IDENTIFICATION OF PADDY DISEASE ALONG ITS PROCESSING TIME

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Abstract. Most tropical and subtropical nations in the world eat rice as their main meal. This involves hectare-sized paddy fields, whose upkeep and care becomes a tiresome undertaking for the farmers. The caregivers are unable to recognize ailments and are unable to finish the time-consuming task of crop care in a timely manner. This research offers a suggestion for a rapid identification of paddy into unhealthy plants as a result of this laborious operation. The purpose of this work is to offer a system for diagnosing and detecting paddy illness based on performance testing and image processing methods. The system, which was developed in C++ and tested using a dataset of contaminated leaf images, is used. The several varieties of spotted leaves caused by paddy disease are provided in this dataset. Image acquisition, pre-processing, feature extraction, and performance measurement are the system's four key processes. These steps each conduct their own tasks. In addition, this research provides a definitive description of the paddy illness. The image is shrunk and made grayscale in the first phase because it is the procedure for carrying out the subsequent actions. The sick areas are then divided into groups and given labels. As a result, the processing time and signal-to-noise ratio are calculated and summarized in the last phase. According to the study's findings, the suggested system can accurately and efficiently identify and categorize paddy disease in plants.

Keywords: *paddy disease, pre-processing, feature extraction, performance, SNR, efficiency*

Introduction

Rice is the second most grown grain crop in the world and is a staple food for many rural populations. It comes in two varieties: japonica and Indica. Rice is a popular food everywhere in Asia and this is partly due to its availability and cheap prices. It can be found, for example, on every continent apart from Antarctica. Over 90% of the worldwide production of rice goes to Asia and it's consumed there over 75% globally. Only 0.07% of production remains which is distributed among Africa (2.95%), America (5.19%), Europe (0.67%), and Oceania (0.15%) (Varma et al., 2017). Rice is not as abundant as it used to be, and it is important that the world aware of the issues at hand. As more people want rice, there's going to be less of it available (Papademetriou et al., 2000). Currently, rice plants are facing major challenges because of the risks for diseases that can ruin both quantity and quality. These problems are often the result of a variety of factors, including difficulties in finding skilled farmers, not understanding fertilizer management and knowing about diseases or pests (Kalita et al., 2016). The plant diseases can also have negative environmental consequences. As these diseases spread globally, they can weaken a plant's overall function and hamper economic prosperity by reducing crop yields (Varshney and Dalal, 2016).

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Rice is vulnerable to a number of bacterial and fungal diseases (Mohan et al., 2016). This includes Sheath blight, NBSD Leaf blasts, and Brown spots. The severity of these problems can be noticed through the damage they cause to rice plants (Noor et al., 2018). Once rice disease, brown spot, is mainly caused by a fungus called Bypolaris Oryza. It often occurs throughout the growing season and is something to watch out for in soil which lacks silicon. The current methods for making rice cultivation more productive must become more sustainable (Phadikar et al., 2012). For example, not using fertilizers and pesticides would provide better environmental performance. Therefore, it is important to monitor the growth of rice paddies in order to maintain rice production (Yasar et al., 2015). The novelty of this research is based on the feature of: (1) to identify the paddy disease in the plants through detection approaches; (2) calculate the signal to noise ratio for the plants complexities; and (3) to notice the processing time of the detection of the disease in plants.

Literature review

The choosen study proposes a depth-wise separable convolutional neural network (CNN) based model for identifying 12 different types of rice plant diseases. The performance of 8 different state-of-the-art CNN models is also evaluated, with a focus on diagnosing rice plant diseases. When compared to current state-of-the-art CNN architectures, the proposed model performs exceptionally well. The experimental results show that the proposed model, despite having a significantly smaller model size, can accurately diagnose rice plant diseases with a validation accuracy of 96.5% and a testing accuracy of 95.3% (Prottasha and Reza, 2022). This study proposes the use of the random forest classifier to identify three common rice plant diseases: rice blast, brown spot, and narrow brown spot. The suggested approach was found to be successful, with an overall accuracy of 93% in the identification of rice plant diseases (Yen and Ling, 2021). The main focus is to develop a deep CNN framework for automatically detecting and identifying various biotic and abiotic stressors in rice crops using field images. The pre-trained VGG-16 CNN model is used to automatically identify images of stressed rice crops taken during the booting growth stage. The trained models were tested on a held-out dataset of 30,000 field images of five different rice crop types with twelve stress categories (including healthy/normal) and achieved an average accuracy of 92.89%. This demonstrates the feasibility of using deep learning approaches to automate resource management and field agriculture operations through the development of mobile applications and decision support systems (Anami et al., 2020).

In this study, the researchers used machine learning to create a model that can identify rice infections. They focused on six major diseases that are commonly found in Bangladesh's rice fields and collected an accurate dataset for each of these diseases with the help of the Bangladesh Rice Research Institute (BRRI). The study used three popular pre-trained CNN models (Inception-v3, MobileNet-v1, and Resnet50) and performed any necessary augmentation and scaling on the dataset before using them. The research produced promising results and demonstrated the potential for machine learning to be applied in agriculture. This research will be beneficial for young people working in agriculture in the future and could also facilitate the adoption of machine learning techniques in the agricultural industry in Bangladesh (Kamrul et al., 2019). An improved fuzzy inference system (OFIS) is proposed for the automatic diagnosis of novel paddy leaf diseases. The collected paddy images are first converted into red, green, and blue bands, and the noise in the green band is removed using a median filter.

The pre-processed green band is then used to extract texture and color attributes, which are used by the OFIS system to classify the image as normal or pathological (Jayanthi and Shashikumar, 2019). A novel hybrid deep learning model for diagnosing paddy leaf diseases is proposed in the presented research. The process begins by collecting input paddy leaf photos from various sources and applying filtering and contrast-enhancing techniques. Adaptive K-means clustering is then used to segment the anomalous region of the paddy leaf, and the Fitness Sorted-Shark Smell Optimization (FS-SSO) is used for the same purpose. The hybrid deep learning model is then used to identify the disease by combining the segmented photos with the Resnet and YOLO models, with the YOLO model replacing the fully connected layer of the ResNet model. The main parameters of the hybrid deep learning model are optimized using the FS-SSO in order to achieve a high recognition rate (Ganesan and Chinnappan, 2022).

According to the study, the paddy diseases can hinder efforts to increase both the quantity and quality of rice production. Hence, descriptors for each lesion image's "S" component were used and probabilistic neural networks (PNN) were employed for identification (Chompa et al., 2022). The article presents a novel method for identifying the diseases based on the RGB value of the affected area in an image. After determining the RGB percentage of the affected area, it is classified into different categories and fed into a simple identifier called Naive Bayes, which categorizes the disease into various groups. This method was found to be effective and was able to identify three rice diseases: rice brown spot, rice blast, and bacterial blight (Asfarian et al., 2013). According to *Table 1*, all the references provide a summary of the experimental based findings with selected and tune-up parameters.

***Table 1**. The summary of selected research articles along with their empirical results.*

References	Method	Results	Parameters	Limitations
Prottasha and Reza (2022)	CNN	Accuracy of 96.5%	Activation Function: ReLU Total Data: 16770 Training Data: 13415 Testing Data: 1600 Image Size: 224×224	Higher identification accuracy cannot be achieved using transfer learning with pre-trained ImageNet weights on modern CNN.
Yen and Ling (2021)	Random forest	Accuracy of 93%	Color Features and Shape features such as area, and eccentricity are the parameters.	13.33% of narrow brown spot diseases were wrongly identified.
Anami et al. (2020)	Iamge processing using deep learning model	Accuracy above 92%	VGG-16 CNN Model is used for image identification.	It is difficult to achieve good results in outdoor environments due to high irregularity.
Kamrul et al. (2019)	Computer vision through pre-trained CNN models	Validaton accuracy rate of 98%	Inception v3, MobileNet v1, and Resnet 50, three popular CNN pre-trained models, were used.	Low validation accuracy on the non-spontaneous dataset.
Jayanthi and Shashikumar (2019)	OFIS system	Accuracy of 95%	The VSSFA algorithm is used to optimize the parameters of the FIS.	There are some limitations to the OFIS method, such as the use of triangular membership and trapezoidal functions.
Ganesan and Chinnappan (2022)	ResNET and YOLO	Accuracy rate is 95.58%	Fitness Sorted-Shark Smell Optimization is used as a parameter.	Data augmentation has not been employed in this research, which is a drawback of the model.
Chompa et al. (2022)	Fractal descriptor method	Accuracy of 83%	PNN is used as an identifier as a parameter.	The technique is limited to identifying

				only 4 types of rice diseases and does not require processing the entire leaf.
Asfarian et al. (2013)	Percentage of RGB	Accuracy above 90%	The Naive Bayes method is used to identify rice diseases.	This technique does not require the processing of the entire leaf.

Materials and Methods

The proposed system for identifying rice diseases involves four steps: image acquisition, pre-processing, feature extraction, and measurement. Images are collected from agricultural fields and used to create a dataset of rice leaves. Pre-processing involves reducing the image dimensions and removing the background. The next step is image segmentation, which uses the k-means clustering algorithm to separate the healthy and diseased areas of the image. The steps of the procedure are displayed in *Figure 1*.

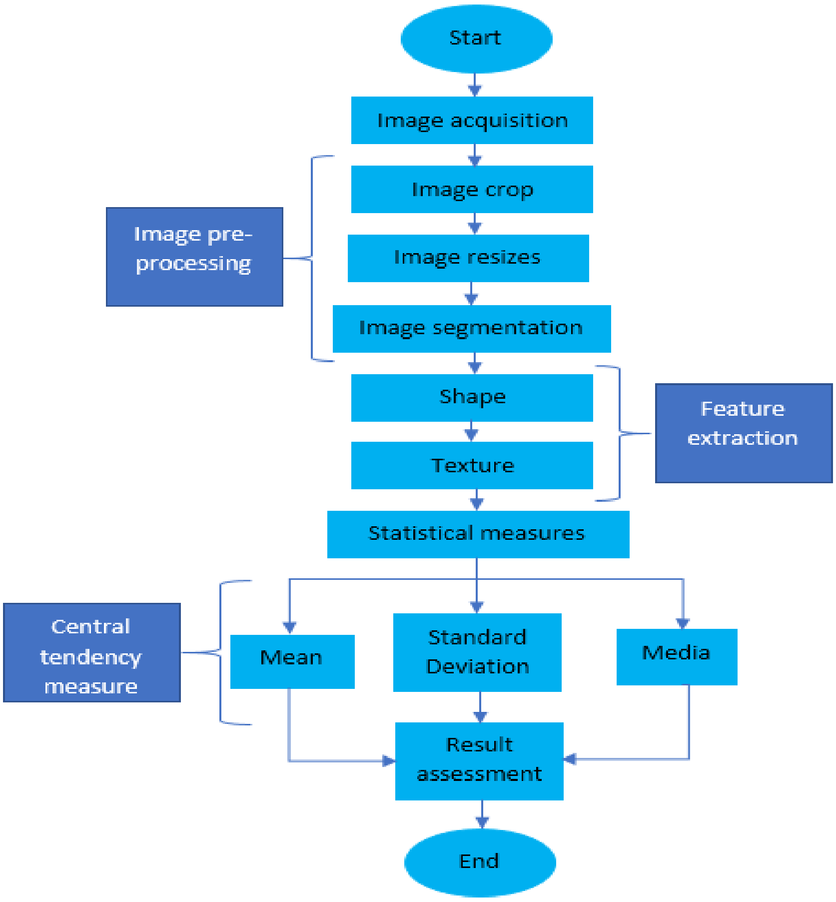


Figure 1. *The proposed framework.*

Image pre-processing

During pre-processing, the photos in the dataset are shrunk and cropped to a dimension of 300 x 450 pixels in order to reduce the need for memory and processing resources. In this step, the image background must be removed using hue values-based fusion. The process begins by transforming the RGB model of the image to HSV, and taking the S value from the HSV model into consideration because it outweighs the whiteness. The image is then transformed into a binary image based on a threshold value of 90, and the binary image is combined with the original RGB image to generate a mask. The K-means clustering algorithm is used for image segmentation. This involves dividing the image into groups or clusters. In the case of a leaf image, clustering is used to separate the healthy and diseased areas. The hue component of the image's HSV model, which represents the actual color without information about brightness or darkness, is used for the clustering. The centroid value is calculated and used to address the issue of randomization in the clusters. The unhealthy green portion of the diseased cluster is also removed. Once the background has been removed from the image, a histogram of the color component is created. This histogram is used to determine the hue values and bin counts. Based on the histogram and the diseased image, a threshold value is determined to distinguish between the normal and sick areas. The color values of the healthy and diseased sections are stored in separate arrays.

The centroid of each cluster is calculated using the color values of the healthy and diseased areas, with the highest value being chosen. The black color value and the selected centroid values are then input into the clustering process. However, the presence of an unhealthy green portion in the diseased area may impact the accuracy of the categorization, as the calculation of the attributes is negatively affected by the green pixels. To address this issue, a binary mask is created based on the range of the green color in the hue model, which is 17.2 to 45 degrees with a minimum value of 0.048 and a maximum value of 0.125. This mask is used to remove the green hue from the diseased area.

Feature extraction

In this phase, both texture and color features are extracted from the image. The texture features include aspects such as homogeneity, contrast, correlation, and energy, which are calculated using the Gray Level Co-occurrence Matrix (GLCM). The color features consist of extracting the mean and standard deviation values of the image's color. After extracting the color and texture features, they are normalized using the Min-Max normalization method to scale the values between 0 and 1. This process ensures that all of the features are on the same scale and can be compared and analyzed more effectively.

Central tendency measure

To calculate the mean (M), median (Med), and standard deviation (S), the following formulas are used such as in Eq. (1), Eq. (2), and Eq. (3); where n represents the total number of pixels and P_{xy} represents the individual pixel values.

$$M_y = \frac{1}{n}\sum_{x=1}^{n} P_{yx} \qquad \text{Eq. (1)}$$

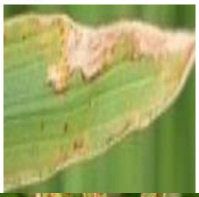
$$Med_y = \left(\frac{n+1}{2}\right)^{P_{yx}} \qquad \text{Eq. (2)}$$

$$S_y = \sqrt{\frac{1}{n}\sum_{x=1}^{n} (P_{yx} - M_y)^2} \qquad \text{Eq. (3)}$$

Results and Discussion

The researchers developed a technique and tested it to see how well it worked for identifying paddy illnesses in plants. This study gathered pictures of paddy leaves from resources, including Kaggle and others, then sorted them into groups based on the various types of disease to create the dataset. This system is implemented in C++ and maximizes its efficiency, to effectively identify sick areas in plants. The system takes an image from the dataset as input, resizes it to a fixed, square dimension, and then transforms it into a grayscale to start the detection process. The system uses OpenCV (version 4) libraries, to determine the processing time for each of detection, which are shown in *Table 2*. The average processing time is found to be 2.25 nanoseconds. This study also evaluated the signal-to-noise ratio of the images used in detection. With an average signal-to-noise ratio of 3.7154957 dB, the images are, of high enough quality to be used for image analysis.

***Table 2**. The empirical testing results of the paddy disease along processing time.*

Index	Origina image	Detected image	Signal-to-noise (dB)	Processing time (nano-sec)
Varma et al. (2017)			2.07	2.5
Papademetriou et al. (2000)			0.70	1.9
Kalita et al. (2016)			0.72	2.1
Varshney and Dalal (2016)			0.80	2.0
Mohan et al. (2016)			4.96	1.6
Noor et al. (2018)			3.29	2.5

Phadikar et al. (2012)			3.90	2.4
Yasar et al. (2015)			4.00	3.6
Prottasha and Reza (2022)			6.27	1.8
Yen and Ling (2021)			10.45	2.1

According to the observation, most of the paddy leaves that are given in as input are correctly identified as unhealthy plants. Because of this, the suggested framework is effective and useful for identifying paddy leaves in all applications. The detection component can recognize the lines in the provided image and, by considering outlines based on size extremities, can calculate the impacted area with a high degree of accuracy. On the input image, the precise regions of concern are highlighted and provided as the result. Finding the whole area impacted can provide enough information to guide judgments about pesticide use and other workable remedies.

Conclusion

This research article has studied how to detect paddy disease in rice plants using image processing techniques. In previous studies, the Random Forest technique as low quality, identified the brown spot disease and is challenging to achieve good results in outdoor environments. Similarly, some other techniques like the Fractal Descriptor method and Percentage of RGB abortive to calculate the processing time of the entire leaf but this study approach can identify any type of disease on the rice leaf and calculate the processing time of the entire leaf in nanoseconds which demonstrates that this system is significantly faster and more efficient than previous approaches. This research can help farmers monitor their rice paddies and improve their production. Future work can focus on developing more accurate and efficient methods for paddy disease detection.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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