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Investigation of classical segmentation's impact on paddy disease classification performance

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ABSTRACT

The key source of information for disease diagnosis and classification in paddy diseases is the leaves. Applying hybrid techniques, such as image processing-pattern recognition (IP-PR) and computer vision-based technologies, is the answer to assessing the health of plants. The following paddy diseases are considered in this paper: bacterial leaf blight (BLB), brown spot (BS), leaf smut (LS), and narrow brown spot (NBS) from the machine learning repository. A classical colour threshold-based segmentation method is implemented newly to separate the patterns of image pixels into the diseased part and the normal part. The human visual impression (VI), a subjective method, and a parametric-based method with an average error rate (ER) and overlap rate (OR) are used to assess the uniqueness of the suggested segmentation technique. Using a multi-class support vector machine (MSVM) classifier, the analysis yielded segmented images using the proposed method with an accuracy of 92% over the existing method with an accuracy of 76.60%. The BLB disease achieved the highest identification accuracy of 91%. Our proposed method evaluates the segmentation performance and achieved consistent accuracy higher than the previous segmentation work.

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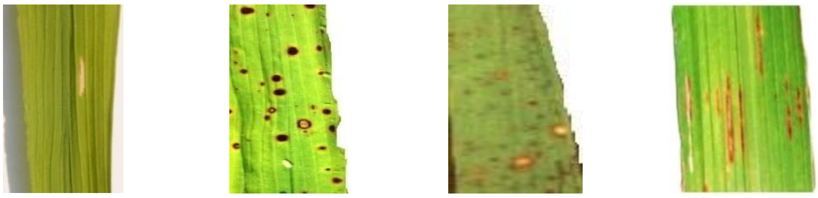
1. INTRODUCTION

India's economy is dependent on agriculture. According to the 2011 Census, 54.6% of the workforce is employed in agricultural and related sector activities, which will account for 18.6% of India's gross value added (GVA) at current prices in 2021–2022 [1]. More than 3.5 billion people depend on rice for more than 20% of their daily calories, making it the main food source for more than half of the world's population. In order to reduce crop loss and fulfil future rice demand, research on the use of entophytes to control these pathogens needs to be accelerated in light of the significance of rice and its numerous pathogen adversaries [2]. The typical approach to disease identification requires suggestions from experts and formers.

The common diseases that damage rice plants are as shown in Figure 1. Their cause, symptoms are described as: Figure 1(a) shows bacterial leaf blight (BLB) caused by *xanthomonas oryzae*. The symptoms include leaf yellowing and seedling wilting. As the disease progresses, infected leaves fold up and turn a greyish-green colour before turning straw-coloured. The disease is particularly dangerous, as with the right environmental factors, it may result in 70% crop loss if it strikes early in the paddy crop [3]. Figure 1(b) shows brown spot (BS) grain's outer husk and the leaf's protective sheath are both infected by the fungus. The symptoms are small, circular, yellow-brown, or brown lesions. Initial lesions may appear on leaves as small, dark brown to purple-BS in later stages with a grey centre and a reddish brown edge brought on by a fungus toxin [3]. Figure 1(c) shows leaf smut (LS) caused by *entylomaoryzae* fungi, is a widespread but somewhat less severe disease of rice. Angled and dark dots on both sides of the leaves are the disease symptoms. Infection is frequently severe enough to kill leaf tips [4]. Figure 1(d) shows narrow brown spot (NBS), the fungus *sphaerulinaoryzina* is the source of the disease. Light to dark brown, parallel, linear lesions on the leaves and sheath are the symptoms. The disease is distinguishable by linear lesions [3], which also have an impact on yield during rare epidemics.



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

Figure1.Common rice diseases (a) BLB, (b) BS, (c) LS, and (d) NBS

Azim *et al.* [5] proposed an effective feature extraction method for rice leaf disease classification, using a dataset prepared in [6]. The disease-affected areas are segmented using hue thresholds and distinct features from colour, shape, and texture domains are extracted from affected areas. These features can robustly describe local and global statistics of such images.

In general, there are two categories of plant diseases: parasitic and non-parasitic. Pathogens, pests, and weeds are the main causes of parasite illnesses. The signs of the common rice disease, which is brought on by bacteria, viruses, and fungus, are visible on the leaf. By utilising the wavelet algorithm and contour grow approach, the segmentation's effectiveness on the health of the brinjal plant is assessed at 98%. Rangarajan and Purushothaman [7] proposed the normalised green-red difference index from a picture has an R-square value and a least mean square error of 0.86 and 0.1, respectively. This task is extremely application-specific and essential to the computer vision system's successful operation [8], [9]. Thresholding based on the local, global, and Otsu methods is the main segmentation technique used in the detection and classification of the paddy/rice disease [10]–[13]. The K-means clustering for segmentation [14]–[16]. Segmentation methods such as active contour-based level set segmentation proposed in [15], super-pixel implemented in [17], mean shift in [18], and edge-based implemented in [19] are used.

Khattab *et al.* [20] proposed a more advanced segmentation technique is colour image segmentation based on various colour spaces. Support vector machine, k-neural network, back-propagation, and neural network-based machine learning algorithms are used to identify/classify the various paddy diseases [7], [10], [12], [17], [19], [21]. These features include colour, texture, shape, statistical, co-occurrence matrix, and lesion features extracted from the segmented images as input vectors. Precision, recall, and dice metrics between the reference and segmented images are used to assess the effectiveness of the segmentation algorithms utilised in the investigation of vegetation diseases proposed in [22]. Additionally, the segmented image's structural elements, normalised cross-correlation, and peak signal-to-noise ratio in [18].

Barbedo [23] identified in comparison to consistent segmentation approaches, inconsistent segmentation will have an impact on the outcomes. In a controlled environment, segmentation performance will be impacted by lighting variations. Asfarian *et al*. [22] suggested any computer vision system must function well, and the segmentation approach that used is essential. The performance of image segmentation is evaluated with direct or indirect human involvement is performed in [24]. Zhang *et al.* [13] proposed the process of extracting information from an image is called image analysis. Size, shape, and noise contained in the components of the ground truth image have an impact on the segmentation approaches, which in turn have an impact on the outcomes of the image analysis. Kappali *et al*. [25] used higher segmentation approaches K-means segmentation, properly, and poorly segmented images are used to analyse the accuracy of the segmentation techniques. Many researchers use machine learning for classification to automate processes. A probabilistic neural network, fuzzy classification model, back propagation neural network, random forest method, support vector machine, decision tree, and convolutional neural network are used to attain a significant level of accuracy. The majority of researchers [11], [18], [22], [26], [27] address accuracy, cross-validation, performance plot, training state plot, and confusion matrix to assess the performance of classification models.

2. METHOD

The procedures for identifying the paddy disease include image preprocessing, the process of getting an image ready for image segmentation. During the preprocessing stages, contrast enhancement, and image cropping are applied. The disease-affected area is separated from its background using image segmentation. A machine learning algorithm will classify images to determine the disease. Due to changes in environmental factors like light, distance, and backdrop, it is a very difficult task.

2.1. Data resource

The primary source of the dataset is the digitally captured field images. Secondary sources of data include the machine learning repository, for research purposes the source is indicated in Table 1. Which included commonly occurring diseases BLB, BS, LS, [28] and NBS [29] are added to increase the classes. These diseases are commonly occur in all regions and may be called by different names [5], [6]. Otsu thresholding and K-means segmentation methods are often used in the identification and classification of paddy diseases. When using the Otsu technique, the grey image intensities are used as a local or global threshold value, and when using K-means clustering, the number of clusters, window size, and seed point inputs are used [11], [30].

Table 1. Paddy disease dataset description

Sl-No	Data set details	Classes of rice diseases
1	Rice leaf diseases dataset	BLB-40, BS-40, LS-40
2	Rice leafs disease dataset	NBS-40

2.2. Proposed segmentation method

The proposed image segmentation method for paddy disease uses the following steps as shown in Figure 2. The RGB and Lab colour spaces were taken into consideration for the proposed task. Red, green, and blue channels are the three main parts of an RGB colour image. The CIE Lab (CIE L* on *b*), often known as the Lab colour space, is made up of three colour ranges: a* from green to red, b* from blue to yellow, and L-lightness from black to white. You can determine the colour wavelength using (1) to (3):

$$X = C\lambda \tag{1}$$

$$x = \frac{X}{X,Y,Z\prime} \tag{2}$$

$$y = \frac{Y}{X,Y,Z\prime} \tag{3}$$

Where x denotes the desired colour and C denotes the speed of light, which is the constant multiplied by length. Colour attributes are defined as (X, Y). X stands for brightness parameters, (X, Y, Z) triple emitting values, and (X, Y) coordinates, which form the basis for all colours. The RGB colour space components are represented in terms of (3) as (4):

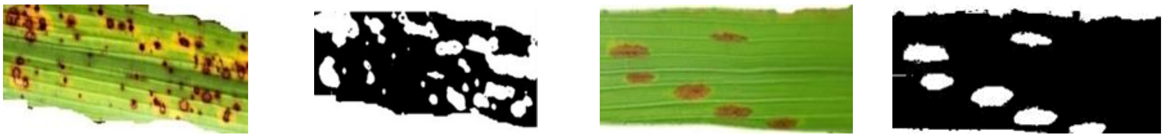
$$\begin{aligned} R &= 3.24054X - 1.537138Y - 0.49853Z \\ G &= -0.96926X \;\; 1.876010Y \;\; 0.04155Z \\ B &= 0.055643X \; 0.204025Y \; 1.057225Z \end{aligned} \tag{4}$$

Similarly, the Lab colour space components are represented as (5):

$$\begin{aligned} L^* &= 116f\left(\frac{Y}{Yn}\right) - 16 \\ a^* &= 500\left\{f\left(\frac{X}{Xn}\right) - f\left(\frac{Y}{Yn}\right)\right\} \\ b^* &= 200\left\{f\left(\frac{Y}{Yn}\right) - f\left(\frac{Z}{Zn}\right)\right\} \end{aligned} \tag{5}$$

The segmentation results are as shown in Figure 3, a visual interpretation was used to choose the right threshold value in each channel to segment the diseased part from the normal part of the leaf in the digital image, which consists of three matrix components of colour space. In Figures 3(a) and (c) shows original images of BS and NBS diseased leaf images, similarly Figures 3(b) and (d) shows the segmented images of BS and NBS diseased leaf images.

Figure 2. Proposed segmentation method



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

Figure 3. Segmentation results (a) BS original image, (b) BS segmented image, (c) NBS original image, and (d) NBS segmented image

2.3. Performance evaluation

The accuracy of the segmentation technique is a fundamental component of image-based disease analysis. Wang *et al.* [31] proposed that the classification algorithm is highly influenced by the segmentation performance; hence, the performance of the segmentation is assessed using subjective and parametric methods.

2.3.1. Subjective evaluation method

Based on the visual impression (VI) (good, average, and poor) derived from the group of professionals utilising a series of questionnaires regarding the output images, the original image and segmented image are evaluated by human intervention [7], [25].

2.3.2. Parametric evaluation method

The segmented image and the masked images obtained in the segmentation are evaluated using the metrics error rate (ER) and overlap rate (OR) [32]. The proportion of pixels in the segmented image that is erroneously identified in comparison to the ground truth input image is measured by the ER, which is given by (6):

$$ER = \frac{FP+FN}{TP+TN+FP+FN} \tag{6}$$

The OR, which assesses how well the segmented picture and the ground truth image agree is provided by (7):

$$\mathrm{OR} = \frac{TP}{TP+FP+FN} \tag{7}$$

where true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These parameters are commonly used performance parameters in image segmentation [7].

2.4. Paddy disease classification

Based on the input, the classification methods are categorized as follows:

2.4.1. Feature-based disease classification

Disease classification based on statistical features extracted from segmented images is the primary use of classification models in agriculture automation [14], [15], [25], [33]. These features serve as the input vectors for support vector machines with multiclass classification algorithms. The key difficulty with feature-based classification is finding out which feature set is unique to which types of disease symptoms.

2.4.2. Image-based classification

The development of computer vision technology, assisted by machine learning, began by using the full digital image as the input vector for classification models and producing the output for diagnosing diseases [17], [26]. In both cases, the goal is to identify $w \in R^p$ and $b \in R$ such that the prediction given by:

Sign(W(T)(x)+b) is accurate for most samples for a given set of training images $x_i \in R^{p}$, i=1,….,n in two classes, and a vector y∈ 〚{1,-1}〛 ^n. The prime objective is given by (8):

$$\min_{w,b,\zeta} \frac{1}{2} W^T w + C \sum_{i=1}^{n} \zeta_i \quad (8)$$

Subjected to$y_i(W^T \phi(x_i) + b) \geq 1 - \zeta_i$, where$\zeta_i \geq 0, i = 1, \dots \dots$, C penalty terms, control the strength. To maximize the margin we are inculcating the hing loss, which is the popular kernel trick in the support vector machine given in (9) [34]:

$$\min_{w,b,\zeta} \frac{1}{2} W^T w + C \sum_{i=1}^{n} \max\left(0,1 - y_i(w^T \emptyset(x_i) + b)\right) \quad (9)$$

Multi-class support vector machine (MSVM) is used to compare segmentation's impact on classification. Model performance is measured by accuracy, precision, recall, and F1. We explore model accuracy and disease prediction probabilities next.

3. EXPERIMENTAL RESULTS

3.1. Experimental setup

This paper's work is implemented on a 64-bit Pentium(R) Dual Core CPU-ES300@2.60GHz device with 4 GB of RAM. MATLAB and the colour threshold tools are utilised. 20% of the data is for testing and 80% is for training. We fine-tuned segmentation using the number of clusters and seed points for the K-means clustering technique. The suggested segmentation used image colour thresholds.

3.2. Results

Applying conventional segmentation to images of paddy diseases such as BLB, BS, LS, and NBS yielded results. In the subjective evaluation, output images with questionnaires were given to farmers and domain experts to include VI. Table 2 shows response-based assessments.

Table 2. VI on segmentation techniques

Segmentation method	VI
Lab color model	Good
RGB color model	Good
Otsu thresholding	Poor
K-means clustering	Poor

The parametric evaluation uses (6) and (7) for error and OR. Parameters are specified for all diseases. Overlap and ER strengthen segmentation. Each disease class's average parameters are listed in Table 3. Colour threshold segmentation was appropriate for paddy vegetation diseases. RGB and Lab colour thresholding methods outperform K-means and Otsu segmentation methods for paddy diseases. Table 3 shows that Lab colour model-based thresholding worked well across all diseases, with an average ER and OR of [36.8%, 96.9%] across all segmented disease images. While the K-means clustering and Otsu methods in the subjective method with poor VI and no correlation in the parametric method for all diseases failed to meet performance evaluation requirements, the colour threshold segmentation method has a highly acceptable correlation between ER and OR.

Table 3. Average value of ER and OR

Performance parameters	Segmentation using			
	Lab color threshold	RGB color threshold	Otsu thresholding	K-means clustering
ER (%)	36.8	41.4	73.0	100
OR (%)	96.9	96.0	75.5	99.0

Investigation is performed using MSVM on how segmentation affects BLB, NBS, BS, and LS paddy disease classification. Lab colour thresholding is compared to K-means clustering [7]. As shown in Table 4, BLB and NBS diseases are appropriately segmented and performed better than BS and LS, which have comparable symptoms. The segmentation strategy improved all disease classification, graphical representations in Figure 4. Table 5 compares the classification performance of the MSVM with the statistical features obtained from K-means segmented images [1] and the proposed colour segmentation method, Figure 5 depicts it.

Table 4. Paddy disease identification performance

Paddy disease	K-means		Segmented images	
	Accuracy (%)	Precision (%)	Accuracy (%)	Precision (%)
BLB	86	67	**91**	**80**
NBS	59	78	90	100
BS	56	38	73	67
LS	40	40	70	60

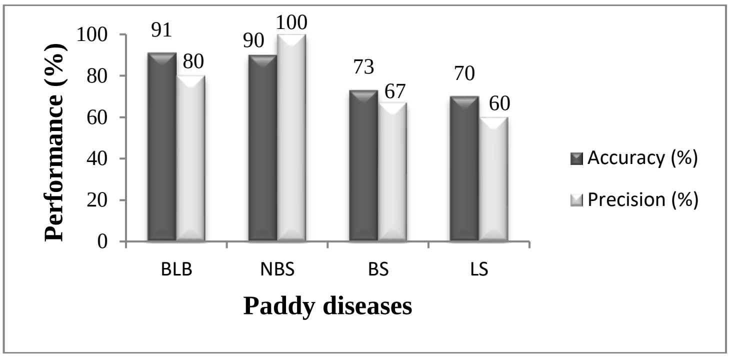


Figure 4. Graphical representation of paddy disease identification performance

Table 5. Accuracy improvement in MSVM

Disease classification using	Accuracy (%)
K-means [25]	76.60
Proposed method	92

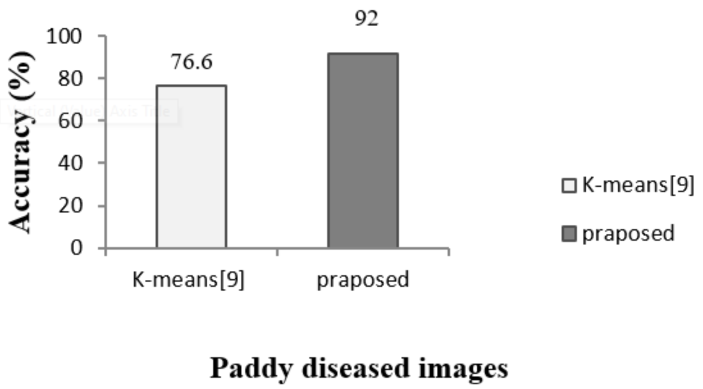


Figure 5. Improvement in MSVM classifier accuracy

3.3. Discussion

Segmentation extracts feature-based disease classification technique characteristics. Rangarajan and Purushothaman. [7] evaluates segmentation strategies using properly and poorly segmented images. The feature-based classification was more accurate with correctly segmented disease images. The colour threshold method is better at segmenting paddy diseases than K-means clustering [7]. Subjective and parametric evaluations assessed segmentation performance. The Lab colour segmentation model outperforms ER and OR, which are appropriately correlated. Images accurately identify diseases, but obtaining accurate features is difficult. Image-based classification performs considerably better than feature-based classification in this region.

4. CONCLUSION

The Lab colour model uses entropy to distinguish diseased and healthy leaves based on the homogeneity of the pixels in the colour channels. A subjective and parametric method is used to evaluate segmentation's impact on classification performance. The parametric evaluation approach showed a 36.8% ER and a 96.9% OR for the Lab colour threshold. BLB and NBS have 91% and 90% classification accuracy, respectively. Mask images and segmented images improve paddy disease identification in different colour channels. The conventional MSVM approach had 92% accuracy, compared to 76.60% for feature-based classification. In paddy disease classification, similar symptoms like BS and LS require improved segmentation. Pixel-level segmentation of the normal and sick paddy leaf improves accuracy. The authors are also creating the regional dataset.

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