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FRACTAL DIMENSION AND *LACUNARITY* COMBINATION FOR PLANT LEAF CLASSIFICATION

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Abstract

Plants play important roles for the existence of all beings in the world. High diversity of plant's species make a manual observation of plants classifying becomes very difficult. Fractal dimension is widely known feature descriptor for shape or texture. It is utilized to determine the complexity of an object in a form of fractional dimension. On the other hand, *lacunarity* is a feature descriptor that able to determine the heterogeneity of a texture image. *Lacunarity* was not really exploited in many fields. Moreover, there are no significant research on fractal dimension and *lacunarity* combination in the study of automatic plant's leaf classification. In this paper, we focused on combination of fractal dimension and lacunarity features extraction to yield better classification result. A box counting method is implemented to get the fractal dimension feature of leaf boundary and vein. Meanwhile, a gliding box algorithm is implemented to get the *lacunarity* feature of leaf texture. Using 626 leaves from flavia, experiment was conducted by analyzing the performance of both feature vectors, while considering the optimal box size r. Using support vector machine classifier, result shows that combined features able to reach 93.92 % of classification accuracy.

Keywords: *leaf classification, fractal dimension, lacunarity, box counting, gliding box*

Abstrak

Tumbuhan memegang peranan penting dalam kehidupan manusia. Tingginya keberagaman spesies tumbuhan membuat metode pengamatan manual dalam klasifikasi daun menjadi semakin sulit. Dimensi fraktal merupakan deskriptor bentuk dan tekstur yang mampu mendeskripsikan kompleksitas dari suatu objek dalam bentuk dimensi pecahan. Di sisi lain, *lacunarity* adalah deskriptor tekstur berbasis fraktal yang mampu mendeskripsikan heterogenitas dari citra tekstur. Namun *lacunarity* belum cukup dieksplorasi dalam banyak kasus dan belum ada usaha yang cukup signifikan dalam mengkombinasikan dimensi fraktal dan *lacunarity* dalam bidang klasifikasi tumbuhan secara otomatis. Penelitian ini berfokus pada ekstraksi dan kombinasi fitur dimensi fraktal dan *lacunarity* untuk meningkatkan akurasi klasifikasi. Metode *box counting* diterapkan untuk memperoleh dimensi fraktal dari bentuk pinggiran dan urat daun, sementara metode *gliding box* diterapkan untuk memperoleh fitur *lacunariy* dari tekstur daun. menggunakan 626 citra daun dari *flavia*, percobaan dilakukan dengan menganalisis performa dari kedua fitur dengan mempertimbangkan ukuran kotak r yang paling optimal. Klasifikasi dengan *support vector machine* menunjukkan bahwa hasil kombinasi kedua fitur mampu mencapai rata-rata akurasi hingga 93.92%.

Kata Kunci*: klasifikasi daun, dimensi fraktal, lacunarity, box counting, gliding box*

1. Introduction

Science associated with plant identification and classification plays an important role in many fields that affects human life, including in the fields of food and agriculture, medicine, industry, environment, and so on. Plant Morphology is a study that focuses on how to examine and identify a plant based on its physical characteristics that can be seen with human naked eyes. With the rising number of plant species acknowledged today, it is important to protect the plants or collect them in the form of information that offers diversity of flora. The introduction of computer-based plant classification system able to recognize the diversity of flora is certainly will be helpful for many researchers in agriculture and plantations, botanist, doctors, and it is also can be used as a learning tools for student in school. There are some characteristics that can be used for identifying a plant. Some plants can be identified by its physical features like flower, fruit, leaf, root or stem [1].

Leaf is the most frequent part that used in plant classification, manually or automatically [2]. Leaf has many special characteristics that can be used as a feature in the classification process, like color, shape, texture, or a combination of these features [3,4]. Color based research in leaf classification faced some problems, since most of leaf have a green color and some types of leaves change their color in certain seasons. Therefore, shape and leaf texture are widely studied in automatic plat identification. Some example of leaves shape features have been analyzed in several studies, like geometric descriptors [5] and fractal dimension [6,7]. Examples of research related to leaf texture analyzing is GLCM and LBP [8] and Gabor [9]. A shape and texture based approach in recognizing shape and texture features of plant leaf is also proposed in this study.

The application of fractal concept for fractal or non-fractal object has been commonly used in image analysis and pattern recognition, where fractal dimension is used to measure the complexity of geometric shapes and textures of an objects in term of fractional dimension [10,11]. However, there is a possibility that two objects with different pattern will likely to display the same fractal dimension's value. Mandelbrot [12] later introduced the concept *lacunarity* that able to measure the spatial distribution of gap with certain size on image texture [13]. Thus, it is stated that *lacunarity* will likely to complement this drawbacks. Low *lacunarity* value indicates that the texture is homogeneous if all gaps indicate the same size. While high *lacunarity* indicates that the texture is heterogeneous. *Lacunarity* has been applied in several areas of texture-based research, such as in the field of spatial data mapping [14,15], medical [16,17], and the agricultural industry [18].

Box counting method [19], is the most common approach used in calculating fractal dimension of an object, with its ability to represent the complexity of the image and its easy implementtation [20]. Therefore, Bruno *et al.* [6] perform a leaf identification based on the complexity of the internal and external shape of leaf to obtain the fractal dimension using box counting method. The result shows a good performance but the misclassification rate was still quite high, so a fractal based texture recognition feature like *lacunarity* might be considered as a good feature to be combined with the fractal dimension in shape analysis to improve the classification accuracy. Although the fractal dimension is widely used in different areas, its only represents an object only by one unique real number. This becomes a drawback for recognition purposes since we may find a lot of objects with the same fractal dimension but completely diverse appearance. To overcome this drawback, we propose to also use all difference values between adjacent element of log r and log N(r) from box counting methods. This technique is expected to be useful since fractal dimension is always extracted from the slope of the straight line of log-log plot.

One of the methods developed to obtain *lacunarity* feature is gliding box by Plotnick [21]. Gliding box is a box of a certain size applied to grayscale or binary image from left to right. This method has disadvantage since its applying a global thresholding. One of box gliding method proposed by Backes *et al.* [13] is the application of a local binary pattern of the input image with local thresholding, where thresholding stage is performed on each box. However, in these studies thresholding value is determined only by simple average gray value. This study will also try to apply a thresholding method that are more developed like Otsu methods. Given the importance of the binary pattern in improving the discriminatory feature of *lacunarity*, application of thresholding on each box in gliding box is expected to maintain the texture of local information that usually lost when applying global threshold.

Meanwhile, Kilic and Abiyev [20] mention that the fractal dimension and *lacunarity* have been examined separately, and there is no significant effort in combining the two features in a better synergy. Therefore, this study proposes the combination of fractal dimension features of leaf shape and *lacunarity* features of leaf texture to improve the classification accuracy compared to previous fractal dimension and *lacunarity* methods. To obtain fractal dimension features, a box-counting method by Bruno *et al* [6] was implemented, with modifycation in amount of features being extracted. *Lacunarity* features were obtained by using one of the gliding-box methods developed by Backes [13] by applying a local binary pattern, with using more advancing Otsu thresholding methods. Also we propose to add more feature along the calculation of *lacunarity*, with various box size *r*.

2. Methods

The proposed method is consist of several steps. The first step is preprocessing and segmentation of

TABLE 1
ASPECT RATIO AND ITS CORRESPONDING SIZE

R = major axis length/ minor axis length	Size (mxn)
$R \leq 1.4$	450 x 450
$1.4 < R \leq 2$	300 x 450
$2 < R \leq 2.4$	210 x 450
$2.4 < R \leq 3$	150 x 450
$3 < R \leq 5$	98 x 450
$5 < R \leq 13$	68 x 450
$R > 13$	15 x 450

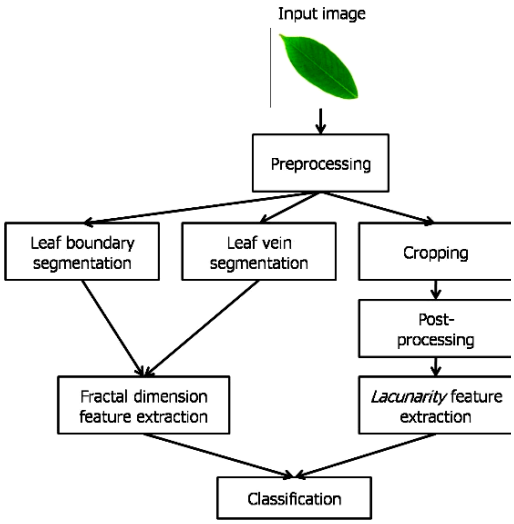


Figure 1. Proposed system

leaf input. In this step, the shape of leaf contour and leaf vein where obtained along with cropped image texture. The next step is post-pre-processing for leaf texture. The fractal dimension feature of leaf shape combined with *lacunarity* feature of leaf texture. The leaf classification task then finally performed at the end of process. Figure 1 shows the proposed system.

Preprocessing and Segmentation

Before an image goes into further steps, it is necessary to do the image preprocessing, a stage in which the image is being prepared in order to produce the desired output image. Image pre-processing result is expected to be used optimally at the next steps. In this study, image preprocess-ing results are used in the process of segmenting the leaf boundary and leaf veins (boundary and veins).

In the process of analyzing the leaf shape, the rotation stage is first performed so that the final image can be invariant towards rotation. The process started by converting a 1600x1200 RGB image into a grayscale image. The image is then rotated by aligned it toward the horizontal line, where the rotation angle is equal to an angle between major axis to horizontal axis of the image. To obtain the leaf boundary, grayscale image is converted into a binary image and the hole filling method is then applied. The binary and grayscale image is cropped until they only fits the bounding rectangle to make the features translation-invariant. All preprocessed leaf image result in varying image size since the image aspect ratio R of each leaf is different. Hence, the image is resized based on 7 type of predefined size to avoid distortion or variation in scale which is result in unbalanced feature length. Table 1 shows the predefined aspect ratio R with its corresponding size. A canny edge detection method is applied in to the binary image to get the corresponding leaf boundary.

Detecting a leaf vein and segmenting it from the leaf objects is quite complicated because of the very low contrast difference between leaf veins and leaf objects [6-7]. We propose to apply the multi-thresholding method in segment-ing the leaf veins and obtained more than one image of the leaf veins. In this study, a canny edge detection method with more than one sigma σ value was applied to the gray image to obtain some images of leaf veins. Furthermore, the stage is ended with masking process between leaf boundary and leaf veins. Figure 2 shows the stages of preprocessing and veins segmentation.

Extracting leaf texture is done by converting input image into a grayscale image. The grayscale image is cropped into a 128x128 pixel size image. Different post-processing stage are then aplied to the cropped image. The post-processing step to get the various texture image are consist of the following step:

Histogram equalization

Histogram equalization methods is aim to enhance the image contrast by transforming the values in an intensity image, or the values in the colormap of an indexed image. The enhancement will make the histogram of the output image approximately matches a specified histogram.

Kirsch Operator

The Kirsch edge detector module detects edges using eight compass filters [23]. All eight filters are applied to the image with the maximum being retained for the final image. The eight filters are a rotation of a basic compass convolution filter. The filters are of the form:

```
NW = [5 -3 -3;5 0 -3;5 -3 -3];
SW = [-3 -3 -3;5 0 -3; 5 5 -3];
SE = [-3 -3 -3;-3 0 -3;5 5 5];
NE = [-3 -3 -3;-3 0 5;-3 5 5];
N = [-3 -3 5;-3 0 5;-3 -3 -3];
W = [-3 5 5;-3 0 5;-3 -3 -3];
S = [5 5 5;-3 0 -3;-3 -3 -3];
E = [5 5 -3;5 0 -3;-3 -3 -3];
```

Canny edge detector

The process of Canny edge detection algorithm consist of 5 different steps [22]: 1) apply Gaussian filter to smooth the image in order to remove the noise; 2) find the intensity gradients of the image; 3) apply non-maximum suppression to remove spurious response to edge detection; 4) apply double threshold to determine potential edges; 5) track edge by hysteresis: finalize the detection of edges by

suppressing all the other edges that are weak and not connected to strong edges.

The Canny edge detector uses a Gaussian filter. The image is convolved with the filter. The filter blurs the image to a degree specified by σ to minimize the effect of unwanted information. The equation for a Gaussian filter kernel of size (2k+1) × (2k+1) is given by equation(1).

$$H_{ij} = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{(i-k-1)^2+(j-k-1)^2}{2\sigma^2}\right) \quad (1)$$

where the parameter σ (sigma) determines the width of the filter and hence the degree of blurring i.e. the greater the value of sigma the more the blurring is. If the value of sigma is high then faint edges will not be detected. On the other hand if sigma is very low then noise may also get detected as edges.

Local Thresholding

Local thresholding method is done by using a moving window that calculate the local binary value of an image by converting the grayscale image into a binary image [13].

Median Filtering

The median filtering is done by applying a filter that find the median value of grayscale image in a specific box size and resulted in a new filtered image. The median filtering is apllied to the local the local thresholding result.

Skeletonization

The skeletonization step is aim to reduce all objects in an image to lines, without changing the essential structure of the image. Figure 3 shows the output of preprocessing results apllied to the cropped leaf image.

Fractal Dimension Measurement

Fractal has a main characteristic called self similarity. These characteristics make the fractal has the ability to model complex and irregular natural objects, unlike euclidean geometry which is only able to determine the integer dimensions of an object. Fractal geometry involves various appro-aches to define fractional dimensions. The most common

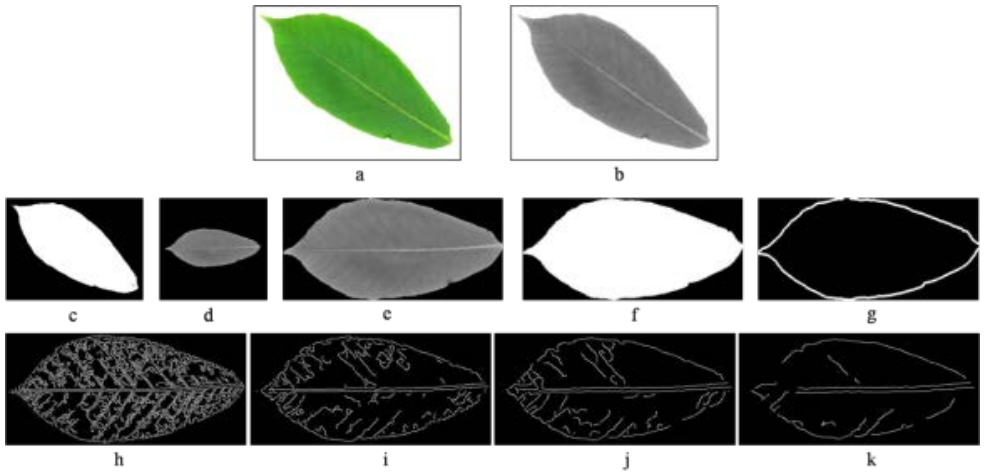


Figure 2. Preprocessing step to get leaf boundary and venation. a: original image; b: grayscale image; c: binary image; d: rotated image; e: shrinked gray image; f: shrinked binary image; g: leaf boundary; h,i,j,k: various leaf veins.

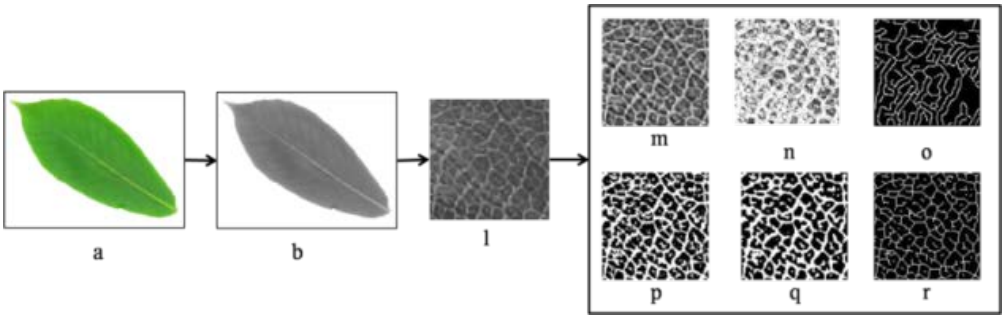
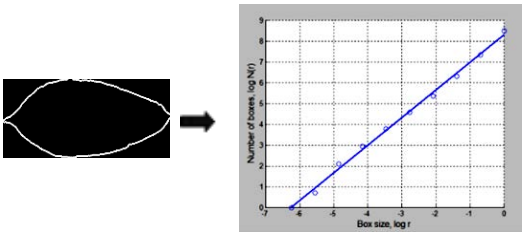


Figure 3. Preprocessing step to get various leaf texture models. a: original image; b: preprocessing image; l: cropped image texture; m: histogram equalization result; n: kirsch filter result; o: edge detection result; p: local thresholding result; q: median filter result; r: skeletonization result.



a b

Figure 4. Fractal dimension measurement of a leaf boundary. a: input image; b: corresponding log-log plot

method used for calculating the fractal dimension of an image is a Box Counting method [6,19]. Fractal dimensions of an image with this method is calculated by the following equation(2).

$$D(r) = \lim_{r \to 0} \frac{\log N(r)}{\log r^{-1}} \quad (2)$$

where N(r) denotes the number of r-sized box that contains information (pixels) object and D (r) is the fractal dimension of the object with the box's size. The algorithm to measure the fractal dimension of an image using box counting method proposed in this study is as follow:

1) divide image into squares with a size r. The numerical value of boxe size are 2^n, with n = 0,1,2,..., and so on. 2^n should not be larger than the size of the image. When the image size is 2m x 2m, then the value of n will stop until m;
2) calculate the number of boxes N (r) containing occupied object in the image. The value of N (r) is highly dependent on r;
3) calculate D (r) with equation(2) for the entire value of r;
4) create a straight line based on the value of log N(r) (y-axis) and the values of log (r) (the x-axis) for each value of r, then calculate the slope of the straight line. The value of the slope is the fractal dimension of an image. The slope of a straight line calculated using the least squares method.

Figure 4 (a) shows an example of leaf boundary image while Figure 4 (b) is the image corresponding log-log plot for fractal dimension measurement. Table 2 shows the result of equation of fractal dimension of the image.

The fractal dimension measurement from Table 2 will result in only one single value. Therefore, we propose to add more features along the fractal dimensional value. This feature is all difference values between adjacent element of log r and log N(r).

This will produce *n* value that highly correlated with the corresponding fractal dimension value at each axes. The different value between N(r) and r are then being divided to get the *n* final values. The fractal dimension feature vectors of each image in this study can be written as follow: $\overrightarrow{fd} = [D_0, D_1, D_2, \ldots D_n]$ where D_0 is the final fractal dimension value, while D_1 to D_n is feature vectors extracted from the log-log plot with *n* is maximum amount of differences value extracted from the log log plot.

TABLE 2
EXAMPLE OF FRACTAL DIMENSION MEASUREMENT

r	N (r)	log r	log N (r)
512	1	-6.24	0
256	2	-5.55	0.69
128	8	-4.85	2.08
64	19	-4.16	2.94
32	44	-3.47	3.78
16	95	-2.77	4.55
8	214	-2.08	5.37
4	541	-1.39	6.29
2	1522	-0.69	7.33
1	4813	0	8.48

Lacunarity **Measurement**

Lacunarity comes from the Latin (*lacuna*) which is also the origin of the word lake in English, refers to a concept which was also introduced by the "father" of the concept of fractals, Mandelbrot, in 1982. This concept defines that an object will be "lacunar" if gap (hole) on an object tends to be large. Low *lacunarity* indicates that the texture is homogeneous, while high *lacunarity* indicates that the texture is heterogeneous [13,20]. High *lacunarity* value means that the pixels spread out over a wider range and surrounded by many and large gaps [20].

Initially, *lacunarity* introduced to describe the fractal characteristics that have the same dimensions but have a different appearance [11,13]. Thus it able to overcome the drawbacks of widely used fractal dimension. Until now *lacunarity* concept being developed in analyzing the texture and is scale-dependents [14,15,25]. One of most common and simple approach to calculate the *lacunarity* of a binary image map is the gliding-box algorithm, introduced by Allain and Cloitre [10]. This algorithm analyzes the image by applying an overlapping box with size r x r that glides over an image from upper left to the right. S is the number of occupied sites or mass of the gliding box. The number of boxes of size r containing S occupied sites is designated by n(S,r) and the total number of boxes of size r by N(r). If the map is M, then the total number of boxes is calculated using equation(3).

$$N(r) = (M - r + 1)^2 \quad (3)$$

This frequency distribution is converted into a probability distribution Q(S,r) by dividing it to the total number of boxes using equation(4).

$$Q(S,r) = n(S,r)/N(r) \quad (4)$$

The first and second moments of this distribution are now determined in equation(5).

$$Z^{(1)} = \sum S\, Q(S,r) \quad (5)$$

$$Z^{(2)} = \sum S^2\, Q(S,r) \quad (6)$$

So the *lacunarity* value Λr of the image with box size r can be defined as equation(7).

$$\Lambda(r) = Z^{(2)}/(Z^{(1)})^2 \quad (7)$$

Leaf texture image is analyzed by using the method of gliding box. Figure 5 is example of leaf texture from each class for *lacunarity* analysis. At this stage, the box with the size *r* move above the grayscale or binary image started from top left to the bottom right. Once the gliding box is finished, the frequency distribution of the mass of the box *r* is calculated so that the value of *lacunarity* can be obtained through the equation(6). The resulted *lacunarity* feature vectors described as follow: $\overrightarrow{\Lambda r} = [\Lambda r_1, \Lambda r_2, \Lambda r_3, \ldots \Lambda r_m]$ where Λr_1 is *lacunarity* value at smallest box size r, and Λr_m is *lacunarity* value at maximum box size r, with $m = 2^n$ and m was lies between 1 to maximum image size. Table 3 is an example of *lacunarity* measurement using box sixe *r*=2 and a 128x128 pixels binary image.

Feature combination is conducted by simply concatenate one feature vector into another feature vector. Therefore, the fractal dimension of leaf shapes (boundary and veins) are concatenated with *lacunarity* feature vector of leaf texture to produce a feature vector with length 1x *n*, where *n* consists of a combination of features D_1, D_2 and Λr. D_1 is the fractal dimension of the shape of leaf boundary, D_2 is the fractal dimension of leaf veins, and Λr is *lacunarity* of leaf texture with box size *r*. The length of the feature vectors will be vary based on the amount of box *r* being applied and the input images.

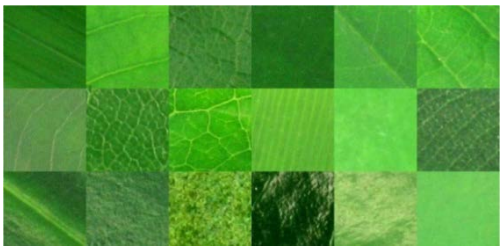
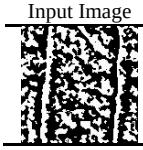


Figure 5. Example of leaf texture from each class for *lacunarity* analysis

TABLE 3
EXAMPLE OF LACUNARITY MEASUREMENT (R=2)

Input Image	$Z^{(1)}$	$Z^{(2)}$	$\Lambda(r)$
	7078124	5.9956×10^9	1.9302

Data set

Dataset used in this study was the *flavia* dataset that available for public using. Figure 3 shows examples of leaves dataset from *flavia*. Image with a white background has previously been acquired by using the scanner to produce images with a size of 1600x1200 pixels and have a *jpeg file format. The dataset can be downloaded at the site *http://flavia.sourceforge.net*. The fundamental properties of the data sets are shown in Table 4.

Experiments

The experiments were conducted to answer the research question of this study: whether there is a better synergy between fractal dimension and *lacunarity* using proposed methods to increase leaf classification accuracy. Three classifiers were used to compare the classification result. The performances of the proposed methods were evaluated using

Figure 6. Example of leaf using in this study

TABLE 4
DATASETS AND THEIR PROPERTIES

Class Label	Species Name	Amount data per-class
1	*pubescent bamboo*	34
2	*Chinese horse chestnut*	36
3	*Chinese redbud*	37
4	*true indigo*	48
5	*Japanese maple*	37
6	*goldenrain tree*	29
7	*Chinese cinnamon*	37
8	*Japanese cheesewood*	36
9	*Sweet osmanthus*	29
10	*ginkgo*	36
11	*Crepe myrtle*	39
12	*oleander*	33
13	*yew plum pine*	32
14	*Ford Woodlotus*	27
15	*Tangerine*	26
16	*Japan Arrowwood*	36
17	*Beales Barberry*	39
18	*Glossy Privet*	35

10-fold cross validation [24]. All datasets were split into 10 data subsets. One subset was used for testing and the other nine subsets were used as training. This procedure was repeated 10 times for all of data sets. To get the accuracy value take the average value of all fold classification result as defined in equation(8).

$$Accuracy = \frac{n\ .correctly\ classified\ data}{number\ of\ all\ data}\ x\ 100\% \quad (8)$$

The experiment we performed is consist of three experiments as follows: 1) an experiment using only fractal dimension feature. In this scenario, all datasets were analyzed to get the leaf boundary and leaf veins. Since we propose to use more than one sigma σ value for edge detection, then we will analyze the effect of the edge detection towards resulted fractal dimension features. The box counting method was applied on each resulted images to get fractal dimension feature vectors; 2) an experiment using only *lacunarity* feature by applying different box size *r*. The experiment is aim is to evaluate the best *r* which able to produce best classification. In this scenario, the amount of grayscale and binary image was observed to see whether it would affect the classification accuracy. When right amount of input images is obtained, the gliding box method was applied to get the expected *lacunarity* feature vectors; 3) an experiment that combines both fractal dimension and *lacunarity* feature vectors. In this scenario, both fractal dimension and *lacunarity* feature vectors are concatenated and then analyzed to see the synergy between the combined features. We then do the comparation between the proposed fractal dimension and *lacunarity* combination to two previous methods.

3. Results and Analysis

Fractal dimension analysis

Using box counting method, we conduct an experiment to analyze performance of the system. To obtain fractal dimension features of the leaf shape (boundary and vein), a canny edge detector is applied. For first test, a single value of sigma σ = 1 is applied to the canny edge detection operator to obtain the leaf veins. At this try, one leaf boundary image and one leaf vein image is extracted. The fractal dimensions of both images are being measured using proposed box counting methods. Classification results show a success rate of 60. 376%.

TABLE 5
COMPARISON OF DIFFERENT SIGMA VALUE OF CANNY EDGE DETECTOR

Input Image	Feature length	Classification accuracy (%)
Leaf boundary, Leaf vein (σ = 1)	1x20	60.376
Leaf boundary, Leaf vein (σ = 1 and σ = 2)	1x30	71.556
Leaf boundary, Leaf vein (σ = 1, σ = 2, σ = 3)	1x40	73.458
Leaf boundary, Leaf vein (σ = 1, σ = 2, σ = 3, σ = 4)	1x50	76.979

However, each of leaf has different brightness and contrast [6]. So it is very difficult to segment with one unified gray level threshold after converted to grayscale images. Therefore, the next testing was conducted to analyze the effect of the amount of sigma value at canny operator to obtain proper leaf veins. The second testing apply the value of σ=1 and σ=2 for canny operator, followed by the third experiment with σ=1, σ=2, and σ=3, and the fourth testing which combine σ=1, σ=2, σ=3, and σ=4 altogether. Table V describes the comparison of classification accuracy when using different sigma values. The highest result shown in the fourth trial, with an average accuracy of 76.979%. From this result, we can see that using only one single leaf vein image was only resulted in 60.376% of accuracy. Figure 7 shows the comparison of classification result using conventional fractal dimension measurement by Backes [6] and our proposed methods. Result shows that using only one single fractal dimension value will produce less classification result compared to our proposed methods. This also suggest that using all difference values between adjacent element of log box size r and log amount of box N(r) as a leaf features was able to increase the classification accuracy.

Lacunarity analysis

To analyze the performance of gliding box method in measuring the *lacunarity* value, we change the size of box *r* that varies according to the input image in order to find an optimal *r* value. Figure 8 shows the classification accuracy with various box size *r*. Result shows that the smaller the box size *r*, the better the accuracy. While the greater the size of the box, then the accuracy decreases.

The result also shows that the overall accuracy is not very high. This is due to the high similarity between classes of leaf textures. This also suggest that *lacunarity* measurement was better performed for data with a few number of classes, like what have been done in previous study [14-18]. At first, we use only one input value, but the result is not quite satisfying. Therefore, we try to combine several images as an input for *lacunarity* measurement. We finally use six input images that represent the uniqueness of image texture. The combined image resulted in 50,169% of classification accuracy.

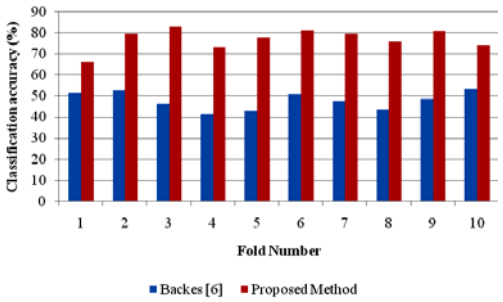


Figure 7. Comparison of previous methods and proposed methods

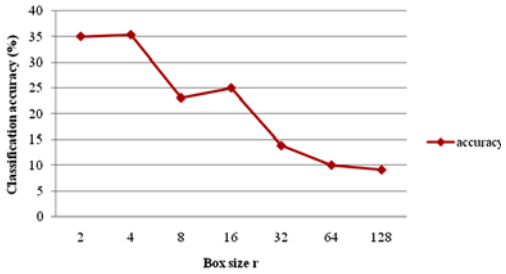


Figure 8. The effect of box size *r* towards classification result

TABLE 6
CLASSIFICATION RESULT USING ONLY ONE IMAGE FOR *LACUNARITY* ANALYSIS

No	Input image		Accuracy (%)
1	Histogram equalization		14.22
2	Kirsch filter		14.54
3	Local thresholding[13]		19.83
4	Median filter		17.09
5	Canny edge detector		16.15
6	Skeletonization		15.32
Combination of 1,2,3,4,5,6			**50.169**

Table 6 describes the classification result if we use the single input image separately, while Table 7 shows the classification accuracy (using all of the 6 images) with various box size r.

Fractal Dimension and Lacunarity Combination Analysis

The final experiment conducted to answer the research question in this study, whether there are a synergy between a combination of fractal dimension of leaf shape and lacunarity of leaf texture. The resulted features $\vec{v}$ concatenated from fractal dimension and lacunarity measurement can be described as $\vec{v} = [D_{10}, D_{11}, D_{12}, ., D_{1max}, D_{20}, D_{21}, ., D_{2max}, \Lambda_1, \Lambda_2, ., \Lambda_{max}]$ where D_1 is a fractal dimension of leaf boundary, D_2 is fractal dimension of leaf veins, while Λ is *lacunarity* value of leaf texture. The feature vectors used in this experiment is consist of combination of best fractal dimension and *lacunarity* feature vectors obtained from previous experiment.

TABLE 7
THE EFFECT OF BOX SIZE IN LACUNARITY

box size r	Feature length	accuracy (%)
2	1x6	35.14
4	1x6	35.47
8	1x6	23.18
16	1x6	25.09
32	1x6	13.90
64	1x6	10.07
128	1x6	9.129
2,4,8,16, 32	1x30	**50.169**

TABLE 8
COMPARISON OF OVERALL CLASSIFICATION ACCURACY

Fold number	Fractal dimension	*Lacunarity*	Combination of both features
1	66.129	53.226	93.548
2	79.365	39.682	93.650
3	82.539	53.968	95.238
4	73.016	60.317	93.650
5	77.777	39.682	95.238
6	80.952	41.269	93.650
7	79.365	60.317	98.412
8	75.806	56.451	93.548
9	80.645	46.774	95.161
10	74.193	50	87.096
Average accuracy	**76.979%**	**50.169%**	**93.919%**

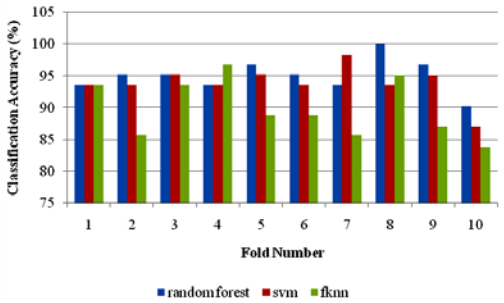


Figure 9. Classification accuracy of proposed method with three classifiers

Table 8 shows the comparison result of each methods when applied alone or combined together using 10-fold cross validation system and SVM classifier. When using fractal dimension of leaf shape alone, the system is able to reach 82.539% of accuracy with average classification accuracy is 76.979%, while analysis of lacunarity feature resulted in 50.169% accuracy with highest classification rate found at 4th fold (60.317%). Combining

both features able to improve the average accuracy up to 93.916% with highest classification result shows in 7th fold that reaches 98.412% of classifycation accuracy.

We also compare the classification result using other classifiers aside of SVM, which are Random Forest and Fuzzy *k*-Nearest Neighbor to see the robustness of this combined features. Figure 9 shows the comparison of classification accuracy when we use different classifiers. Result shows that the ensemble classifier, Random Forest, is able to outperform SVM and F-Knn classifier with average 95.048% of classification accuracy, while SVM resulted in 93.92% and Fknn produce 89.93% of accuracy. From this experiment, we can see the robustness of the proposed feature extraction and combination methods. We also able to prove the hypothesis that expects a better synergy between fractal dimension and *lacunarity* when combined together rather than using each feature alone. This also suggests that using fractal dimension and *lacunarity* in leaf classification task will lead to a promising result.

4. Conclusion

We have presented a study to analyze the synergy of combined features of fractal dimension and *lacunarity* to improve plant leaf classification accuracy. Experiment is performed using 626 of leaf images from *flavia* leaf dataset. To obtain the leaf boundary and vein, an edge detection opera-tor with multi-threshold value was applied to obtain the most representative features. Then we propose a method to extract a sequence of fractal dimension value from a log-log plot after applying a box counting methods. *Lacunarity* value obtained by applying a gliding box methods on leaf texture image. Parameter of box size *r* was analyzed in the *lacunarity* calculation to determine an optimal *r* value. Furthermore, the extracted fractal dimension feature vector was concatenated with *lacunarity* feature vectors. Experiment result shows that highest success rate in the calculation of fractal dimension value can be obtained when combining images with sigma value of 1 to 4.

Meanwhile, best results at *lacunarity* calculation is obtained when the size of the box *r* used is a combination of *r* = 2,4,8,16,32. Combination of each of the best features of fractal dimension analysis of leaf shape and *lacunarity* analysis of leaf texture able to achieve an average 95.948%, 93.92% and 89.93% of classification accuracy using Random Forest, SVM, and F-Knn classifiers respectively. These result indicates that the combining both fractal dimension and *lacunarity* features are better than using these methods separately. It is also able to prove the hypothesis that there is a synergy between the two features. In the future, a fractal based feature combination might considered as a good references in the field of plant leaf classification.

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