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Identification of paddy leaf diseases based on texture analysis of Blobs and color segmentation

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ABSTRACT

There are three types of paddy leaf diseases that have similar symptoms, making it difficult for farmers to identify them, namely blast, brown-spot, and narrow brown-spot. This study aims to identification paddy plant diseases based on texture analysis of Blobs and color segmentation. Blobs analysis is used to get the number of objects, area and perimeter. Color segmentation is used to find out some color parameters of paddy leaf disease such as the color of the lesion boundary, the color of the spot of the lesion, and the color of the paddy leaf lesion. To get the best results, four methods have been chosen to obtained the threshold value, Otsu threshold value, variable threshold value, local threshold value and global threshold value. The best accuracy of the four methods using threshold variables is 90.7%. The results of this study indicate that the method used has been very satisfactory in identifying paddy plant disease.

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1. INTRODUCTION

There are various types of pests and diseases in paddy plants, including blast, brown spot, narrow brown spot, sheath blight, bacterial leaf blight, tungro, white pest, stem borer, rat pest, green ladybug and stink bug [1, 2]. This study will focus on 3 types of paddy plant diseases, blast, brown spot and narrow brown spot. Three types of this diseases have characteristics that are almost the same as each other so that this makes it difficult for farmers to identify the disease and require special expertise to be able to distinguish the three types of diseases [3, 4]. Apart from that, the three types of diseases are very widespread and can be found in more than 80 countries [2, 5]. The most important thing of the three types of diseases is the result if the paddy plant has been infected with this disease, namely a marked decrease in yield, because it causes the panicle to rot or break, this will inhibit the process of filling the grain, causing the grain to become empty. This will certainly lead to a decrease in paddy production and if production decreases, it will certainly have an impact on losses. The disease caused by this fungus is estimated to have caused reduction of a production in the range of 10-15% in tropical Asia. Reduction are even higher in the East Asia region and some areas that have higher climate temperatures [2, 6].

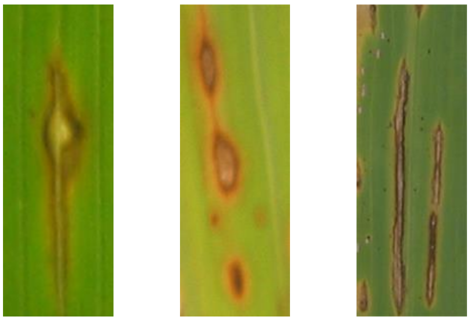
At this time the handling of paddy diseases with conventional methods is to make observations using direct observation of the naked eye by experts. If this is done in a very large planting area, it certainly requires a large number of experts and requires a lot of time to monitor and observe it, besides that the level of accuracy is also low [7, 8]. At the same time farmers do not have good knowledge about plant diseases and if they bring in experts, of course, require large costs and long time. Under these conditions, the recommended technique proved useful in monitoring large plant areas is automatic detection of plant diseases by looking at symptoms on plant leaves by utilizing image processing and computer vision techniques [9, 10].

Several studies related to paddy diseases using image processing techniques, among others, have been conducted [11], development of rice plant disease system diagnosis, with an accuracy rate of 79.5% [12]. Identification of rice plant disease using back propagation artificial neural network, with an accuracy rate of 93% [13]. Expert system for management of rice plants with levels accuracy of 85%, [12]. Identification of rice leaf disease using image processing techniques with an accuracy of 88% [14], identification of rice plant diseases based on texture analysis 85% [15, 16] and diseases identification system in paddy plant using image processing with levels accuracy of 94.7% [17]. Various methods have been developed in the research mentioned above, the development of this method to get accurate results with small errors, including using the rule base expert system, fuzzy expert system and artificial intelligent. Based on the background above, this study aims to identification of paddy leaf diseases namely blast, brown spot and narrow brown spot using texture analysis of Blobs and color segmentation. These techniques used to get characteristics of diseased leaf, this characteristic is then used to identify the type of disease using a rule-based expert system.

2. RESEARCH METHOD

2.1. Data collection

Capturing images of diseased paddy leaf is the first part of this study. To get an image that has a uniform brightness level, the environment must be controlled, some important parameters are, flash camera and distance of the object from the camera. The distance between the object and the camera is between 15-30 cm and using the flashlight on the camera. The image was taken during the day and the process of taking the paddy leaf image must be carried out quickly after the paddy leaf are cut from the tree. Otherwise, the leaf will immediately roll. Image of paddy leaf is resized into images with a resolution of 105×305 and stored in bitmap format (*.BMP). Examples of sample images and characteristics of the lesion to diseased paddy leaf as shown by Figure 1.

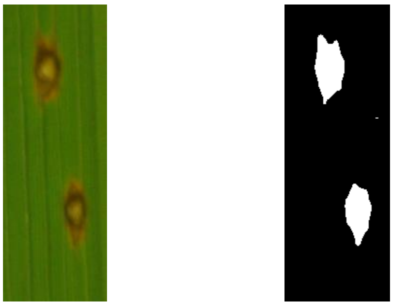


(a) (b) (c)

Figure 1. (a) Blast, (b) Brown spot (c) Narrow brown spot

2.2. Image segmentation

Before doing the image segmentation process, the image is prepared to have dimensions of 105x305 pixels in the RGB color format. This research applies four methods to obtained the threshold value: global threshold value, Otsu threshold value for automatic threshold value [18], local threshold value and the variable threshold value. The RGB image as in shown by Figure 2 (a) will be converted to a gray level image. Furthermore, image segmentation is applied based on gray level threshold segmentation, after which the image repair process is performed using a median filter and morphological operators are applied to remove unnecessary spots by using a region filling technique, so that a binary image that is free from noise is generated as in shown by Figure 2 (b).



(a) (b)

Figure 2. (a) RGB image, (b) Binary image

2.3. Blobs analysis

Blobs analysis is used to extract the features of an object, namely the shape of the object, the object area, the hole area of the object, the perimeter. Object is a lesion on the paddy leaf. Shape texture analysis uses Blobs analysis by calculating the ratio of the boundary box, which is height/width. The boundary of the box is the value of the coordinates of the upper left point, the width and height of the square border of the object, as shown in Figure 3.

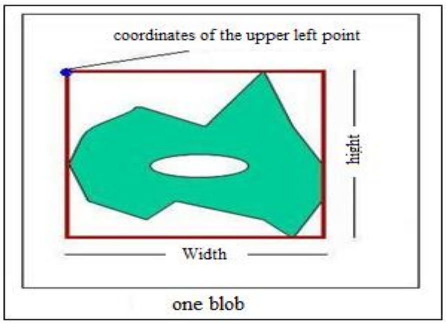


Figure 3. Boundary box

Based on 100 diseased paddy leaf images, consisting of 20 images for each type of disease, analyzed to obtain height and width values and then obtained rules to determine the type of damage, as shown in Figure 4. If value of height and width greather-than or equal to 2.8 and less-than 4.1 the type of object shape is spindle. If value of width less-than or equal to 2.8 the type of object shape is taper. If value of width greather-than or equal to 2.8 the type of object shape is oval. If value of height and width greather-than or equal to 2.8 the type of object shape is round and if value of height and width less-than or equal to 2.8 the type of object shape is spot. Usually there is more than one type of lesion on the paddy leaf disease. Therefore, the number of object form numbers is an important information to determine the symptom of the major lesion type. Based on Malaysia Agricultural Research and Development Institute (MARDI) experts, sequence of types of diseased leaf lesion forms as follows: spindle shape, oval shape/round shape/tapered shape, spot shape.

According to MARDI experts, if there is a form of spindle on a diseased leaf, then the type of spotting is spindle. When there are oval, round and taper shapes, the clearest and most obvious shapes will be chosen, as shown in Figure 5. If number of object spindle greather than 0, type of lesion is spindle. If number of object oval greather-than or equal to number of object round and number of object oval greather-than or equal to number of object taper the type of lesion is oval. If number of object round greather-than or equal to number of object taper the type of lesion is round. If number of object oval equal to 0 and number of object round equal to 0 and number of object taper equal to 0 the type of lesion is spot, othewise the type of lesion is taper. In diseased rice leaf usually there is more than one type of object that is in the rice leaf. therefore to get the shape characteristics it is necessary to count the number of objects that appear on the rice leaf using the 8-connected environment technique, as shown in Figure 6.

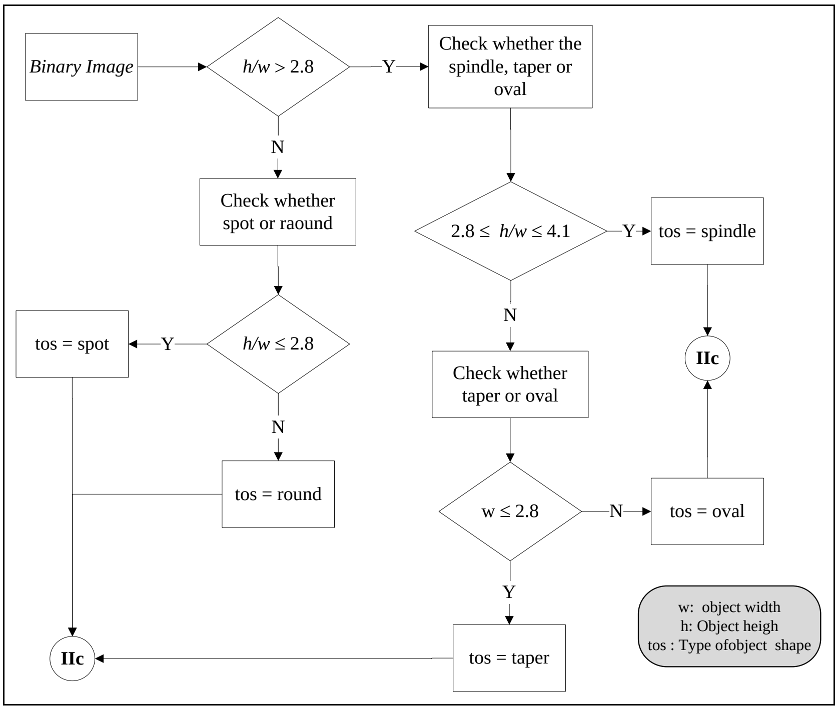


Figure 4. Flowchart type of object shape

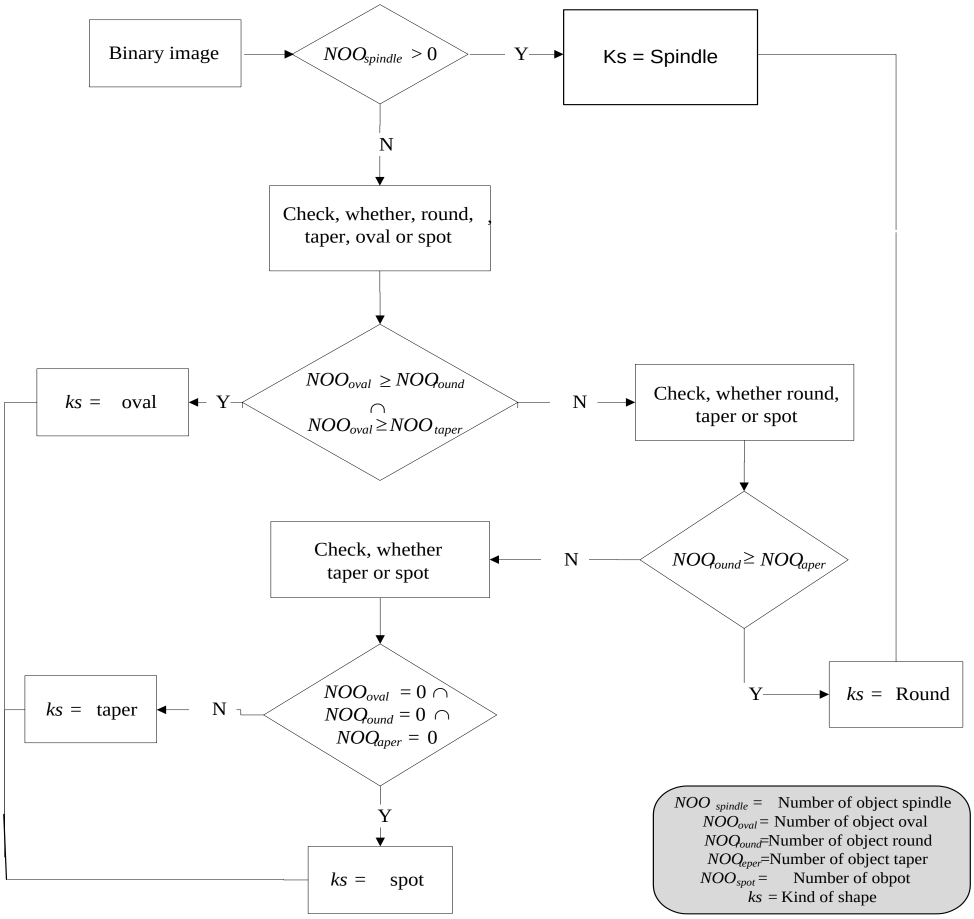


Figure 5. Flow chart of the type of lesion

The last part of this process is calculating the area of the object. The area of the object is calculated based on the binary image as shown in Figure 6 (b). for example I (x, y) = 0 represents the pixel object and I (x, y) = 1 represents the pixel background. then to calculate the area of an object is:

$$object = \sum_{i=1}^{n} \sum_{x_i, y_i} I(x_i, y_i), \quad (1)$$

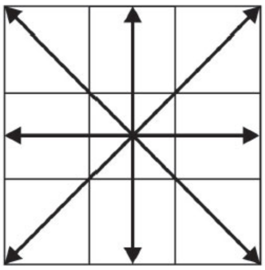
where *n* is number of the object. By calculating the percentage of lesion paddy leaf, we get the area as shown in (2) and (3),

$$image = width \;\; x \;\; height, \quad (2)$$

where *image* is area of the image with *width*= 105 and *height* = 305, and

$$Lesion = \left(\frac{object}{image}\right) \;\; x \;\; 100\%, \quad (3)$$

To get the height and width of each object shape, measurements were taken of 50 images of various types of the lesion so that the rules were obtained as follows;
- Spot: width<=34 ∩ height<=34
- Round: ((height: width) <=2.8) ∩ (width <=46)
- Oval: ((height: width) <=4.1) ∩ (width<=46)
- Taper: ((height: width)>4.1) and (width<=15.5)
- Spindle: ((width: height > 4.2) ∩ (width > 15.5)) or ((width: height<=4.1) ∩ (width > 46))



(a)

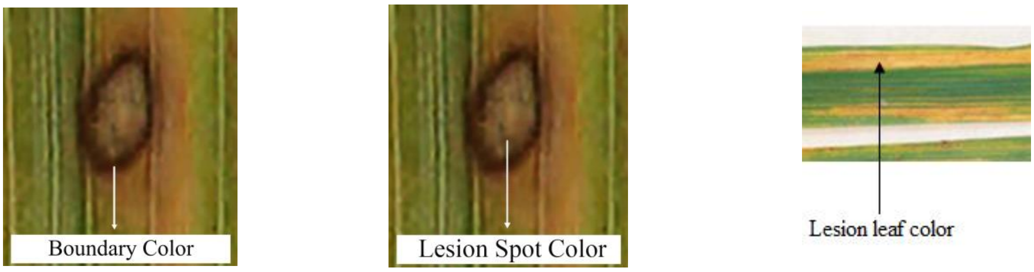
(b)

Figure 6. (a) 8-Connected neighbourhood pixels, (b) binary image

2.4. Color segmentation

Color texture is a spatio-chromatic pattern, which can be defined as a "surface color distribution", as opposed to a gray-scale texture that focuses only on the brightness of the image [18]. Color and texture analyzes have been extensively studied [19]. It is used to classify images but the results are not the best. Some researchers are proposing to combine color and texture analysis to improve classification results. In a study conducted [20-22], texture characterization was first calculated on a gray scale and then combined with color histograms and moments values. While [23] classified images into different color spaces independently or independently using energy parameters to select the space that best rated the classification.

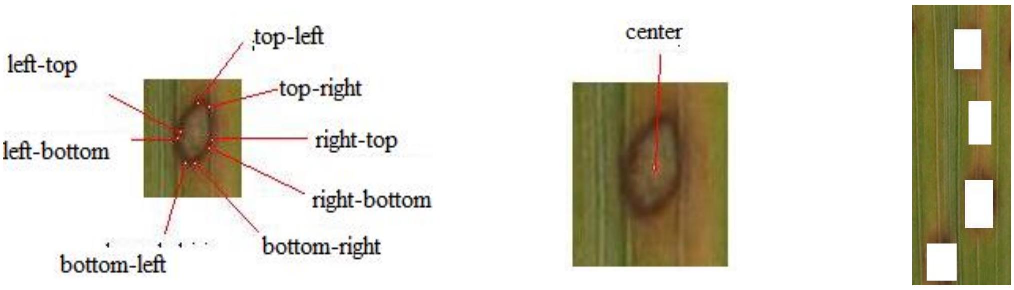
The use of RGB color space to represent image data is very common in image processing studies, especially since images generated from cameras are in the form of RGB images. But RGB color space is not a uniform space of perception that can distinguish between colors (for example, Euclidean distance) in three-dimensionality. RGB color space is not suitable for color differences as per human perception [21, 24]. For this reason, the international commission on colorimetry (Commission internationale de onlyéclairage-CIE) defines two uniform color spaces of perception, namely L * a * b * and L * u * v * [23]. Uniform color space perceptions have been widely used in image processing studies [7]. However, no studies have allowed such use of color space in terms of its effectiveness compared to RGB color space [25]. Color texture analysis in this study was used to obtain the symptoms of lesion boundary color, lesion spots color and the lesion leaf color as shown in Figure 7. The color of the lesion boundary is the color of the edge or the boundary of the lesion spot as shown in Figure 7 (a) and the color of the lesion spot is the color of the center of the lesion spot as shown in Figure 7 (b). While the color of lesion leaf is the color of diseased paddy leafe as shown in Figure 7 (c).



(a) (b) (c)

Figure 7. (a) Lesion boundary color, (b) Lesion spot color, (c) Lesion leaf color

Boundary color of the object is obtained by specifying 8 coordinates at different locations of the boundary object, i.e. left-top, top-left, top-right, right-top, right-bottom, bottom-right, bottom-left, bottom-left, and top-left as shown in Figure 8 (a). According to experts, for spindle shapes, oval and round shapes, the boundary color of the lesion leaf should be determined, whereas for the tapered shape and the spot bondary color the shape is not required. The color of lesion spots is obtained by defining the center coordinates of the object as shown in Figure 8 (b). While the color of the lesion leaf is obtained by specifying the coordinates of each pixel on the leaf image except for pixels on the object as shown in Figure 8 (c).



(a) (b) (c)

Figure 8. (a) Boundary coordinate, (b) Spot coordinate, (c) Leaf coordinate

This study uses CIE color space L * a * b * and Euclidean distance calculations to obtain similar colors. The following is an algorithm (algorithm 2.1) for converting RGB color space into CIE L * a * b * color space while the formula for calculating Euclidean distance is shown in (4),

$$\Delta E^*_{ab} = [(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2]^{\frac{1}{2}}, \quad (4)$$

where ΔL^* is the difference in brightness between two colors, Δa^* and Δb^* is the chromatic difference between the two colors.

Algorithm 2.1. Color model algorithm *CIE L*a*b**

Input: color space RGB (R_{ij}, G_{ij}, B_{ij})
Output: color space *CIE L*a*b**

1: Convert the RGB value (R_{ij}, G_{ij}, B_{ij}) into *CIE XYZ* color model (5).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} .4124 & .3576 & .1805 \\ .2126 & .7152 & .0722 \\ .0193 & .1192 & .9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (5)$$

2: Convert *XYZ* value into *CIE L*a*b** color model by calculate *L**, *a** dan *b** (6.a) and (6.6b).
The value of *L** (*luminance*) is derived from (6.a):

$$L^* = \begin{cases} 116\left(\frac{Y}{Y_n}\right)^{113}, & \frac{Y}{Y_n} > 0.008856 \\ 903.3\left(\frac{Y}{Y_n}\right), & \frac{Y}{Y_n} \leq 0.008856 \end{cases} \tag{6.a}$$

The chroma coordinate *a** dan *b** are obtained from (6.b):

$$a^* = 500\left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right],$$
$$b^* = 200\left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right], \tag{6.b}$$

where

$$f\left(\frac{\alpha}{\alpha_n}\right) = \sqrt[3]{\frac{\alpha}{\alpha_n}}, \quad \frac{\alpha}{\alpha_n} > 0.008856,$$
$$f\left(\frac{\alpha}{\alpha_n}\right) = 7.87\frac{\alpha}{\alpha_n} + \frac{16}{116}, \quad \frac{\alpha}{\alpha_n} \leq 0.008856$$

α represents X, Y dan Z
by using the white point D_{65} $(X_n, Y_n, Z_n) = (95.0155, 100, 108.8259)$

The color difference ΔE^*_{ab} between two colors, in terms of L^*, a^*, b^* is given by the Euclidean metric in (4). The smallest distance (ΔE^*_{ab}) represents the pixel most closely match to the color marker.

Experts have visually determined the colors involved in determining lesion boundary color, lesion spot color and lesion leaf color as shown in Figure 9. These colors were obtained from previous researcher [13]. There are three categories for the lesion boundary color, namely brown, orange and yellow as shown in Figure 9. In the lesion spot color, there are two color categories, namely gray and brown as shown in Figure 10. While the lesion leaf color, there are four color categories, namely brown, orange, yellow and green as shown in Figure 11.

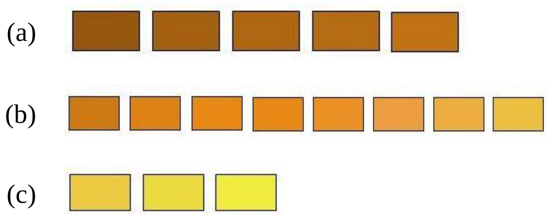


Figure 9. Lesion boundary color;
(a) brown; (b) orange; (c) yellow

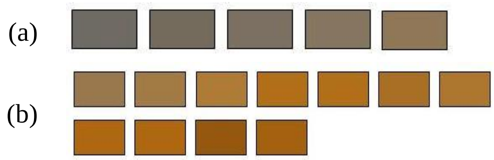


Figure 10. Lesion spot color;
(a) gray; (b) brown

Figure 11. lesion leaf color (a) brown; (b) orange; (c) yellow; (d) green

2.5. Classification

The final part of the identification of paddy leaf disease is classification. It is an important step after the segmentation process as well as texture analysis. A rule-based system becomes very useful for classifying images if the number of classes is fixed and known. Based on interviews with experts, rules have been developed based on characteristics such as area, number of objects, color, shape, and perimeter.

3. RESULTS AND ANALYSIS

To get the best results, four methods have been chosen to determine the threshold value, Otsu threshold value, variable threshold value, local threshold value and global threshold value. The Otsu method to obtain threshold values automatically by separating univariate data into two groups by considering variance between classes. The second method applies global threshold values for all images. Threshold values are set at 95 for all images, this is the average value of the variable threshold value. The third method uses the variable threshold value. This is chosen manually to get the best results. And the last method is the local threshold value by making fixed-sized blocks in the image and then each block is looking for the threshold value.

Seventy-five samples consisting of 26 images of blast, 18 images of brown spot and 31 images of narrow brown spot were tested using four threshold methods and compared with experts. So that the accuracy of the four methods is 49.3%, 56%, 60% and 90.7% for the Otsu method, global threshold, local threshold and variable threshold respectively as shown in Table 1. Because the intensity values are different for each image, global threshold values, local threshold values and automatic threshold values using the Otsu method cannot perform segmentation tasks accurately. This is caused by differences in time and distance when shooting. Shooting depends on the light source. This paper uses sunlight as a light source. That makes the source of illumination can not be controlled so that it is perfectly centered to the surface of the image being seen and it affects the intensity value of the image.

The error rate for each different threshold value method is shown in Table 2. Incorrect amounts in Table 1 have been analyzed to get the error rate. Errors can occur in the process of segmentation, feature extraction, or classification. Determination of the threshold value is an important step in the segmentation process. Inaccurate determination of threshold values can result in inaccurate segmentation results and leads to incorrect classification.

Table 1. Accuracy rates for threshold value

Threshold type	Correct	Incorrect	Accuracy rate (% Correct)
Variable	68	7	90.7%
Global	42	33	56%
Local	46	29	60%
Otsu	37	38	49.3%

Table 2. Error rates for threshold method

Error	Variable	Global	Local	Otsu
Segmentation	-	-	-	44.4%
Feature extraction	9.3%	61.5%	62.8%	33.4%
Classification	90.7%	38.5%	37.2%	22.2%

4. CONCLUSION

The image processing techniques were used to establish the identification of paddy leaf diseases based on texture analysis of blobs and color segmentation. Five characteristics; lesion percentage, lesion type, boundary lesion color, spot lesion color, and lesion paddy leaf color were tested for the classification task. The ratio of height and width of the lesion object provided a unique shape characteristic for determine type of the lesion. Four thresholding methods have been applied to get the best results in identifying seventy-five images of diseased paddy leaf. The best accuracy of the four methods using threshold variables is around 90.7%. That's because the intensity values are different for each image, so the global threshold and automatic threshold values using the Otsu method cannot segment tasks accurately.

REFERENCES

[1] S. Savary, A. Nelson, L. Willocquet, I. Pangga, and J. Aunario, “Modeling and mapping potential epidemics of rice diseases globally,” *Crop Prot.*, vol. 34, pp. 6-17, 2012.
[2] Scardaci, “Rice Blast: A New Disease in California,” *Agronomy Fact Sheat Series. Department of Agromomy and Range Science*, 1997.
[3] Z. Liu, J. Huang, J. Shi, R. Tao, W. Zhou, and L. Zhang, “Characterizing and estimating rice brown spot disease severity using stepwise regression, principal component regression and partial least-square regression,” *J. Zhejiang Univ. Sci. B*, vol. 8, no. 10, pp. 738-744, 2007.
[4] T. Kobayashi, E. Kanda, K. Kitada, K. Ishiguro, and Y. Torigoe, “Detection of rice panicle blast with multispectral radiometer and the potential of using airborne multispectral scanners,” *Phytopathology*, vol. 91, no. 3, pp. 316-323, 2001.
[5] S. Savary et al., “International agriccltural research tackling the effects of global and climate changes on plant

diseases in the developing world," *Plant Dis.*, vol. 95, no. 10, pp. 1204-1216, 2011.
[6] S. Savary, A. Mila, L. Willocquet, P. D. Esker, O. Carisse, and N. McRoberts, "Risk factors for crop health under global change and agricultural shifts: A framework of analyses using rice in tropical and subtropical asia as a model," *Phytopathology*, vol. 101, no. 6, pp. 696-709, 2011.
[7] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 41-49, 2017.
[8] P. No, M. Suresha, K. N. Shreekanth, and B. V Thirumalesh, "Researh Article Diagnosis and Classification of Diseases in Paddy Leaves," vol. 6, no. 10, pp. 6448–6452, 2017.
[9] S. Arivazhagan, R. N. Shebiah, S. Ananthi, and S. Vishnu Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," *Agric. Eng. Int. CIGR J.*, vol. 15, no. 1, pp. 211-217, 2013.
[10] N. P. Dhaygude, S B., & Kumbhar, "Agricultural Plant Leaf Disease Detection Using Image Processing," *Int. J. Adv. Res. Electr. Electron. Instrum. Eng.*, vol. 2, no. 1, pp. 599-602, 2013.
[11] Rossilawati S. et al., "The development of diseases diagnosing system in paddy plant (E-Paddy)," *Pros. Antarabangsa Teknol. Mklm.*, pp. 424-432, 2003.
[12] S. Phadikar and J. Sil, "Rice disease identification using pattern recognition techniques," *Proc. 11th Int. Conf. Comput. Inf. Technol. ICCIT 2008*, pp. 420-423, 2008.
[13] TNAU "Expert system for paddy," 2014. [Online]. Available: http://www.agritech.tnau.ac.in/expert_system/paddy/Index.html
[14] S. Phadikar, "Classification of Rice Leaf Diseases Based onMorphological Changes," *Int. J. Inf. Electron. Eng.*, vol. 2, no. 3, pp. 460-463, 2012.
[15] N. N. Kurniawati, S. N. H. S. Abdullah, S. Abdullah, and S. Abdullah, "Texture analysis for diagnosing paddy disease," *Proc. 2009 Int. Conf. Electr. Eng. Informatics, ICEEI 2009*, pp. 23-27, 2009.
[16] N. N. Kurniawati, S. N. H. S. Abdullah, S. Abdullah, and S. Abdullah, "Investigation on image processing techniques for diagnosing paddy diseases," *2009 International Conference of Soft Computing and Pattern Recognition*, 2009.
[17] A. Wenda, N. P. Miefthawati, and M. Zein, "The Development of Diseases Identification System in Paddy Plant Using Image Processing Technique," *Proceeding International Conference on Science and Engineering*, vol. 2, pp. 231-236, 2019.
[18] M. Szpringer, "Pourazowe zniekszta??cenie przednich zeb??w sta??ych i zwiazane z tym trudno??ci lecznicze.," *Czas. Stomatol.*, vol. 26, no. 8, pp. 855-860, 1973.
[19] H. Permuter, J. Francos, and I. Jermyn, "A study of Gaussian mixture models of color and texture features for image classification and segmentation," *Pattern Recognit.*, vol. 39, no. 4, pp. 695-706, 2006.
[20] M. M. P., Petrou, and C. Petrou, "Image Processing: The Fundamentals, 2nd Edition," *2nd ed. Wiley*, 2010.
[21] G. Paschos, "Perceptually uniform color spaces for color texture analysis: An empirical evaluation," *IEEE Trans. Image Process.*, vol. 10, no. 6, pp. 932-937, 2001.
[22] A. Asfarian, Y. Herdiyeni, A. Rauf, and K. H. Mutaqin, "Paddy diseases identification with texture analysis using fractal descriptors based on fourier spectrum," *Proceeding-2013 Int. Conf. Comput. Control. Informatics Its Appl. "Recent Challenges Comput. Control Informatics", IC3INA 2013*, pp. 77-81, 2013.
[23] S. N. Ghaiwat and P. Arora, "Detection and Classification of Plant Leaf Diseases Using Image processing Techniques: A Review," *Int. J. Recent Adv. Eng. Technol.*, vol. 2, no. 3, pp. 2347-2812, 2014.
[24] K. M. Chen and S. Y. Chen, "Color texture segmentation using feature distributions," *Pattern Recognit. Lett.*, vol. 23, no. 7, pp. 755-771, 2002.
[25] M. Sarifuddin and R. Missaoui, "A new perceptually uniform color space with associated color similarity measure for content-based image and video retrieval," *Proc. ACM SIGIR 2005 Work. Multimed. Inf. Retr.*, 2005.