Digital Image Classification for Malaysian Blooming Flower

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***Abstract*— Digital image processing is a rapidly growing area of computer science since it was introduced and developed in the 1960's. In the case of flower classification, image processing is a crucial step for computer-aided plant species identification. Colour of the flower plays very important role in image classification since it gives additional information in terms of segmentation and recognition. On the other hand, Texture can be used to facilitate image-based retrieval system normally and it is encoded by a number of descriptors, which represented by a set of statistical measures such as gray-level co-occurrence matrix (GLCM) and Law's Order approach. This study addresses the application of NN and on image processing particularly for understanding flower image features. For predictive analysis, two techniques have been used namely, Neural Network (NN) and Logistic regression. The study shows that NN obtains the higher percentage of accuracy among two techniques. The MLP is trained by 1800 flower's dataset to classify 30 kinds of flower's type.**

Keywords-Flower; Classification; Neural Network; Multilayer Perceptron

I. INTRODUCTION

Digital image processing is a rapidly growing area of computer science since it was introduced and developed in the 1960's [1]. Many fields which traditionally used analog imaging approach are now widely switching to digital systems such as medical photography and remote sensing [2], [3]. Digital image processing allows one to enhance image features of interest and extract useful information from it.

Image processing is a serial of sequence operation on image to improve the imperfections or quality of images. An important goal of image processing is to understand the contents of an image and be able to automatically gain an understanding of a scene, implying an extraction and recognition of an object [4]. However, the image processing and the process of translating an image into a statistical distribution of low-level features is not an easy task. These tasks are complicated since the acquired image data often noisy, and target objects are influenced by lighting, intensity or illumination. Thus, there is a need to automate the image processing algorithms, for image smoothing, textured image segmentation, object extraction, tracking, and recognition. Image processing depends on the type of equipment that generates the images and the characteristic of them. In the case of flower classification, image processing is a crucial step for computer-aided plant species identification [5].

Classification is one of the most active research and application areas of data mining and most frequently encountered decision making tasks of human activity [6]. It is a process in which a group of something or class it belongs to according to their features by finding common traits or characters [7]. The main objective of classification is to predict categorical class labels for new samples [8]. There are two main classification schemes; *Unsupervised* and *Supervised* Classification [9]. Unsupervised Classification performs clusters pixels in a data set based only on their statistics without using previous knowledge about the spectral classes present in the image. On the other hand, Supervised classification is the process of using samples of known identity or training data to classify pixels of unknown identity. Some of the most commonly used supervised classification methods are Maximum Likelihood, Minimum Distance, Mahalanobis Distance, and Neural Networks.

Colour of the flower plays very important role in image classification since it gives additional information in terms of segmentation and recognition [10]. [11] describe the "*colour of the flower is defined by the colour names present in the flower region and their relative proportions*". Some types of flowers have different colours. As an example, same types of hibiscuses have different colours such as red, white and yellow and distinctive texture such as orchid and Anthurium.

Texture also plays important roles in flower image classification, since it carries information about the distribution of the gray levels of a connected set of pixels, which occurs repeatedly in an image region. Texture can be used to facilitate image-based retrieval system normally and it is encoded by a number of descriptors, which represented by a set of statistical measures such as gray-level co-occurrence matrix (GLCM) and Law's Order approach [12]. One of the methods to synthesis texture algorithm is 'Texture Mapping' [13].

This study addresses usage and usefulness NN and its applications on image processing particularly for understanding flower image features. For predictive analysis, two techniques have been used namely, Neural

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Network (NN) and Logistic regression. The study shows that NN obtains the higher percentage of accuracy among two techniques.

II. DIGITAL IMAGE PROCESSING

Digital imaging creates information of an image for processing and analysis task. The system converts digital image and transferred to a computer for processing and storage by using different processes such as image capturing, image digitization, noise filtering and feature identification [14]. According to [15], digital image processing is one of division in electronic area where image being modified to pixels, stored in a digital storage and processed by computer. In effect, it reduces cost increasing computational speed, and flexibility. The core task of digital image processing is storing images and enhances them to the new information structures, so as to provide a better basis for obtaining and analysis of related activities [16]**.** In addition, digital image processing leads to enhancement of image features' interest and therefore useful information about the scene from enhanced image could be computed [15].

Image processing has been applied to medical diagnosis [17], weather forecasting [18], food quality control [19] and galaxy monitoring [20]. Among the famous technology that applies image processing technique is Face Recognition [21], [22].

In addition, digital image processing is also widely used in content-based application. [23] applied digital image processing technique to display high quality and efficient transmission for tele-teaching application. [24] used image processing to extract a set of potential emphysematous regions of Computed Tomography (CT) image and used NN to separate true emphysema from artifacts. The processing steps involved image segmentation, intensity correction, image smoothing and thresholding. The combination of image processing and neural networks has produced better and accurate method for emphysema detection.

[25] introduce an approach for design of effective NN ensembles to produce a high performance image classification system with an accuracy of 95%. In another study, a region-based image retrieval system with customized k-means clustering algorithm to enhance the accuracy of image segmentation has been developed [26]. As a result, the algorithm shows an improvement in image segmentation accuracy compared to other techniques such as Geometric Histogram, FuzzyClub and IRM. [27] combined image processing techniques with hybrid NN in images classification system. Images are divided into three features; regions, colour and texture features. These features were extracted and being composed to a numbers of support vector machines (SVMs). The accuracy based on confusion matrix was recorded at 58.6% with average precision of 51% for recall where 300 images were classified through 25 SVMs.

In education, digital image processing was used to motivate learners as suggested by [28]. The findings indicate that image processing concepts are possible to be introduced to students at primary school. An activity that implement basic digital image processing for 9 and 10 years primary school students as learning activity were implemented. The results show that the activity was successful and the students agree that the activity was worthwhile. They enjoy learning new things about image processing that usually offered to student at tertiary educations [29].

III. IMAGE PROCESSING WITH NEURAL NETWORKS

Neural Networks (NN) are supporting tools for image processing in any classification problems and it present a potentially appealing alternative in image processing field [30]. NN are models that are designed to imitate the human brain through the use of mathematical model. It consists of a series of processing units which are collectively connected like the synapses in the human brain [31].

[32] designed a procedure to extract road centerline from high resolution satellite images by combining the image processing algorithms with CAD-based facilities whereby NN was implemented to discriminate between road and non-road pixels. [33] applied Bayesian MLP neural networks in their image analysis to solve the converse problem in electrical impedance tomography and locate trunks of trees in forest. In another research, [34] developed a back propagation NN model to distinguish young corn plants from weeds using colour feature in image as inputs. Using NN, the accuracy of corn plants classification is 100% and the accuracy rate for weed recognition is 80%.

[21] take the advantage of Multilayer Perceptrons capability when they developed a hierarchical medical image classification method using shape and texture features, and the accuracy result is 98%. [35] proposed an image rating system that rates and distinguish image and classified them as adult images or non-adult images. The results show that the system rates images into multiple classes with the rate of over 70%. [36] make use of Probabilistic Neural Network in automated leaf recognition for plant classification. The model was able to classify 32 types of plant with accuracy of more than 90%.

[37] introduces Integrative Co-occurrence matrices as new features for colour texture classification analysis and added intensity independent colour textures. Classification results were improved by 20% for gray-scale texture analysis and 32% for colour histogram analysis. [38] applied K-means algorithm technique and Gaussian Markov random field model to describe the texture information of different pixel colours in an image. The experimental results show that the colour feature is more meaningful than the texture feature in recognizing different image. [39] proposed a new skin detection method which integrates colour, texture and space information. Texture filter was constructed based on texture features extracted from Gabor wavelet transform to False Acceptance Rate. At the end, they compare their result with Skin Probability Map (SPM) and the results shows that their

True Acceptance Rate increases up to 2.1%. A number of successful implementation of NN in image classification is summarized in Table I.

TABLE I. The application of NN in Image Classification

Author (Year)	Process	Learning algorithm
Bhattacharya, Chaudhuri & Parui (1997)	Texture segmentation	MLP
Gori (1998)	Pattern recognition	MLP
Chaudhuri, Bhattacharya (2000)	Pattern recognition	MLP
Yang et al (2000)	Crop and weeds recognition and classification	MLP
Orlov et al. (2006)	Pattern recognition of Muscle tissue	Bayesian, MLP
Zhang (2007)	Clinical pattern recognition	MLP
Ma & Li (2007)	Iris diagnosis	SVM
Kang & Park (2009)	Sports image classification	Fusion NN
Caicedo et al (2009)	Medical image classification and retrieval	MLP, SVM
Alsmadi et al. (2009)	Fish recognition	MLP

NN has been used by flower image researchers in order to understand the flower image features. [40] and [41] classified flower images by combining the colour, texture, and shape using nearest neighbour and multilevel associaton rules respectively, while [42] include spatial information feature using colour clustering and domain knowledge. To overcome the problem of indexing images of flowers for searching a flower patents database, [11] use the colour feature as target.

The characteristic of shape and colour that was extracted from the flower images was used by [43] when Image Retrieval System of Flowers for Mobile Computing (COSMOS) was developed. The result of their experiment shows that the percentage of getting the target image is about 92% in just 90 seconds. Colour and shape flower attributes was used by [44] to develop content based image retrieval system to characterize flower images. A novel Virus Infection Clustering (VIC) is proposed to cluster the image database to enhance the searching efficiency. The results explained that clustering by using both the colour and shape features produces better retrieval results than clustering by only either colour or shape separately.

[45] investigate the numbers of feature's combination in order to improve classification performance on a large dataset of similar classes. About 103 class flower dataset was computed from four different features for the flowers; shape, texture, colour and petal's spatial distribution. The entire features then combined using a multiple kernel framework with a Support Vector Machine (SVM) classifier. The results show that learning the optimal combination of core elements significantly improves the performance, which produce 55% for the best single feature to 73% for the combination of all features. A study of flower images with features used to represent the dataset is exhibit in Table II.

TABLE II. The selected features if flower image researches

Auhtor (Year)	Selected features
Hong *et al.* (2003)	Colour, texture, shape, spatial information
Hong *et al.* (2004)	Colour, shape
Tseng *et al.* (2005)	Colour, texture, shape
Nilsback & Zisserman (2006)	Colour, texture, shape
Aulia (2005)	Colour, texture
Kim *et al.*(2008)	Contour
Suppaiboonvong (2009)	Colour, shape

Since NN was designed to solve complex problems such as pattern recognition and classification, therefore NN plays a significant role in classification process. It is able to train and classify arbitrarily complex datasets such as flower images [46], [1]. Hence, in this study NN were employed to obtain the flower classification model.

IV. DATA PREPARATION

Data preparation is an important phase since the prepared dataset becomes input to the neural network training and testing. The image processing techniques are applied on this image after images being captured and extracted. The overall stage of image processing is illustrated in Fig. 1.

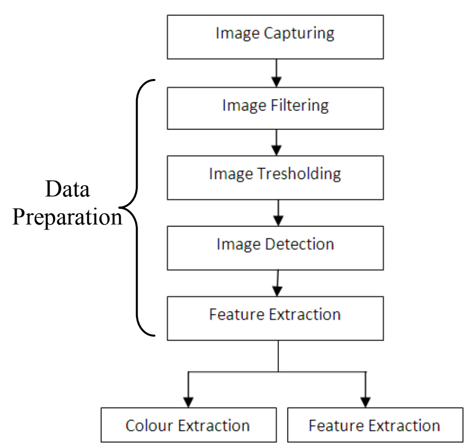

Fig. 1. The Process of Image Processing

Image capturing

The first phase of the study is the image capturing phase. During this phase, flower images were captured based on [47] method whereby the flower was placed in the centre and must be well focused on flower with defocused background (Fig. 2).

Fig. 2. The Sample of flower image

Image Filtering
Image filtering is a technique to modify or enhance an image in order to emphasize certain features or remove them from image. This step smoothen the image slightly to avoid counterfeit errors caused by noise [48].

Image Segmentation
Image segmentation acquires advantage of the colour differences between regions to separate the regions and background image so that region of interest (ROI) of the flower is obtained. To do this, the image should be converted to binary format whereby the image must be converted into grayscale format first using formula as in (1)

$$Gray = 0.2989*R+0.5870*G+0.1140*B \qquad (1)$$

where R represents Red, G represents Green and B represents Blue [36].

Image Thresholding
To perform the extraction process based on the colour-based region, the value of threshold level has to be identified. The Otsu's method was applied at this stage in order to compute a global threshold that later can be employed to convert an intensity of image to a binary image ([49]). After flower's ROI was detected then the morphology process was applied to remove noises [50]. The morphology technique included such as *opening morphology*, *closing morphology* and *cleaning morphology.*

Region Fill
In this phase, the holes in the binary image were filled in order to obtain the flower regions. The image is then converted to RGB colour space again, so that the colour and texture extraction obtained as shown in Fig. 3.

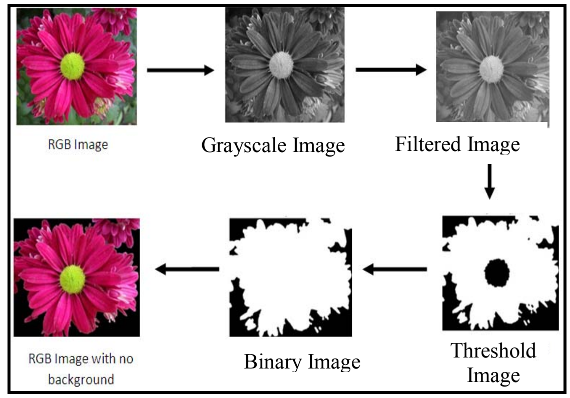

Fig. 3. The Process of Data Preparation

Feature Extraction
Feature extraction aims to capture the essential characteristics of the patterns [51]. Two feature extractions were emphasized in this study, namely the colour extraction and texture extraction of the image. In colour extraction, the images were transformed from RGB colour space to HSV colour space. The conversion formula is as Table III [52]:

TABLE III. Mathematical formula for convert from RGB colour space to HSV colour space.

Name	Mathematical Formula
Hue	$H = \cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\}$
Saturation	$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)]$
Value	$V = \frac{1}{3}(R+G+B)$

On the other hand, the image texture is calculated based on gray-level co-occurrence matrix (GLCM) to obtain the contrast, correlation, energy and homogeneity of the image. From texture samples, several ROI such as the petal region and petal intersection were considered as suggested by [40]. Fourteen (14) features can be calculated from each GLCM but for this study, only four features were extracted. The features such as Contrast, Correlation, Energy and Homogeneity are used for texture calculations. The formula is depicted in Table IV.

TABLE IV. Mathematical Formula for Contrast, Correlation, Energy and Homogeneity GLCM

Feature	Formula
Contrast	$\sum_{i,j} \lvert i-j \rvert^2 p(i,j)$
Correlation	$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$
Energy	$\sum_{i,j} p(i,j)^2$
Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$

V. RESULTS

A total of 1800 images have been selected to represent the whole dataset used in the experiment. For each type of flowers, 60 samples of ROI have been identified to represent such a category. An example of data is shown in Table V.

TABLE V. Example of flower data

Hue	Saturation	Value	Contrast	Correlation	Energy	Homogeneity	FlowerCode
0.5574	0.2557	0.7223	0.07	0.9733	0.2646	0.9657	Turnera Ulmifolia
2.8497	0.4834	0.2151	0.0989	0.9137	0.3003	0.9517	Alamanda

Several data allocation has been explored to determine the Malaysian flower percentage of accuracy. The results are depicted in Fig. 4. The graph exhibits data allocation of 70:15:15 exhibit higher NN percentage accuracy with various number of hidden unit. However, the highest accuracy is achieved by data allocation of 80:10:10 with accuracy of 68.63% as compared to 67.47% (70:15:15) and 66.7% (60:20:20).

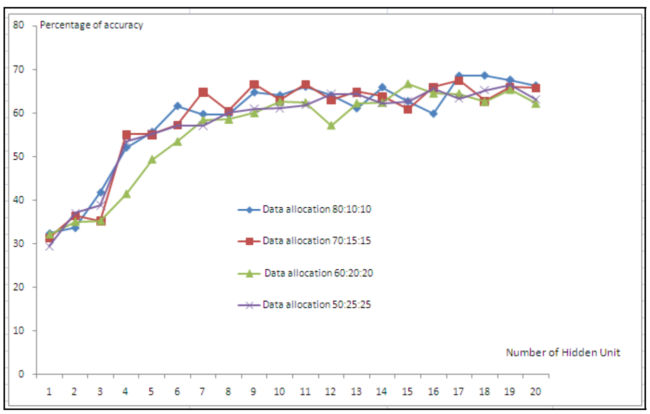

Fig. 4. NN results with various data allocation

Further analysis on the performance of NN with hidden unit 17, 18 and 19 indicates that hidden unit 19 obtains higher average of accuracy compared to hidden unit 17 and 18. Average performance of NN results also review that hidden unit 19 reached nearly 67% of average percentage accuracy as oppose to hidden unit 17 (61.8%) and hidden unit 18 (63.14%).

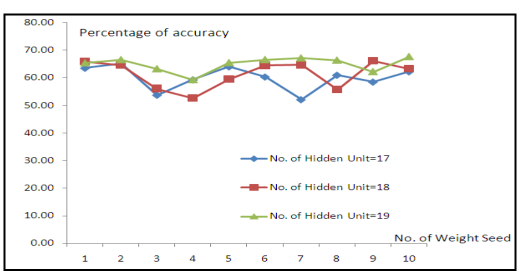

Fig. 5. NN results with various numbers of hidden unit and weight

The same dataset has been model using logistic regression of SAS 9.13 version. The prediction accuracy of logistic regression is 26.8%. Therefore based on 1800 samples of Malaysian flower images, NN has shown a higher average prediction results vs. logistic regression.

VI. CONCLUSION

Since NN has shown its potential in building Malaysian flower model, future studies can be focused or extending the dataset built in this study. Verities sample of images can be captured for a particular flower with various colours. This indirectly can improve the sensitivity of NN algorithm and thus leads to a higher percentage of accuracy. Nevertheless, the flower model developed in this study can be used to develop a Malaysian blooming flower recognition system in the future. In order to further improve the classification accuracy, shape features of flowers can be included as one of the important attribute in Malaysian blooming flowers system.

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