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RESEARCH ARTICLE

Intelligent detection of rice leaf diseases based on histogram color and closing morphological

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ABSTRACT

Harvest drop in rice because of leaf blast is a vital issue in the country's food stock and social life where rice is the primary source of food. Epidemics can cause leaf blasts due to weather conditions or environmental transformation. Therefore, early detection of leaf blast is needed to take precautions action to save the harvest. This research presents a new approach for rice leaf blast detection. It seizes colour distribution and shapes to determine the damaging leaf. Two main features: colour and shape, are key points to measure the similarity of an image by comparing the image query and database. The image extraction uses histogram colour throughout the pre-processing phase. The approach will take the dominant colour of leaf. Since this green colour dominated the leaf, the green will be converted from RGB to the HSV domain with 256 range. The shape feature extraction based on morphology closing will calculate the images' area, diameter, and perimeter. The process is continued by resizing the image and convert into a grayscale mode to apply canny edge detection. The experiment uses 267 images dataset and 74 testing data consisting of 2 categories: blast disease leaf and healthy leaf. The trial results achieve an 85.71% accuracy rate to detect blast disease by colour feature, 71.42% by shape feature, and 85.71% by combined colour-shape features.

Keywords: Harvest Drop; Closing Morphological; Histogram Colour Detection

INTRODUCTION

Rice (Oryza sativa L.) is essential nutrition consumed by half of the world's populace, especially the crowded area with quick evolution (Fageria, 2007). The structure paddy plant consists of greenery, twig, root, and flower. Rice has unique characteristics on its grain that are represented by its colour (Shinta et al., 2014). Rice is also considered a vital crop in Africa, and it becomes primary consumption after maise and wheat. The request for rice for people in Africa raised significantly, while the manufacture is declining over the year. It is due to the rice blast disease that hit the crop and makes a loss until 60-100% of crop rate (Kihoro et al., 2013). Rice grownup under pre and post disease attack, primary inoculation got infected by blast fungus or ordinary contagion. It will reduce height, grain per plant, grain mass, and grain harvest. The initial investigation leads to this crop failure because of the least and neck blast disease (Koutroubas et al., 2009). The paper is divided into five main sections: First, Introduction discusses the research's motivation, followed by related works discussion to reveal the research gap in the latest trend. The third phase is the research methodology, followed by the fourth stage, the result and discussion section. It describes how to implement research. Finally, Section 5 conclude the outcome of the study. Designing a harvest production can help people guesstimate crop declination caused by various diseases such as weather and insect attacks (Bastiaans, 1993). Leaf blast on paddy will endanger worldwide food stock. Therefore an investigation of this particular disease is essential to keep food at bay (Asibi et al., 2019). Leaf blast disease has become a major concern for many countries because it causes around 30% degradation of rice manufacture. This amount is enough for 60 million individuals. These sufferers surge the worldwide rice value and lessen buyer happiness and food haven (Nalley et al., 2016). Automation for leaf blast recognition is essential. Meanwhile, deep learning and artificial intelligence are being used for effective solutions to image recognition

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even though they still need improvement in terms of accuracy(Liang et al., 2019).

The diseases classification and image segmentation technique are able to detect plant disease with significantly less computational efforts automatically (Halder et al., 2018). Identification of scorching and blast sickness through leave image performed by histogram analysis. This method will benefit agriculturalists to identify leaf blasts efficiently (Tejonidhi et al., 2016). Another research of image processing uses mathematical morphology to analyze and depict the texture and shape signature. The mathematical morphology-based image process system has attracted attention worldwide, particularly the intelligently recognition agriculture disease (Qiao, 2009). Image pre-processing is the first stage of detection to improve the quality of images(Kurniasari et al., 2019). The Canny Edge Detection Algorithm gives a simple edge detection operation, which reduces time and memory consumption (Kabade, 2016). On the other hand, the concept of smart farming was also introduced to detect the leas disease in early stage by capturing the leaf condition through IOT Sensor (Basori et al., 2020). Different image sizes will carry extra information, too, so the best image size needs to be examined in detail (Barnouti, 2016). The purpose of image resizing is to produce a lower data size, which hastens the processing time (Dharavath et al., 2014). Grayscale is a series of shades of grey without apparent colour (Jeyalaksshmi and Prasanna, 2017). The lightness information is preserved while the chroma and hue information is ignored (Hantoush Alrubaie and Hameed, 2018). Morphological are applied to find and measure objects on the image's surface (Zeng et al., 2014). The previous studies focused mostly on black sickness, chroma and morphological of image surface of the leaf. The detail comparison is depicted in Table 1.

MATERIAL AND METHODS

Material this research related to image resizing, grayscale, canny edge detection, closing morphological method, colour feature extraction, matrix, and similarity measurement.

Table 1: discussion on previous studies

Author	Finding
Liang, W et.al (2019)	Apply CNN for leaf disease detection by using CNN, however they mentioned a data augmentation still needed to improve the result accuracy.
Tejonidhi, M.R (2016)	The author used histogram with Bhattacharya's similarity calculation. However this method still lack of morphological shape of leaf.
Basori, et. al.(2020)	It proposed a smart system based on IoT and deep learning for managing the farm.
Proposed method	We have applied histogram colour and morphological shape of the leaf as parameter for the leaf disease detection.

Image resizing

Image resizing is responsible for the scaling process to limit variation of size during identification phases. The threshold for image scaling is 0.1.

Grayscale

The colour composed of equation (1) should be the red, green, and blue channels. The most common method of converting from colour to grayscale is reducing three bands to one band. Grayscale conversion use equation 1 for computation, where Wr + Wg+Wb = 1 and W means weight for red, green and blue.

$$grayscale = Wr{*}Ir + Wg{*}Ig + Wb{*}Ib \tag{1}$$

Canny edge detection

Canny is one of the famous algorithms to detect the boundary of an image known as the edge. The main process covers five main phases:

a. Noise Lessening: The derivation math plays a significant role in this process because edge detection affected by image noise. A smoothing process encompasses gaussian blur to reduce the noise. The kernel of Gaussian with 3x3 size, refer to equation 2(Hantoush Alrubaie and Hameed, 2018).

$$f\left(x, y, \sigma\right) = \frac{1}{2\pi\sigma^2} \frac{(x^2 + y^2)}{2\sigma^2}), -\infty < x,$$
$$y < \infty, \sigma > 0 \tag{2}$$

b. Gradient computation: the gradient level represents the edge strength and its direction. The intensity value ranges: 0-255 that have a non-uniform value. It is computed through equation 3 that describe image gradient vertical and horizontal (Assirati et al., 2014).

$$A\left(x, y\right) = tan^{-1}\left(\frac{\partial f(x, y) / \partial y}{\partial f(x, y) / \partial x}\right) \tag{3}$$

c. Non-maximum conquest: This approach will enforce travelling overall matrix nodes for gradient strength then discover the maximum edge rate. The fundamental steps:

- Produce a matrix with 0 value
- Find the path via angle of matrix
- Make a comparison for the adjacent pixel with higher intensity and the one under the handle.
- Use non-max suppression for image reoccurrence.

d. Double Threshold: Hysteresis edge tracing: the transformation of low-intensity pixel become high if only one adjacent pixel possesses a strong intensity

Closing morphological method

The process of the morphological image is based on the linear procedure. Another purpose resulting is correlated with the form or morphology of an image. The operator of closing will expand then shrink the image via the same approach. The generated output will contain maximum intensity around all pixels. Binary format enforce pixel value to be 1 if any adjacent neighbouring pixels with intensity 1. The dilation process will increase the visibility of the object by finishing the hole inside the noise. Therefore, this approach is very useful to build a bridge between adjacent pixels.

Colour feature extraction

The first Stage for colour feature extraction is pre-processing by colour matrix, continued by colour feature extraction by histogram colour. Matrix convolves with a small portion of the input image. It is happening for each plane separately. Including the results of each plane are added to produce one single output value in the feature map. The colour model of HSV was used for converting the RGB to HSV format. RGB is an additive model to define any color that should specify the Red (R), Green (G) and Blue (B) (Riskiawan et al., 2018). It will take the upper and lower value of each R, G, and B value. Afterwards, the process will continue with finding equivalent colours from HSV colour space. Equation 4 represents the computational model of this conversion (Iwanowski and Skoneczny, n.d.).

$$R' = \frac{R}{255}, G' = \frac{G}{255}, \quad B' = \frac{B}{255}$$

$$C_{max} = MAX\left(R', G', B'\right)$$

$$C_{min} = MIN\left(R', G', B'\right)$$

$$\Delta = C_{max} - C_{min}$$

$$H = \{60^\circ x \left(\frac{G' - B'}{\Delta} mod 6\right),\ C_{=} R'\ 60^\circ x$$

$$\left(\frac{B' - R'}{\Delta} + 2\right),\ C_{=} G'\ 60^\circ x \left(\frac{G' - B'}{\Delta} + 4\right),\ C_{=} B'$$

$$S = \{0\ ,\quad \Delta = 0\ \ \frac{\Delta}{C_{max}}, \Delta <> 0$$

$$V = C_{max} \tag{4}$$

Matrix

The matrix for shape future extraction is an area, equivalent diameter, perimeter. The matric for colour feature extraction is green value, RGB range 0-255. A site is an actual number of pixels in the region, returned as a scalar. Equation 5 calculates the are value.

$$A_i = \sum_{i,j=0}^{M,N} b\left(i, j\right) \tag{5}$$

The measurement of this high-speed image using a 2D image, so equivalent diameter is the diameter of a circle with the same area as the image shadow. The formula of the equivalent diameter is equation 6(Saravanan et al., 2016).

$$d = \sqrt{\frac{4A_i}{\pi}} \tag{6}$$

Perimeter is the distance around the boundary of the region returned as a scalar. The formula for this is equation 7 (Wang and Dong, 2009).

$$\sum_{i,j=0}^{M,N} E_d\left(i, j\right) \tag{7}$$

Similarity Measurement

This section explains how to compare two things and compute its similarity. It will use a high value if found similarity while null or negative value if the matters are dissimilar. Generally, Euclidean distance is used for measuring the similarity of the objects by calculating the certain point of the objects. Euclidean distance is the most used due to its simplicity of measurement with this formula (8) (Wang et al., 2005).

$$d^2 E\left(x, y\right) = \sum_{k=1}^{MN} \left(x^k - y^k\right)^2 \tag{8}$$

Methodology

Fig 1 portrays the methodology of our system. There are five main functions of the proposed approach. It has five main steps: (1) shape feature extraction, (2) colour feature extraction, (3) matric, (4) similarity measurement (5) result.

The techniques of pre-processing are image resizing, grayscale, canny edge detection. Image resizing is a critical pre-processing step for varied image databases. The aim of resizing is to establish a base size for all images. Grayscale is a grayscale value distribution showing the frequency of occurrence of each grey-level value. One of the representative edge detection algorithms is Canny. Besides, the morphological closing method is used for Shape feature extraction. Closing morphological by reconstruction preserves shapes in the image.

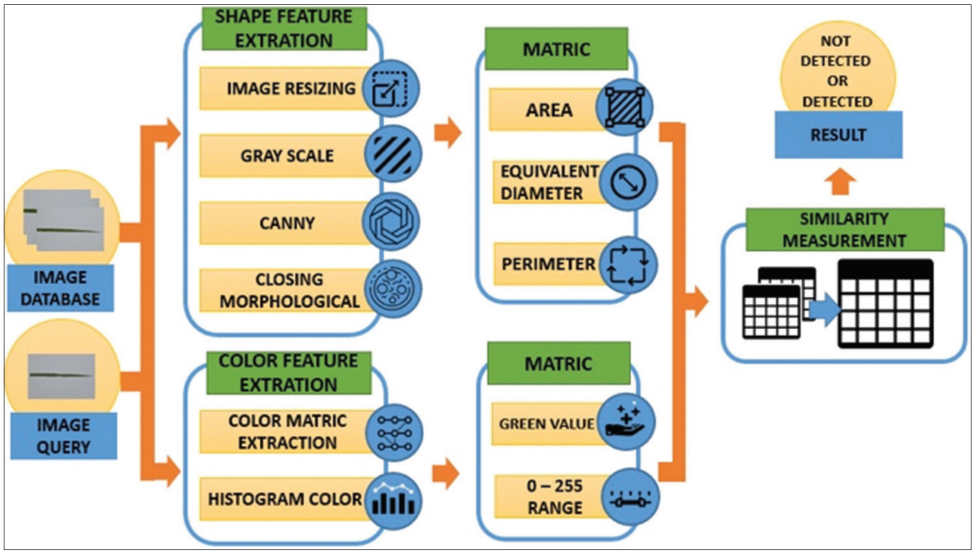

Fig 1. The system design of research.

RESULT AND DISCUSSION

The system extracts two features: colour and shape; a combination of features is added to measure the similarity between the image query and the image database. Fig 2 and 3 are shown the healthy rice leaf and blast disease in rice leaf for the data training 267 objects and 74 for data testing.

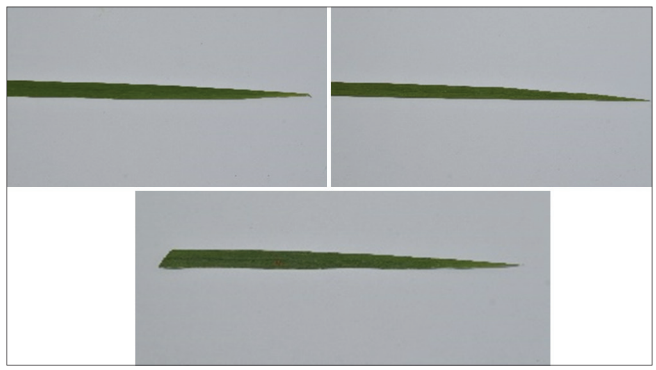

Fig 2. The example of healthy rice leaf.

The histogram colour is used for extracting image colour features, pre-processing of the histogram is set up with converting RGB to HSV value, and only taking green values are arranged into 256 values shown in Fig 4. At the same time, the shape feature extraction used Morphology Closing, which is calculated as the area value, equivalent diameter, and perimeter of each image. The pre-processing stage for the shape is set by resizing the image and then converted to a grayscale image. This edge detection result is utilised for the morphology closing method in the last step, refer to Fig. 5 – 9.

Fig.5 is the result of the grayscale conversion process, while Fig.6 shows the leaf's boundary where the edge of the leaf appeared after the edge detection execution.

Fig.7 represents the morphology closing method to enhance the image and remove its noise, whilst Fig.8 depict the highlighted are that will be computed for other purposes.

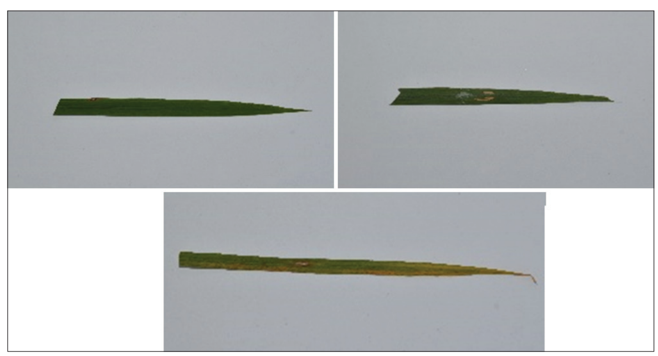

Fig 3. The example of Blast disease rice leaf.

The result of perimeter computation will highlight the picture with a red boundary that indicates the area ready for calculation. As referred to in purpose depicts, the highlighted area another purpose we applied the system into two categories: blast disease leaf and healthy leaf, as described in Fig 10 dan 11. We can use this system by adding objects from other devices then continue with the calculation. The results represent several properties such as:

- the number of areas
- equivalent diameter
- perimeter
- colour result
- shape result
- combination colour
- shape

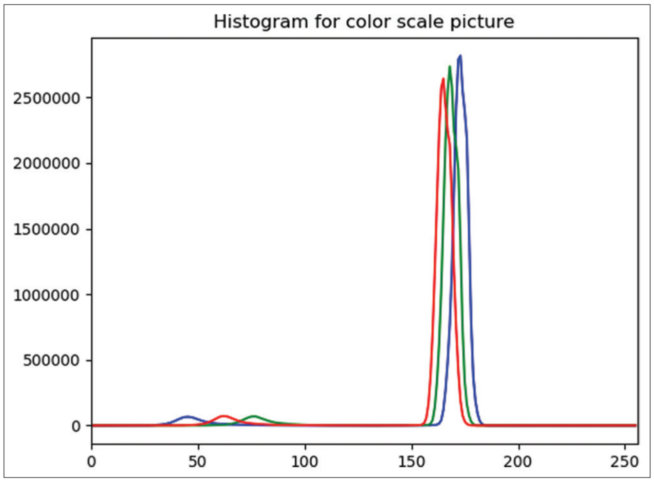

Fig 4. The result of the histogram colour scale picture.

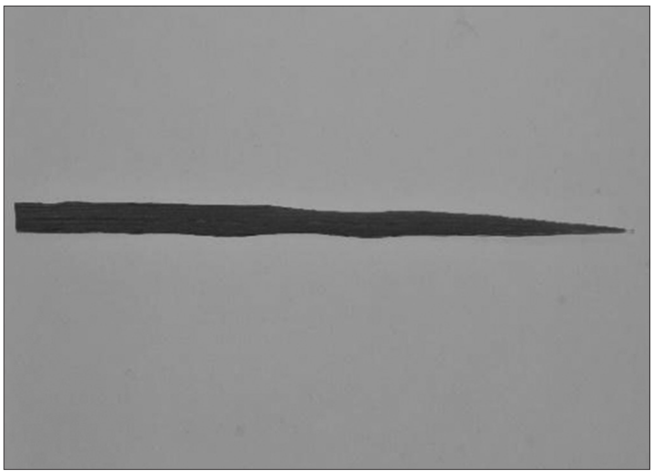

Fig 5. Picture of grayscale rice leaf.

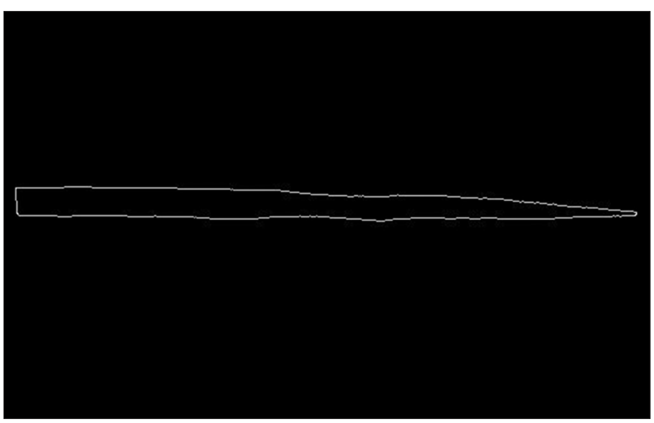

Fig 6. Picture of canny edge detection.

The condition of the leaf-based is determined by calculation and the resulting image of a histogram.

Fig.10 describes a healthy leaf's image properties for each process sequence, such as grayscale, canny, morphology closing, area and perimeter. Similarly, the same process for blast leaf is shown in Fig.11.

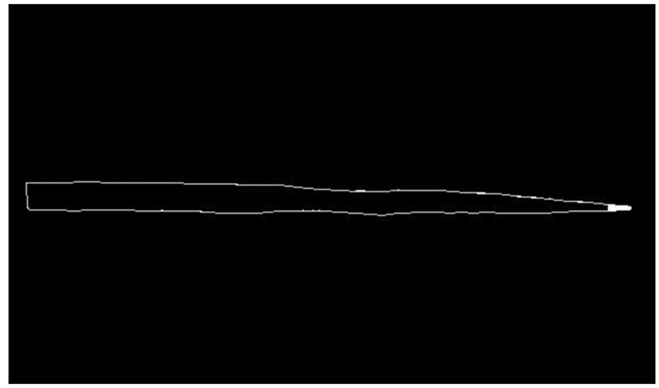

Fig 7. The morphology closing method.

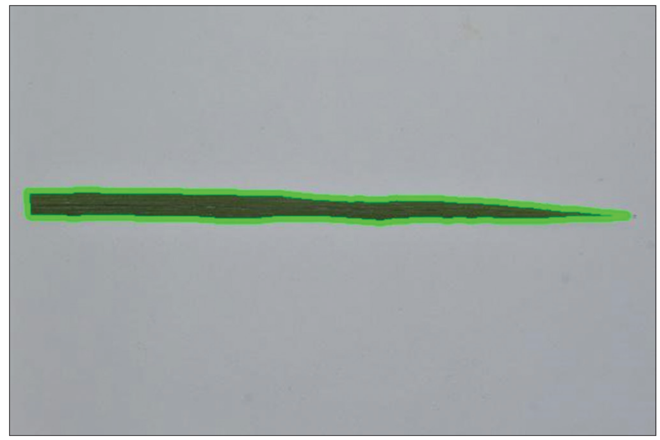

Fig 8. The picture of area calculation.

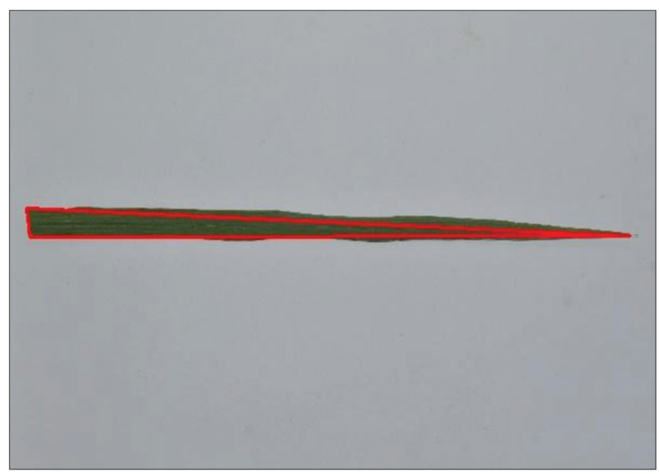

Fig 9. The resulting picture of the perimeter.

The experimental result in Table 2 is a result of a comparison between shape and colour. The calculation showed an achieved 85.71% accuracy rate to detect blast disease by colour feature, 71.42% by shape feature, and 85.71% by combined colour-shape features. So, in conclusion, the experiment proved that a combination of shape and colour bring more accuracy and better detection

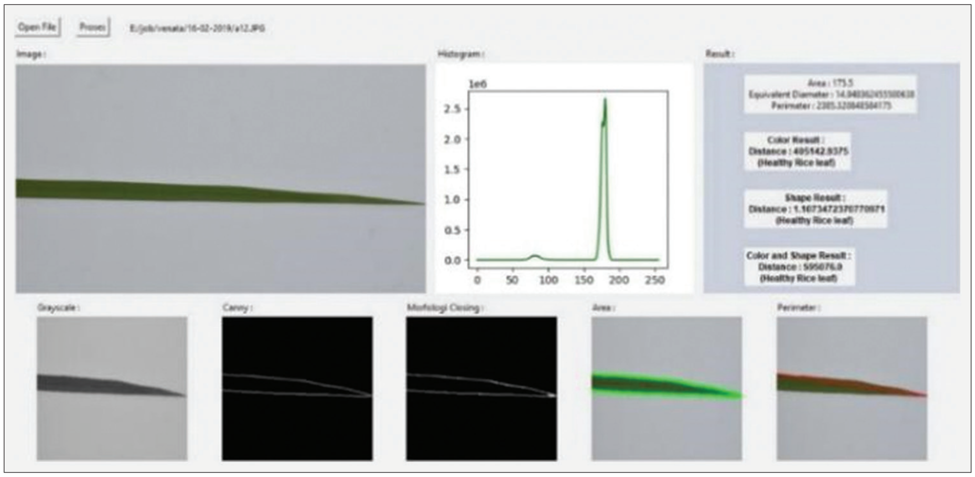

Fig 10. The resulting system for healthy leaf.

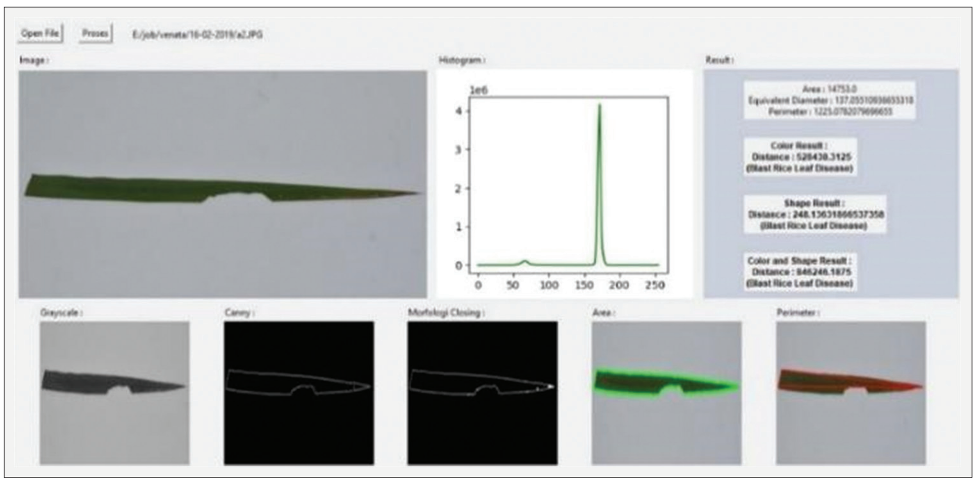

Fig 11. The resulting system for disease blast leaf.

Table. 2: The Comparation accuracy of the method

Colour+shape	256		RGB	shape	Colour+shape
80,95238095	accuracy all	Accuracy	85,71428571	71,42857143	85,71428571
19,04761905	error all	error	14,28571429	28,57142857	14,28571429

CONCLUSION

Blast disease on rice leaves may reduce harvest production. It can be prevented by early detection of the leaf condition. Therefore, our system proposed better detection by using a hybrid method of colour and shape. It uses an image query and database of the image with several features. The detection step is started by colour conversion from RGB to HSV value by selecting only green value. Afterwards, morphology closing is used to compute the area and perimeter of each image. The edge detection process involves image conversion into grayscale mode and canny to perform edge detection toward leaf images. The experimental result with 267 images dataset classified into two main categories: blast disease and healthy leaf has run successfully. The proposed method has achieved 85.71 % accuracy in detecting blast disease, while the colour feature obtains 71.42%. The hybrid method between colour and shape features receives an 85.71% accuracy rate. In the future, the result with a hybrid method might have increased accuracy with more datasets.

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