice diseases— brown spot, leaf smut, and bacterial leaf blight—based on lesion size, shape, and colour. Otsu's global thresholding enhances detection by reducing background noise [10]. Another study applied transfer learning models to predict rice diseases accurately. A different investigation analyzed pepper plant leaves using MATLAB for feature extraction and image recognition [11], employing morphological operations, edge detection, and Fourier filtering for pre-processing.

In [12], the authors utilized K-means algorithms to detect paddy leaf diseases, specifically targeting blast disease, brown spot disease, and narrow brown spot disease. In Bangladesh, research identified common rice diseases like leaf smut, bacterial leaf blight, and brown spot infections using machine learning techniques such as KNN, J48, Naive Bayes, and logistic regression. A decision tree algorithm demonstrated accuracy exceeding 97% following 10-fold cross-validation. In [13], the authors employed pattern recognition algorithms and the HIS model for segmentation and spot detection to identify affected leaf areas. The Vels Institute of Science, Technology & Advanced Studies (VISTAS) aimed to develop an automated segmentation method for rice leaf images, taking into account various environmental factors [14]. Another study created an automated rice disease detection system using computer vision, integrating image processing, machine learning, and deep learning. This system achieved significant results with a combination of support vector machines and CNNs [15]. Additionally, a paper introduced a lightweight deep CNN for rice leaf disease detection, surpassing 21 benchmark models with fewer trainable parameters. This model achieved high precision, recall, and F1-score using an enhanced dataset containing 95 newly annotated images. An open API for automatic annotation was also introduced to support crop health monitoring and research [16]. Another author marked diseased leaf areas as indicators of poor health through segmentation techniques and applied feature extraction methods to classify unhealthy leaves based on colour, shape, and other proper- ties [17]. In [18], the authors used support vector machines (SVM) for classification and segmentation to extract critical image features while another groups developed a framework to identify diseases in paddy leaves using histograms de- rived from RGB-to-grayscale image conversion, producing distinctive patterns for each disease type [8]. In [19], the authors introduced an automated framework incorporating pre-processing, image acquisition, segmentation, and classification, using advanced methods like Discrete Wavelet Transform (DWT), Gray Level Co-occurrence Matrix (GLCM), and scale- invariant feature transform for classification. The features were processed through classifiers such as K-Nearest Neighbors (KNN), neural networks, backpropagation, multiclass SVM, and Naïve Bayesian to distinguish healthy and diseased plants.

Most existing studies emphasize disease management after symptoms appear, which complicates control, especially when diseases progress to advanced stages. Therefore, early detection is essential for effectively managing and reducing the impact of rice plant diseases on crop productivity and sustainability.

3. Materials and methods

Before delving into the specifics, the overall framework of this study is outlined in Fig. 1.

Image Processing

Image preprocessing is a pivotal phase in preparing data for deep learning, aiming to enhance the quality and uniformity of input images. This step involves a series of transformations designed to optimize image data for model training, ensuring consistency and robustness across the dataset.

Resizing images

Standardizing image dimensions is a critical aspect of preprocessing, facilitating a uniform input size for neural networks. In this study, images were initially resized to dimensions of 50x50 pixels, later adjusted to 224x224 pixels, a size conducive to balancing computational efficiency with data integrity. This choice mitigates potential issues associated with varying image sizes, such as computational overhead, increased memory usage, potential loss of critical details, and heightened risk of overfitting. The dataset comprised 3,355 images, underscoring the importance of managing image size to optimize resource usage and model performance. By selecting the 224x224

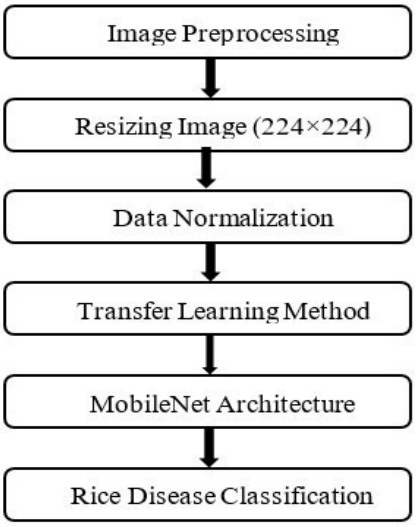


Fig. 1. General framework of the study

dimension, a practical compromise was achieved, enhancing the model's ability to learn effectively while maintaining manageable computational demands.

Data normalization

Normalization is essential for stabilizing the training process, as pixel values in images naturally exhibit variability in intensity. By rescaling pixel values to a standardized range, typically from 0 to 255 as managed by OpenCV in this study, normalization facilitates improved convergence during model training. This adjustment ensures that pixel intensity variations do not adversely affect the learning process, enhancing the model's efficiency and performance.

Transfer learning method

To leverage existing knowledge from pre-trained models, this study employs transfer learning using Convolutional Neural Network (CNN) architectures extensively trained on large- scale datasets like ImageNet. This approach capitalizes on the ability of pre-trained CNNs to recognize fundamental image features, such as edges and textures, which are transferable across various tasks and domains. By fine-tuning the final layers of these networks, the models are adapted to the specific task of rice disease classification.

MobileNet

MobileNet, a family of lightweight CNN architectures, is particularly designed for efficient deployment on mobile and embedded devices. It achieves high accuracy across diverse computer vision tasks while maintaining a compact model size and low computational requirements. This is primarily achieved through the use of depth-wise separable convolutions and other optimization techniques. In this study, MobileNet was explored for its potential to deliver a balance of efficiency and accuracy, although its performance was benchmarked against other variations for optimal results.

This section outlines the comprehensive methodology employed for classifying rice diseases using deep learning. Key preprocessing steps, such as resizing images to 224×224 pixels and normalizing pixel values, are crucial for ensuring consistency and enhancing model performance. The utilization of MobileNet and other CNN architectures through transfer learning forms the foundation of the classification approach, with a focus on maximizing both efficiency and accuracy.

4. Result analysis

This section aims to present empirical results, evaluating the effectiveness of the proposed methods and providing insights for future research directions.

Binary classifier's classification report

This study initially focused on identifying healthy and un- healthy leaves using a binary classification approach, and the obtained results are reported in Table I. The model achieved an impressive overall accuracy of 0.93,

accurately predicting approximately 93% of the cases in the dataset. It demonstrated outstanding precision, recall, and F1-score of 0.93 across all classes, highlighting the model's high performance in evaluating healthy and unhealthy leaves equally. Taking into account the class distribution disparities within the dataset, the weighted average precision, recall, and F1-score also remained consistently at 0.93.

Table 1. Classification report for the binary classifier

Factors	Precision	Recall	F1-score	Support
Accuracy			0.93	5760
Macro Average	0.93	0.93	0.93	5760
Weighted Average	0.93	0.93	0.93	5760

As depicted in Fig.2, the binary classification model successfully identified 2,574 healthy samples as healthy out of a total of 2,880 images, while incorrectly classifying 306 healthy samples as non-healthy (true negatives). Conversely, the model accurately classified 2,761 non-healthy images but misclassified 119 non-healthy images as healthy. These results indicate a high level of precision and robustness in distinguishing between healthy and unhealthy leaves.

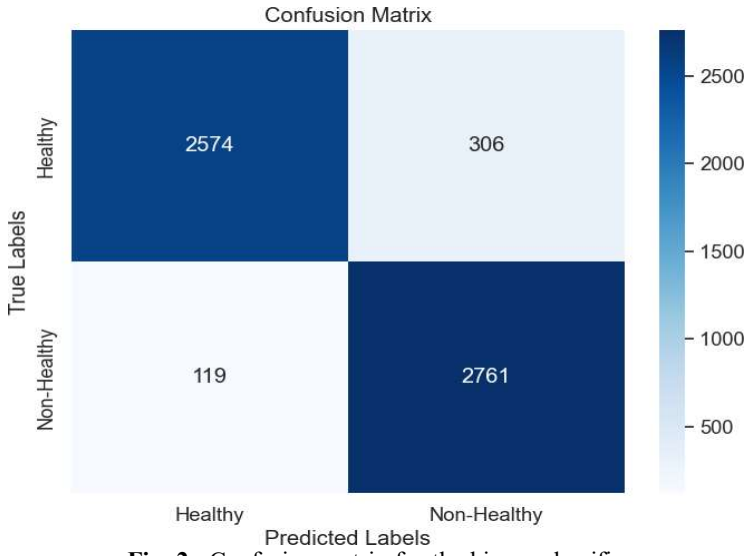


Fig. 2. Confusion matrix for the binary classifier

Multiclass classifier's classification report

For the multiclass classification, the model's overall accuracy was 0.78, meaning it correctly predicted around 78% of cases in the dataset, as reported in Table II. The model achieved an average precision of 0.84, an average recall of 0.77, and an average F1-score of 0.79 across all classes, indicating a generally high precision in its predictions. However, due to class imbalances, the weighted average precision, recall, and F1-score slightly declined to 0.82, 0.79, and 0.78, respectively. The lower F1-score in the weighted average suggests that classes with fewer occurrences may have slightly poorer performance, which impacts the model's overall effectiveness.

Table 2. Classification report for the multiclass classifier

Factors	Precision	Recall	F1-score	Support
Accuracy			0.78	5760
Macro Average	0.84	0.77	0.79	5760
Weighted Average	0.82	0.79	0.78	5760

In Fig. 3, the left graph illustrates the loss curve, while the right graph depicts the accuracy performance during model training. The blue line represents training metrics, and the orange line denotes validation performance. The gradual de- crease in the loss function indicates that the model is learning smoothly as the epochs progress. This smooth learning process is further reflected in the accuracy graph, showing continuous improvements, particularly

during training and validation phases. These findings underscore the model's potential for effective multiclass classification, albeit with some limitations due to class imbalances.

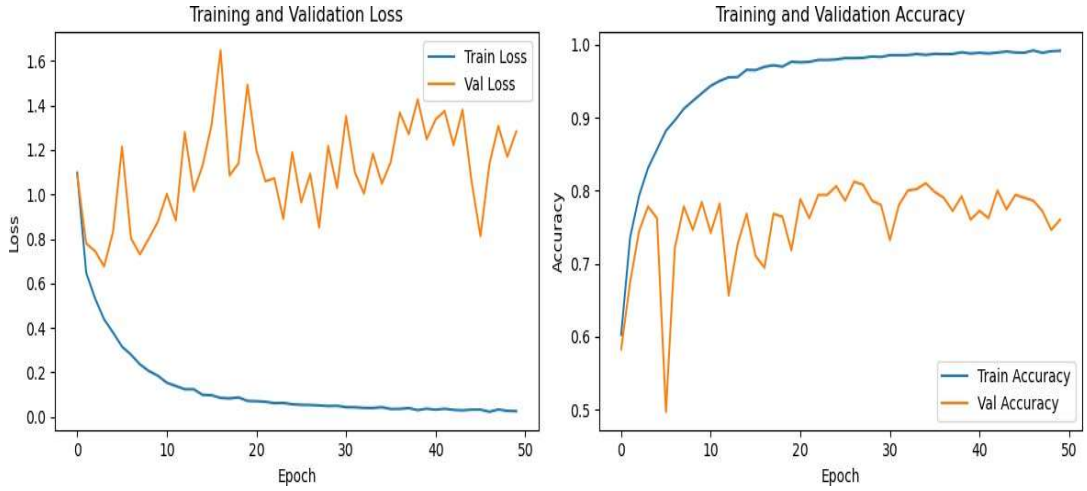


Fig. 3. Loss and Accuracy Curves for the Multiclass Classifier

5. Discussion

This study initially focused on binary classification, where the model achieved a high overall accuracy of 93%, with precision, recall, and F1-score each reaching 0.93. While the binary model effectively identified healthy samples, some misclassifications did occur. When extended to multiclass classification, the model achieved an overall accuracy of 78%, with average precision, recall, and F1-score of 0.84, 0.77, and 0.79, respectively. Considering class imbalances, the weighted averages for precision, recall, and F1-score were 0.82, 0.79, and 0.78. The steady decline in the loss function over epochs reflects a consistent learning process, resulting in progressively improved accuracy. Overall, the model demonstrated strong performance in both binary and multiclass classifications, achieving the expected levels of effectiveness and reliability across diverse scenarios.

6. Conclusion

Rice, a crucial food source for more than half of the global population, faces significant threats from diseases like brown spot, hispa, and blast leaf. These diseases undermine food security and reduce crop yields in major rice-growing areas. This research investigates the use of deep learning techniques for classifying rice diseases, specifically targeting rice leaves, by employing the MobileNet architecture for transfer learning. By using a pre-trained MobileNet model, the study effectively addresses data limitations and improves model robustness, achieving a commendable overall accuracy of 78%. This represents a significant advancement in early- stage disease detection and differentiation. The initial focus on binary classification resulted in an outstanding accuracy of 93%, with precision, recall, and F1-score all at 0.93, though some misclassifications occurred. When expanded to multi- class classification, the model achieved an overall accuracy of 78%, with average precision, recall, and F1-score of 0.84, 0.77, and 0.79, respectively, and weighted averages of 0.82, 0.79, and 0.78, respectively, accounting for class imbalances. The consistent decrease in the loss function across epochs reflects a smooth learning process, with steadily improving accuracy, highlighting the model's strong performance in both binary and multiclass tasks. These results emphasize the potential of advanced deep learning techniques to enhance disease management strategies and support sustainable rice production through effective and accurate diagnostic tools.

7. References

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