

Detection and Recognition of Paddy Leaf Diseases Using Image Processing

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Abstract - The importance of agriculture to humanity cannot be denied. The need for food is rising in tandem with population growth; hence production should be boosted as much as possible. In order to accomplish this, crops need to be safeguarded against bacterial, viral, and fungal infections. A fast and precise diagnosis of illnesses in paddy leaves enables the timely initiation of agricultural practises, which greatly lowers economic losses. The paddy leaf disease was identified and classified for this purpose using image processing techniques. The segmentation of the diseased region, the non-diseased part, and the backdrop in image processing was done using a clustering method. The use of straightforward image processing and machine learning techniques was suggested as a better method for early rice leaf disease identification. In this publication, the four paddy leaf diseases Brown Spot, Sheath Blight, Blast Disease, and Narrow Brown Spot are highlighted. First, the necessary photos of healthy and diseased paddy leaf were taken directly from various paddy fields. Using mask in the pre-processing stage, the extraneous background of the leaf photos was removed. The output is then input into the segmentation stage, where the normal and sick portions of the leaf pictures were separated using K-means clustering. Finally, the Support Vector Machine (SVM) algorithm was used to categorise the disorders stated. The system's accuracy is 94%. This method can be used to identify plant leaf diseases everywhere in the agricultural sector.

Keywords: Paddy Plant, Leaf Disease Detection, Image Processing, Machine Learning, Support Vector Machine (SVM), K-Means Clustering

I. INTRODUCTION

The majority of the world's nations, particularly those in South Asia, have enormous populations wholly dependent on agriculture, which also serves as their primary source of income. The demand for the consumption of rice rises along with the population growth. Large yield losses are a result of rice disease [1]. Rice output needs to expand by more than 40% till 2030 in order to fulfil the rising food demand. The main cause of the rice plant's significantly decreased paddy production is leaf diseases. Along with the loss of the farmers, it has a big effect on the economy of the nation. The paddy leaves typically display the symptoms of paddy plant diseases. [1]

Numerous illnesses, including Blast Disease, Brown Spot, Sheath Blight, Uninfected Bacteria Leaf, Narrow Brown Spot, and Infected Bacteria Leaf Disease, among others, can harm paddy plants. This research reviewed and distinguished between four different leaf disease kinds, including Brown Spot, Blast Disease, Narrow Brown Spot, and Sheath Blight Spot. The primary signs of Brown Spot disease, which is brought on by a fungus, are brownish

circles on the whole surface of the affected leaves. Blast Disease is characterised by patches on paddy leaves with dark green borders and white to grey-green wounds.[2] Light to dark brown growths or lines that are parallel are indications of the narrow brown spot illness. Sheath Blight Spots typically appear above

II. EXISTING WORKS

An automated system was suggested in a study by S. Phadikar, J. Sil, and A. K. Das to classify the brown spot and blast diseases of rice plant leaves. They classified the disorders in their research using Bayes and SVM Classifier [1]. The goal of a study by Vimal K. Shrivastava, Monoj K. Pradhan, Sonajharia Minz, Mahesh, and P. Thakur from KIIT, Bhubaneswar, is to identify rice plant leaf diseases early on and classify them. They employed Deep Convolutional Neural Networks (CNN) that had already been trained for feature extraction and Support Vector Machines (SVM) for classification in their study [2].

An image processing technique is being used in a study by K. Jagan Mohan, M. Balasubramanian, and S. Palanivel

from Annamalai University in Annamalainagar to identify and classify various rice plant diseases. Scale Invariant was used in their study.

The primary goal of a study by Indian researchers Jagadeesh D. Pujari, Rajesh Yakkundimath, and Abdulmunaf S. Byadgi is to discover and categorise fungal infections of various agricultural or horticultural products. They conducted research using image processing techniques to find signs of fungal infections in various agricultural goods [5].

Priyanka B. Rajand, Soumya G. Hegde, Pooja R., and Dr. Neha Mangla of the Atria Institute of Technology in Bengaluru, Karnataka, India, offered an idea to identify and manage numerous plant diseases in the agricultural sector. They used a few image processing techniques in their study to identify and categorise paddy plant leaf diseases [6].

III. METHODOLOGY

Five key components make up the technique of the suggested system: image acquisition, image pre-processing, image segmentation, feature extraction, and classification. Fig. 1 depicts an overview of the suggested methodology.

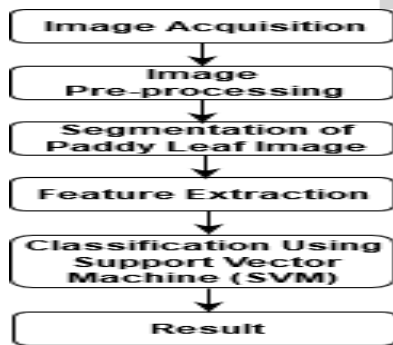


Fig. 1. Block Diagram of the Proposed System

A. Image Acquisition

A vast number of excellent photographs of various paddy leaf types from paddy plants of various ages were required for this study. This led to the selection of almost ten thousand photos of diverse paddy leaves from various sources. A clear camera records an image of a diseased, impacted paddy.

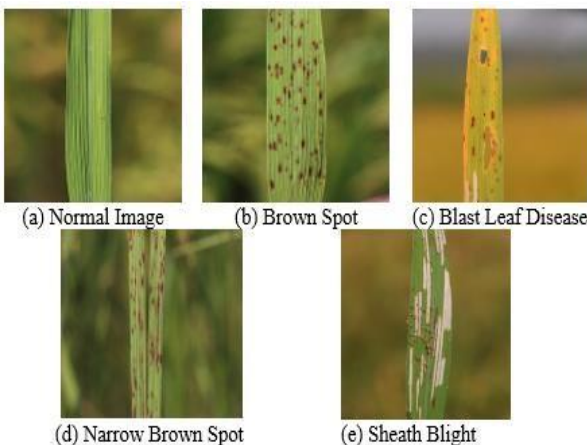


Fig. 2. Sample Images of Normal and Disease Paddy Leaf

B. Image Pre-Processing

Upgrading the picture information and improving the image qualities is the procedure's primary premise. For displaying, storing, and transmitting pictures, pre-processing of the image is essential. The use of RGB shading position enhances the appearance of the paddy leaf image. For image segmentation and feature extraction, picture pre-processing is a requirement. The chosen photographs in this part were scaled to 256*256 pixels for a variety of reasons, including memory usage, image transfer, and display. The removal of the image's unneeded background was a significant undertaking. The RGB images that were recorded were afterwards converted into an HSV model. Due of its whiteness, Saturation Value (S Value) was computed for the procedure using the HSV colour model. After a few attempts, the threshold value of 85 was chosen. [4]The image was converted into a binary image based on this value, which was then combined with the original acquired image, which was initially in RGB model, to create a shadow or mask. By applying '0' as the value of the pixel, where black colour is expressed by '0' in the RGB (Red-Green-Blue) colour model, the technique erased the image's unneeded background. Only the sick area of the leaf from Fig. 3 is visible after the image's backdrop has been removed.

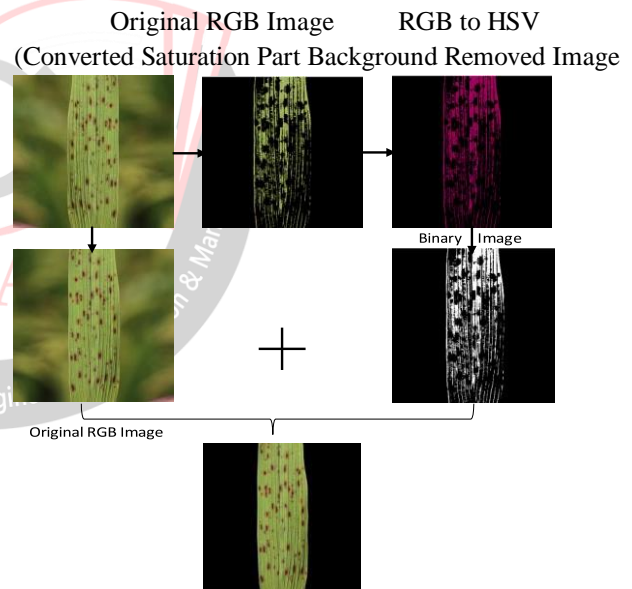


Fig. 3. Pre-processing Steps for Background Elimination

C Image Segmentation

The brightness of the flash, ambient light, frequency distortion, and other environmental conditions has an impact on the image quality. These elements contribute to image noise. By utilizing CNN's deep convolutional neural network technique, they can be eliminated. For the noise reduction procedure of disease detection in paddy crops, the deep convolutional network technique is employed. By analyzing the intricate details using a mobile application, CNN gives agriculturalists the opportunity of spotting pests

at an early stage. Due to CNNs' highly automated feature learning methods from the edited paddy images, they are widely used for disease identification in paddy.

Digital images were divided into several segments during image segmentation. Image segmentation is accomplished using K-Means Clustering. For picture segmentation, a variety of approaches are utilized, including the Otsu and Threshold techniques. However, K-means clustering is a better method of dividing the normal component from the sick portion. [5] This is how a group of things are separated. RGB photos were first transformed to binary images for the K-means clustering, and then a centroid matrix was created. After that, RGB (Red-Green-Blue) input photos were transformed to HSV (Hue, Saturation Value) color space. Features would be extracted using K-mean clustering, however just one of the 'n' produced clusters needed to be chosen. Three clusters were chosen for this system. In Figure 4 shows after the segmented figure. [2]

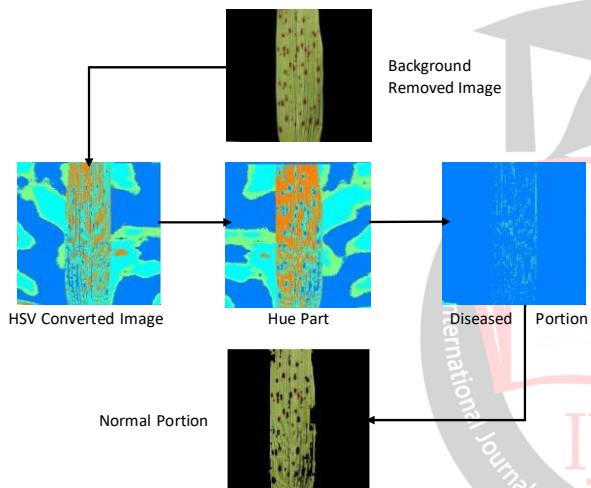


Fig. 4. Clustered Image from the Hue Part

C. Feature Extraction

A crucial function of the entire system is feature extraction. It is a technique for extracting an image's visual information for indexing. Gray-Level Co-occurrence Matrix was used to extract features in this study (GLCM). GLCM used feature frames, texture analysis, and pattern recognition. It is a technique for statistically analyzing texture. It offers the square element's sum. Higher series textures should consider three pixels or more. Using color and texture features, which are important in image processing for independent features, this feature is extracted from the diseased area. For the quantity of the fluctuations in redundancy value at the pixel of interest, texture and feature computations employ the GLCM object. A formula of contrast, homogeneity, correlation, and energy is calculated by GLCM. The paddy leaf disease has a variety of lesion shapes and colours due to various disease kinds such nematodes, blasts, smuts, and spots. Disease identification

relies heavily on characteristics like shape and colour. By measuring the height and width of the paddy diseased image to get the object's pixel count, shape can be determined. In order to determine the Grey-Level Co-occurrence Matrix, the pixels are then used to differentiate between RGB values (GLCM).

E. Classification

First, an image was trained using the classification-related SVM algorithm. Here, four different types of diseases—brown spot, blast disease, sheath blight, and narrow brown spot of paddy leaf—are detected and diagnosed using support vector machines.

In this study, Support Vector Machine (SVM) is utilized to categories leaf diseases on rice plants. It used labeled data and was a supervised learning algorithm. Each data point is separated in n-dimensional space by this procedure. Two-class SVM supervised sorting is used. Classification carried out using decision surface discovery. SVM is a binary classifier that uses the decision surface or hyper-plane between two classes to make classification decisions. Different classes on either side of falling data points can be assigned to the hyper-plane. The SVM optimizer will locate the decision surface that will maximize the margin of separation between the two classes using the training vectors [3]. In Fig. 5, this procedure is depicted.

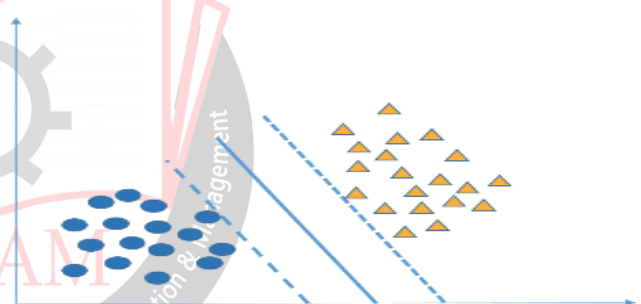


Fig. 5. SVM in Linearly Separable Conditions

Here is the step-by-step algorithm for using SVM to classify diseases:

- Step 1: Open the data set and load some sample photos.
- Step 2: Next, create data using two-column matrices with measurements of the sepal width and sepal length for 150 irises.
- Step 3: Subsequently, create a new column vector to distinguish between data and non-data.
- Step 4: Next, choose training and test sets at random.
- Step 5: Finally, visualize the ordered data using a linear kernel function trained on the trained data.

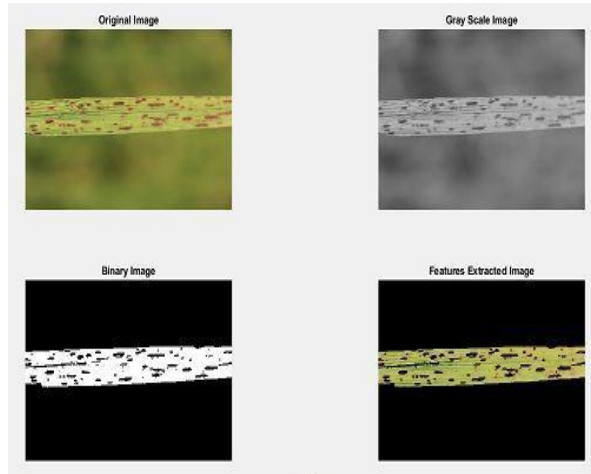
F. Implementation

Because of its ease of use and superior interactive capabilities, the "MATLAB R18a" programming language has been used to develop the suggested system for paddy

plant leaf disease detection.

The pre-processing, segmentation, feature extraction, classification, and diagnosis of Leaf illness were all key steps in developing the suggested method. Fig. 6 illustrates how the system was created to be efficient and user-friendly.

Fig. 6. Frontend Interface of the Proposed System



This system can easily be operated by the minimum literate persons, because this system gives a visual content-based frontend.

IV. RESULT ANALYSIS

Analysis of four paddy plant leaf diseases was done for the suggested system. In contrast to conventional systems 1, 2, and 3, which use various methods to categories diseases and achieve varying degrees of accuracy, this system uses SVM for classification. SVM and Bayes were utilized in conventional system 1's classification, and they produced results of 79.5% and 68.1%, respectively. CNN was utilized by conventional system 2 to classify data, and it had a 91.37% accuracy rate. K-NN and SVM were utilized in the traditional system 3 for classification, with respective success rates of 86.66% and 90.14%. But compared to other traditional systems, our proposed approach performed more accurately (94% accurate).

Table- I: Comparative Accuracy of Paddy Leaf Diseases Classification

System	Identified Diseases				Applied Technique	Average Accuracy Rate (%)
Conventional System-1 [1]	Normal Leaf 92%	Brown Spot 96.4%	Blast Image 84%	Sheath Blight 82%	Bayes' and SVM	79.5% and 68.1%
Conventional System-2 [2]	Rice Blast 89.45%	Bacterial Leaf Blight 90.39%	Sheath Blight 91.37%	Healthy Leaf 88%	CNN	91.37%
Conventional System-3 [3]	Brown Spot 88%	Leaf Blast 89%	Bacterial Blight 90%	Uninfected Leaf Disease 93%	SVM and K-NN	86.66% and 90.14%
Proposed System	Brown Spot 94%	Sheath Blight 95%	Narrow Brown Spot 93%	Blast Image 96%	SVM	94%

V. CONCLUSION

An initial stage detection system for rice leaf diseases was conceived and created in an effort to boost paddy production in the agriculture sector. With the agreement of the field owners, pictures of healthy and sick rice leaves were taken directly from several paddy fields in rural locations for this study. This study's major goal was the prompt and accurate identification of several paddy leaf diseases in the early stages. This system was created by first employing a mask to remove extraneous background from the taken photos. The output was then supplied into the segmentation component, where the group of objects for feature extraction was then separated then, using the color feature and the texture feature, extract the color and calculate the texture characteristics for the illness section. Then, using a training data set, an SVM was used to categorize this characteristic, leading to the identification of the disorders. Four distinct leaf diseases in rice plants were found by this technique. The technology offers a better way

to find leaf illnesses. The created system's accuracy, which is 94%, was also compared to a number of conventional systems. Farmers are also benefited from this system by detecting the paddy leaf diseases. The new researcher who wants to investigate image processing and machine learning techniques for leaf disease detection in a user-friendly interface where users can quickly select the affected area, learn the name of the disease, and take the appropriate action in due time, which aids in increasing paddy production, will find this paper to be helpful.

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