Plant Leaf Identification using Moment Invariants & General Regression Neural Network

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Abstract*— Living plant identification based on images of leaf is a very challenging task in the field of pattern recognition and computer vision. However, leaf classification is an important component of computerized living plant recognition. The leaf contains important information for plant species identification despite its complexity. The objective of this study is to compare the effectiveness of Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI) and Tchebichef Moment Invariant (TMI) features in extracting features from leaf images. Then, the features extracted from the most effective moment invariant technique are classified using the General Regression Neural Network (GRNN). There are two main stages involved in plant leaf identification. The first stage is known as feature extraction process where moment invariant methods are applied. The output of this process is a set of a global vector feature that represents the shape of the leaf images. It is shown that TMI can extract vector feature with Percentage of Absolute Error (PAE) less than 10.38 percent. Therefore, TMI vector feature will be the input to the second stage. The second stage involves classification of leaf images based on the derived feature gained in the previous stage. It is found that the feature vectors enabled the GRNN classifier to achieve 100 percent classification rate. Thus, the finding from this study can provide useful information for developing automated plant classification tools.

Keywords-plant leaf identification; moment invariants; regression neural network

I. INTRODUCTION

There are many kinds of plant species on earth. Unfortunately, as human progress, more and more plant species are at the margin of extinction. Therefore, it is important to correctly and quickly recognize the plant species in order to understand, manage and archive them before it's too late. However, correctly identifying plant species requires expert knowledge only botanists can provide. Due to the limited number of botanists, it is necessary to acquire some of their knowledge and automate the recognition process.

Plant species identification is a process in which each individual plant should be correctly assigned to descending series of groups of related plants, as based on common characteristics [1]. Plant classification not only recognizes different plants and names of the plant but also provides the differences of plants and expands the scheme for classifying plants.

Plants can be classified according to the shapes, colours, textures and structures of their leaf, bark, flower, seedling and morph. Plant taxonomy methods still adopt traditional classification method such as morphologic anatomy, cell biology and molecular biological approaches. The traditional method is time consuming and requires tremendous efforts from botanists. However, due to the rapid development in computer technologies, there are now opportunities to improve the ability of plant species identification.

Computerized plant classification systems are mostly based on two-dimensional images. This makes plant classification based on leaves as the appropriate choice compared to the use of shapes of flowers, seedling and morph of plants which are three-dimensionally complex in structure. Plant classification based on leaves involves leaf feature extraction. Leaf feature extraction is a process of identifying features which can discriminate different kinds of leaves. Wang *et.al* [2] introduced a method of recognizing leaf images based on shape features using hyper-sphere classifier with 92.2% recognition rate.Wu *et al.* [3], on the other hand, extracted and processed 12 features using Principal Components Analysis (PCA) to form input vector and further classified the leaves using Probabilistic Neural Network (PNN). The authors achieved 90% recognition rate. Hossein and Amin [4] also used a PNN classifier, but extracted the leaf features using simplified extraction methods. They recorded a 91.41% recognition rate. Leaf feature extraction combining a thresholding method and H-maxima transformation based method was proposed by [5] to extract the leaf veins.

The objective of this study is to compare the effectiveness of Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI) and Tchebichef Moment Invariant (TMI) features in extracting features from leaf images. Then, the features extracted from the most effective moment invariant technique are classified using the General Regression Neural Network (GRNN). Thus, the finding from this study can provide useful information for developing automated plant classification tools.

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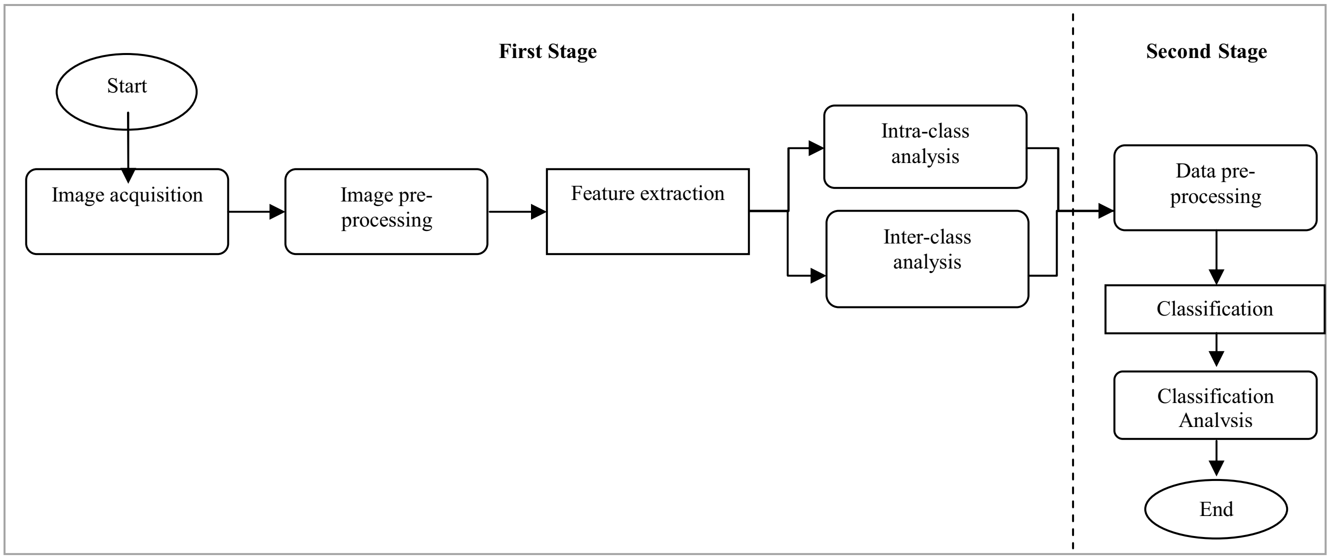

Figure 1. Stages in the Research Framework.

II. RESEARCH METHODOLOGY

There are two main stages involved in order to accomplish the objectives of this research (refer Fig. 1). The first stage involves four processes; image acquisition, image pre-processing, feature extraction and inter-class and intra-class analysis. For the second stage, three processes are involved. The processes are data pre-processing which involve numerical image, plant leaf classification using a General Regression Neural Network and lastly, analyzing the classification rate.

III. SYSTEM IMPLEMENTATION

A. First Stage

The first stage is the extraction of leaf features. The features are extracted using Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI) and Tchebichef Moment Invariant (TMI). These features will be compared to find the most effective moment invariant technique.

1) Image Source

The collection of leaf images are from variety of plants. The leaf from the plant is plucked and the digital colour image of the leaf is taken with a digital camera. In this research, 10 species of different plants were used (refer table 1). Each species includes 10 samples of leaf images. These leaf images come in different sizes, shapes and class. Figure 2 show samples of the leaf images.

2) Image Pre-processing

Image pre-processing improves image data by suppressing undesired distortions and enhances the image features that are relevant for further processing. In this process, a series of sequential operations were done on the leaf image which are prescribing the image size, converting the gray-scale images to binary images (monochrome) file and modifying the scaling and rotation factors of the image.

TABLE I. TYPES OF LEAVES

Family	Image Name
Sapindaceae	Rambutan Leaf
	Pulasan Leaf
	Mata Kucing Leaf
Moraceae	Jackfruit Leaf
	Cempedak Leaf
Anacardiaceae	Apple Mango Leaf
	Malgoa Mango Leaf
	Kuini Leaf
Myrtaceae	Water Apple Leaf
	Guava Leaf

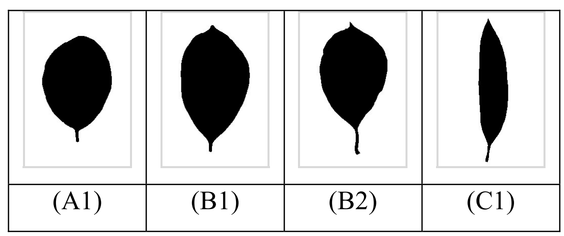

Figure 2. Sample leaf images

The digital images are first minimized to 210 x 314 pixel dimensions in order to ease the computational burden. The grey scale images are further converted into binary images. Each image has its own threshold value; therefore the value is not fixed.

The leaf images undergo scaling and rotation transformations to produce variants images. Each leaf images have 12 variant images with different scaling and rotation factors (refer table 2) so that moment invariants methods can extract the leaf features from variant images. Therefore, there will be 120 images used for this study.

3) Feature Extraction using Moment Invariants

Moment invariants have been used as feature extractions in variety of object recognition applications during the last 40 years. It is a well-known technique of calculating and comparing the moment invariants of the shape of a feature in image processing for recognition and classification. This technique is chosen because of the following reasons [6]:

- It gives a lot of information about the different types of geometrical features inherent in the image.
- It generates a set of features that is invariant.

TABLE II. SCALING AND ROTATION FACTORS

No.	Geometric Transformations Factors
1	The image is reduced to 0.5x
2	The image is reduced to 0.75x
3	The image is enlarged to 1.2x
4	The image is enlarged to 1.4x
5	The image is rotated to 10°
6	The image is rotated to 20°
7	The image is rotated to 45°
8	The image is rotated to 90°
9	The image is reduced to 0.5x and rotated to 10°
10	The image is reduced to 0.75x and rotated to 20°
11	The image is enlarged to 1.2x and rotated to 45°
12	The image is enlarged to 1.4x and rotated to 90°

For this study, three moment invariants techniques are used; Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI) and Tchebichef Moment Invariant (TMI).

a) Zernike Moment Invariant(ZMI)

The geometric moment definition has the form of the projection of $f(x, y)$ onto the monomials $x^n y^m$. Unfortunately, the basis set $\{x^n y^m\}$ is not orthogonal. Consequently, these moments are not optimal with regard to the information redundancy. Moreover, the lack of orthogonal property causes the recovery of an image from its geometric moments strongly ill-posed. Therefore, [7] introduced the use of continuous orthogonal polynomials such as Zernike moments to overcome the shortcomings of information redundancy present in the geometric moments.

Zernike moments are scaling and rotation invariant. Scale and translation invariance can be applied using moment normalization. A convenient way to express Zernike moments in terms of geometric moments in Cartesian form is given by the eq. 1.

— (1)

where,

(2)

$$\varphi_1 = Z_{p0}\ ; \quad \varphi_2 = |Z_{pq}|^2 \tag{3}$$

From eq. 2, it can be seen that Zernike moments use polynomials of the image radius instead of monomials of Cartesian coordinates and a complex exponential factor of the angle. This makes the complex modulus invariant to rotation. Their orthogonal property renders image reconstruction from its moments feasible and accurate.

b) Legendre Moment Invariant(LMI)

Legendre moments were introduced by [7]. Legendre Moment Invariants (LMI) belongs to the class of orthogonal moments and they were used in several pattern recognition applications. They can be used to attain a near zero value of redundancy measure in a set of moments corresponding to independent characteristics of the image.

The Legendre moments of order (p + q) with image intensity function $f(x, y)$ are defined as eq. 4. In eq. 5, $|x| \le 1$ and (n – k) is even.

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \sum \sum a_{pi} a_{qj} \tag{4}$$

$$a_{pi} = P_n(x) = \sum (-1)^{(n-k)/2} \frac{1}{2^n} \frac{(n+k)!x^k}{2^n (\frac{n-k}{2})!(\frac{n+k}{2})!k!} \tag{5}$$

$$v_{pq} = M_{00}^{-\gamma} \sum \sum [(x-\bar{x})\cos\phi + (y-\bar{y})\sin\phi]^p \times [(y-\bar{y})\cos\phi - (x-\bar{x})\sin\phi]^q f(x,y) \tag{6}$$

where,

$$\gamma = \frac{n+m}{2} + 1 \tag{7}$$

$$\phi = 0.5 \tan^{-1} \frac{2\mu_{11}}{\mu_{20} - \mu_{02}} \tag{8}$$

c) Tchebichef Moment Invariant(TMI)

One common problem with the continuous moments is the discrete error, which accumulates as the order of the moments increases [8]. Mukundan *et al.* [9] introduced a set of discrete orthogonal moments function based on the discrete Tchebichef polynomials to face this problem. The discrete orthogonal polynomials is used as basis functions for image moments to eliminate the need for numerical approximations and satisfies the orthogonal property in the discrete domain of image coordinate space [10].

The *p*th order Tchebichef moment T_p of one-dimensional *N* point signal $f(x)$, is defined as [11]:

$$T_p = \frac{1}{\tilde{\rho}(p,N)} \sum_{x=0}^{N-1} \tilde{t}_p(x) f(x) \tag{9}$$

where $p = 0, 1, 2, \ldots$, $\tilde{t}_p(x)$ denotes the *p*th oder scaled Tchebichef polynomials and ρ (p, N) is the squared-norm of scaled polynomials [9]. They are given by:

$$t_p(x) = \frac{p!}{N^P} \sum_{k=0}^{P} (-1)^{p-k} \binom{N-1-k}{p-k} \binom{p+k}{p} \binom{x}{k} \quad (10)$$

and

$$\rho(p,N) = \frac{N(1-(1/N^2))(1-(2^2/N^2))...(1-(p^2/N^2))}{2p+1} \quad (11)$$

The $(p + q)$th order Tchebichef moment T_{pq} of two-dimensional image function $f(x, y)$ on the discrete domain of [0, N-1] x [0, M-1] is defined as [11]:

$$T_{pq} = \frac{1}{\rho(\tilde{p},N)\rho(\tilde{p},N)} \sum_{x=t}^{N-1} \sum_{y=0}^{M-1} \tilde{t}_p(x)\tilde{t}_q(y) f(x,y) \quad (12)$$

d) Intra-class analysis

Intra-class analysis is an analysis on the same object representing the images with different scale and rotation factors. To conduct the analysis, the Invariant Error Computation (IEC) [12] was used. The computation uses the following equations; Absolute Error (eq. 13), Percentage Absolute Error (eq. 16), Percentage Mean Absolute Error (eq. 17 and eq. 18), and Total Percentage Mean Absolute Error (eq. 19 and eq. 20).

$$AE_m^a(\gamma_i) = \Delta_m^a \gamma_i = | H_a(\gamma_i) - F_m^a(\gamma_i) \quad (13)$$

where

$$H_a(\gamma_i) = \{\gamma_i, \gamma_{i+1}, \gamma_{i+2}, ..., \gamma_n\} \quad (14)$$

$$F_m^a(\gamma_i) = \{\gamma_i, \gamma_{i+1}, \gamma_{i+2}, ..., \gamma_n\} \quad (15)$$

Eq. 14 refers to the features vector of the original image where a refer to the class name and i is the feature dimension, whereas eq. 15 refers to the features vector for the variations of images where m is the type of variations of class a.

$$PAE_m^a(\gamma_i) = \frac{\Delta_m^a \gamma_i}{|H_a(\gamma_i)|} \times 100 \quad (16)$$

$$PMAE1_m^a(\gamma_i) = \frac{1}{I} \sum_{i=1}^{I} PAE_m^a(\gamma_i) \quad (17)$$

$$PMAE2^a(\gamma_i) = \frac{1}{M} \sum_{m=1}^{M} PAE_m^a(\gamma_i) \quad (18)$$

$$TPMAE_a = \frac{1}{M} \sum_{m=1}^{M} PMAE1_m^a(\gamma) \quad (19)$$

$$TPMAE_a = \frac{1}{n} \sum_{i=1}^{n} PMAE2^a(\gamma_i) \quad (20)$$

e) Inter-class analysis

Inter-class analysis is conducted by making a comparison between feature vectors based on the original image. The comparison is made based on the characteristic of feature vectors value, the similarity and dissimilarity of the values.

From the analyses, the feature vectors from the most effective moment invariant technique will be used as input for the Second Stage.

B. Second Stage

The second stage involves classification of plant leaf images based on the derived feature obtained in the previous stage. Classification is performed by comparing descriptors of the unknown object with those of a set of standard shapes to find the closest match. The classifier plays significant role in the plant leaf recognition process in the second stage. A General Regression Neural Network (GRNN) is implemented as classifier for this study. The performance of GRNN learning algorithm in plant leaf recognition will be evaluated.

1) Data pre-processing

The data obtained from the feature extraction methods are in numerical form. Therefore, in order to obtain an effective training of neural networks, the numerical data should be scaled. This process is known as normalization. One form of suitable data normalization can be achieved using eq.21 which is known as Linear Transformation equation. The scaled variable should be within the range of 0 to 1.

$$v' = \frac{v - v_{min}}{v_{max} - v_{min}} \quad (21)$$

$$v' = \frac{v_o}{v_{max}} \quad (22)$$

where:

v' is the new feature value that been normalized.
v_{min} is minimum feature value in the data sample.
v_{max} is maximum feature value in the data sample.
v_o is the old feature value before normalized.

2) General Regression Neural Network

The General Regression Neural Network (GRNN) is based on radial basis function and operates in a similar way to Probabilistic Neural Network (PNN) but performs regression tasks. The GRNN architecture used as the classifier for this research (fig. 3) consists of four layers which are:

- **Input layer** – There is one neuron in the input layer for each predictor variable.
- **Hidden layer** – This layer has one neuron for each case in the training dataset. The neuron stores the values of the predictor variables for the case along with the target value.
- **Summation layer** – There are only two neurons in this layer. One neuron is the denominator summation unit and the other is the numerator summation unit.
- **Decision layer** – This layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value.

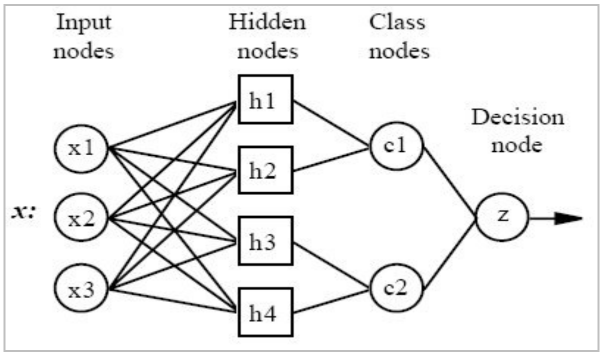

Figure 3. GRNN Architecture

The GRNN is a memory based neural network, based on the estimation of a probability density function. The network's estimate $\hat{Y}(X)$ can be thought of as a weighted average of all observed values Y_i, where each observed value is weighted according to its distance from X.

The eq. 23 is for $\hat{Y}(X)$, where the resulting regression which involves summations over the observations is directly applicable to problem involving numerical data.

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} Y_i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=0}^{n} \exp\left(\frac{D_i^2}{2\sigma^2}\right)} \quad (23)$$

where D_i^2 is defined as:

$$D_i^2 = (X - X_i)^T (X - X_i) \quad (24)$$

The GRNN provides estimates of continuous variables and converges to the underlying regression surface. The main advantages of GRNN are fast learning and converge to the optimal regression surface as the number of samples becomes very large.

IV. Results and Discussions

The results from the three analyses; inter-class analysis, intra-class analysis and classification analysis are presented. The results are presented based on the features of image *AI.*

1) *Results of intra-class analysis*

From eq. 13, the Absolute Error (AE) value for ZMI is consistent, with values in the range of 0.00 to 0.08. However, the AE value for LMI is greater than ZMI, where the range is between 0.00 to 1.74. As for TMI, the AE value is in the range of 0.00 to 6.72 and these AE value is higher compared to ZMI and LMI.

The Percentage Absolute Error (eq. 16) for PAE for TMI is the lowest with less than 10.38% of error while ZMI less than 31.69% and LMI less than 29.38%.

The main purpose of PMAE1 calculation (eq. 17) is to find out the distribution of error among image variations for one object. From Figure 4, it can be seen that the scaling factor of 0.5x with rotation factor of 10° generate the highest error compared to other factors for all moment invariant applied. Even so, TMI generated the lowest PMAE1 value for almost all variations of image A1. On the other hand, LMI produced the highest error compared to ZMI and TMI.

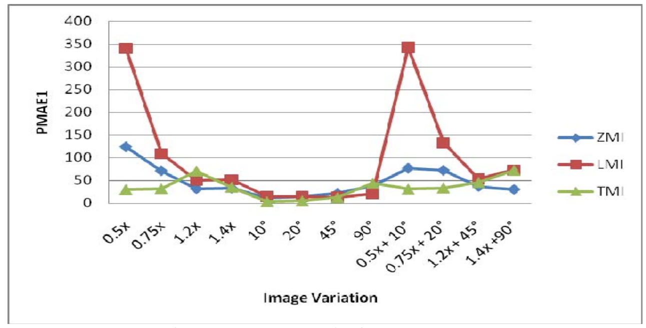

Figure 4. PMAE1 for image A1

PMAE2 calculation using eq. 18 is used to examine an error distribution along the dimension of feature vector. Based on Figure 5, it is found that when the order of ZMI is increased, the value of PMAE2 also increases. However, TMI shows the lowest error compared to the other two moment techniques, whereas, LMI generated the highest value of PMAE2 compared to other moment techniques.

Lastly, the total error of image A1 for each moment techniques is calculated by using eq. 19 and eq. 20. This is to measure the invariant performance of the techniques. From table 3, the value of TPMAE for TMI indicates that TMI generated the lowest total error compared to ZMI and LMI. Therefore, it can be concluded that TMI are better in feature extraction of leaf images because it produces smaller total error compared to ZMI and LMI.

2) *Results of inter-class analysis*

To obtain the result of inter-class analysis, a comparison between values of feature vectors based on the original image is conducted. Theoretically, different class or family of the leaf will have different feature vectors. However, it was found that some of the leaf images from different class have almost similar feature vectors. From the graph, the value of feature vectors produce by Apple Mango (C1) leaf, Malgoa Mango (C2) leaf and Kuini (C3) leaf are near to each other since these leaf belong to the same family, Anacardiaceae. On the other hand, Rambutan (A1) leaf, Pulasan (A2) leaf and Mata Kucing (A3) leaf belong to the same family, Sapindaceae but the feature vectors value from one of this leaf is near to the value of the Jackfruit leaf (B1) belonging to Moraceae family.

3) *Results of classifcation analysis*

The input data for the GRNN classifier are numerical values extracted from leaf images using TMI technique. The dataset consists of 120 total samples. The k-fold cross validation is used to determine the performance of the learning algorithm. The entire dataset was split into four subsets where two subsets composed of 32 data (fold 1 and 3) and another two subsets consists of 33 data (fold 2 and 4). The network training and testing are repeated four times (*k* times).

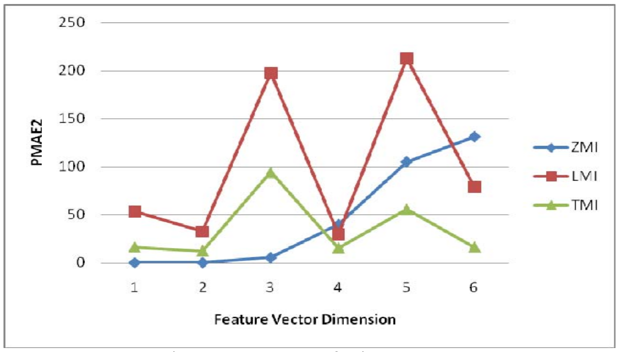

Figure 5. PMAE2 for image A1

TABLE III. TPMAE VALUE

Moment techniques	*TPMAE value*
ZMI	***46.89***
LMI	***100.77***
TMI	***34.97***

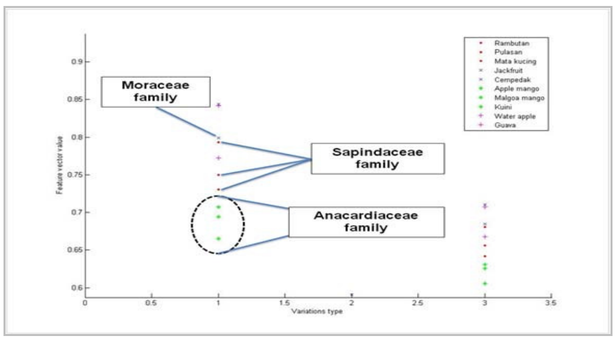

Figure 6. PMAE2 for image A1

The cross validation estimate is identified as the number of correct classification k divided by the number of data points. The percentage of correct classification (PCC) is given by eq. 25 and the number of correct classification (NCC) is given by eq. 26. If the testing vector is true, σ $(x, y)_t = 1$. Otherwise, σ $(x, y)_t = 0$.

$$PCC_k = 100\frac{1}{G}\sum_{k+1}^{k} NCC_k \quad (25)$$

$$NCC_k = \sum_{t=1}^{n} \sigma(x,y)_t \quad (26)$$

where n refers to the number of data tested.

The classification results of GRNN classifier is given in Table 4.

V. CONCLUSIONS

The work described in this study concerns two challenging phases in image analysis applications which are feature extraction and classification phase. Three moment invariants technique, ZMI, LMI and TMI were compared to determine the most effective technique in extracting leaf images. TMI was found to be the most effective. The features extracted using TMI were then input into the GRNN classifier. A 100% classification rate was recorded. This may be due to the possibility that the features extracted using TMI closely representing the actual leaf images. Further research needs to be done to confirm this due to the small number of images used which may caused an overfitting of the GRNN.

TABLE IV. CLASSIFICATION RESULT

k	**Data Unit**	**Time Taken (Second)**	**NCC**	**PCC**
1	32	4.49	32	100
2	33	0.60	33	
3	32	0.44	32	
4	33	0.42	33	

k = Group of sample data
Data Unit = Number of data in sample group

REFERENCES

[1] J. X. Du, et *al.*" Computer-aided plant species identification (CAPSI) based on leaf shape matching technique". *Transaction of the Institue of Measurement and Control*. Vol 28, 2006. pp275-284.

[2] X. F. Wang, *et al*. "Recognition of Leaf Images Based on Shape Features Using a Hypersphere Classifier". *International Conference on Intelligent Computing, 2005.* pp87–96.

[3] S. G. Wu, *et al*. "A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network". *2007 IEEE International Symposium on Signal Processing and Information Technology*. 2007. pp 11-16.

[4] J. Hossain and M. A. Amin, "Leaf Shape Identification based Plant Biometrics," Proc. Int. Conf. on Computer and Information technology 2010 (ICCIT 10), online http://ieeexplore.ieee.org

[5] N. Valliammal and S. N. Geethalakshmi, "Hybrid Image Segmentation Algorithm for Leaf recognition and Characterization," Proc. Int. Conf. on process Automation, Control and Computing 2011 (PACC 11), online http://ieeexplore.ieee.org

[6] Puteh Saad "Feature Extraction of Trademark Images Using Geometric Invariant Moment and Zernike Moment-A Comparison". *Chiang Mai Journal of Science*. Vol 31, 2004, pp217-222.

[7] M. R. Teague, "Image Analysis Via The General Theory Of Moments" *Journal of the Optical Society of America.* Vol. 70, 1980, pp920-930.

[8] PT. Yap, *et al.*. "Image Analysis by Krawtchouk Moments". *IEEE Transactions on Image Processing*. Vol 12 (11), 2003, pp 1367-1377.

[9] R. Mukundan, e*t al.* "Image Analysis by Tchebichef Moments". *IEEE Transactions on Image Processing*. Vol 20 (9), 2009, pp 1357-1364.

[10] L. Kotoulas, and I. Andreadis, "Real-time computation of Zernike Moments." *IEEE Transactions on Circuits and Systems for Video Technology.* Vol 15 (6), June 2005, pp 801-809.

[11] G. Wang, and S. Wang, "Recursive computation of Tchebichef moment and its inverse transform". *The Journal of the Pattern Recognition Society*. Vol 39 (1), 2006, pp 47-56.

[12] Shahrul Nizam Yaakob and Puteh Saad. "Generalization Performance Analysis between Fuzzy ARTMAP and Gaussian ARTMAP Neural Network". *Malaysian Journal of Computer Science*. Vol 2, 2007, pp13-22.