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LEAF LESION CLASSIFICATION (LLC) ALGORITHM BASED ON ARTIFICIAL BEE COLONY (ABC)

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ABSTRACT

In this paper, an algorithm to classify leaf disease severity based on lesions is presented. The algorithm involved three main steps, filtration, recognition and detection. Artificial Bee Colony, Fuzzy Logic, Otsu and Geometry formula were incorporated to achieve the goal. Ninety-four leaf images were used in this algorithm combination experiment. The study was conducted in four phases, filtration, recognition, detection and evaluation. Comparison was made with four other algorithms, Otsu, Canny, Robert and Sobel. Results showed that the Leaf Lesion Classification (LLC) algorithm based on Artificial Bee colony (ABC) produced an average 96.83% of accuracy and average 1.66 milliseconds of processing time, indicating that LLC algorithm is better than algorithm such as Otsu, Canny, Roberts and Sobel. The study makes a substantial contribution to the body of knowledge in image processing.

Keywords: leaf lesion, fuzzy logic, area size, hybrid, artificial bee colony, otsu, geometry formula.

INTRODUCTION

Drastic climate change or extreme weather such as drought, heavy rain, and very hot days are contributing factors for plant disease occurrences. Millions of people will be deprived of food if plants with diseases are not treated (Chakraborty & Newton, 2011). Plant disease can be identified by measuring the level of leaf lesion severity. Leaf lesion severity is the percentage of seriousness of a lesion's appearance. For example, the green color on the leaf surface will slowly change to yellow if it is infected with a disease. The color will then change to red dark if the plant is dying. Plant disease can be divided into five categories, grade 0 (infection-free), grade 1 (0 – 25% leaf area infected), grade 2 (26 – 50% leaf area infected), grade 3 (51 – 75% leaf area infected), and grade 4 (>75% leaf area infected) (Faudziah Ahmad & Ahmad Airuddin, 2014a; Horsfall & Heuberger, 1942).

The level of severity can be determined using color features (Abdul, et al., 2013). Leaf Color Chart (LCC) has been popularly used by farmers to classify the grade of plant disease. However, two major problems existing in LCC are time consuming in determining the level of disease, and the results are less accurate. Thus, to overcome the problems, methods such as fuzzy logic, k-means, clustering, histogram matching, wavelet decomposition, and neural networks have been used (Arivazhagan, Shebiah, Ananthi, & Varthini, 2013; Dadwal & Banga, 2012). Based on their studies, these methods cannot classify leaf diseases correctly and the methods could only classify leaf images into two categories, healthy and unhealthy leaves. The problem with these two categories are those dying leaves (unuseful) will be categorized as unhealthy, thus are inclusive in the dataset. The inclusion will result into irrelevant data and still will be processed. To improve the processing time, dying leaves need to be identified and then remove from the dataset. By removing them, only relevant data will be contained in the dataset, thus resulting to a faster classification process. Recently, leaf lesions have been used to determine the level of plant disease's severity (Ahmad, et al., 2010; Chen, 2005). For example, [8] have used leaf segmentation to search for a lesion such as Otsu, Canny, Sobel, Robert and etc. However, segmentation method could not speed up processing time. This is because the method involve checking one pixel at a time sequentially until an object is detected in an image (Patil & Bodhe, 2011). This method is less accurate in determining a lesion area as the method sometimes over counts the pixels and sometimes understate the number of pixels (Weizheng, Yachun, Zhanliang, & Hongda, 2008). In another study, (Phadikar, Sil, & Das, 2012) used the threshold method known as Otsu to measure the lesion area. However, Otsu was found to be unsuitable for images of large size. There are also cases where some lesions are not recognized by the method. Due to the limitation of the methods, a better method has been sought.

Several researchers explored the possibilities of using artificial intelligence methods. In one of the attempts, Artificial Bee Colony (ABC) has been shown to be capable of handling problems related to thresholding, segmentation and object detection. For example, Ye et al. (2011) proposed an automatic choosing threshold algorithm using ABC and compared its performance with thresholding segmentation algorithm. Their results shown that the performance of ABC algorithm was better than the thresholding segmentation algorithm. In another research by Zhang and Wu (2011), ABC had been used to achieve multi-level thresholding image segmentation. They used ABC to overcome time consumption problem. They identified that ABC was faster than other optimization algorithms. Another method known as Fast segmentation in Synthetic Aperture Radar (SAR) and combining with ABC had proposed by Ma et al. (2011). The objective of their study was to enhance the threshold optimal value of grayscale between pixels. They found that ABC produced better quality than Artificial Fish Swarm (AFS) and Genetic Algorithm (GA) in terms of accuracy in segmentation and time. Application of ABC for recognition of an object within certain images was introduced by (Chidambaram & Lopes, 2009). The objective of their work was to find a pattern or template of an object anywhere on a target scene. The experimental results, using grayscale and color images shown that the performance of ABC was faster in finding a pattern than a comparable technique such as Evolutionary Algorithm (EA). However, in terms of object detection using ABC, reviews of past literatures shown that there is no work has been done on lesion detection. The positive reviews produced from past works have resulted in an attempt to use ABC in detecting an object, specifically lesions.

The major problems of the current algorithms are; (i) cannot classify a leaf specifically and correctly, (ii) inaccurate detecting leaf lesions, and (iii) time consuming to measure the leaf lesion for determining the level of disease. In this study, ABC algorithm is the basis for developing the proposed classification algorithm to overcome the problems. ABC is used to (i) search randomly intensity pixel of mean RGB (in Phase 1) for filtering the useful image which is unhealthy leaf that used in this experiment, (ii) search randomly global intensity pixel (in phase 2) for identifying the lesion's location and (iii) search randomly local intensity pixel (in Phase 3) for identifying point of maximum and minimum major and minor axis to calculate the lesion area. Otsu and Geometry formula were also incorporated to calculate the total lesion area and determine the leaf disease severity level. The Leaf Lesion Classification (LLC) algorithm is an important research topic as it may prove benefits in monitoring large field of crops, and thus automatically detect diseases from symptoms that appear on plant leaves. Thus, automatic detection of plant disease with the help of image processing technique provides more accurate and robot guidance for disease management.

The organization of the paper is as follows. Section 2 describes the methodology of the study. Section 3 and 4 presents analysis of results and discussion. Conclusions and future research are shown in Section 5.

METHODOLOGY

The research was conducted in four phases, filtration, recognition, detection and evaluation.

PHASE 1: Filtration

The aim of this phase is to produce an algorithm that categorizes leaf images into three categories, healthy, unhealthy and dying. Healthy and dying categories are not meaningful for this study, thus need to be eliminated. With the identification of three categories, it would be easier to capture healthy and dying images, and remove them from the dataset.

The steps for the phase can be listed as follows:

Step 1: Convert images from JPEG or RGB to TIFF

The study used green leaf images from www.forestryimages.org. The images, initially in RGB and JPEG format, were converted to TIFF format using the Microsoft Paint software. The images were converted to TIFF format because TIFF images are sharper than images in JPEG or RGB.

Step 2: Convert TIFF images into grayscale

In a color image, each pixel contains three color values, red, green and blue. Converting the color image into grayscale will reduce the number of colors to one. This will reduce the storage size that will result in a decrease in computing time. The conversion was done by using Octave software.

Step 3: Data cleansing

The aim of this step is to filter grayscale images from noises such as dust, blurriness, and unwanted spots. This will produce sharper, smoother and noiseless images (Rajan, 2012). For this process, Gaussian technique was used.

Next step is to develop a filtration algorithm. The algorithm is to categorize the clean grayscale leaf images into three categories, healthy, unhealthy, and dying. The steps to develop the algorithm can be found in (Faudziah Ahmad & Ahmad Airuddin, 2014a).

PHASE 2: Recognition

In this phase, a recognition algorithm is developed. The algorithm will randomly search for points from intensity pixels. The lesion recognition algorithm has been developed. Details of the algorithm can be found in (Faudziah Ahmad & Ahmad Airuddin, 2014b).

The algorithm was evaluated in terms of percentage of correctness, percentage of error and detection time. Figure-1 shows the output obtained from running the algorithm.

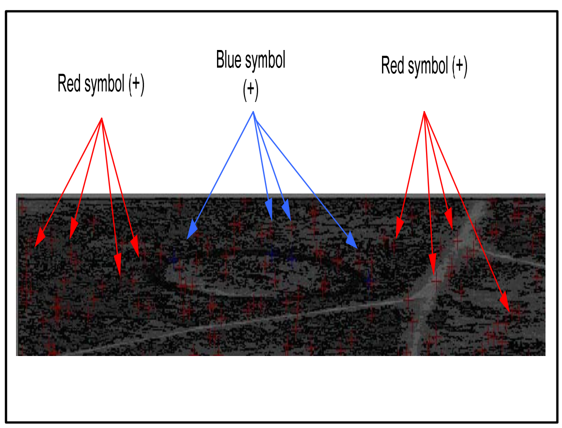

Figure-1. Lesion image that are Recognized or Unrecognized.

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From the Figure-1, several blue (+) symbols and red (+) symbols were spotted. The symbols represent intensity points that recognize or unrecognized an object. The blue (+) symbols show that an object has been recognized, while the red (+) symbols show unrecognized objects. For the research, only the blue (+) symbols are used for analysis. Based on the blue (+) symbols, the x and y coordinates are gathered.

PHASE 3: Detection

The aim of this algorithm is to calculate the overall lesion area. The algorithm has also been developed. The detail description can be found in (F. Ahmad & A. Airuddin, 2014).

In short, the process can be described as follows. The algorithm starts by creating a small window based on the coordinates obtained from Phase 2. The window is used for determining the minimum and maximum values of major and minor axis. Major axis represents the height of a lesion image, while the minor axis represents the length of a lesion image.

Based on the minimum and maximum values of major and minor axis, the lesion area is calculated using the ellipse geometry formula. Figure-2 shows a lesion area. The red oval line represents an ellipse.

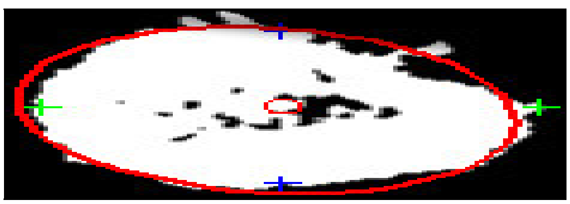

Figure-2. Detection lesion area.

Next step is to calculate the ellipse area. The process is repeated for other ellipses (if more than one ellipses are found in an image). Finally, the total ellipse area is obtained.

PHASE 4: Evaluation

This phase contains 2 parts; Part 1 performs combination of the three algorithms, and Part 2 evaluates the combined algorithm.

Part 1 develops an algorithm to determine the severity of leaf disease. The algorithm is a combination of three algorithms that are obtained from Phase 1, Phase 2 and Phase 3. The algorithm is known as Leaf Lesion Classification (LLC) algorithm as shown in Figure-3. The algorithm is constructed by implementing the first algorithm (from Phase 1), followed by the second algorithm (from Phase 2) and finally the third algorithm (from Phase 3). The output of Phase 1 is used for input in Phase 2. Then, the output of Phase 2 is used for input in Phase3. Figure-3 shows the algorithm flowchart.

In Part 2, LCC is tested on 94 leaf images. The images consist of three groups: 1 to 5 lesions (61 images), 6 to 10 lesions (20 images), and 11 to 32 lesions (13 images).

Then, the algorithm is compared with 4 existing algorithms, Canny, Otsu, Sobel and Roberts. Its performance is measured in terms of percentage of accuracy, and processing time in millisecond (ms).

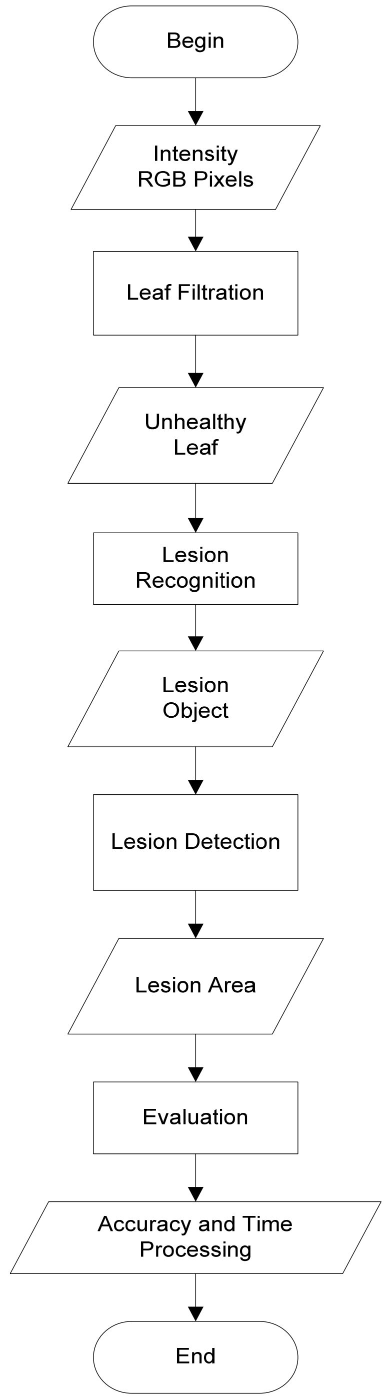

Figure-3. Flowchart of LCC.

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RESULTS AND DISCUSSIONS

Table-1 and Table-2 shows the results.

Table-1. Comparison percentage of accuracy.

	Accuracy (%)			**Average**
Algorithms	Lesion (1-5)	Lesion (6-10)	Lesion (11 and above)	
LLC	96.1	98.5	95.88	96.83
Canny	83.72	81.47	81.75	82.31
Otsu	96.08	93.54	93.63	94.42
Roberts	30.45	33.25	47.05	36.92
Sobel	18.27	25	12.15	18.47

Table-2. Comparison percentage of processing time.

	Time Processing (Ms)			**Average**
Algorithms	Lesion (1-5)	Lesion (6-10)	Lesion (11 and above)	
LLC	1.65	1.77	1.56	1.66
Canny	3.01	3.02	3.47	3.17
Otsu	13.97	14.14	14.08	14.06
Roberts	4.00	4.32	3.95	4.09
Sobel	11.18	10.78	12.28	11.41

Based on the Table-1, column 1 until 3 denotes the percentage of accuracy. Table-2, column 1 until 3 denotes the whole processing time. The measurement unit used are average percentage of accuracy, and average processing times in milliseconds.

From Table-1 and Table-2, it can be seen that the LLC outperforms other algorithms in terms average percentage of accuracy, and the average processing time.

CONCLUSIONS

This study produced a classification algorithm that is based on ABC. Results showed that LLC algorithm could detect faster and more accurately than other algorithms such as . The LLC algorithm performs 96.83% average of accuracy percentage and 1.66 millisecond for processing time. This indicates that incorporating ABC in a classification algorithm can produce an innovative, efficient and fast interpreting algorithm which will not only detect the disease but also classified it into various grade levels.

RECOMMENDATIONS

Further experiments will be conducted to test on a larger set of data and using leaf images that contain more lesions.

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