MATLAB Based Rice Leaf Disease Detection Using Texture Analysis of Digital Image Processing

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Abstract: ***Every day, our society becomes more and more reliant on technology. However, agriculture is essential to our continued existence. One of the main food grains by agriculture production is rice. Approximately half of the global populace depends on it for food, and it creates a significant number of jobs. Therefore, it is crucial to mitigate rice plant diseases properly. Three rice leaf diseases - bacterial leaf blight, brown spot, and leaf smut are proposed to be detected using the model developed in this study. Texture analysis of digital image processing has been used in this paper. In MATLAB statistical features of texture analysis has been calculated for diseases affected and healthy leaf of rice. Calculated values have been compared for detection and classification. The precision level of the results has been very satisfactory (bacterial leaf blight-71%, brown spot-87% & leaf smut-73%).***

Keywords: Rice leaf diseases, Histogram analysis, Image Features, Texture analysis

1. Introduction

Since rice is the primary food source for more than three billion people globally, it is one of the most important crops. It is a staple food in south Asia & some of from Africa. The general populace is impacted by everything that affects the amount and quality of rice production. Consequently, ongoing illness detection and monitoring are crucial for effective mitigation. In the event that treatment is delayed, sickness may have a detrimental impact on output. Thus, one area of intense interest in agro-informatics is automatic plant disease identification. Among the most common diseases affecting rice plants are bacterial leaf blight, brown spot, and leaf smut. Compared to healthy plants, rice from affected plants is produced in smaller quantities and of inferior quality. The national economy, food security, and the general populace are all adversely and directly affected by this yield loss. The Bangladesh Rice Research Institute (BRRI) states that bacterial leaf blight can cause a 47.4% reduction in production [1]. Rice yield can also be harmed by brown spot disease a lot. In previous years people of Bangladesh have been suffered lots due to low productions of rice. A straightforward, automatic, and trustworthy disease detection system may have prevented this output loss. Undoubtedly, a technique like this can produce noticeable outcomes quickly. Our goal in this work is to develop a collection of useful characteristics that will enable us to diagnose rice leaf diseases more accurately. This document presents a five-step, concise overview of the approach. First, a dataset of images of rice leaf disease is gathered;

Prajapati et al. prepared and published the dataset [2] [3]. Following picture gathering, the photos' backgrounds are eliminated, and the disease-affected areas are then segmented. Features values of texture analysis are taken out of the pictures. The values are compared with health images features values for further classification.

2. Background & Related Work

2.1 Background

Dataset, which comprises photos of three classes—bacterial leaf blight, brown spot, and leaf smut—each with forty images, is the dataset utilized in this study. Natural lighting and a white background are used to snap pictures. Among these, *Xanthomonas oryzae* is the bacteria that cause bacterial leaf blight sickness. A region that is hot and humid is conducive to the disease's spread. That explains why it is so prevalent in those areas like Asia, Africa, and some other country in South America that produce rice. Crop loss in a bacterial leaf blight pandemic might reach up so high. It can harm seedlings and paddy leaves, causing the leaves to eventually get parched and wilt and die. At first, the leaves may ooze milky fluid. A type of fungus known as *Cochliobolus miyabeanus* is the cause of brown spot disease. It impacts the rice plant's leaves, seedlings, sheath, and stems, among other aspects. Production may be around fifty percent or lower. The disease-affected areas on paddy leaves have an oval or circular shape. It significantly reduces the quality and amount of harvest by causing the damaged section of the plant to die. Entyloma oryzae is the name of the fungus that also causes leaf smut. Despite not being a serious illness, it can lead to other diseases by fostering an environment that is conducive to the growth of other fungi. The lesions have a rough texture and a round to oval shape that is not uniform. It is crucial to extract significant features in order to create a trust worthy classification model. For that reason, a concise presentation of the diseases has been given bellow.

Bacterial Leaf Blight: Mostly taking place during the time when it rains, particularly when rice fields are inundated with water, *Xanthomonas Oryzae* Pvoryzae is the causative agent of bacterial leaf blight (BL). It can lower agricultural productivity by up to 50% or even 80% in some Asian regions.[4]

Brown Spot: Caused by *Bipolaris Oryzae* (Breda de Haan) Shoemaker, brown leaf spots are another dangerous rice disease that affects people all over the world. Throughout the growth season, leaf spots are the main symptom. These are small, circular to oval-shaped, dark brown to reddish-brown dots, with an aged appearance that has a light, reddish-brown or grey center encircled by a dark to reddish-brown perimeter [5].

Leaf Smut: A form of smut disease that infects rice plants, leaf smut is brought on by the fungus Entyloma Oryzae. On spikelets, it does not, however, result in smut balls. Rather, the rice plant's leaves develop dark brown to black lesions due to leaf smut. Fungal spores in large quantities make up these lesions. Grain weight decreases as a result of chalkiness brought on by false smut. Moreover, it reduces seed germination. Smut balls made of velvet atop spikelets, Spore balls are one of the recognizable signs of leaf smut; they start off orange and turn greenish black when they mature. When the spikelet is almost mature, the second stage of infection starts.

2.2 Related Works

These days, research on the use of computers and information technology in agriculture is very popular. Diverse researchers are engaged in various facets of this domain. While Prajapati et al. [6] evaluated numerous methods used in rice plant disease detection; Garcia et al. [7] conducted a survey on various image processing and classification strategies in this field. CNNs were used by Shimamura et al. [8] to automatically detect tipburn in artificially lit plant factories. In their study, Sugimoto et al. [9] discussed how weeds in rice fields can reduce output. They created a robotic method for eliminating paddy weed. The problem of automatically detecting plant diseases from leaf photos was taken up by many researchers. From a dataset comprising two grape leaf classes and two wheat leaf classes, Wang et al. [10] retrieved 50 characteristics. In order to reduce dimensionality and classify diseases, they employed back propagation neural networks in conjunction with K-means segmentation and PCA. Back propagation neural networks using statistical features from color picture datasets containing Blast, Brown Spot, and bacterial leaf blight illnesses were also employed by Orillo et al. [11]. Suman et al.'s research [12] focused on rice blast, brown spot, narrow brown spot, and bacterial leaf blight. They classified the diseases using SVM and segmented the diseases using 8-connected component analysis. They used a variety of color and shape features to create a model that was 70% accurate. Singh et al. [13] employed K-means clustering to segregate damaged spots. With SVM, they were able to classify data with 82% accuracy. Sethy et al. also employed K-means [14]. Shape and texture features were used with SVM as the classifier by Yao et al. [15]. Phadikar and associates [16] dealt with brown spot and rice blast illnesses. Radial distribution of hue and other color and form features were extracted. Ostu's segmentation approach with hue threshold was used to carry out the segmentation. They obtained 79.5% accuracy with the Bayesian classifier and 68.1% accuracy with the SVM for 10-fold cross-validation. Using a pattern recognition technique, Phadikar et al. [16] worked with four illness classifications and achieved 82% accuracy. It has been noted that the rice leaf disease does not have a standard dataset. Each of the aforementioned researchers created and employed their own dataset. Researchers studying rice leaf disease would greatly benefit from an open and standardized image resource. Additionally, it is mentioned that the K-means clustering algorithm is the main technique for segmenting disease-affected spots, and it is used in [10, 13].

3. Methodology

The block diagram of our suggested method is displayed in Figure 1. At first the collected images are called on MATLAB software. The images are converted to grayscale from RGB. Converted grayscale image then passed through histogram analysis for histogram count. As histogram analysis of multiple images may be same, the images have been gone through texture analysis for statistical feature value extraction. The Statistical features are average intensity, average contrast, smoothness, third moment, uniformity, and entropy. Finally feature values are comparing with healthy leaf images for classification.

Figure 1: An outline of the suggested approach

3.1 RGB to Grayscale Image

The RGB to grayscale function in Matlab allows an image to convert RGB images to grayscale images while maintaining brightness. It does the work by keeping the brightness information intact while deleting the information about saturation and color.

3.2 Histogram Analysis

The image histogram is a fundamental tool used in the design of point operations on digital images, as well as many other operations. The plot or graph representing the frequency of occurrence of each gray level in digital picture f is called the histogram H_f. Accordingly, H_f is a one-dimensional function with a possible range of 0 to the number of pixels in the picture, MN, and a domain of $\{0, \ldots, K-1\}$.

3.3 Average intensity

A range of intensities is seen when viewing digital photographs. The ability of the eyes to distinguish between various intensity levels is a crucial factor to take into account when presenting image processing results. The average intensity of each pixel in a grayscale image is its brightness.

To calculate average intensity, we have applied the subsequent formula:

$$m = \sum_{i=0}^{L-1} z_i p(z_i) \quad (1)$$

Where $p(z_i)$ is the region's intensity levels histogram., where L is the range of intensity levels that are possible and z_i is the intensity of a random variable.

3.4 Average Contrast

The ability to easily discern between things in an image is aided by average contrast. High contrast photos provide a wide range of unique intensity levels. Additionally, there aren't many different intensity values for low contrast. An image with a wide range of intensity values and a significant difference between the least and highest intensity values is said to have good contrast. There are numerous formulas for contrast. As an illustration,

$$Contrast = \frac{Change\ in\ luminance}{Avarage\ Luminance} \quad (2)$$

The average contrast for our research project has been determined using standard deviation (σ).

3.5 Smoothness

An approximation function that eliminates noise and other fine-scale phenomena while attempting to capture significant patterns in the data in image processing and statistics, smoothing is essential. When an image is smoothed, the data facets of a signal are changed such that noise at each individual point is reduced and the points are increased, resulting in a smoother signal that is not higher than the neighboring points. The following equation has been used to measure smoothness:

$$R = 1 - \frac{1}{1+\sigma^2} \quad (3)$$

Where R stands for relative smoothness and its value approaches one (1) for regions with significant deviations in the intensity levels' values and zero (0) for regions with constant intensity. The variance is expressed as sigma square.

3.6 Third Moment

The instant is highly helpful for describing objects after segmentation. Simple characteristics of a picture include its centroid, area (or total intensity), and orientation information. These are known as image moments. The third moment was chosen because it provides information on the skew-ness, or asymmetry, of the mean intensity. The third moment can be found using the following equation:

$$Third\ Moment = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i) \quad (4)$$

For symmetric histograms, this measure is zero; for left-skewed histograms, it is positive and skewed to the right about the mean. We apply the same divisor to standardize the variance; we employed to bring this measure's values into a range of values when compared to the other five measures: $(L-1)^2$.

3.7 Uniformity

We utilize uniformity to measure different types of image lighting as well as the drop-off in illumination at the image's edges. We gave it the following definition:

$$U = \int_{i=0}^{L-1} p^2 (z_i) \quad (6)$$

When z_i is a random variable, L is the intensity level, and p is the histogram. When all intensity levels are equal, uniformity reaches its greatest value and then starts to decline.

3.8 Entropy

A scalar variable known as entropy is used to represent grayscale images. Being a randomness measure based on statistics, it can be used to explain the supplied image's texture. It is defined by the following equation:

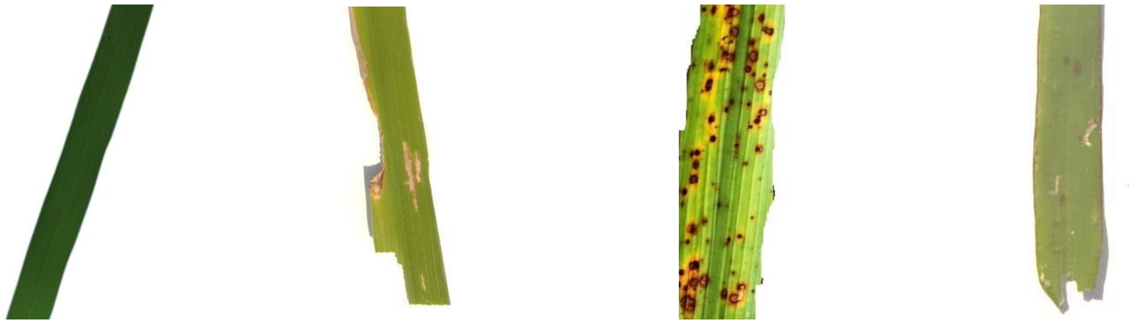
$$Entropy = -\sum_{i=0}^{L-1} p(z_i) log_2 p(z_i) \quad (6)$$

Where $p(z_i)$ is the histogram and z_i is a random picture.

Statistics form the basis of the histogram features that we took into consideration for the histogram models of the probable distribution of the image's intensity levels. These statistical features were stored by the attributes of the image's intensity level distribution. An image that is brilliant will have a high mean, whereas one that is dark will have a low mean.

4. Result & Discussion

For our experiments MATLAB 2024a version has been used for process the different images like healthy, bacterial leaf blight, brown spot and leaf smut rice leaf images. Healthy and affected leaf's picture are collected from different reliable sources [2]. As we stat earlier that histogram may be same of different images but the texture values like average intensity, average contrast, smoothness, third moment, uniformity and entropy give different values. The different texture which are found via MATLAB program than compared for classification. We did not include all the MATLAB findings of those images in our research in order to prevent redundancy. The images for the findings shown in Table 1 have been shown in Figure 2. Table 2 shows the average of statistical features value of all the leaf images.



(a) (b) (c) (d)

Figure 2: Rice Leaf (a) Heathy (b) Bacterial leaf blight (c) Brown Spot (d) Leaf Smut

Statistical Features	*Healthy Leaf*	*Bacterial leaf blight*	*Brown Spot*	*Leaf Smut*
Average Intensity	223.0944	187.5491	199.3954	98.6441
Average Contrast	71.6832	51.046	64.8348	68.7704
Smoothness	0.0732	0.0385	0.0607	0.0678
Third Moment	-10.3307	-2.587	-3.0544	4.2854
Uniformity	0.6835	0.0654	0.2434	0.0105
Entropy	1.5476	4.9087	4.7728	7.2818

Table 1: Statistical features values for different rice leaf image.

Statistical Features	*Healthy Leaf*	*Bacterial leaf blight*	*Brown Spot*	*Leaf Smut*
Average Intensity	213.267	186.4631	182.8573	176.0134
Average Contrast	68.21773	55.3098	49.9941	55.3379
Smoothness	0.066867	0.04518	0.0383	0.0469
Third Moment	-5.81063	-1.59363	-0.5582	-0.6033
Uniformity	0.514467	0.0768	0.0804	0.0811
Entropy	2.432933	5.31915	5.4702	5.2226

Table 2: Averages of Statistical features values for different rice leaf images.

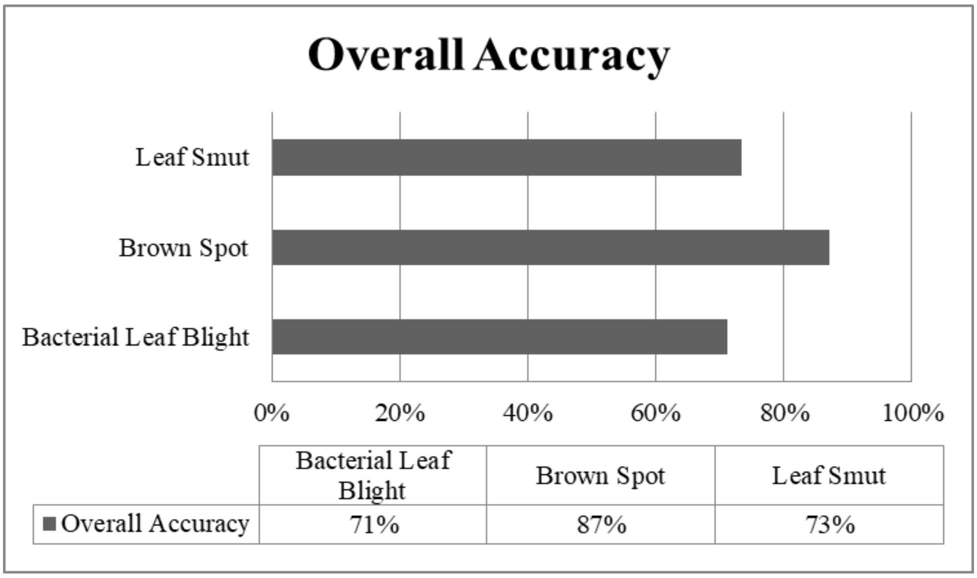


Figure 3: Overall Accuracy of detecting various diseases.

In Table 1 we can see that the absolute values for healthy leaf are higher than any other disease affect leaf. This is a clear indication of findings of disease affected leaf. As naked eyes cannot find the real leaf image all the time our experiments can be a solution of this. For classifications of different disease, we use manual process by comparing them with threshold values of each statistical feature. Figure 3 compares the overall and class-wise accuracy of our method of detection disease affected leaf.

5. Conclusion

In this research, we offer a system for categorizing rice leaf diseases. Three rice leaf diseases are detected by this method. In this investigation, the affected leaf is investigated using textures values. When leaves are affected, the diseases show distinct symptoms. From the photos, a number of statistical features related to the texture, color, and shape domain are retrieved via

MATLAB Program. The results are quite satisfactory based on image processing but we are working to compare with chemical properties of leaf which are more important for leaf. So that the accuracy level can be more trusted. Besides this suggested approach will be made available as an app for smartphones so that farmers can use it to identify illnesses in the field.

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