Identification of Rice Leaf Disease based on Rice Leaf Image Features using the k-Nearest Neighbour (k-NN) Technique

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Keywords: Rice Leaf Disease, Digital Image Processing, k-NN, k-nearest Neighbour, Rice Leaf Image Features System

Abstract: Increasing productivity of rice plants is crucial to offset the rate of population growth because rice for most of the world's population is the primary energy source. The phenomenon of degradation of fertility and disease in rice plants poses a severe challenge, prevention and control measures are needed. The health of rice is the main factor that influences productivity. Diseases of rice leaves include various fungal pathogenic diseases such as rice blast, brown spots, and leaf blight. It is difficult to identify the type of rice leaf disease. This study discusses a digital image processing model for classifying rice leaf disease use leaf image features. Experiments conducted in this study used three types of rice leaf diseases, namely rice blast, brown spots, and leaf blight. The k-Nearest Neighbour algorithm was used as the primary technique to classify the image based on its features such as features of shapes, patterns, and feature colors. The results of the experiment showed that the average accuracy performance was 77% for the precision and recall was 74%.

1 INTRODUCTION

Rice attributes are the essential food for most of the world's population (Kim, Lee, & Jang, 2011) especially for 144 countries from all continents were more than 90% of rice is produced and consumed in Asia (The Food and Agriculture Organization, 2000).

Constraints in increasing rice production are increasingly complex because they are also influenced by various changes and developments in the strategic environment besides the agricultural sector (Hasil Sembiring, 2015). The phenomenon of degradation of fertility and disease in rice plants is one of the causes of the difficulty of increasing food productivity in addition to shrinking rice fields and conversion of rice fields to non-agricultural purposes. Factors that can cause a reduction in the quality and quantity of agricultural products include disease attacks on rice plants (Zahrah, Saptono, & Suryani, 2016).

Because rice leaves have a broad cross-section compared to other parts, resulting in changes in color and shape can be seen more clearly, then the leaves can be used as an initial step to detect disease in rice (Zahrah et al., 2016). Generally, rice leaves are often influenced by several diseases, including blast, brown spot disease, and blight (Farhana Tazmim Pinki, Nipa Khatun, 2017). Plants that are infected with these fungal pathogenic diseases will experience a decrease in the quality of rice produced by these plants, dry plants, puso, and even death, making farmers fail crops and losers. Furthermore, increasing rice productivity and food security will be more challenging to achieve. However, if symptoms of rice disease can be detected early, appropriate measures can be taken to control it. From the shape of the spots, color, and also texture become parameters (Dewi & Anjarwati, 2009) in the introduction of the type of rice leaf disease. This study discusses a digital image processing model for classifying rice leaf disease use leaf image features. The k-Nearest Neighbour algorithm was used as the primary technique to classify the image based on its features, such as features of shapes, patterns, and feature colors.

2 RELATED WORK

The proposed method of Phadikar et al (Phadikar & Goswami, 2016) the acquisition image is calculated using the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation

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Index (GNDVI), Enhanced Vegetation Indices (EVI), Soil Adjusted Vegetation Index (SAVI) and determine the best vegetation indices to be segmented with the Otsu method and then classified. Research on the introduction of rice leaf disease was carried out (Mutalib et al., 2017) using morphological operations, the method of canny edges and BPNN Classifications (Back-propagation Neural Network). (Suresha M and Shreekanth K N, 2017) Achieved 76.59% accuracy in recognizing rice leaf blast and brown spots. From the RGB image that was acquired through a digital camera, it was then converted to HSV color model before being segmented by the otsu method. Furthermore, the extraction of geometrical features (minor axis length, primary axis length, perimeter) were classified by the k-nearest neighbor technique.

Pinki et al. 2017, (Farhana Tazmim Pinki, Nipa Khatun, 2017) propose the image of diseased rice leaves to be segmented with k-means clustering. Then use the support vector machine to do the classification process. On (YAO et al., 2017) propose 3 (three) layer models, namely a combination of HOG feature and Boost Classifier then Gabor and LBP feature in the second layer and on the third layer do the HOG feature and SVM Classifications methods. Research (Mutalib et al., 2017) utilizes morphological operations and canny methods before classifying using backpropagation neural networks. The input used comes from the RGB image that is changed into the LAB color space. Component a and component b are taken from the previous color descriptor through the stages of segmentation. (Suresha M and Shreekanth K N, 2017) Achieved 76.59% accuracy in recognizing rice leaf blast and brown spots. From the RGB image that was acquired through a digital camera, then it was converted to HSV color model before being segmented with the otsu method. Furthermore, the extraction of geometrical features (minor axis length, primary axis length, perimeter) were classified by the k-Nearest Neighbor technique.

3. THE PROPOSED APPROACH STEP- BY-STEP DETAILS

The subjects in this study were making a model classify the types of rice leaf diseases by utilizing digital image processing. The model for the introduction of rice leaf disease proposed using the k-Nearest Neighbour classification technique, which was carried out in several stages. The first stage is the initial processing stage (pre-processing) which aims to prepare the image before it is processed; in this stage, image quality improvement and noise removal are carried out. The RGB images are converted into color space of l x a x b because they can represent colors better. (Mendoza, Dejmek, & Aguilera, 2006; Tazmim Pinki, Nipa Khatun, 2017; Prakash, Saraswathy, 2017).

The experiments were conducted used several images of diseased rice leaves obtained from previous studies conducted by Farhana Tazmim Pinki et al., 2017. Table 1 describes the number of data sets used.

Table 1: Amount of data image used

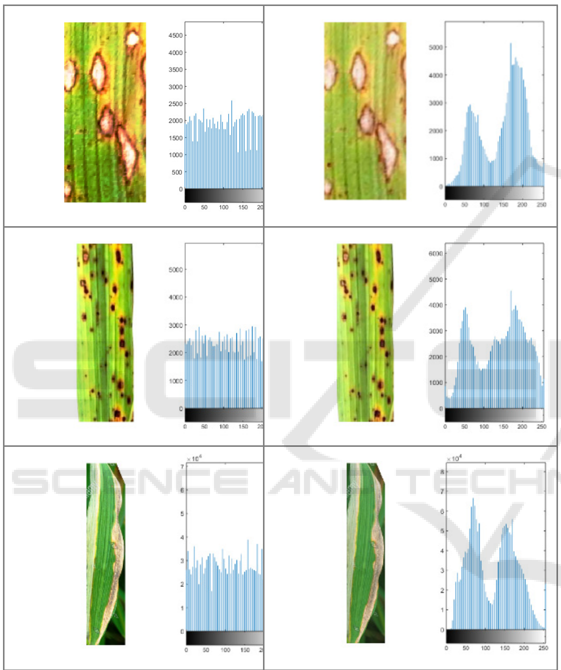
Type of image		Amount of data
Training Image		
1	Leaf Blight	24
2	leaf blast	34
3	brown spots	31
Testing Image		
1	Leaf Blight	12
2	leaf blast	15
3	brown spots	11

In our approach, we proposed with RGB images and converted into grey space. Next, it is segmented with a threshold technique so that the cluster region of interest is separated and extracted using its image features. Finally, the k-Nearest Neighbour classification method is used to identify its class (Prakash, Saraswathy, 2017). The proposed method of introducing rice leaf disease, input image data will go through the pre-processing and segmentation stages at the beginning, then the region of interest (ROI) extracted images utilize color features, texture features, and form features.

Noise is the result could occur in the image acquisition process or during electronic transmission. This noise can change the original pixel values that affect the intensity of real images (Mishra, Lambert, & Nema, 2017). So that at this stage the process is carried out: Histogram equalization, Wiener filter, Median filtering, Unsharp mask filtering, Decorrelation stretch (Mishra et al., 2017), (Phadikar & Goswami, 2016), (Farhana Tazmim Pinki, Nipa Khatun, 2017), (Singh, 2015). The next stage after the image is scratched manually, then the quality of the image is improved, such as eliminating noise (noise), increasing contrast use the following framework:

```
INPUT: Q ← Image
OUTPUT: Q ← Segmentation Result
BEGIN
```

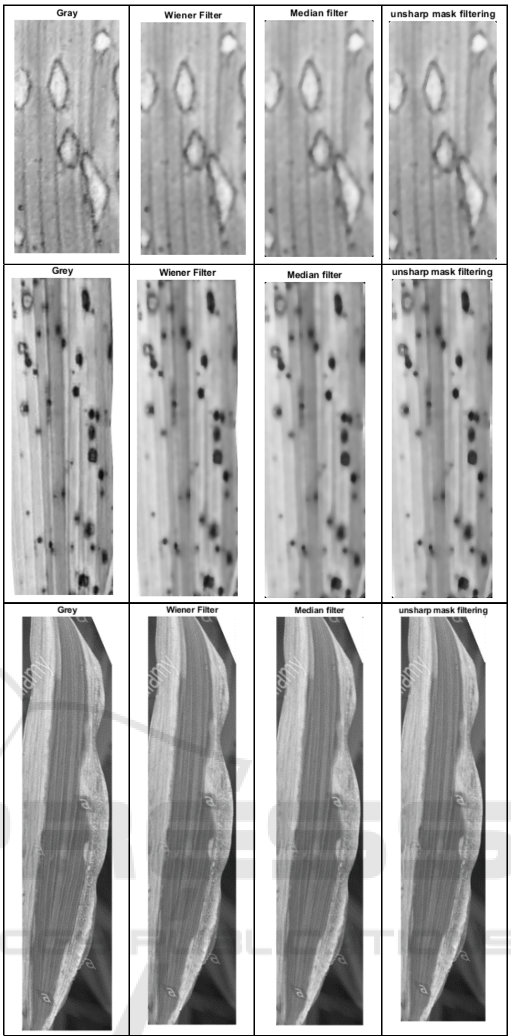
```
Histogram Equalization
b = total pixel image
I = 1
IF I <= b
I++
ELSE
← Convert RGB to GRAY
 END IF
 ← Wiener filter (5x5)
 ← Median filtering (5x5)
 ← Unsharp mask filtering
 ← Decorrelation stretch
 RETURN Q
 END OF BEGIN
```



(a) (b)

Figure 1: histogram equalization image of diseased rice leaves. a) input image, b) output image enhancement histogram equalization process Substructure 2 against Z

One method used in this pre-processing stage is histogram equalization. The histogram of the data is modified to improve image quality. Histogram alignment changes the distribution of grey degree values on the data to be uniform so that each grey degree will have a relatively equal total of pixels. Figure 1 shows the result of histogram equalization. Figure 2 shows the enhancement processing image of diseased rice leaves: gray color image, Wiener filter, Median filtering, unsharp mask, and Decorrelation stretch filtering.



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

Figure 2: enhancement processing image of diseased rice leaves. a) gray color image, b) Wiener filter, c) Median filtering, d) unsharp mask, e) Decorrelation stretch filtering

In other words, the more dominant green color will be eliminated, and this has succeeded in image data in the form of diseased images of paddy leaves. As an improvement to further research, segmentation can be done by dividing the pixels of the image data into several groups so that each group can represent each class, such as using the k means clustering algorithm. So that the ROI (regions of interest) will be identified as in a particular cluster. Segmentation results from complete image data can be seen in figure 3.

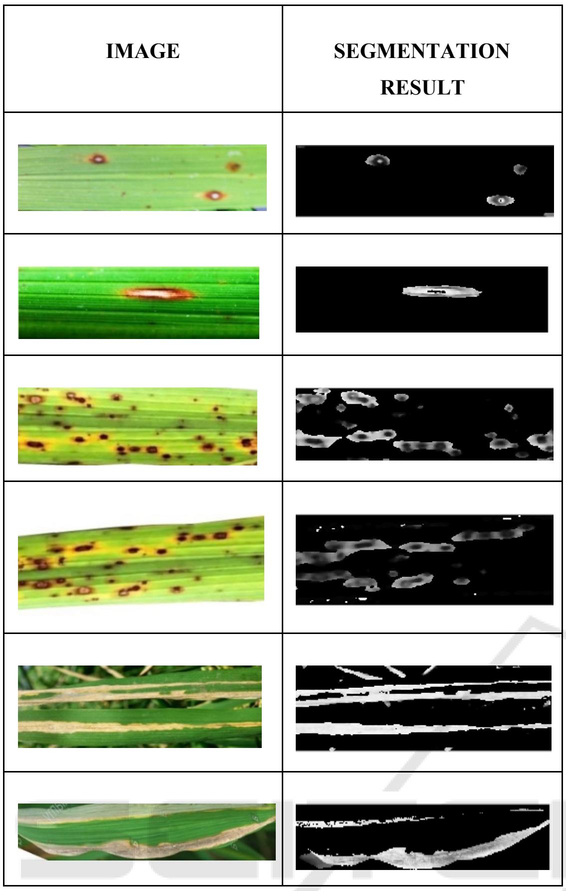


Figure 2: Segmentation results from complete image data

The extraction value used as data for the classification process comes from 11 features consisting of area, RMS, mean, kurtosis, skewness, standard deviation, energy, entropy, contrast, correlation, homogeneity. Six of the features used to utilize the GLCM algorithm (gray level co-occurrent matrix). Table 2 defines those features. These features are derived from feature pattern, color feature, feature shape as visual content-based because of the features that represent most of the human vision. Extraction approach with color features is one feature that can represent images. Utilizing color moments, namely mean, skewness, RMS, variance, standard deviation, kurtosis to produce color distribution (Athanikar & Badar, 2016). Extracted features consist of Contrast, Energy, Entropy, and Correlation, while form features take advantage of area values.

Table 2: extraction value used in the experiment

Mean	$m = \sum_{i=1}^{L-1} r_i p(r_i)$
RMS	$RMS = \sqrt{\frac{1}{MN}\sum_{i-1}^{K}\sum_{j=1}^{K}(I_{ij} - I)}$
Variance	$\mu 2(r) = \sum_{i=1}^{L-1}(r_i - m)^2 p(r_i)$
Kurtosis	$\mu 4(r) = \sum_{i=1}^{L-1}(r_i - m)^3 p(r_i) - 3$
Kontras	$Con = \sum_{i=1}^{K}\sum_{j=1}^{K}(i-j)^2 p_{ij}$
Energi	$E = \sum_{i=1}^{K}\sum_{j=1}^{K} p^2{}_{ij}$
Korelasi	$Cor = \sum_{i=1}^{K}\sum_{j=1}^{K}\frac{(i - m_r)(j - m_c)p_{ij}}{\sigma_r \sigma_c}$

The classification technique used in recognizing types of the blast, brown patch, and blight is a K-Nearest Neighbor (Krithika & Grace Selvarani, 2018), (Tay, Hyun, & Oh, 2014)

```
Classify (X, Y, x)
// X = Train Dataset
// Y = Class Label
// x = Prediction
FOR i = 1 to m DO
Compute distance d (X i, x)
END FOR
Compute set I containing indices for the k
smallest distances d (Xi, x)
RETURN majority label {Yi where I ϵ I}
```

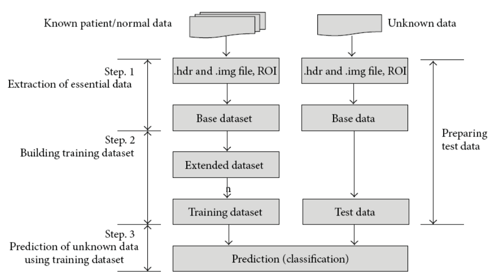


Figure 3: Classification Process

The framework of our classification process is illustrated in figure 3.

4 RESULT AND DISCUSSION

Labeling is used in each type of rice leaf disease: Rice Blast, Brown Spots, and Leaf Blight. In the evaluation process to the proposed system model in a multiclass configuration matrix, we obtained the performance of precision and recall are mentioned in table 3. Figure 4 shows the average performance accuracy obtained from the overall experiment.

Table 3: Evaluation Result

No	Class Label	Precision	Recall
1	Rice Blast	72.72 %	66,6 %
2	Brown Spots	75 %	90 %
3	Leaf Blight	83,3 %	66 %
Average		77%	74%

The results obtained from this research have reached above seventy percent where in previous studies with different methods have achieved excellent results, 73.1% by (YAO et al., 2017), 76.59% of the results of Suresha et al (Suresha M and Shreekanth KN, 2017) and 70-80% accuracy achieved by mutalib et al (Mutalib et al., 2017)

Table 4: Average performance accuracy

No	Desease	Accuracy	Performance
1	Rice Blast	75 %	76,59 %
2	Brown Spots	72 %	
3	Leaf Blight	83 %	

5 CONCLUSION

This study intends to develop a system for automatic recognition of rice leaf disease with digital image processing. By utilizing image feature extraction and the k-Nearest neighbor classification technique Experiments that have performed the performance of identification of rice leaf disease resulted in a performance of 76.59%. This accuracy is comparable to the research conducted by Suresha et al. (Suresha M and Shreekanth K N, 2017) which utilizes k-NN's shape features and techniques to classify two (2) types of rice disease, blast, and brown spots, its accuracy is 76.59%. However, this research was conducted to classify three (3) types of rice leaf disease, namely blast disease, brown spots, and blight.

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