

Research article

Detection and Classification of Rice Leaf Diseases Using OpenCV and Deep Learning

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Received: 28 August 2023, Revised: 18 November 2024, Accepted: 21 February 2025, Published: 28 March 2025

Abstract

Traditional methods for identifying plant diseases in Bangladesh present numerous challenges, such as inadequacy of method, time-consuming processes, and expensive costs for farmers. To address these issues, this study proposes an innovative approach that leverages deep learning and computer vision techniques, which have already demonstrated effectiveness in various agricultural applications. Our research specifically targets the detection and classification of rice leaf diseases, employing a two-step process designed to enhance diagnostic accuracy and reliability. In the first step, OpenCV technology is used to analyze the shape, size, and color of rice leaves, categorizing them into four distinct groups: bacterial leaf blight, brown spot, leaf smut, and healthy leaves. In the second step, a convolutional neural network (CNN) extracted features from images of these categorized diseases. We thoroughly evaluate our model's performance by examining accuracy and loss curves, providing a comprehensive assessment of its effectiveness in diagnosing rice leaf diseases. Our findings indicate that the innovative application of OpenCV for initial disease identification, based on shape and color, is highly effective. Furthermore, the CNN model achieves an impressive 99% accuracy rate in distinguishing between actual labels from predicted labels, highlighting the potential of this methodology to significantly improve disease management strategies for rice crops in Bangladesh.

Keywords: precision agriculture; rice leaf disease; OpenCV; classification; detection

1. Introduction

Bangladesh is one of the countries in Asia that produces most of the rice because of the vast number of populations and available fertile land. However, the increasing population can cause global warming and rapid climate changes (Yadav et al., 2021). As a result, rice plants are infected by various diseases due to the evolution of the environment. Researchers and scientists believe that environmental change significantly impacts rice quality, quantity, and productivity (Jiang et al., 2020; Khatun et al., 2021).

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<https://doi.org/10.55003/cast.2025.260191>

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Over the past few years, various types of leaf diseases have emerged in rice fields, leading to a noticeable decline in rice production. Scientists have identified numerous rice plant diseases, including brown spot, leaf blast, brown plant hopper, leaf scald, leaf smut, stack burn, and many others (Jiang et al., 2020). These diseases can affect any part of the rice plant such as the leaf, neck, or ear, and are responsible for 11% to 16% of total productivity losses (Ficke et al., 2018). However, in a worst-case scenario, farmers may lose up to 50% to 60% of their crops, severely impacting both farmers and the broader economy of a country (Tian et al., 2021; Elmitwally et al., 2022).

Machine learning, deep learning, and computer vision techniques are well-suited for plant disease detection because they can effectively analyze and classify images of plant leaves and other plant parts, that are often used as key indicators of plant health. Python OpenCV and deep learning methods enable automated analysis of large datasets, saving time and reducing errors compared to manual methods. In particular, deep learning (a form of machine learning involving multiple-layered neural networks) can automatically learn and extract features from images, improving model accuracy. Consequently, the use of computer vision and deep learning for plant disease detection is promising, as these methods can enhance the accuracy and efficiency of disease detection, which is crucial for crop management and food security (Barbedo, 2013; Sujatha et al., 2021; Wani et al., 2022; Das et al., 2024).

Conventional methods of plant disease detection are often challenging to implement or are insufficient for identifying the wide range of potential rice leaf diseases. Therefore, adopting a more advanced technical approach is preferable to relying on traditional manual observation. Hence, the development of intelligent agriculture supported by advancements in information and communication technologies can boost rice productivity by optimizing fertilizer use and ensuring the timely application of pesticides. Artificial intelligence, convolutional neural networks, and computer vision and machine learning algorithms can significantly expedite and simplify the classification of various diseases. Numerous studies have proposed different methodologies and approaches for detecting rice leaf diseases, a few of which are highlighted below.

The application of a DCNN with a Bayesian learning procedure for disease categorization in various plants was explored by Sachdeva et al. (2021). A total of 20,639 photographs from the Plant Village database were used in the study, encompassing both healthy and unhealthy leaves, which were categorized into 15 different classes. The results of this study indicated that this model was a valuable tool for identifying and classifying plant ailments.

Hossen and Barman (2022) utilized Python OpenCV for detecting the contours of shapes and color of real images. They performed an R-CNN-based study on soybean fungal diseases using synthetic images, reporting an accuracy of 83.34% despite a relatively small dataset. In another similar investigation, an SVM was implemented to detect deep feature-based rice crop diseases using 5,932 on-field images that included blast, brown spot, tungro, and bacterial blight. The performance of this method was evaluated based on specificity, accuracy, sensitivity, false positive rate, and F1-score, and it compared favorably with other models such as CNN (Zhang et al., 2021). Similarly, several successful studies have explored segmentation and classification through machine learning and deep learning-based approaches (Nagaraju & Chawla, 2020; Sethy et al., 2020; Xiong et al., 2020; Das & Rupa, 2023).

Moreover, convolutional neural networks were used to classify images of infected rice leaves with an accuracy of 98.67% (Hossen, 2022; Shoaib et al., 2022). A similar study conducted by Rahman et al. (2020) employed a CNN model to detect leaf blast and bacterial leaf blight in rice images, achieving accuracies of 98.33% and 99.33% on the test

set, respectively. Another deep learning–based investigation (Narmadha et al., 2022) classified rice leaf images into healthy or infected categories for four different diseases, reporting an overall accuracy of 94.2% and an accuracy of 96.8% for the individual disease categories. Additionally, a deep learning-based rice leaf disease identification system achieved 99.17% accuracy on a dataset of rice leaf images (Lu et al., 2017; Chen et al., 2020).

In this research, we focused on the diagnosis and detection of rice leaf diseases using OpenCV and a convolutional neural network (CNN). The main objective of this research was to identify the shape, size, and color of rice leaf diseases and to develop a model that compares predicted labels with actual labels in the training dataset.

2. Materials and Methods

To perform shape and color detection of rice leaf diseases using Python and OpenCV (Howse, 2013; Prajapati et al., 2017; Shibi et al., 2022), we followed the steps below:

1) Data collection: We randomly gathered a dataset of rice leaves, ensuring that it covered a range of diseases and severities, as well as healthy leaves. This approach allowed us to capture a wide range of lesion shapes, colors, and patterns.

2) Preprocessing: We preprocessed the collected images to enhance their quality and remove any irrelevant information. This step involved resizing, cropping, and adjusting the brightness or contrast of the rice leaf images.

3) Color detection: We converted the preprocessed images into a suitable color space (e.g. HSV) to better represent color information. Then, we defined specific color ranges (thresholds) for each disease, determined empirically through experimentation expertise. Next, we applied OpenCV's thresholding or masking techniques to isolate regions in the image that fell within these color thresholds. Finally, we applied morphological operations like erosion and dilation to refine the detected regions and remove noise (Harpale et al., 2020).

4) Shape detection: We first converted the preprocessed images to grayscale. Then, we applied edge detection techniques, such as canny edge detection or Sobel operators, to identify edges in the images. Basically, we used OpenCV's contour detection to extract contours from these edges. Then, we filtered out unwanted contours based on criteria such as contour area, aspect ratio, or circularity. The remaining contours were classified based on their shape characteristics —circular, elongated, or irregular (Harpale et al., 2020).

5) Disease classification: We combined the results from the color and shape detection steps to identify and classify the rice leaf diseases. A decision rule or machine learning approach was then used to make predictions based on the detected color and shape features.

6) Post-processing and visualization: We analyzed the classification results and applied post-processing techniques. Finally, we overlaid bounding boxes, annotations, or color-coded regions on the original images to visualize the detected diseases.

Machine learning and deep learning methods commonly use CNN for image recognition and classification tasks, including rice leaf disease detection (Shopa et al., 2014; Rahman et al., 2020). An outline of how we used CNN for this purpose is described below:

1) Data preparation: We collected a dataset of rice leaf images containing both healthy and diseased leaves. This dataset was then split into training, validation, and testing sets. All images were preprocessed to standardize their size and color.

2) Preprocessing data: This involves cleaning and organizing the images into a consistent format. Specific tasks included resizing, normalization and noise reduction.

3) Transformation of data: We converted the images into multidimensional arrays (tensors) so that the CNN model could process them. Each pixel was converted into a numerical value in the tensor. Next, the dataset was split into training, validation, and testing subsets. This separation is crucial for evaluating the model performance and mitigating overfitting.

4) Feature extraction: The CNN model automatically performed feature extraction through its convolutional and pooling layers, activation functions, and flattening layers, capturing relevant patterns for classification.

5) Recognizing Leaf: After preprocessing, and feature extraction, the data was fed into the CNN model for training. Once trained, the model could accurately classify new leaf images based on learned patterns and predict the type of diseases affecting them.

By following these steps (see Figure 1 for a high-level workflow), CNN can effectively detect rice leaf diseases from images with high accuracy.

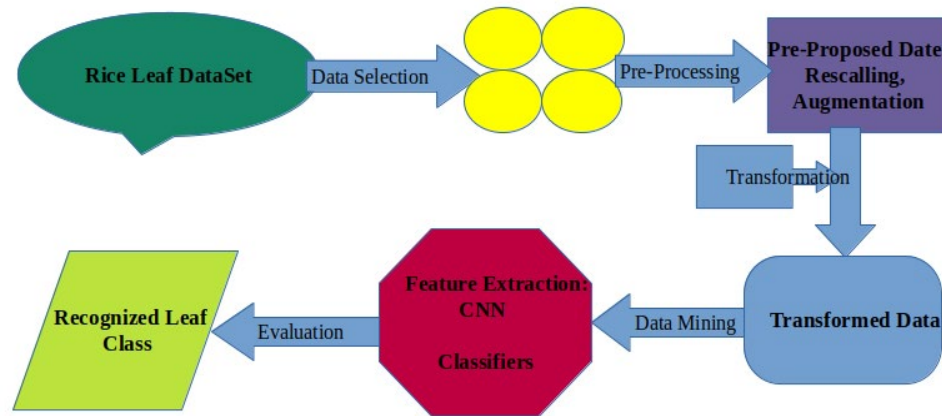


Figure 1. Proposed CNN-based workflow for rice leaf disease detection, showing data selection, preprocessing, transformation, feature extraction, and final classification steps

3. Results and Discussion

This study focused on three main areas: (1) procedures and strategies for collecting data from rice fields of Bangladesh, (2) disease detection using the Python OpenCV library, and (3) the performance evaluation of a CNN model by comparing predicted and actual image labels.

The dataset for this study was collected from several major rice-producing regions of Bangladesh, including Sylhet, Jessore, Satkhira, and Khulna, using mobile phones and digital cameras. At the outset, we encountered two primary challenges; selecting suitable images from diverse geography locations, and identifying diseases in rice leaves via Python OpenCV. These challenges were carefully managed by focusing on areas with high rice productivity. Figure 2 shows a green rice field in Bangladesh, where much of our data was gathered. Next, we divided the rice leaf images into four categories: bacterial leaf blight, leaf smut, brown spot, and healthy.



Figure 2. Rice fields of Bangladesh
(a) Rice Field, Jessore, Bangladesh (b) Disease on rice leaves (red dash line)

Data collection is a crucial step in training a deep learning model. We acquired about 2000 images in *.jpg format, totaling approximately 2 GB in size. In our model, 80% of the images were used for training, 10% for testing, and 10% for validation, thereby meeting the needs of our research. We ran our model on Google Colab, using the latest Python version. At the final stage, we applied the Python-OpenCV library and a CNN algorithm to achieve the desired results.

Figure 3(a) shows a healthy rice leaf which appears purely green without any visible spots. Figures 3(b), 3(c) and 3(d) depict bacterial leaf blight, brown spot, and leaf smut, respectively. Each displays distinct irregularities shapes that indicate different disease characteristics.

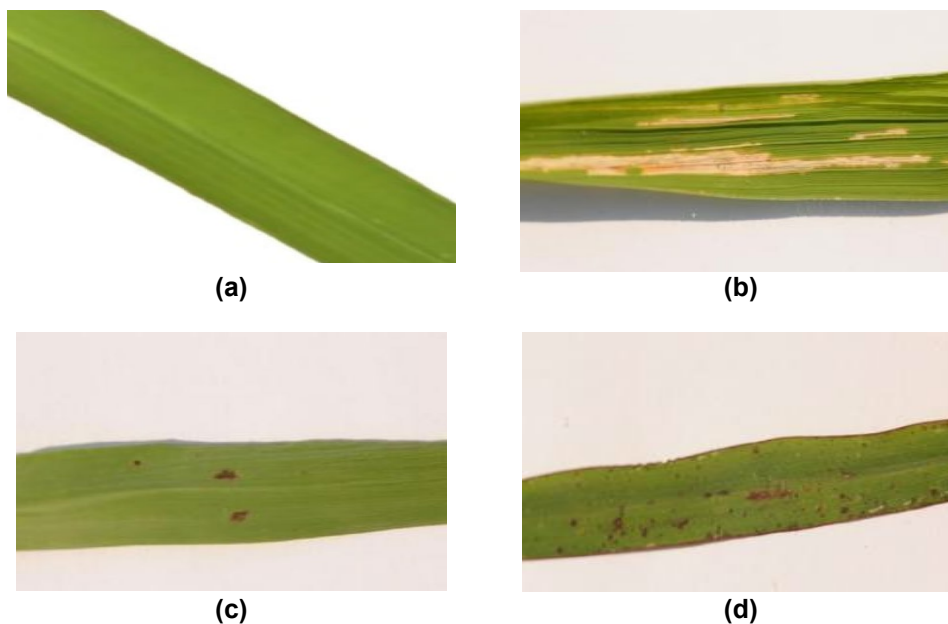


Figure 3. The four categories of rice leaf diseases
(a) Healthy leaf (b) Bacterial leaf blight (c) Brown spot (d) Leaf smut

3.1 Shape and color detection of diseases using OpenCV

A common challenge for farmers is the need to diagnose leaf diseases quickly and effectively using the conventional methods. To address this, we employed the Python OpenCV library (Lei et al., 2019) to evaluate the quality and condition of rice leaf images. Our dataset comprised both healthy leaves and leaves that were affected by three different diseases: bacterial leaf blight, brown spot, and leaf smut.

First, we focused on healthy rice leaf, as shown in Figure 4(a). A healthy leaf typically has a vibrant green color, indicating the presence of chlorophyll and active photosynthesis. Healthy leaves are broad and sword-shaped, without any yellowing, browning, or unusual spots. Although the leaf sizes may vary, they generally remain free from diseases or other irregularities. In Figure 4(c), the surface of a healthy leaf is smooth and free of lesions, and its veins appear as a symmetrical structure along the central midrib. After applying the mask (see Figure 4(b)), the leaf is free from any visible signs of disease, such as leaf smut or brown spots.

In the rice field studied, we observed that bacterial leaf blight emerged as a common and destructive disease significantly affecting rice plants. Figure 5(a) shows an example of the lesions caused by bacterial leaf blight, characterized by their irregular shapes on the leaves. Conventionally, the shapes of these lesion are difficult to analyze, so we used OpenCV to extract their color and monitor disease progression. The lesions of bacterial leaf blight were initially observed as light yellow or light brown (see Figure 5(a)) and were observed to extend along the length of the rice leaf, as shown in Figures 5(b) and 5(c). Upon closer inspection, the yellowish lesions became increasingly evident. In Figure 5(c), our model removed the yellowish color, allowing us to clearly detect the lesion shapes an important advantage in this study.

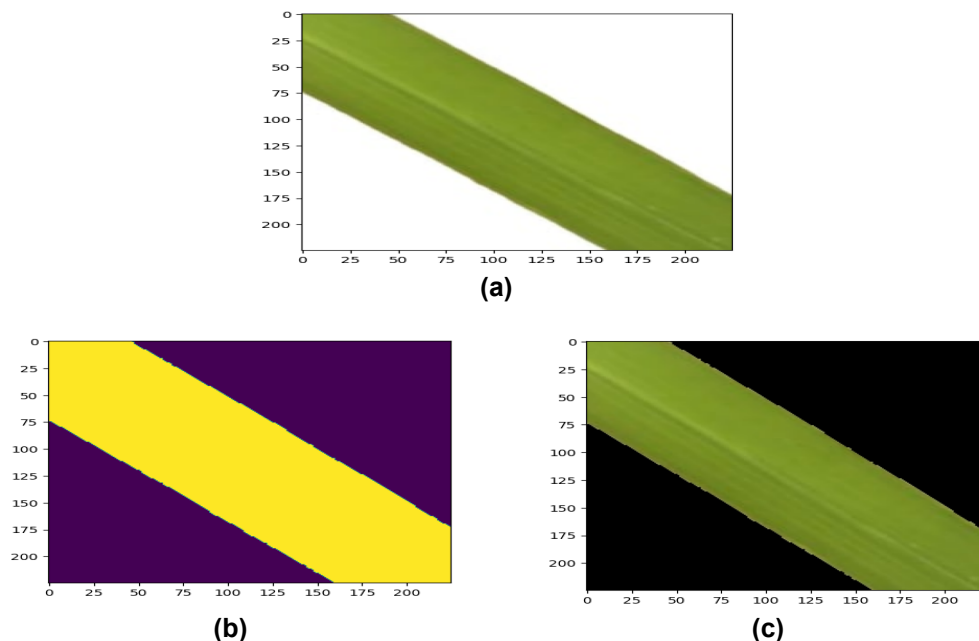


Figure 4. Disease detection of healthy image

(a) Healthy leaf (b) Mask of the healthy leaf and (c) Healthy leaf with no fault detection

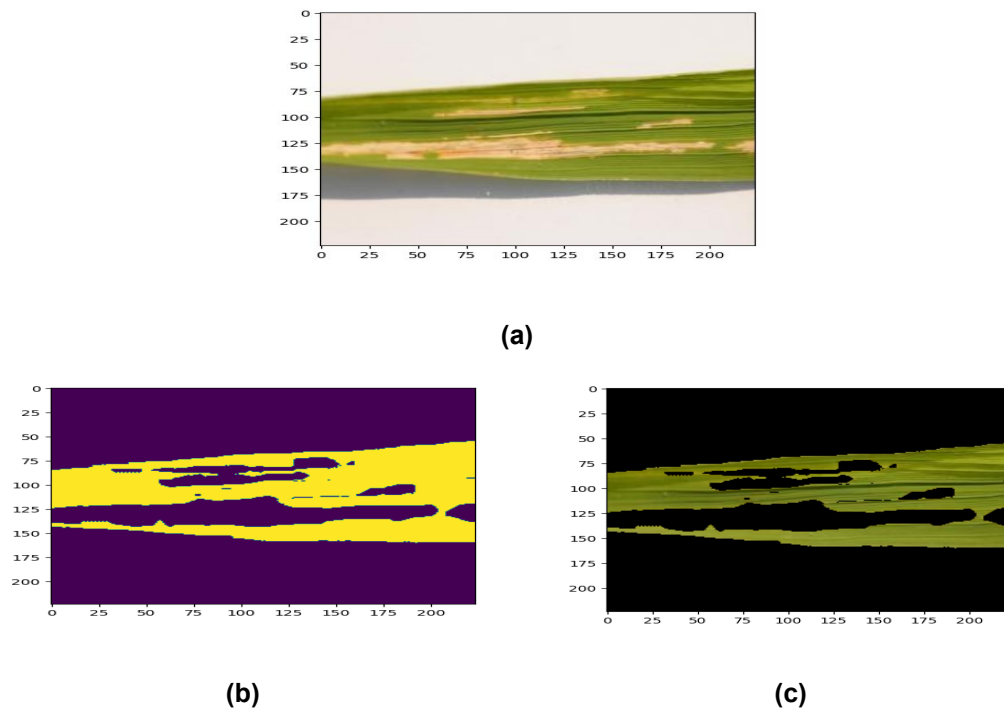


Figure 5. Disease detection of bacterial leaf blight image
 (a) Bacterial leaf blight (b) Masking of bacterial leaf blight and (c) Bacterial leaf blight with lesions

In the rice field, brown spot is a common fungal disease that can significantly affect rice plants. As shown in Figure 6(a), brown spot disease typically presents as small, oval-to-elliptic lesions on the leaves. Because these lesions are relatively small, so we relied on the OpenCV library to accurately identify the lesion color and spot of disease progression. Initially, these lesions appear as light brown (Figure 6(a) and can extend along the leaf's length, as illustrated in Figures 6(b) and 6(c). Their size typically ranges from 1-10 mm long. After applying our computer vision approach to detect brown spot disease, we observe that our model accurately identified even the less visible lesions (Figure 6(b)). In Figure 6(c), our model removed the brownish color, revealing the irregular shapes of the lesions more clearly.

In the rice field, we observed that leaf smut was a typical fungal disease that substantially impacts rice plants. The characteristic sign of lesions from leaf smut is depicted in Figure 7(a) when we analyzed the symptoms of leaf smut irregularities. Similarly, we used the same OpenCV library to accurately detect the color of the lesions and the course of the yellow-brown spot illness. According to Figure 7(a), lesions with leaf smut usually start as yellow brownish. Our model produced a highly accurate output of the chosen photos, even for the hidden leaf smut diseases, as shown in Figures 7(b) and 7(c), after the concept of computer vision techniques were applied.

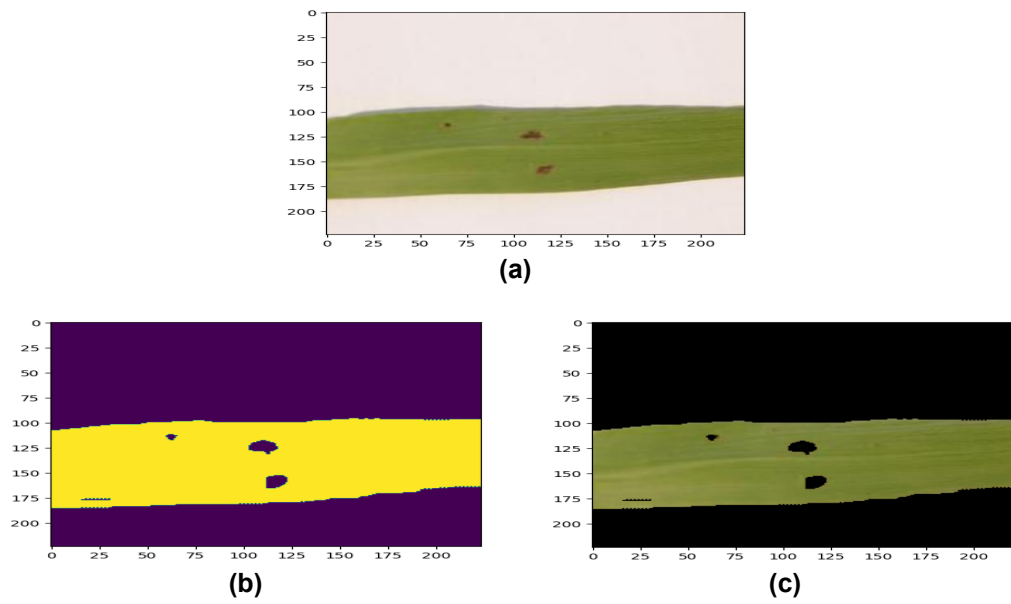


Figure 6. Disease detection of brown spot image
 (a) Brown spots (b) Masking of brown spots and (c) Brown spots with lesions

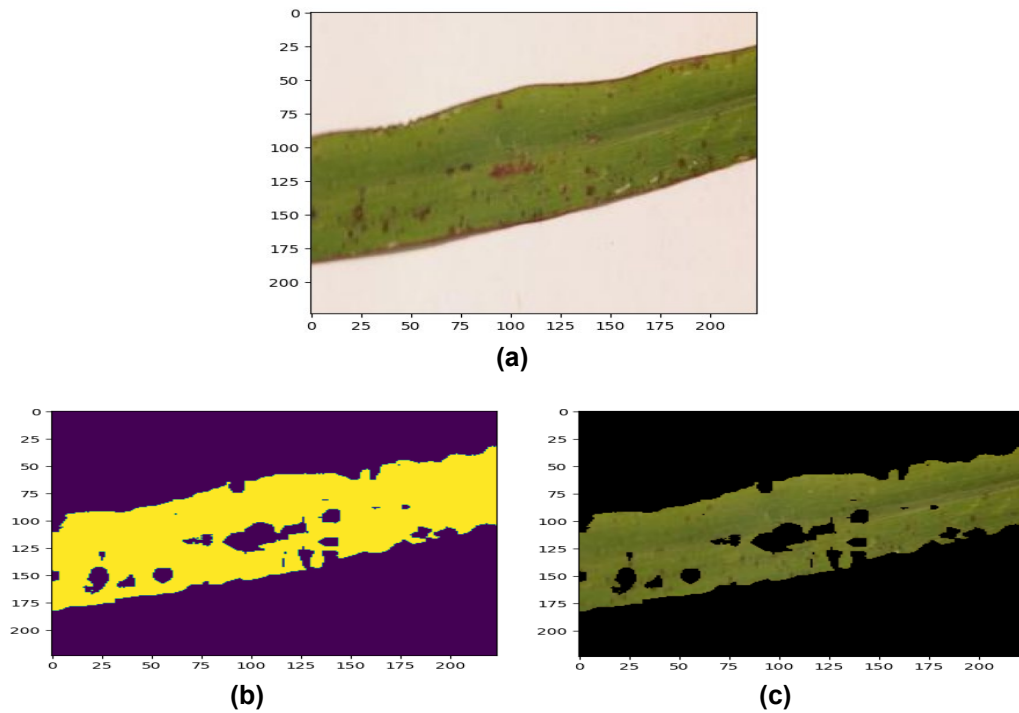


Figure 7. Disease detection of leaf smut images
 (a) Leaf smut (b) Masking of leaf smut and (c) Leaf smut with lesions

We further refined and applied our detection technique to identify the hidden rice plant diseases. Diagnosing these invisible lesions was particularly challenging because we did not know their shape and color. Based on our previous experiments, we examined images such as the one in Figure 8(a), which shows less minor or virtually invisible lesions, indicating a low-level infection. Figures 8(b) and 8(c) show the same image after running the model. Figures 8(b) and 8(c) depicted the same images processed by our model, making the disease apparent, and especially to those working in the rice field who otherwise might not be able to detect such infection. Despite this improvement, the complexity remained high. We could not definitely conclude that the lesions represented a specific disease (such as leaf smut), as they could potentially develop into brown spots within a few days. Therefore, in the subsequent studies, our focus shifted to diagnose these hidden diseases more accurately. We developed the model to detect such obscure infections and to predict otherwise invisible illnesses on the rice leaves with greater precision.

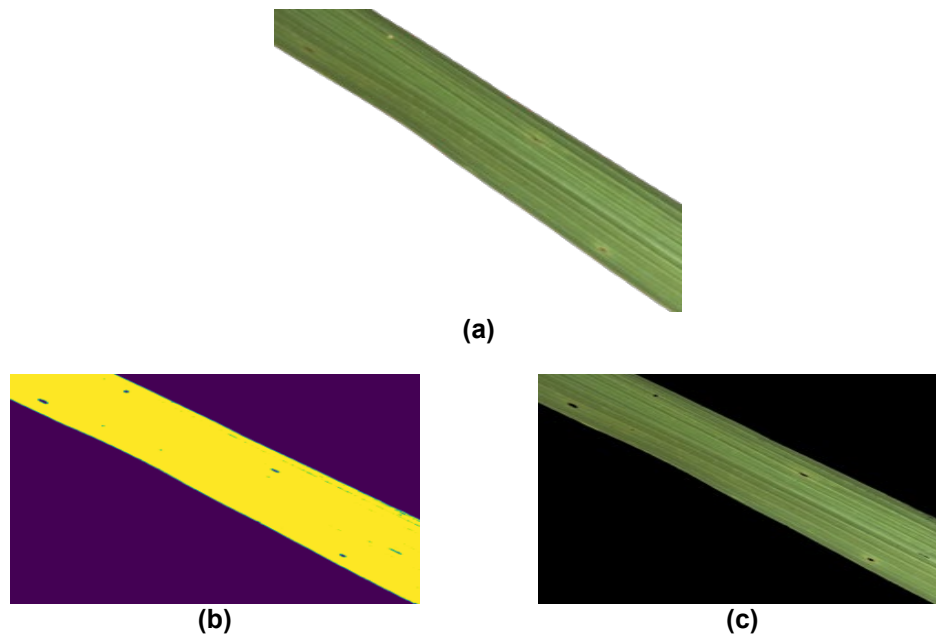


Figure 8. Almost invisible disease detection

(a) Hidden spot in a leaf (b) Masking the hidden spot in a leaf and (c) Hidden diseases lesions

3.2 Performance analysis of CNN model

To create a practical CNN model, we installed libraries such as TensorFlow and Keras. After importing these libraries, we performed data preprocessing and modifications. For example, we resized the images to a suitable input size and set the batch size to 32. We then used the ImageDataGenerator function to normalize the data before applying image augmentation. This transformed data was split into training, validation, and test sets at a ratio 80:10:10, respectively.

In this setup, two convolutional layers were used for filtering the images, employing 16 and 32 filters. It took a few hours to train the model, which was trained over 150 epochs. Once training was completed, we utilized the matplotlib library to visualize the model accuracy, validation accuracy, and training loss. We also wrote a script to display six images illustrating four different disease categories. These six images were randomly selected after 1000 shuffles, as shown in Figure 9, where the difference among the four specific diseases can be observed in a single frame. Figure 10 demonstrated the model performance on similar images, showing the actual labels, predicted labels, and confidence levels.

The training and validation accuracy and loss curves represent the model performance throughout the training process, illustrating how effectively the model learns and generalizes from the training dataset. The accuracy curve shows how the model accuracy changes or improves over the number of epochs (plotted on the x-axis), while the y-axis represents both accuracy and loss. Accuracy is calculated by comparing the model's predictions with the actual labels of the training dataset.

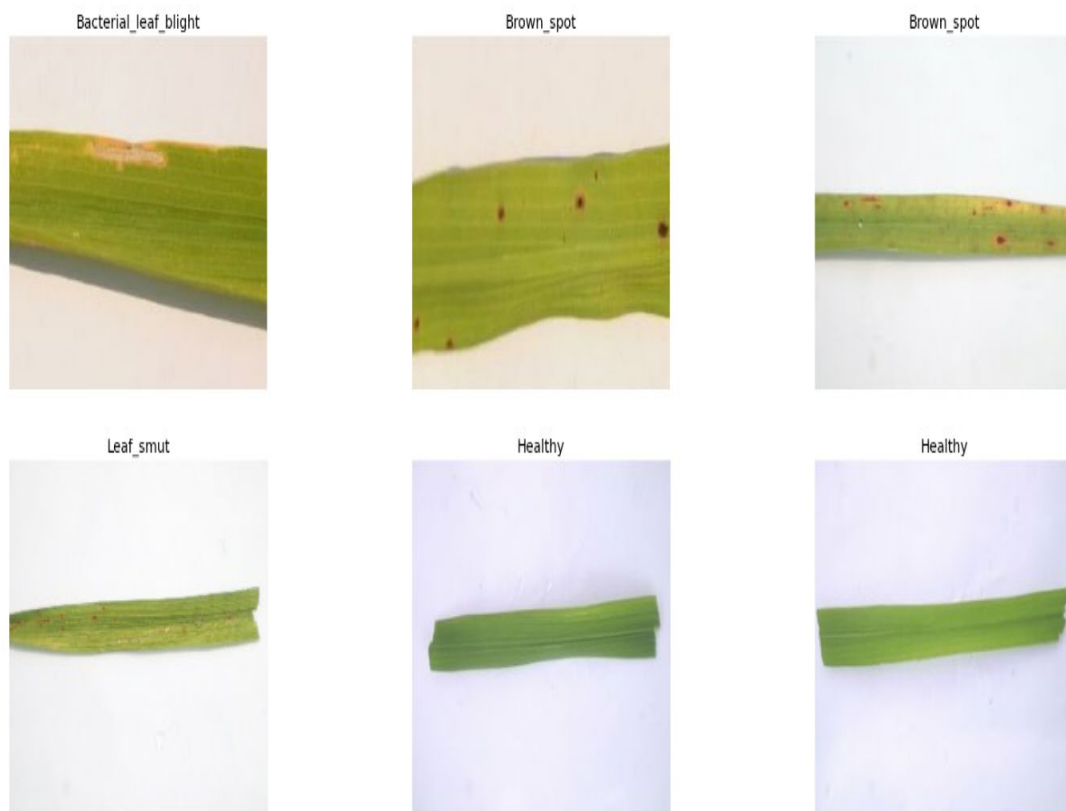


Figure 9. Images of four categories of diseases

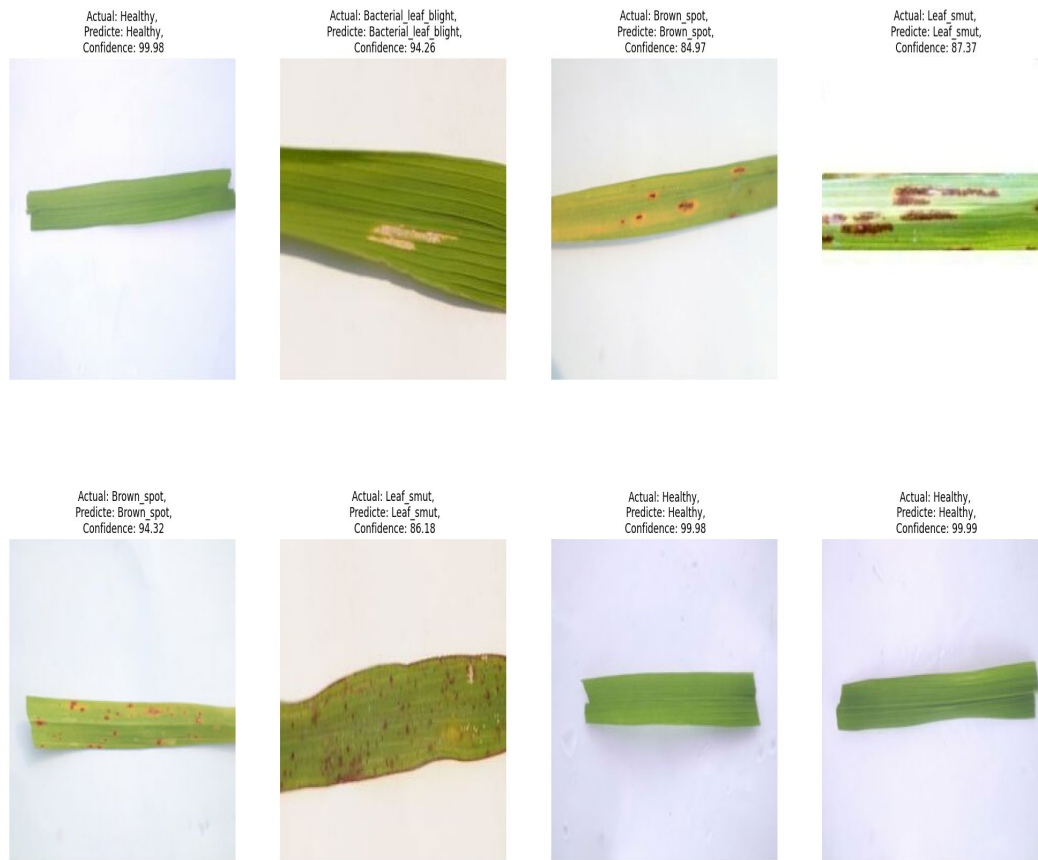


Figure 10. Detection of the actual and predicted images and the confidence levels

The loss curve, on the other hand, illustrates how the loss function value changes throughout training. The loss function measures the discrepancy between the anticipated outputs and the actual labels of the model. This curve is also plotted against the number of epochs. As shown in Figure 10, our model produced excellent results: the predictions closely matched the actual images, and the confidence level was close to 100%, indicating high accuracy. Occasionally, a confidence level of about 85% was observed; however, this did not result in any mismatches of images. The main difficulty at this stage was a 1-4% mismatch between the actual and predicted images. To address this, we tuned our model and increased the number of training epochs from 80 to 100, which led to improve performance as demonstrated in Figure 11. In this Figure, the accuracy curve gradually increased during training, with both training and validation accuracy approaching 1. Conversely, the loss curve decreased over the training process, and the final loss values for both training and validation were near 0. Overall, these findings indicated that the developed CNN model performed effectively in the detection of rice plant diseases.

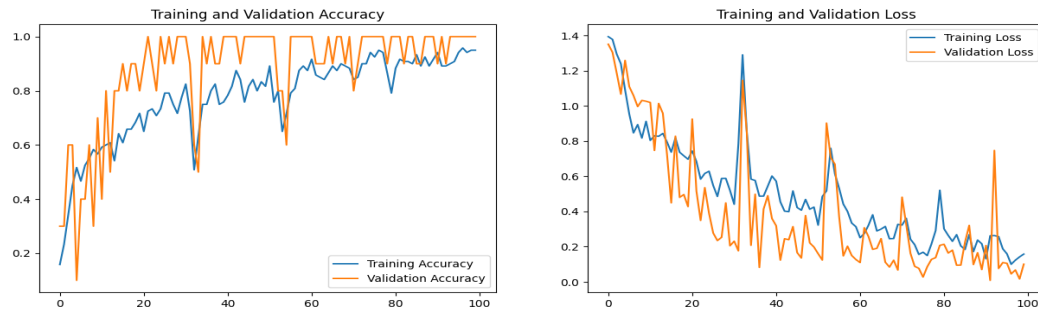


Figure 11. Comparison between accuracy and loss during training and validation period

4. Conclusions

Rice is currently being produced in high demand within the smart agriculture sector of Bangladesh. However, rice plant diseases pose a significant concern in Bangladesh and worldwide, as the incidence of these diseases is increasing daily, resulting in reduced rice productivity. It is imperative to control these diseases at an early stage by applying innovative technology. Therefore, we developed a new model that could detect and diagnose visible and invisible rice leaf diseases with high accuracy and low cost. In this study, we employed a model using computer vision and deep learning techniques to detect and recognize the irregularities and discoloration associated with rice leaf diseases. Our research comprised two experiments: one using OpenCV and the other employing CNN. In the first phase, we developed an OpenCV model to address early-stage rice leaf diseases by detecting the exact location, size, and color of lesions on the leaves. The model performed well in identifying bacterial leaf blight, brown spot, leaf smut, and healthy leaves. However, diagnosing the deep-level hidden diseases in the rice leaf remained a complex task. In the second phase, we developed a CNN model to measure accuracy by comparing the actual and predicted labels of the training dataset. Our model showed a good fit in both the accuracy and loss curves, indicating its effectiveness in the detection and diagnosis of rice leaf diseases.

5. Acknowledgements

We would like to express our special thanks to the Sylhet Agricultural University research system and the University Grant Commission for providing the funding (SAURES-UGC, 2022/23) that enabled us to successfully conduct this research. Their financial support played a crucial role in the completion of this study.

6. Conflicts of Interest

The authors declared no conflicts of interest. The funding received from the Sylhet Agricultural University research system did not influence the design, execution, or outcomes of the research.

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