

Literature Review of Diagnosis Rice Leaves Diseases Using Image Processing

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Abstract

Rice has been identified as the most popular primary energy source for about half the world. Many diseases can infect the paddy plant, and those diseases directly affect the yield loss. With the advancement of new technologies, researchers are interested in identifying paddy diseases through machine learning and image processing techniques to help farmers identify infectious diseases separately and accurately. This paper reviews articles related to paddy leaf diagnosis up to 2020. Image analysis is discussed with image acquisition, processing methods, image segmentation, feature extraction, and classification techniques.

Key Words: **Diagnosis, Rice, Leaves, Diseases, Image Processing**

Introduction

Rice is the staple food of Sri Lanka, and as such, Paddy cultivation in Sri Lanka is given utmost importance in the agriculture industry (Gunawardana, 2018). Ancient and Traditional farmers were self-sufficient in rice production, and ancient Ceylon has been among the foremost paddy exporters globally (Gunawardana, 2018; Seneviratne and Jeyanandarajah, 2004). Rice is the primary source of energy for over half of the world's people. Depending on rice's strain, it can contain decent amounts of fiber, protein, Vitamin B, iron, and manganese (Chaudhary et al., 2012). This means it can play a vital role against malnutrition.

Traditional varieties were cultivated throughout the country until the early 1960s (Rambukwella and Priyankara, 2016). Since it usually gives low yields, people are accustomed to applying artificial fertilizers to increase yields regardless of the possibility of the plant being attacked by pathogens (Seneviratne and Jeyanandarajah, 2004). Every year farmers face a loss of yield and financial losses due to the pests and the diseases on the rice plants (Seneviratne and Jeyanandarajah, 2004). Many diseases can infect paddy plants (Rambukwella and Priyankara, 2016; Seneviratne and Jeyanandarajah, 2004). Due to infection caused by viruses, fungus, and bacteria, there is a huge loss of rice quality and quantity (Mangla et al., 2019; Sethy et al., 2020). Traditional farmers identified those diseases using their previous experiences. It is important to identify the disease that has infected the paddy field to control the disease and prevent the infection to other plants. The farmers who do not have good knowledge about paddy fielding cannot quickly identify correct diseases without others' help.

Considering the advancement of technology, the younger generation of farmers uses the newly developed technologies to increase the yield. The traditional ones have overcome new and easier technologies. Diagnosis requires a methodology rather than observation with the naked eye.

Related Work/ Background Study

Researchers have proposed various techniques for the diagnosis of rice plant diseases using image processing with machine learning.

Phadikar and Sil (2008) classified diseased rice plant images using Self Organizing Map (SOM) neural network (Matera, 1998), where train images are obtained by extracting features of the infected parts of the leaves. Zooming algorithms (Battiatto et al., 2002) and simple computationally efficient techniques have been used to extract images' features.

Mukherjee et al. (2010) was converted the original resized image into a gray image such that the pixels corresponding to the leaf image are the same. Then histogram was used to calculate the change in the pick value. Following steps have been proposed to diagnosis the rice blast, Bacterial Leaf Blight, and Rice tungro using image processing.

- A. Image Enhancement
- B. Image pre-process
- C. Image Segmentation
- D. Transformation to Histogram
- E. Paddy Disease Detection

Orillo et al. (2014) proposed a methodology for diagnosis crop Brown Spot, Rice Blast, and Bacterial Leaf diseases using the neural network concept with MATLAB. The neural network is trained through a database of diseased images. In this research, fraction covered by the disease on the leaf, arithmetic mean values for the R, G, and B color components of the disease, the standard deviation of the R, G, and B color component of the disease, and mean value of the H, S, and, V of the disease have been extracted. The number of repetitions of the back-propagation algorithm (Buscema, 1998) is practiced until satisfactory results are obtained.

Deshmukh (2015) proposed paddy leaf disease diagnosis with three main phases: image segmentation, feature extraction, and classification. The artificial neural network (Gupta, 2013) was used as a classification, and the k-means cluster (Vora, 2013) was used to identify the infected parts of the leaf.

Shah et al. (2016) have surveyed the detection and classification of Rice Plant Diseases to introduce the important criteria of applying image processing and machine learning to identify and classify the diseases in rice plants. Those criteria include the size of the image database, no. of Classes(diseases), Preprocessing, segmentation techniques, types of classes, the accuracy of classes, etc.

Multilevel color image thresholding has been used for the disease diagnosis system of Rice Leaf Blast disease (Bakar et al., 2018).

Mangla et al. (2019) proposed Otsus' method (Chen Yu et al., 2010) and vegetation segmentation for identifying the threshold values in images and use textual analysis to feature extraction and also Support Vector Machine (SVM) algorithm (Noble, 2006) has been proposed to classify the images considering the extracted features.

Taking into account, the lack of knowledge of farmers about the early symptoms of rice plant diseases, Agus et al. (2019) developed an Expert System (ES) for Indonesian farmers to detect rice plant diseases. This system was developed based on a rice specialist's pest and disease experience, using a model of the Waterfall Paradigm and Unified Modeling Language (Booch et al., 1996).

Sethy et al. (2020) surveyed image processing methods for rice plant diagnosis and compared study bases based on image fragmentation, feature extraction, feature selection, and classification. Image pre-processing has been used to remove noise and enhance the image while converting it to a binary image. Other than that, according to Sethy et al. (2020), Researchers have used thermal imaging equipment for the diagnostic process using image processing, which is expensive and is for research purposes only, and most paddy leaf diagnostic systems cannot be used by the average user.

A good platform has been proposed for Crop Health Advisory Boards to atomize crop health problems and solutions. It presents robust and straightforward image processing methods comparing crop leaf color with leaf color chart (LCC) and mathematical modeling (Singh and Singh, 2015).

Focused primarily on leaf color, the background noise independent algorithm has been implemented to isolate disease spots using image processing methods. 'A' component of CIELAB color mode (Ly et al., 2020) has been used to segmentation disease spots. It has been comparing the effects of CIELAB (Ly et al., 2020), HSI (Hue, Saturation, Intensity), and YCbCr color space (Chai and Bouzerdoun, 2000) on the disease identification process. In this algorithm, median filter (Perreault and Hebert, 2007) has been used for image smoothing, and the Otsu method (Chen Yu et al., 2010) has been applied to the color component to detect the disease spots in the leaf. The

algorithm has been tested on various “Monocot,” and “Dicot” family plant leaves with a noisy and noiseless background (Chaudhary et al., 2012).

Methodology

Image processing methods have been used to identify the leaf's color distribution and the edges of the leaf to detect any abnormal color changes in the leaf. Taking into account the color scheme of the leaves determined whether the leaves are healthy leaves or not. Infected leaves are compared with previous dataset features and image processing methods that identify similarities with diseased images. Below are the steps that are relevant to achieve this process.

Image Acquisition and Data Gathering

Shah et al. (2016) have proposed to prepare an image database using the images which are acquainted from the live farm—using a digital camera to get them directly in digital form with numerical values so that digital image processing can be applied.

Two Olympus E-450 cameras are mounted five meters above the ground in a fully automatic mode and transfer photos from the paddy field to a remote computer via 3G data transmission (Bai et al., 2018).

Ramesh and Vydeki (2020) used the Redmi Note 5 camera with high pixel intensity to capture images for normal and diseased parts of the rice leaf. The total leaf samples taken from the rural area were resized to 256 * 256 pixels.

Kamlapurkar (2016) created a photo database of powdery mildew and downy mildew images using the DSC T-90 Sony camera and saved it as a JPEG format.

Under the image acquisition step, the secondary dataset has been provided by the UCI machine learning repository (<https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases>) belong to below mentioned three diseases.

Bacterial Leaf Blight

Bacterial Leaf Blight (*Xanthomonas Oryzae*) is a disease caused by bacteria called *Xanthomonas Oryzae* P_v. *Oryzae*. This disease mostly occurs in rainy and dry-wet sessions (Ihsan et al., 2020).

Brown Spot

Brown spots were caused by the fungus *Helminthosporium Oryzae* on plantations. The death of young plants and reduce grain quality are the consequences of brown Spot disease (Ihsan et al., 2020).

Leaf Smut

Leaf Smut caused by the fungus *Entyloma oryzae* is a widely distributed but somewhat minor disease of rice. They have slightly raised, angular, black spots on both sides of the leaves. Although rare, it also can produce sites on leaf sheaths. The black spots are about 0.5 to 5.0 millimeters long and 0.5 to 1.5 millimeters wide, and many spots can be found on a leaf, but the spots remain distinct from each other (Groth and Hollier, n.d.)

Image Pre-Processing

Image pre-processing has been used to remove unwanted noises from collected images. Several image pre-processing techniques have been suggested by research.

Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations that intensify or reduce specific image details enable a more effortless or fast evaluation. Users can optimize a camera image with just a few clicks. It involves cropping, rotating, normalizing, contrast enhancement, filtering, angle correction, and various graphical operations (Mukherjee et al., 2010). Image preprocessing was used to remove noises like dust, dewdrops, insect excrements from digital images, and different types of noise removal filters have been used to remove noises and distortion of some water drops and shadow effects.

Bakar et al. (2018) have used mainly three image pre-processing techniques to transform the original image into a new color space, which is fundamentally like the original image but differs in certain aspects. Image resize, image restoration, and image enhancement have been mentioned as follows: involvement steps in this process.

A. Resize

Considering the memory capacity and the computational complexity, original images are resized to fixed resolution with the dimension 640 * 480 pixels.

B. Noise Restoration

Noise can be caused by motion between camera and object, improper shutter opening, atmosphere disturbance, and mis-focusing.

C. Image Enhancement

Mukherjee et al. (2010) used Image enhancement for adjusting digital images so that the result was more suitable for display or further analysis.

According to Khirade and Patil (2015), the following equation (Equation 1) has been used to convert RGB (Red, Green, Blue) images into gray images using color conversion.

$$f(x) = 0.2989 * R + 0.5870 * G + 0.114 * B$$

Equation 1 RGB to grey conversion equation

Image enhancement was used to adjust digital images so that the result was more suitable for display or further analysis (Mangla et al., 2019).

Considering the ease of color separation, Ramesh and Vydeki (2020) have proposed converting RGB images into HSV (Hue, Saturation, Value) because the HSV represents the Hue, saturation, and value part of the images.

Considering the ability to reduce the background effect, the images were converted to HSI color space, and histogram analysis of the intensity channel has been used to obtain an opening that could increase the image contrast (Kamlapurkar, 2016).

RGB images on leaves are converted to HSI color space representations to facilitate color specification in a generally accepted way. After that, green color pixels were identified through specific threshold values and were removed entirely from the image (Arivazhagan et al., 2013).

Segmentation

Image segmentation has used to divide the images into segments for analysis. Images have been converted into another format base on appropriate features.

The segmentation of image states represents an image into another meaningful format that is easier to analyze (Mukherjee et al., 2010). Images have been divided into particular regions or objects to analyze and extract the data's useful features (Shah et al., 2016).

Mangla et al. (2019) used Otsu's method (Chen Yu et al., 2010) and setting the threshold to mean pixel intensity to find the threshold values. Blob analysis (Moeslund, 2012) has been used to shape feature extraction to get the number of objects for labeled regions in a noise-free binary image. It is then combined with the color characteristics extracted from the digitized image and classified using the Support Vector Machine (Noble, 2006).

Image segmentation means partitioning an image into several parts that have the same similarities or same features. Segmentation has been done using various methods like k-means clustering (Vora, 2013), converting RGB image into HIS model, Otsu's method (Chen Yu et al., 2010), etc. (Kamlapurkar, 2016).

K-Means clustering (Vora, 2013) has been used for image segmentation. Moreover, the trial and error method (Prather, 1971) is selected to select K value in the K-means algorithm (Ramesh and Vydeki, 2020).

According to Bakar et al. (2018), the image segmentation process consists of background subtraction, feature extraction, and image analysis. Image segmentation is performed by selecting the appropriate threshold range to separate the infected area from the background. The threshold values are chosen from the bottom and top of the image histogram. Considering the non-uniform distribution of the disease zone, Bakar et al. (2018) have identified that one process at the threshold is ineffective. Therefore, a multi-level entry based on pixel-based segmentation was proposed.

Based on a Fuzzy logical grading system in the query image, the disease section and the healthy part are divided (Jhuria et al., 2013).

According to Chaudhary et al. (2012), if there is a sharp and deep valley between two peaks in the histogram, the bottom of the valley has been chosen as the threshold. Otherwise, this tactic cannot be used to separate objects from the background. Therefore, the Otsu method (Chen Yu et al., 2010) has automatically selected the most appropriate threshold value.

Feature Extraction

To distinguish between paddy leaf diseases, selected features are extracted from the images. Components are selected based on the image database. The colors and shape of paddy leaves are identified as the main features that can separate one disease from others.

According to Mangla et al. (2019), shape feature extraction and color base segmentation should focus on this stage. Inherent characteristics or features of objects present within the image have been focused on this stage (Shah et al., 2016). Color, shape, and texture were the main features extracted from fragmented objects (Mangla et al., 2019). The color element plays a crucial role in classification because it can distinguish one image from another (Mangla et al., 2019; Shah et al., 2016).

Color Extraction: extract the color changes from the digitalized image.

Shape Extraction: identifying the shape of a given rice leaf by taking into account the color difference of the digitized image.

An automatic shape recognition algorithm was developed to detect and identify different shapes of any color and non-color images. The algorithm deals with grayscale images, and the contrast-limited adaptive histogram equation is applied to enhance the contrast, and the enhanced image is converted to a binary image (Rusiñol et al., 2007).

According to Narvekar et al. (2007), color image features in the visible light spectrum provide additional image characteristics than traditional grayscale representation. Therefore, the color co-occurrence method (Vadivel et al., 2007), representing both color and texture features as a unique feature, has been used to extract features from the grape leaves image.

An edge is a key expression of local features and image integrity. Edges define the boundary between object and their background. Edge can be mathematically represented by first and second-order differential equations (Shanmugavadivu and Kumar, 2013).

Khirade and Patil (2015) have proposed two methods to extract features from the plant leaves.

- i. Color co-occurrence Method (Vadivel et al., 2007).
- i. Leaf color extraction using H and B components (Khirade and Patil, 2015).

Kamlapurkar (2016) used Gabor filtration (Nazarkevych et al., 2017) to extract the color and morphological features of the leaf's spots. The mean and variance of the red, green, and blue channels at the location were identified as color features, and the shape of the leaf was assumed to be elliptical.

Bakar et al. (2018) chose the Coni Edge detector to identify the boundaries between objects' areas and backgrounds compared to other algorithms in thin lines, continuous edges, and different lighting conditions. Before applying edge detection, Gaussian smooth filters (Basu, 2002) were used to reduce the appearance of high-frequency noise. To distinguish the regional boundary and the image contour, border tracking was used to extract the contours. Green's theorem was used to calculate the infected area of the disease from the color image.

The gray level co-occurrence matrix (Vadivel et al., 2007) method is a two-dimensional matrix of joint probability between the pair of pixels separated by a distance in a given direction. Contrast, homogeneity, correlation, the energy was calculated, and discrete wavelet transform (DWT) (Ghazali et al., 2007) was used to extract the features from the paddy leaf image (Deshmukh, 2015).

Ramesh and Vydeki (2020) calculated statistical features such as mean value, standard deviation, and GLCM (Gray-Level Co-Occurrence Matrix) (Vadivel et al., 2007) for healthy and infected leaves. Statistical features

have been used to identify whether they have infected the leaves, taking into account the crop's characteristics and various symptoms.

Image Analysis and Diagnosis

According to Chaudhary et al. (2012), the threshold of RGB images cannot be used to accurately identify the spot of disease from brown infected rice leaves and the threshold on 'H' component of HSI color model and 'Cr' component of YCbCr color model (Basilio et al., 2014) are sometimes identified disease spots but not in all. However, the threshold on the 'a' component of CIELAB (Ly et al., 2020) color model allowed accurate detection of disease spots and is independent of background effects.

The histogram and saturation and intensity components of the red, green, and blue components are calculated in paddy leaf images. Still, the accuracy of the results depends solely on the Hue components. Therefore, decisions were made based exclusively on Hue histogram analysis (Singh and Singh, 2015).

The image is analyzed with the extracted features to determine if the image has the above three diseases' symptoms. Color histogram and pixel arrangement in paddy leaf images have been used to separate paddy leaf images based on infected disease. According to Bakar et al. (2018), a border tracing algorithm can be used to extract contours from images. The image has been transformed into a histogram before analyzing the features of an image.

The following are the main features of each disease (Table 1) that will be used to differentiate the disease from others in the analytical step. Symptoms may vary depending on the disease level, the number of infected days, and the paddy type. The age of paddy cultivation should also be considered in this research.

Table 1 main features of diseases

	Bacterial Leaf Blight	Brown Spot	Leaf Smut
Color	golden yellow	brown spots with yellow/white inner circle	Tiny Dark brown/black spots
Shape	stripes patches	oval to round	oval to round
Patch Size	1.2 x 0.8-1.0 mm	5–14 mm	0.5 to 5.0 mm
Location of disease in the leaf	leaf blades or leaf tips	leaves, leaf sheath	Both side of the leaves

Conclusion

This article reviews the different types of paddy diagnostic methods done through image processing and machine learning. Image capture, image processing, segmentation, and feature extraction are identified as the first steps before applying image processing or classification methods to diagnose the disease. Considering the ease of finding the threshold value of the histogram equation, many researchers have converted images from the RGB color range to another color format or a grayscale. Noise has been identified as a significant problem to be solved in the image processing process. It plays a vital role in image resizing and image enhancement in research using machine learning classification. Under the segmentation step, the Otsu method has been used to select the threshold value range, and the K-mean cluster method is also used to separate the infected parts from the image. Color, shape, and texture have been identified as the main features obtained from the paddy leaf image to diagnose diseases. These features can be used for diagnosis with SVM and ANN machine learning concepts. The accuracy of the diagnostic process depends primarily on the classification algorithm. Instead of a machine learning process, a histogram equation with multiple values has given some accuracy in distinguishing rice leaf diseases.

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