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Malaysian Journal of Science and Advanced Technology

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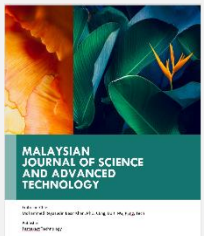

Detection of Paddy Blast: An Image Processing Approach with Threshold based OTSU

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KEYWORDS

Paddy blast
Rice blast
Threshold based OTSU
Image Processing
Plant disease

ARTICLE HISTORY

Received 10 September 2022
Received in revised form 3 October 2022
Accepted 21 October 2022
Available online 22 October 2022

ABSTRACT

If rice infections spread, the agricultural industry as well as the people who eat rice as their primary food grain suffer greatly from production and financial losses as well as food shortages. One of the deadliest diseases that can affect paddy plants at any stage of development and hinder the growth of rice plants is paddy leaf blast. Because the brown spot and the leaf blast have the same appearance but distinct shapes, it is quite difficult to distinguish between them. In this case, paddy leaf blast is detected using computer vision methods. But because of their resemblance to other spots and poor color channel selection, previous procedures are difficult, time-consuming, and poorly able to detect blasts. In this article, an effective and automated image analysis method has been proposed to identify paddy leaf blasts that can identify leaf blasts by utilizing various shapes. Additionally, the process minimized pointless data exploration and provided superior accuracy of 95.34 percent.

1. INTRODUCTION

The primary food crop grown in nations with agricultural economies like Bangladesh, India, Myanmar, Vietnam, Laos, Cambodia, Thailand, and many more is rice (Oryza sativa). To achieve food sustainability and preventing economic losses, it is important to take proper care of rice plants. Rice fields are often brutally damaged by natural calamities and diseases. Natural disasters are out of human control, yet it is still possible to take the essential precautions to protect plants from illnesses. Many different diseases, including sheath blight, bacterial blight, rice blast, sheath rot, brown spot, narrow brown spot, and others, affect rice plants [1]. Among all the rice plant diseases, rice blast is the most common one [2] and considered as one of the deadliest disease [3]. Rice blast disease is found in more than 80 countries around the world [4] and causes approximate loss of $55 million only in South and South-east Asia [5]. As a consequence, rice blast disease requires special take care and pre-caution for preventing outbreak. Although there are numerous causes of paddy leaf blast, fungus is the primary factor in rice blast [6].

Blast can occur at any stage of growth and can be detected in the rice plant's leaf collar, leaf node, and neck [7]. This disease is more prevalent in areas with low humidity, frequent or lengthy rain showers, and chilly daytime temperatures [7]. Because of certain similarities between a blast and a brown spot, identifying a blast can be challenging [8]. If it is a far view, distinguishing rice blast from brown spot becomes more difficult. The agriculturalist claims that the brown spot and blast disease have elliptical and diamond-shaped basic structures, respectively. White spot for rice blast and brown spot for brown spot illness are two additional distinctions between the two [9]. However, personally inspecting and identifying rice blast in a wide field is time-consuming. Utilizing computer vision technology in conjunction with agriculture experts is required to take advantage of this time-consuming monitoring in order to boost productivity, prevent blast outbreaks generally, and promote food sustainability. With the incredible progress in pattern recognition and image processing technologies, identification and classification of rice blast has become simplified. Few approaches [3][7][10][11] are taken with an aim to detect rice blast with acceptable accuracy. However, the existing works adopt complex machine learning algorithms along with poor selection of color channel, that make the system time consuming and suffers much to detect the blast shape.

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In this paper, a practical method for identifying paddy blasts is proposed that combines Otsu's [12] thresholding technique with appropriate color channel selection. The suggested method decreases application time while increasing higher horizontal precision.

2. Literature Review

Over the years, numerous studies have been undertaken to identify various plant diseases.

2.1 *Detecting and Classifying with Machine Learning*

R.P Narmadha and G. Arulvadivu [3] proposed a method for detecting and classifying paddy leaf diseases from cropped images. They used gray scale images converted from RGB. The proposed system used K-means algorithm for removing noise and unnecessary spots from the image. After extracting the feature, they applied SVM, ANN, fuzzy logic for classification. According to their research ANN and fuzzy classification correctly identified the disease of the paddy plant. In another study worked on blast, brown spot, narrow brown spot diseases where color and shape features were incorporated for rice blast disease identifications. In total 4 types of machine learning algorithms (K-means, naïve Bayes, SVM and KNN) were implemented for identification of blast diseases. At the beginning de-noising was carried out using median filter followed by K-means clustering for segmentation. During segmentation 50 features were extracted and finally classification algorithms were used to detect the disease using the extracted features. The results were not satisfactory since the most accuracy rate found by Naïve Bayes (79.5%) followed by SVM (68.1%) and the rests were under 60% [13-14].

2.2 *Image Analysis*

Phadikar, Santanu, and Jaya Sil [11] proposed an approach which can detect infected paddy leaf blast regions from digital color images. Entropy based bi-level threshold was used for segmentation followed by 8- connectivity method for boundary detection. Finally, classification approaches were used to detect the region of interests. Nunik Noviana Kurniawati et al. [15] in their research the approached for a diagnosis system for several paddy fungal diseases. The research used binary images converted from RBG by local entropy and OTSU method. They used probability distribution for generating occurrence matrix. In their research to get a clear image they used median filter for removing unnecessary spots. The research approached for blob analysis for extracting shape feature. After extracting the featured the approached system diagnosed the disease with 94.7% accuracy. Research study by [16-20] incorporated paddy leaves for analysis where median filter was used for noise reduction. Segmentation technique using k-means clustering was incorporated and finally Artificial Neural Network (ANN) was used for classification. The accuracy rates were 92%, 90%, 93%, 84% and 87.7% respectively. Al-Hiary, H., et al [10] improved the accuracy and time compared to the previous research works. At the beginning of this study RGB color images were transformed to a color structure. Secondly, green pixels were masked and removed while incorporating threshold operation. Finally, feature information was used to detect the disease. The accuracy rate was found 94%. Their proposed approach is 20% faster than previous approaches.

2.3 *OTSU threshold*

As part of their research, Kurniawati, Nunik Noviana, et al. [15] first used a median filter to minimize noise before using an OTSU threshold technique to convert segmented RGB images into binary images. Finally, the regions of interest were categorized using a classification technique. A simple method to detect paddy blasts was investigated employing segmentation by OTSU threshold on the blue channel. Whereas this research employed straightforward ways to identify paddy blast, the research mentioned above used numerous algorithms to identify and diagnose paddy blasts.

3. Proposed Method

The working steps of the proposed method are shown in Figure 1. The first step begins with image acquisition. Further steps include filter operation, segmentation, and identification of ROI.

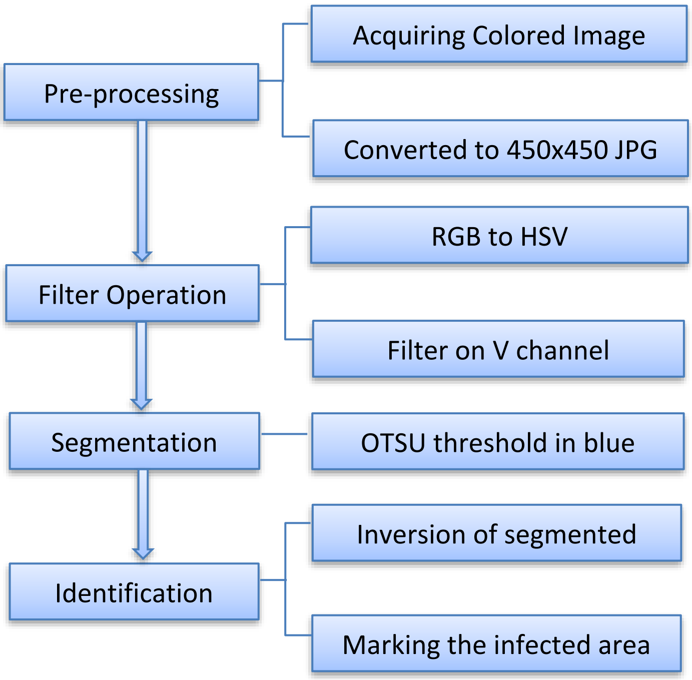


Fig. 1. Proposed Methodology

3.1 *Image Acquisition*

Image acquisition is the first step for image processing approach. This study test color images were collected from plant protection (Bangladesh Agriculture Research Institute) in .JPG format with a size of 450 × 450.

3.2 *Filter Operation*

The acquired RGB images are firstly transformed to cylindrical coordinate representation termed as HSV (Hue, Saturation, Value). In this representation, hue colors are organized in a radial part ranging from bottom to top as black to white, surrounding the central axis of neutral colors.

Saturation channel resembles several tints of radiantly colored paint and the value channel resembles the combination of those paints with varying amounts of black or white paint. Hue is represented with degrees where H ϵ [0, 360] where saturation and value are fixed from zero to one i.e. S ϵ [0, 1], V ϵ [0, 1]. The value (V) channel is applied to perform enhancement as well as filter operation. As the images are represented as R,G,B ϵ[0, 1], the V channel is calculated as:

$$V = X\_max=max(R,G,B) \in [0,1]. \quad (1)$$

Three well-known filter operations known as mean, median, and Gaussian is used in this research.

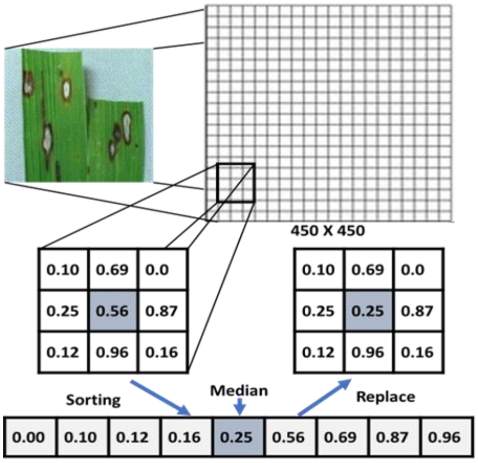
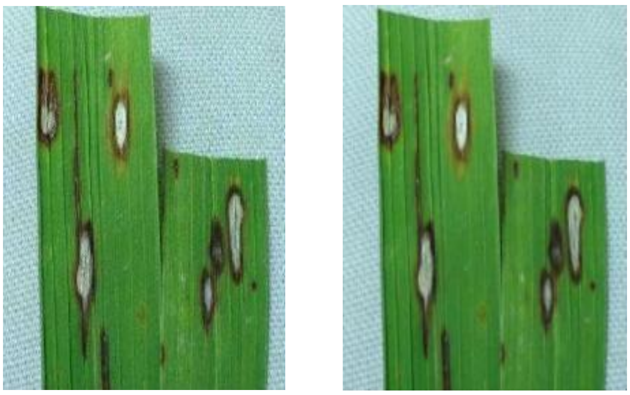


Fig. 2. Filter operation on image of affected paddy leaf.

Median performs better in presence of edge for noise removal than others. Figure 2 depicts the mechanism of filter operation where Figure 2. Shows the result obtained through filter operation and Figure 3. Shows the result image.

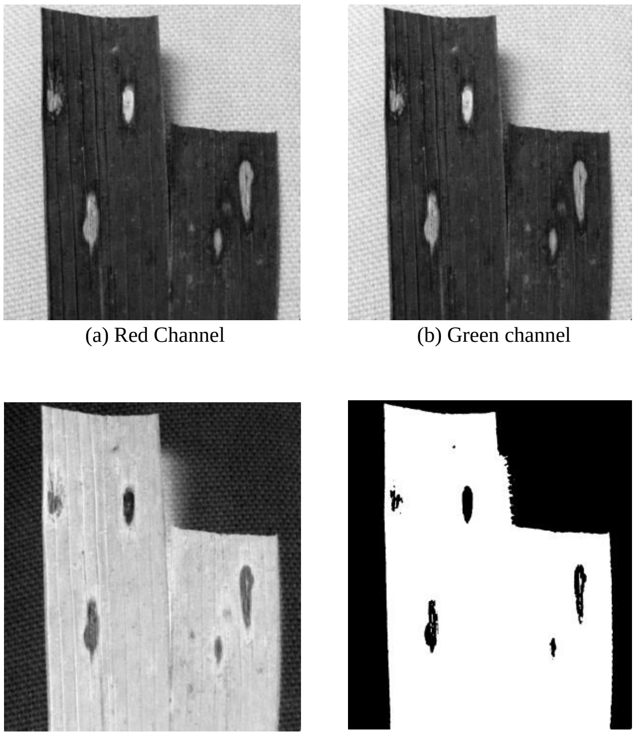


(a) (b)

Fig. 3. (a) Original test image (b) Filtered Image

3.3 Segmentation

After filtering, image segmentation is applied to partition the filtered image into multiple segments with a view to find out desired affected regions of paddy leaf. The aim of segmentation is to change the image representation into more expressive and simplified manner for easier investigation. However, faulty segmentation (over or under segmentation) can lead to a faulty identification or regions of interests. Existing research works [12] uses green channel during segmentation. Experiments shown that green channel propagates the darker regions to deep dark and lighter regions to shadow. As a result, it is very difficult to find out the damaging region from filtered image of paddy leaf. This research come up with a solution to prevent the problem through using blue channel instead of using green channel incorporated with Otsu's [12] thresholding method. The Otsu’s method results in a single intensity threshold that isolates pixels into two separate classes i.e., background and foreground. This threshold is ascertained through maximizing inter-class variance or minimizing the intra-class intensity variance which assists to identify regions of interests smoothly [12]. Figure 4 shows the segmented result of this study test image.



(a) Red Channel (b) Green channel

(c) Blue channel (d) Segmentation on blue channel

Fig. 4. Segmentation result using OTSU threshold on blue channel

Otsu’s method minimizes the intra-class variance through comprehensive threshold searching, which can be defined as the summation of the two weighted classes variances:

$$\sigma_\rho^2(\tau) = \rho_o(\tau)\sigma_o^2(\tau) + \rho_1(\tau)\sigma_1^2(\tau) \quad (2)$$

Here, the variance of two classes is assumed as σ_o^2 and σ_1^2, the weights ρ_o and ρ_1 are the probabilities for each class which are separated by threshold τ.

The class probability $\rho_{o,1}(\tau)$ is calculated from the histogram with γ bins:

$$\rho_o(\tau) = \sum_{i=0}^{\tau-1} P(i) \quad (3)$$

$$\rho_1(\tau) = \sum_{i=\tau}^{\gamma-1} P(i) \tag{4}$$

For both classes, maximizing inter-class variance is equivalent to minimizing intra-class variance: [12]

$$\begin{aligned}\sigma_\gamma^2(\tau) &= \sigma^2 - \sigma_\rho^2(\tau) \\ &= \rho_o(\varphi_o - \varphi_t)^2 + \rho_1(\varphi_1 - \varphi_t)^2 \\ &= \rho_o(\tau)\rho_1(\tau)\rho_o[\varphi_o(\tau) - \varphi_1(\tau)]^2\end{aligned} \tag{5}$$

Here, ρ is the class probability and φ is the class mean, where the class means $\varphi_o(\tau)$, $\varphi_1(\tau)$ and φ_t can be expressed as:

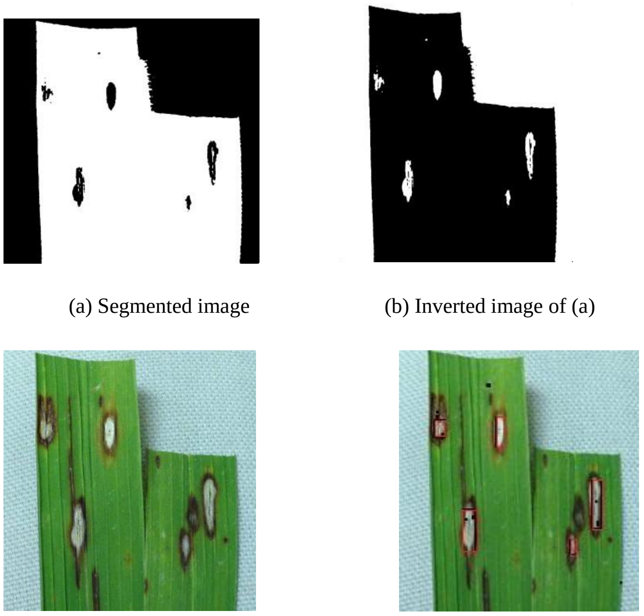
$$\varphi_o(\tau) = \frac{\sum_{i=0}^{\tau-1} iP(i)}{\rho_o(\tau)}$$

$$\varphi_1 = \frac{\sum_{i=0}^{\gamma-1} iP(i)}{\rho_1(\tau)}$$

$$\varphi_t = \sum_{i=0}^{\gamma-1} iP(i) \tag{6}$$

3.4 Identification

Segmented binary images from segmentation step were used for identification in this step. After segmentation the visible regions were found to be the paddy leaf blasts. However, some features i.e., area, maximum axis length, minor axis length, solidity and color features provided by the agriculture engineers were used to identify the leaf blast regions. First, segmented images were inverted and then placed over original test images. Finally, a simple red block boundary algorithm using color information was applied to the images using shape, size, and color features to identify the blast regions. Figure 5 shows the results image of identified regions of paddy leaf blast.



(a) Segmented image

(b) Inverted image of (a)

(c) Image (b) is placed over original test image

(d) Detected regions marked in red box

Fig. 5. Identified results of leaf blast marked in red box boundary

4. Result Analysis

In this study, an SVM classifier was used to calculate the accuracy rate. In this section, the permormance analysis of the proposed method is discussed.

Table 1. Result Analysis of the proposed method

Dataset (No. of Images)	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy
Batch1 (142)	135	0	3	4	95.07%
Batch2 (133)	126	1	3	3	94.74%
Batch3 (151)	146	0	2	3	96.67%
Total = 426	407	1	8	10	**Average = 95.34%**

To detect paddy rice blast, this research study used three batches of photo files. Comprehensive information regarding the test results from this investigation is shown in Table 1.

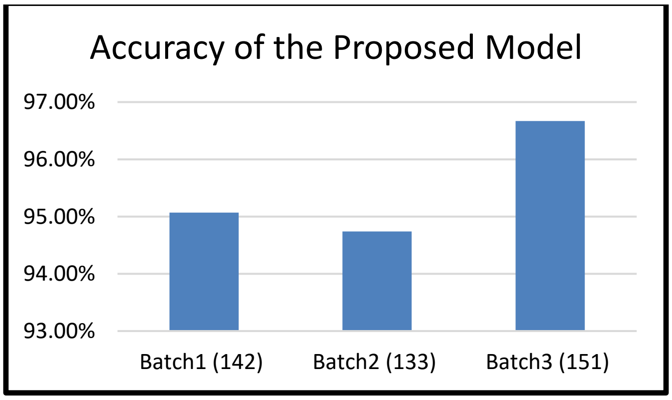


Fig. 6. Accuracy of the Proposed Method for different batch Size

Figure 6 displays the accuracy rate for each batch used in this study. Batch 1 had 142 instances and had an accuracy rate of 95.07%, while batch 2 had 133 samples and had an accuracy rate of 94.74%. Batch 3 had 151 samples and had an accuracy rate that outperformed the other batch sizes, coming in at 96.67%. The proposed approach in this study performs better and is more accurate than other existing approaches, as evidenced by its average accuracy rate of 95.34%.

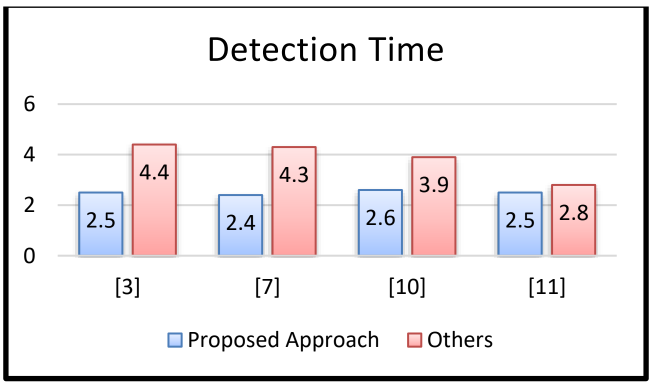


Fig. 7. Identified results of leaf blast marked in red box boundary

In terms of time complexity, the results were also compared with those of various past studies. The difference shown in Figure 7 illustrates how the method suggested in this study detects paddy blast 2.5–2.7 seconds earlier than other methods. It is speedier than other approaches because a complex procedure is not used.

5. CONCLUSION

Although the accuracy rate is already higher than other methods now in use, it is still possible to increase it even further. If image batches are of good quality, the accuracy rate might increase. Other fungi-related diseases, including as brown spot, sheath rot, sheath blight, and others, can also impact paddy leaf. These illnesses similarly cause spots on paddy leaves, although they differ from one another in terms of color, shape, and texture. The approach utilized in this study, which only focused on paddy blast, is notable in terms of how quickly it may identify and diagnose additional fungal diseases that affect paddy leaves. Future research will also take into account more picture batches and investigate various paddy leaf diseases.

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