CLASSIFICATION MODELING FOR MALAYSIAN BLOOMING FLOWER IMAGES USING NEURAL NETWORKS

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Abstrak

Pemprosesan imej merupakan bidang penyelidikan dalam bidang sains komputer yang berkembang pesat sejak ia diperkenalkan dan sehingga kini ia masih merupakan satu masalah yang mencabar dalam bidang multimedia dan perkomputeran. Bagi imej bunga-bungaan, masalah utama adalah disebabkan persamaan yang ketara di antara setiap bunga dengan bunga lain dari segi warna dan tekstur. Rupa bentuk imej seperti pencahayaan yang berbeza, kesan bayangan terhadap permukaan objek, saiz, bentuk, putaran dan kedudukan, latar belakang imej, keadaan bunga yang mengembang atau mula mengembang merupakan masalah yang dihadapi dalam pemprosesan imej. Oleh kerana pengecaman nama bunga masih lagi kompleks, kajian ini dijalankan bertujuan untuk membangunkan model pengkelasan bunga bungaan Malaysia yang mengembang dengan menggunakan Rangkaian Neural berasaskan *backpropagation*. Imej bunga diekstrak melalui *Region of Interest* (ROI) di mana nilai warna dan tekstur sahaja yang akan diberi penekanan dalam kajian ini. Sejumlah 960 imej telah diekstrak daripada 16 jenis bunga. Setiap jenis bunga diwakili oleh 60 sampel ROI, manakala setiap ROI diwakili oleh 3 sifat warna (*Hue, Saturation* dan *Value*) dan 4 sifat tekstur (*Contrast, Correlation, Energy* dan *Homogeneity*). Menerusi fasa latihan dan pengujian, analisis dilaksanakan untuk meninjau prestasi rangkaian neural berdasarkan *difficult to learn pattern* yang digandakan (dirujuk sebagai DOUBLE) kerana ia mungkin dapat memberi gambaran mengapa imej bunga sukar untuk dikelaskan. Dapatan kajian menunjukkan bahawa Rangkaian Neural berdasarkan DOUBLE memperoleh ketepatan sebanyak 96.3% dan data asal sebanyak 68.3% manakala ketepatan Regresi Logistik dengan data asal ialah 60.5%. Hasil pengkelasan pohon pemutusan menunjukkan j*Chi-Squared Automatic Interaction Detection* (CHAID) dan *Extended Chi-Squared Automatic Interaction Detection* (EX-CHAID) memperoleh prestasi yang paling tinggi sehingga mencecah 42% dengan DOUBLE. Dapatan kajian menunjukkan bahawa Rangkaian Neural dengan set data DOUBLE memperoleh prestasi tertinggi berbanding Regresi Logistik dan Pohon Pemutusan. Oleh itu Rangkaian Neural mempunyai potensi dalam pembangunan model bunga-bungaan Malaysia. Kajian pada masa akan datang boleh menumpukan kepada penambahan saiz data kajian dan ROI yang mungkin dapat meningkatkan prestasi ketepatan. Model klasifikasi bunga yang dibangunkan dalam kajian ini boleh dijadikan sebahagian daripada sistem pengecaman bunga Malaysia pada masa akan datang di mana warna dan tekstur diperlukan dalam proses pengecaman bunga.

Kata kunci: Klasifikasi imej, Rangkaian neural, Perseptron berbilang lapisan, Pohon pemutusan, Regresi logistik.

Abstract

Image processing is a rapidly growing research area of computer science and remains as a challenging problem within the computer vision fields. For the classification of flower images, the problem is mainly due to the huge similarities in terms of colour and texture. The appearance of the image itself such as variation of lights due to different lighting condition, shadow effect on the object's surface, size, shape, rotation and position, background clutter, states of blooming or budding may affect the utilized classification techniques. This study aims to develop a classification model for Malaysian blooming flowers using neural network with the back propagation algorithms. The flower image is extracted through Region of Interest (ROI) in which texture and colour are emphasized in this study. In this research, a total of 960 images were extracted from 16 types of flowers. Each ROI was represented by three colour attributes (Hue, Saturation, and Value) and four textures attribute (Contrast, Correlation, Energy and Homogeneity). In training and testing phases, experiments were carried out to observe the classification performance of Neural Networks with duplication of difficult pattern to learn (referred to as DOUBLE) as this could possibly explain as to why some flower images were difficult to learn by classifiers. Results show that the overall performance of Neural Network with DOUBLE is 96.3% while actual data set is 68.3%, and the accuracy obtained from Logistic Regression with actual data set is 60.5%. The Decision Tree classification results indicate that the highest performance obtained by Chi-Squared Automatic Interaction Detection(CHAID) and Exhaustive CHAID (EX-CHAID) is merely 42% with DOUBLE. The findings from this study indicate that Neural Network with DOUBLE data set produces highest performance compared to Logistic Regression and Decision Tree. Therefore, NN has been potential in building Malaysian blooming flower model. Future studies can be focused on increasing the sample size and ROI thus may lead to a higher percentage of accuracy. Nevertheless, the developed flower model can be used as part of the Malaysian Blooming Flower recognition system in the future where the colours and texture are needed in the flower identification process.

Keywords: Image classification, Neural networks, Multilayer perceptron, Decision tree, Logistic regression.

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CHAPTER ONE
INTRODUCTION

This chapter presents the background of the project that focuses on Malaysian Blooming Flowers classification. The problem statements and objectives of the study are also mentioned in this chapter. In addition, the research questions are formulated, the research scope as well as the significant of the research also provided in this chapter.

1.1 Overview

Classification is an active research area in data mining which most frequently involve the decision making (Zhang, 2000).Classification aimstopredict categorical class labels for new samples (Dehkordi&Shenassa, 2006). It involves the process of grouping objects (information) accordingly into their belonging classes or groups based on their characteristic (Qi & Davidson, 2009).

In classification, there are two main schemes that are commonly used namely *Supervised* and *Unsupervised* classification. *Supervised* classification is the process of using samples of known identity or training data to classify pixels of unknown identity (Riviera & Manian, 2008). The training data are used to train the classifier which is tested with testing samples to evaluate the accuracy of the classifier which in turn is testing using test samples to evaluate the accuracy of the classifier. Some of the most commonly used supervised classification methods are Maximum Likelihood, Minimum Distance, Mahalanobis Distance and Neural Networks

(Cudney *et al.,* 2007). Meanwhile unsupervised classification clusters pixels which formed in a data set based only on their information without using previous knowledge about the spectral classes present in the image (Li, 2010).

Image processing is a rapidly growing area of computer science since it was introduced and developed in the 1960's (Miao, Gandelin & Yuan, 2006). By definition, image processing is a serial of sequence operation on image to improve the imperfections or quality of images. It allows enhancement of image features and useful information extraction about the scene from the enhanced image.

The 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 (Siraj *et al*., 2004). Image classification studies have been conducted in numerous fields such as medical (Antani *et al.*, 2003; Lau & Ozawa, 2003), pattern recognition (such as flowers and trademark) (Hong *et al.,* 2003; Nilsback & Zisserman, 2006; Tseng *et al.,* 2005; Hong *et al.,* 2004, Peng & Chen, 1997; Leung & Chen, 2002) and remote sensing (Samaniego & Schulz, 2009).

Image classification classifies images into a number of predefined categories. Even though it has been studied for many years, image classification remains a challenging problem within multimedia and computer vision fields. The major difficulties arise from the background complexity, occluding objects, semantic gap (between low-level visual features) and also high-level semantic concepts. These difficulties as well as the heavy computational burden have limited the practical application of image classification in many scenarios, such as web image search (Wen, Zhu and Peng, 2009), video surveillance **(**Girisha & Murali, 2009**)** and medical image system (Wu *et al.*, 2007).

Some of represented image contents come with visual features. Visual features provide the content description of images that can be addressed by low-level features such as colour, texture, shape, or spatial information (Wang *et al.*, 2002, 2004; Dong & Yang, 2002; Ruxanda, 2006).

Prior to classify images, image processing is an important activity. In image processing, colour is one of the features that is vital for image classification. A colour in an image would make a huge impact to image analysis due it's capability of giving additional information on image segmentation and recognition (Al-Tayeche& Khalil, 2003). Colour is derived from the light spectrum, reflected from light and then absorbed by object's surface before received by the human visual perception (eye) and processed by the brain as in RGB colour space. It is then converted into another colour space. This is because RGB colour space is easily influenced by lighting from the sun or flashlights as well as shadow which can lead to misclassification on some region of interest (Cheng & Sun, 2000). To obtain more accurate classification result, RGB will be converted to HSV, YCbCr (Chai & Bouzerdoum, 2000) and *C.I.E. L* a* b* (Somatilake & Chalmers, 2010).

For feature-based retrieval image systems, the most common approaches to extract information are by using the low-level image features such as colour, texture and shape (Saad, 2008; Mayron, 2008). Colour can provide powerful information about image content. One way to identify colour images is using colour indexing algorithm (Swain and Ballard, 1991). The 3D histograms generated for the input and target images in the database will be matched using the histogram intersection method. The method is simple but provides good performance. Another approach is to utilize multiple features, such as colour, texture and shape for representing images. QBIC Photobook, Virage, VisualSEEK, Netra and MARS are examples the earliest applications that have been using this approach in 1990's (Flickner *et.al.,* 1995; Pentland, Picard & Sclaroff, 1996; Bach, 1996; Smith & Chang, 1996; Ma, Manjunath & Netra, 1997; Rui*et al.,* 1998).

Beside colour attribute, texture also plays important roles in flower image classification. Texture 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 besides the colour and shape and regions (Cheng & Chen, 2003). Normally, textures are 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 (Baskaran, Deivami & Kannan, 2004). One of the methods to synthesis texture algorithm is *Texture mapping* (Ashikhmin, 2001). To acquire the images by using textures is not always easy even though texture mapping method itself is simple.

In flower images classification, colour, texture and shape can be used in conjunction with nearest neighbor and multilevel association rules (Nilsback and Zisserman, 2006; Tseng *et al.*, 2005). Spatial information feature using colour clustering and domain knowledge could also be used (Hong, 2003). Since this is the first attempt to collect, process and classify the Malaysian blooming flower images, therefore this study focuses on colour and texture features extraction only as stated by Aulia (2005) and Vansteenkiste *et al.* (2004).

Given an image of a flower, the task is to assign a species label to image by examining the visual content of the images. Not all types of flowers can be classified visually due to several limitations that occur during in this research such as noise images, blur images, under exposure and over exposure images.

1.2 Problem Statements

The major problems that usually happened in any image classification tasks are the appearance of the image itself. The object appears in an image are usually inappropriate variations, mostly on image conditions such as:

Variation of Lights

- This occurs due to different lighting condition, intensity or illumination of the light declining from diverse angle that can cause shadow effect on the object's surface (Warhade, Merchant and Desai, 2008). Hence, the colour pixel of the flowers will slightly differs from each other. The examples are shown in Figure 1.1.

Figure 1.1: Allamanda's images taken under various lighting condition

Variations of viewpoint

- The variation of viewpoint may cause significant change in terms of object's appearance such as size, shape, rotation and position. Figure 1.2 show images of from various viewpoints.

Figure 1.2: English Daisy's flower images taken from different viewpoints

Background Clutter

- Generally, image taken include background clutter. In the flower images, clutters frequently have some similarity of each other and this can give the wrong reading in the classifiers. Figure 1.3 exhibits few examples of background clutter.

Figure 1.3: Background clutter for different flowers is similar to each other

Blooming and Non-blooming flower

- Flowers undergo different states of blooming, they are; (i) budding, (ii) inflorescence and (iii) blooming. Within each stage, there will be various differentiations on shape, colour, size and texture of the flowers. Such a condition is illustrated in Figure 1.4.

Figure 1.4: Same flower but different state of blooming

Due to importance of image-based retrieval system as stated by Snead (2007), it is undeniable a research towards images feature based searching for images have a lot to offer (Smith, 2001). As addition, due to the complex problem of indentifying the name of flowers, so this study focuses on only the blooming flowers and Region of Interest (ROI) of the flowers. The content of the flower's images is emphasized on colour and texture. The experiment conducted in this study reveals the classification model for the blooming flower with various accuracies.

There is a challenge in flower image classification due to huge similarities between each flower in term of colour, texture, shape and flower is a non rigid object which is deformable in various ways.

Currently, the flower contains more than 250,000 species around the world (Hong, Chen, Li and Zhang, 2004). Although images of flowers may be sufficient, classifying a flower still needs a guidebook at hand due to the level of expertise required.

The advance in digital and mobile technology make it easy to take picture of flowers, nevertheless it is difficult to identify them. Once the name of the flowers is known, more information about such a flower can be obtained on the web. However, the link between obtaining an image and acquiring its name is missing. Therefore, classifying an image of a flower becomes a necessity to establish the missing links for relevant information on the web. To accomplish the goal, the flower features and relevant classification approaches were explored in this study.

1.3 Objectives

The main aim of this study is to investigate the effect of Region of Interest (ROI), colour and texture on NN classification based on accuracy of Malaysian blooming flower images. Specifically, the objectives of this research are:

i. To identify the ROI of blooming flower images for classification modeling.

ii. Develop a classification model for Malaysian flowers based on flower's features.

iii. To compare the performance of classification model with respect to texture and colour of the flower images as well as the performance of the classifiers with respect to duplication of difficult pattern to learn

iv. Develop and evaluate classification model for Malaysian flowers based on flower's features.

1.4 Research Question

Based on the research objectives, the research question are as follows:

1. How to segment and choose ROI for higher flower classification result?
2. How to develop a theoretical framework for segmentation method of flower classification?
3. How to develop Malaysian flower classification modeling?
4. How to extract flower's features such as colour and texture from images?

1.5 Scope of the research

For this res`earch, Malaysian flower categorized based on book entitled *Bunga-bungaan Malaysia* by Ismail Saidin (1993). Some flowers are from the same types but having different colours. From each type of flower will be explored in the experiments.

1.6 Significance of the research

This research provides an initial study on Malaysian flower image classification and can be used by the developer of a search engine, content-based image retrieval, digital library or any image databases. In addition, the image provided when coupled with information for a specific course can be used as a supplementary material to e-learning of botany or horticulture courses.

1.7 Thesis Overview

The rest of this research is comprised in FIVE (5) chapters. Chapter ONE (1) is the introduction of this research which discusses about the background of the research, problem statements, objectives, scope, and significance of the research. In Chapter TWO (2), the literature reviews about image processing, classification, image classification, image features, AI classifiers and previous research regarding flower image classifications are presented. The methodology employed in this research described in Chapter THREE (3) meanwhile in Chapter FOUR (4) presents the experiment results and discussion. Finally, the conclusion and the recommendations as a result of this study are presented in Chapter FIVE (5).

CHAPTER TWO

LITERATURE REVIEW

In this chapter of literature review concerning on the issues and theories of this research were presented. The theories regarding this research such as image processing, classification, image classification and the classifiers were presented based on previous research that have been done by many researchers around the globe. This chapter also provides an overview of existing methods and algorithm used in this research.

2.1 Image processing

Image processing is a method of converting an analogue image into a digital format which involves several operations in order to improve the quality of images. It aims to carry out all the information contains in it, at the same time improve the visual quality to make it easier to be understandable by a human eye sight or any perception devices (Fonsesca, Namikawa & Castejon, 2010). According to Siraj, Yusof and Lam (2004), image processing is an approach to understand image contents and it gains an understanding of a scene from the image, implying an extraction and recognition of an image object automatically. Image processing tasks are processed by digital computers to perform the task quickly, flexibly and accurately (Rapp and Joyner, 1996).

There are two types of image processing; analog and digital image processing. Analog image processing process images via any 2D analog devices such as human eye, analogue camera also analogue film. Digital image processing process images by using any digital computer hardware (Gonzalez & Woods, 2008).

There are several steps involved in image processing namely; image acquisition, image segmentation, image representation, image extraction and images classification and recognition. Digital image captured in image acquisition by using digital image capturing devices. In image segmentation, digital images will be segmented based on needed criteria. Images will be converted into a data set when segmentation process will be done. The data produced will be classed accordingly based on their features. Lastly in image recognition, the data of the image will be assigned by label based on the information taken from the overall (Gonzalez & Woods, 2004).

Nowadays, image processing has been widely used in many fields such as Lisboa *et al.* (2003) used it in medical technology, mechanics engineering (Chung *et al.*, 2004), military (Buzasi, 2005) and remote sensing (Fonseca, 2009). As examples, Hu (2000) applied the image processing technique to display high quality and efficient transmission for tele-teaching application.

Friman *et al*. (2002) used image processing to extract a set of potential emphysematous regions of Computed Tomography (CT) image and used NN to distinguish true emphysema from artifacts. The processing steps involved image segmentation, intensity correction, image smoothing and thresholding. The combination of image processing and NN has been shown to yield an accurate method for detecting emphysema.

2.2 Feature Extraction in Image Processing

Image processing feature was applied to describe the attributes of objects (Sonka, Hlavac & Boyle, 1993). This features are often used to represent an image instead of using the original pixel values and able to transform the input data into more meaningful form.

Good features in an image help to determine the properties of category which can make a distinction between foreground (object) and background. As example, colour feature can be the best use to differentiate between strawberry and mangosteen, shape feature can be used to make a distinction among banana and pineapple meanwhile texture can be use to compare between watermelon and lychee skin (Duda, Hart and Stork, 2001).

Features can be computed over the entire image (global) or computed over the region of interest (local). Some of the example of global features is histogram, eigenspace, shape and texture (Deselaers, Keysers and Ney, 2007). The sensitivity of a global feature is high, due to the variation of images. According to Lisin *et al.*, (2005) and Ulusoy and Bishop, (2006) the position of object differs by lights condition and background clutter.

The information of content derived from an image can be categorized into three levels of image feature (Huang, 1998; Osadebey, 2006) as depicted in Table 2.1.

Table 2.1: Categories of image features

Level	Information
Low-Level	Include visual features such as colour, texture, shape, spatial information and motion (for video).
Middle-Level	Include the existence or arrangement of specific types of objects, roles, scenes and regions or spots.
High-Level	Include impressions, emotions and meaning associated with the combination of perceptual features. Examples include objects, semantic categories of event depicted in images or scenes with emotional or religious significance.

In image processing research, feature extraction (FE) process is a must. FE is a process to extract low-level image features that appear in a given image. Feature extraction can be the best-input representation in classification works.

The objective of this FE is to capture the essential characteristics of the images and makes the retrieval process based on image more realistic. Mathematically, a feature in an image can best describe as *"an n-dimensional vector, with its components computed by some image analysis"*, whereby the *'n'* components of a feature can be achieved from the combination of colour and texture feature (Tsang et al., 1998). The most commonly used features are colour, texture, shape and spatial data. There are two steps to extract feature to determine the ROI and to describe region (Noh et al., 2003). The most commonly used features are colour, texture, shape and spatial information. However this research was limited on low-level types which are colour and texture.

2.2.1 Colour

One of the most important and famous perceptual feature in image classification, indexing and CBIR systems is colour (Huang, 1998; Prasad et al., 2004). In definition, colour is a visual attribute which derived from the reflections of an emitted light. The emitted lights are formed in various visual spectrums which come in certain wavelength. When the wavelength has been absorbed into an object's surface, the wavelength will reflect back to any visual perception devices system, such as eyes and camera lenses. The wavelength received by eyes perception then called colour.

Colours are formed in various colour spaces (Uchikawa, 1999). According to Ford and Roberts (1998) colour space helps human and computer to describe and specifies colours, which are appearing in any object's surface. Most of colour space are composed in three or four dimension space (Aulia, 2005). For example, RGB colour spaces (Figure 2.1) are formed by three or four primary colours whereby each colour was assigned to their allocated pixels such as Red, Green and Blue; CMYK (Cyan, Magenta, Yellow and Black); YUV (a Luma and two Chrominance); HSV (Hue, Saturation and Luminance) and HSL (Hue, saturation and lightness). All these different colour space are applied in different purpose or application with different types of hardware or equipment.

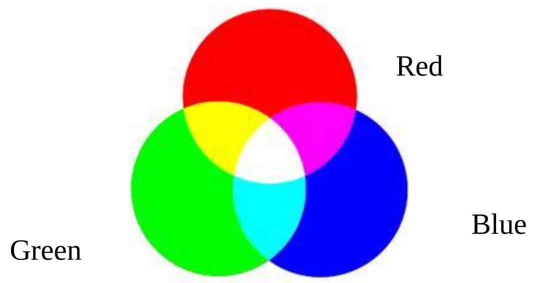


Figure 2.1: Red, Green and Blue (RGB) colour model

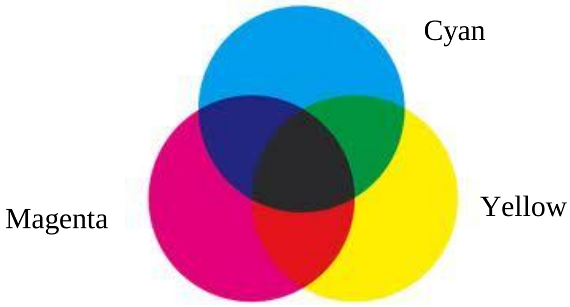


Figure 2.2: Cyan, Magenta, Yellow and Black (CMYK) colour model

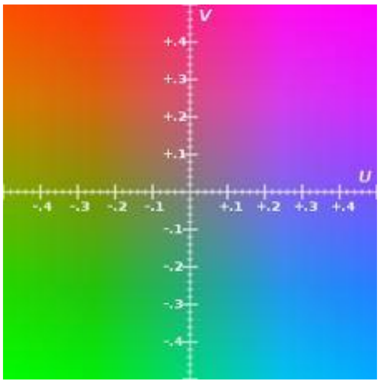


Figure 2.3: Luma and Chrominance (YUV) colour model

Common technique used to extract colour features of images is colour histogram as exhibited in Figure 2.4 (Rasheed *et al.*, 2008). It is a technique used to explain the global colours distribution in the images and each histogram bin characterizes colours in selected colour space like RGB or HSV (Novak & Shafer, 1994; Hafner *et al.*, 1995). Most of histogram distances have been used to define the similarity of two color histogram representations (Jeong, 2001).

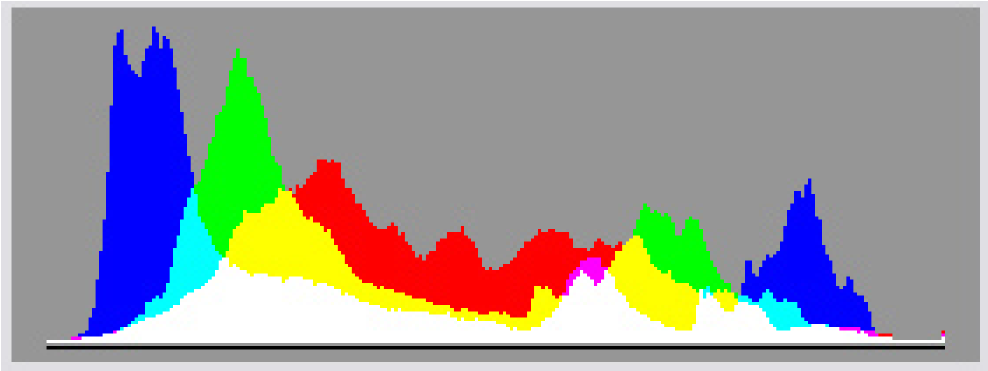


Figure 2.4: Example of Colour Histogram

Colour histogram was used by Dong and Yang (2002) to index the images and Principal Component Analysis (PCA) to represent an image as a vector in an orthogonal basis. A novel rough set based image classification method has been proposed by Singh (2009) which uses RGB colour histogram to distinguish images of different themes by applying the concept of discernibility. It can analyze RGB colour values to find optimum colour intervals to categorize different scene from different images.

Finding one or several visual features that are robust for all types of images or for all image analysis tasks are very difficult. Thus in practice, different sets of visual features may be used to represent different types of images. An efficient colour-based segmentation method has been carried out by Hong *et al.* (2004) which contains knowledge of the domain to extract flower regions from flower images. The colour histogram was used to extract the colour features of flower. The proposed method produced accurate flower regions and performed better than a method based on the global colour histogram.

This result was supported by Cho and Lim (2006). They conducted a research on a development of CBIR system to characterize flower images efficiently by extracting the flower's colour and shape attributes. The colour features were extracted from the HSV colour model (Hue, Saturation, and Luminance) where the hue and saturation were considered. The volumes of light intensity falling onto the image are not necessary and would not affect the clustering. The obtained results showed that clustering flower image by colour and shape produced better retrieval results rather than individual clustering.

A method for image retrieval by colour and shape similarity matching using metric indexing was presented by Ruxanda (2006). Colour features were extracted into the HSV colour with 101-bin histogram and the shape features extracted using Fourier descriptors. The combined colour and shape features vectors were indexed into an M-tree. Experimental results confirm the efficiency and the correctness of the proposed method.

2.2.2 Texture

Another important characteristic of feature extraction is texture. Texture has been used to classify and recognize objects surfaces (Ion *et al.,* 2008). It is an important visual attribute in computer vision and image processing field due to most objects encountered in real life have textured surfaces (Bhattacharya, Chaudhuri & Parui, 1997).

Texture is a pattern with regularity (Palm, 2004). It has been identified as the uniformity, density, coarseness, roughness, regularity, intensity, directionality of discrete tonal features and spatial relationships (Haralick and Shapiro, 1991). Generally, pattern consists of sub-patterns and connected to the pixel distribution in a certain region and characteristics of the image object such as size, brightness and colour (Backesa *et al.*, 2009).

The pioneer of texture analysis is Haralick *et al.* (1973). They measure co-occurrence matrices from 14 second-order statistics. Among the descriptors used to represent the image are Contrast, Energy, Dissimilarity, Entropy, Correlation and Homogeneity.

Laws (1980) filtered the image using 5 x 5 kernels and then applied a non-linear moving-window averaging operation to compute the texture energy in a neighborhood. These 5 x 5 kernels are constructed using outer products of five 1-D kernels, which he called level, edge, spot, wave and ripple, each of length 5. These texture energy values with a linear discriminator to classify pixels into different texture classes.

An investigation on flower classification performance by combining shape, colour and texture has been done by Nilsback and Zisserman (2006). The experiment has done with three (3) different combinations which are a combination of shape and texture only, shape and colour only and combining all features. The result shows that the best performance achieved by combining the three features.

A study performed by Aulia (2005) investigates the accuracy of the result returned by CBIR based on colour and texture features. The region-based segmentation was used to extract the object from its background. The performance from the experiments shows that region-based segmentation provides better accuracy in image segmentation and classification.

Colour and textural information in extremely high resolution satellite image classification have been compared by Vansteenkiste *et al.* (2004). The investigation involved classification by colour features only, and combination of colour texture features. Colour features performs well in easy classification tasks, meanwhile colour texture features produced a very high classification rates.

The literature on image classification problem indicates that shape, colour and texture are the most important features to be considered for feature extraction. Among the three features, shape is the most difficult to deal with in this study. Initial attempt has been carried out to use shape as one of the features. Thus, the study will be focused on Vansteenkiste *et al*. (2004) and Aulia (2005) methods for feature extraction.

2.3 Classification

Classification is one of the most active research and application areas of data mining. It is most frequently encountered decision making tasks of human activity (Guoqiang Peter & Zhang, 2000). In Longman Dictionary Online (2009) classification is defined as *"a process in which you put something into the group or class it belongs to, or group that it belongs to"* meanwhile Qi and Davidson (2009) describes classification as*"place any objects, ideas, or information into groups according to their characteristics by finding similarity of their traits or characters*". The main objective of classification is to predict categorical class labels for new samples (Dehkordi & Shenassa, 2006).

There are two main classification schemes; *Unsupervised* and *Supervised* Classification. *Unsupervised* Classification performs clusters pixels and was formed in a data set based only on their statistics without using previous knowledge about the spectral classes present in the image (Riviera, 2009).

Meanwhile *Supervised* classification is the process of using samples of known identity or training data to classify pixels of unknown identity. The training data are used to train the classifier which is tested with testing samples to evaluate the accuracy of the classifier.

Image classification has the ability to allocate images in various predefined categories automatically. However, image classification becomes a problem when the multimedia elements and computer vision are involved. The main difficulties come from the complexity of background images, occluding objects, the semantic gap between low-level visual features and high-level semantic concepts, and so on. These difficulties of heavy computational burden have limited the practical application of image classification in many scenarios, such as web image search, video surveillance, and medical image system (Wu *et al*., 2007)

There are many researches has been done in the general field of image classification. They are on Content-Based Image Retrieval (CBIR), medical (Antani *et al*., 2003; Lau & Ozawa, 2003), flower (Hong et al., 2003; Nilsback & Zisserman, 2006; Tseng *et al*., 2005; Hong *et al.*, 2004) and trademark (Peng & Chen, 1997; Leung & Chen, 2002). Currently, image content-based queries are becoming popular in image databases rather than with the textual features or keywords (Wang *et al*., 2003). Some researchers have conducted research on representing image contents with visual features. Visual features provide the content description of images that can be addressed by low-level features such as colour, texture, shape, or spatial information (Wang *et al*., 2002, 2004; Dong & Yang, 2002; Ruxanda, 2006).

An image classification method by using colour, texture and regions has been proposed by Cheng and Chen (2003). In this research image-based features related to colour and local edge patterns has been used to reduce irrelevant database images. The image content were organized in a two-level tree, where the root node at the top level represents the whole image and the child nodes at the bottom level represent the homogeneous regions of the image.

Image processing is a very important way in sensing environment (Ni *et al*., 2008). Image processing is a serial of sequence operation on image to improve the imperfections or quality of images. 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.

This is not an easy process since it depends on the type of equipment that generates the images and the characteristics. In the case of flower classification, image processing is a crucial step for computer-aided plant species identification (Hong et al., 2003).

2.4 Artificial Intelligence Classifiers for Image Classification

There are quite few numbers of classifiers that can be used in image classification using Artificial Intelligence technique. In this research, three classifiers were used to classify the flower image. The description of Neural Networks, Logistic Regression and Decision Tree is explained below.

2.4.1 Artificial Neural Networks

Artificial neural network (ANN) is at the heart of an emerging technique, which many academicians and practitioners are using very productively due to its high performance in addressing complex problems. ANN can be used as a support tools in image processing and its preserve their function as non-parametric classifiers, non-linear regression operators, supervised or unsupervised feature extractors (Cristea, 2009).

As a pattern of processing information, ANN was inspired by the way of biological nervous systems and its mimicking human brain processing all the information (Stergiou and Siganous, 1996). The structure of ANN was composed by a large number of highly interconnected processing between elements neurons (sets of input and output) to solve the specific problems (Angelini et al.,2008). ANNs carry out parallel processing of information and adapt to the new data, which enables them to solve problems which previously it was described as difficult (Lamamra, Belarbi and Mokhtari, 2009). These neurons are reacting to each other by an equation. It is defined by a choice of a weight matrix and activation function (Ralph, 2009).

In general, ANN is a structured system that receives an input, does the data processing and endow with an output. The ANNs consists of a series of processing units which are collectively connected like the synapses in the human brain. The network consisting three types of neutron's layers; input layer, hidden layers and output layer as exhibited in Figure 2.5 (Lamara, Belarbi and Mokhtari, 2006).

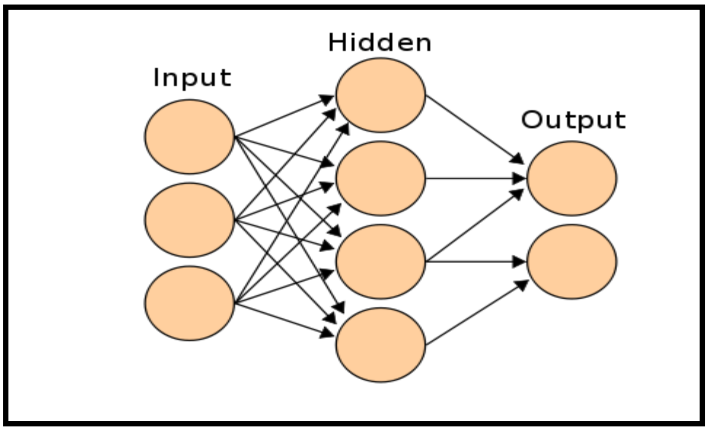


Figure 2.5: Artificial Neural Networks

Input layer functions to feed raw data. Raw data can be anything in any types of form. Once inputs are fed to the ANN and a target response was set at the output, an error was composed of the difference of the desired response and the real system output. After that, the data will be sent to the hidden layer. There are two processes happen in this hidden layer which are weight summation and activation function. These two functions will be the benchmark of the output value. Then, the estimated property values are being produce in the output layer.

ANNs has been applied widely to almost domain within Artificial Intelligence sector (Jordan & Bishop, 1996) such as business (Tang & Chi, 2005), engineering (Haykin, 2008), telecommunication (Boloni & Turgut, 2005) and education (Guo, 2009). As an addition, NN also have been applied in the medical field, such as the application that used to prognosis after surgery for breast cancer (Lisboa et al., 2008), application to predict the dysfunctions of the lower urinary area (Gil et al., 2007) and application to diagnose the cardiovascular disease (Ha *et al.*,2007)

ANN classification algorithm can be used to extract patterns and detect trends that are too complex to be noticed by either humans or computers. The ANN classifier is a non-parametric method and has the capacity of self-learning and high robust (Mao *et al*., 2002). Due to ANN capabilities to classify patterns, ANNs offer an appealing solution for image processing from low level up to high level image features (Cristea, 2009)

ANN works with two phases which are training phase and testing phase. The objective in the training phase is to set the most suitable weight for the specified ANN. This can be achieved by providing input to the sample into ANN for weights modification. After the training phase, ANN takes the query input and then produces output results according to the weights (Xing, 2007).

In ANN there are two types of networks which connect to neurons; feed forward networks and dynamic networks (Lamamra, Belarbi and Mokhtari, 2006). The technique used in this research is a Multi-Layer Perceptrons (MLP) network which is a feed forward networks.

2.4.2 Applications of ANN

ANN is best at patterns classification and recognition. Numerous research has been done throughout this decade based using NN. Some of the researches are pattern classification (Chaudhuri and Bhattacharya, 2000; Orlov *et al.*, 2006; Deepthi et al., 2007), text characters recognition (Sural & Das, 2001), emotion recognition (Kee, 2006), fingerprints classification (Umammageswari *et al.*, 2007), plants recognition (Wu *et al.*, 2007), shape recognition (Rajini and Reddy, 2010), handwritten word recognition (Huang, 2008), colour recognition (Shinmoto *et al.*, 2003) and items recognition through colour and texture (Lizier *et al.*, 2009)

ANN has been proved as a very good tool in making prediction or forecasting such as in industrial process control (Lu and Tsai, 2007), target marketing (Levin and Zhavi, 2005), data validation (Yu, Wang and Lai, 2006), bankruptcy prediction (Chauhan, Ravi and Chandra, 2009), sales forecasting (Yu *et al.*, 2010) and stock market prediction (Zhu et al., 2008).

2.4.3 Multilayer Perceptron (MLP)

MLP networks model is among the most important model in NN, others than Kohonen self-organizing network (Kohonen, 1982) and Hopfield Network (Hopfield, 1982). MLP network tool has been used to supervise NN technique and used as a prediction tool. The network constructs a model based on examples of data with known outputs. Mainly MLPs are used for analyzing data in the real world problems (Pardo & Sberveglieri, 2002).

MLP also known as multi-layer feed-forward NN (Lek & Guegan, 1999; Pukrittayakamee, 2009) which it has the capability in modeling complex relationships between variables. Feed-forward NN refers each neuron receives signals from the preceding lay's neurons and the information circulates in just one direction (Lamamra, Belarbi & Mokhtari, 2006). It allows prediction of an output object for a given input object.

Based on the theory above, the architecture of the MLP are arranged in successive layers, and information flows unidirectional, from the input layer to the output layer, through the hidden layers (Lek & Guegan, 1999). The MLP architecture consists of the connectivity of an input layer, hidden layer and output layer. Figure 2.6 shows the architecture of Multilayer Perceptrons.

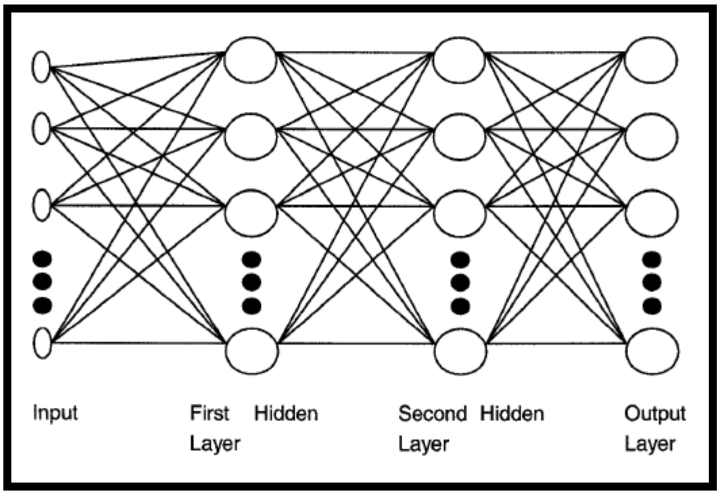


Figure 2.6: Architecture of Multilayer Perceptrons

2.4.4 MLP in Pattern Recognition

MLP has been enormously used in the area of pattern recognition in the last 20 years (Gori, 1998). Currently researches on image analysis and classification based on MLP are widely discovered. Das, Manmatha and Riseman (1998) developed an automatic iterative segmentation algorithm to solve the problem of indexing images of flowers for searching a flower patents database by colour.

An automatic iterative segmentation algorithm with knowledge-driven feedback was used to isolate a flower region from the background. Natural language colour classification and retrieval system was proposed to utilize domain knowledge encoded into rules for automatic segmentation of the ROI from the background. The results obtained from 50 queries of different types. The research shows that the retrieved flowers matched up with their perception of the colour name used in the query or the colour of the example flower.

A demonstration to figure out the advantages of using Bayesian MLP neural networks for image analysis was done by Vehtari and Lampinen (2000). The Bayesian approach provides a consistent way to do inference by combining the evidence from the data to prior knowledge from the problem. Bayesian methods for MLPs were reviewed in two case studies. In the first case, MLPs were used to solve the inverse problem in electrical impedance tomography. Bayesian MLP provided consistently better results than other methods. In the second case, they tried to locate trunks of trees in the forest. At the end, they concluded Bayesian approach gives the predictive distributions for outputs, which can be used to estimate reliability of the predictions.

A back propagation ANN model was developed by Yang *et al.* (2000) that to distinguish young corn plants from weeds. It was assumed that the ANN model could develop the ability to use other information by using only the colour indices associated with image pixels as inputs. The images were taken and then being cropped to 100x100 pixel images depicting only one plant, either a corn plant or weeds. 40 images of corn and 40 of weeds were used in their study. The ability of the ANNs to discriminate weeds from corn was then tested on 20 other images. 80 images of corn plants and weeds were used for training purposes. The success rate for NN in classifying corn plants was as high as 100% and the highest success rate for weed recognition was 80%. This was considered as successful, due to the limited amount of training data and the computer hardware limitations.

A research on implementing MLP to classify multispectral satellite images were carried out by Ventakesh and Raja (2003). They developed an algorithm for single-band data classification. What they did was, initially they segmented one set of multispectral satellite images using the K-means clustering algorithm and use the output of the algorithm were used for training and testing the classification's accuracy. The MLP gives a higher classification accuracy compared to the conventional Gaussian maximum-likelihood classier.

Cho and Lim (2006) proposed a system to characterize flower images that supported efficient content based image retrieval (CBIR). The image processing techniques were used to extract colour and shape attribute of the flower. Then, a novel Virus Infection Clustering (VIC) algorithm is proposed for clustering the database and in the same time to enhance the searching efficiency. The results showed that clustering by the colour and shape features yields better retrieval results than clustering by only either colour or shape individually.

Ros, Laurent and Lefebvre (2006) presented neural network architecture which is known as natural image classification for local images features. The image content is described by a distribution of local prototype features obtained by projecting local signatures on a self-organizing map. The local signatures describe singularities around interest points detected by a wavelet-based salient point's detector. The classification step based on MLP shown to be efficient. This has produced high classification rates at the same time consumes small computing times.

An image rating system that rates images according to the unsafe to the minors was proposed by Kim, Lee and Yoon (2006). This system classifies images into one of multiple classes to distinguish adult images and non-adult images. NN was employed for the classification model. The system developed in this research consists of four modules that have a hierarchical structure. Each module learns corresponding classification task according to the feature values extracted from MPEG-7 descriptors. The selected MPEG-7 descriptor was used as inputs of the network. It classifies the images into multiple classes (5 classes). The results show that the system rates images into multiple classes with the rate of over 70%.

Hierarchical medical image classification method using a perfect set of various shape and texture features recommended by Pourghassem and Ghassemian (2008). A tessellation-based spectral feature as well as directional histogram has been proposed. In each level of the hierarchical classifier, using new merging scheme and multilayer perceptrons (MLP) classifiers, homogenous classes are created from overlapping classes in the database. This procedure is progressive to achieve more classes. The proposed algorithm were evaluated on a database consisting of 9100 medical X-ray images of 40 classes. It provides accuracy rate of 91% on 25 merged classes in the first level. With the correct class is considered within the best three matches, the accuracy value was increased to 98%.

MLP also was applied to evaluate Alzheimer's disease (Santos *et al.*, 2008). Image analysis and classification of synthetic multispectral images was composed by diffusion-weighted magnetic resonance (MR) cerebral images to evaluate the cerebrospinal fluid area and its correlation with the advance of Alzheimer's disease. Result shows that the MLP method is proven good as the arithmetic average among the rates obtained by the other methods and indicates that multispectral classification of diffusion-weighted MR images furnish a good alternative to the analysis of the Apparent Diffusion Coefficients (ADC) map.

2.5 Logistic Regression

Logistic regression (LR) is a variation of ordinary regression. LR is used when the dependent covariate is a dichotomous and the independent covariate are continuous, categorical, or both. The goal of LR is to find the best fitting and reasonable model to describe the relationship between dependent and independent covariates.

LR allows researchers to forecast the existence or non-existence of an attribute derived from values of set of variables prediction. An LR model specifies that an appropriate function of the fitted probability of the event is a linear function of the observed values of the available explanatory variables.

It is an important technique for analyzing and predicting data with categorical attributes in order to do modeling or predicting categorical data and frequently used in pattern recognition and classification tasks (Mojsilovic, 2005). LR is a machine of statistics and is associated to methods used in Machine Learning (Briggs *et al.*,2010), Perceptron and Support Vector Machine (Minka, 2007).

In real-world data mining purposes, the difficulty of not having the complete set of data in advance is always happening. It is often demanded to recover LR models of a large data set with access, not for the raw data, but also for sketchy information of divided chunks of the data set (Xi, Lin & Chen, 2009).

Mathematically, LR was written as

$$p(y = \pm|\mathbf{x}, \mathbf{w}) = \sigma(y\mathbf{w}^{\mathbf{T}}\mathbf{x}) = \frac{1}{1 + \exp(-y\mathbf{w}^{\mathbf{T}}\mathrm{x})}$$

(Cox and Snell, 1970)(2.1)

LR has been widely applied in many types of the field especially in image processing. The major area of implementing LR in image processing task are in medical, remote sensing, content-based image retrieval and biometric. Doppler Parameter classification system was developed by Ergun *et al*. (2004) to classify the carotid artery stenosis of patient with diabetes. The parameters of blood velocities were gained from a total of 168 diabetic patients. Eight input were identified and then be evaluated by using LR algorithm. The result shows that by overall, LR able to classify correctly up to 67.7%.

Multi Scale image analysis was developed by Desok Kim *et al.* (2010) to improve the trabecular bone thickness detection. During the healing period, thickness of trabecular bones always got changes. 50 set radiographs' images of trabecular bone losses were selected and it was categorized into two cases; Success and Failed. Each of case contains 25 sets of images and model’s prediction for the successful treatment. The case was tested by LR. It produced results of successful accuracy up to 96% Successful cases and 18.6% for failed cases.

Remote sensing employs LR to simulate and analyze certain area from taken satellite images. A spatial autocorrelation modeling of land use types was investigated by Wu et al., (2009) to derive a better spatial land-use based on the terrain features and infrastructure conditions. They proposed an approach that able to predict the probability models of urban land-use pattern by using auto logistic regression paired with Geographical Information System (GIS). 12 variables were chosen to represent the geophysical and socioeconomic conditions. The auto logistic regression model showed better goodness of fitting and higher accuracy of fitting.

Qin *et al.* (2005) used LR as a tool to predict the risk factors of Salmonella Typhimurium bacteria infections. The classification of Salmonella Typhimurium infections has used LR for training data is 78.9% and test data is 77.3%.

In predicting risk of breast cancer, the mammography logistic regression model demonstrated shows high discrimination accuracy and has the potential to be used as decision support tools once they are integrated into clinical practice (Ayer *et al*., 2009).

LR also has been applied in face recognition system. Givens *et al.* (2004) have done a research on face recognition and comparing the between LR and ANOVA statistical method in order to observe how the subject factors of human such as age, gender, skin type, make up, bangs and others can affect the difficulty of three main algorithms to recognize face recognition classes. Three algorithms were tested are Principal Component Analysis (PCA), Interpersonal Image Difference Classifier (IIDC) and Elastic Bunch Graph Matching (EBGM). 2144 images were used in this research and LR was employed to relate subject co-variation in order to rank the similarity of input and target images. Based on the result shows whatever algorithm were tested, both ANOVA and LR give the result that the older subject were easier to recognize compared to younger subject.

2.6 Decision Tree

Decision tree (DT) is a technique to predict target values from observations. It is one of decision support tool which is constructed to help make a better decision making for hard and difficult problems solving issue. The main idea of DT is modeling for the possible consequences of outcomes (Pao, 1989).

Decisions trees are formed by analyze a set of training examples for known classes and applied to categorize previously hidden examples. If trained on high-quality data, decision trees can create highly accurate predictions (Caruana and Mizil, 2003).

A simple analogy to depicted DT has been made by Clark (2009). According to him, DT can be depicted as people who have to carry out a decision whether he should wear a coat or not in certain weather. If the weather is cold, so a he need to put a coat on him. If not, so do not put coat. The overall image of a DT is exhibited in Figure 2.7.

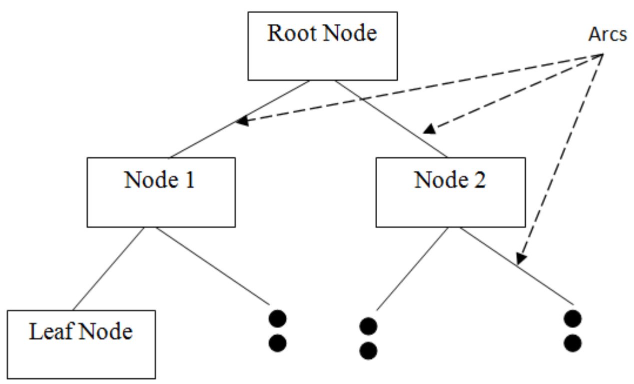


Figure 2.7: Decision Tree Diagram

A DT consist three types of different nodes that carry a set of records from the original data. The nodes are decision nodes, chance node, and end nodes. Decision nodes stand for all of the rows in the data. Chance node is a point where the decision maker learns about the amount of events meanwhile the end nodes are the final result of a combination of decisions and events.

2.6.1 Decision Tree in Image Processing and Image Classification

The research on classification of hyper spectral data of corn images was done by Yang *et al.* (2003) by employing DT to classify corn images. The corn image was categorized into 5 different image classes based on different stages; tillage practice, residue level, cropping practices and combination of tillage with residue. The result shows that DT classifies very good in distinguishing tillage practice with 89% of accuracy compare to logistic regression (78%).

A DTR was proposed the research of Min Xu *et al.* (2005) to establish class proportions within a pixel from remote sensing data. The purpose was to produce soft classification in forecasting the class proportion pixels for particular images. The results show that DTR score accuracy of 74.45% compared to Maximum Likelihood Classifier (55.25%) and Fuzzy c-Means (54.40%). In addition, they conclude that DT is very good tool in order to discover the hard and complex relationships between features and classes. DT is capable to recognize the combination of features between any two classes.

DTR also has been used in Ginoris *et al.* (2006) research as one of the classifiers in analyzing and recognizing the image of protozoa and metazoans which are found in the wastewater treatment plants activated sludge. The overall recognition performance of using DT is 60.9%.

Decision Tree Induction (ID3) was employed by Patel, Mehta, and Pradhan (2009) while developing a robust watermarking technique. ID3 make the decision for embedding watermark processes. Decision tree identified the suitability of image block watermarking. The results show Decision tree correctly which classifies the instance up to 87.7%.

A facial expression recognition technique was proposed by Xiao, Ma and Khorassani (2006). The purpose was to recognize the anger, sadness, happy and surprise expression. In this research, a number of 120 images of front view face were using with allocation of 60 men and 60 women. DT was used to perform the recognition process whereby DT was combined with NN based nodes chosen to divide the facial expressions systematically. The result shows that recognition is 97.5%.

2.7 Previous researches on flower image classification

NN has been used by flower image researchers in order to understand the flower image features. Tseng, Wang and Su (2005) and Nilsback and Zisserman (2006) combined colour, texture, and shape feature using nearest neighbor and multilevel association rules respectively classified flower images while Hong, Chen and Wung (2003) include spatial information feature using colour clustering and domain knowledge. Miao, Gandelin and Yuan, (2006) used the colour feature as a target to overcome the problem of indexing flowers images in flower patents for database searching system.

Colour and shape attributes have been used by Cho and Lim (2006), to develop a (CBIR) system to differentiate flower images. They proposed a novel Virus Infection Clustering (VIC) to cluster the image database in an attempt to enhance the retrieval process.

The results point out that both colour and shape features produce better retrieval results than clustering by only either colour or shape separately.

The characteristic of shape and colour that was extracted from the flower images was used by Makiko *et al.* (2002) in Image Retrieval System of Flowers for Mobile Computing (COSMOS). The result of their experiment shows that the percentage of getting the target image is about 92% in just 90 seconds.

An investigation on the numbers of flower's feature combination has been carried out by Nilsback and Zisserman (2006) in order to improve classification performance on a large dataset of similar classes. A dataset was computed from four different features by using 103 classes of flower. The main concerns were in shape, texture, colour and petal's spatial distribution. The multiple kernel frameworks with a Support Vector Machine (SVM) classifier were applied to combine all features stated above. The results show that learning is the optimal combination of core elements are improving. The best performance for a single feature is 55% to 73%.

Nakamura *et al.*(2001) constructed a flower classification database which contains flower image and text data. Every flower images stored in database was indexed by using colour and shape features whereby the accuracy of flower classification produced is 62%. This technique was enhanced by Okomura *et al*. (2004) by implementing new parameter to every pixel comprised in the image as addition to the colour information of that pixel.The values ofeach parameter was trained by NN to classify colours that are regular for flowers. The result shows that technique used in this research improve the classification rate up to 87.8% wihich is better than Nakamura et. al (2001).

A summary of research on flower images with features used to represent the dataset is exhibit in Table 2.2.

Table 2.2: The selected features in previous flower image classification.

Authors (Year)	**Selected features**	**Method**	**Performance**
Tseng *et al.* (2005)	Colour, texture, shape	Multilevel Asscociatiion Rules	Classification accuracy up to 90% by raising minimum support to 0.05.
Nilsback&Zisserman (2006)	Colour, texture, shape	SIFT Descriptor to classify shape features, k-means clustering for colour and MR8 Filter for texture.	Accuracy colour classification: 73.7%; shape feature 71.8%
Kim *et al.*(2008)	Contour	Zero Crossing Rate to extract contour feature	Recognition accuracy up to 95%
Suppaiboonvong (2009)	Colour, shape	Minimum Distance	99.12 % accuracy rate for the training set and 100 % for the non-training set.
Pornpanomchai *et al.* (2011)	Colour, Shape	Euclidean Distance	Flower recognition accuray 74%

2.8 Summary

From the literature, there are three classifiers which have been used in many images processing by the flower image classification researches. There are Logistic Regression, Neural Networks and Decision Three. Among of them, NN is widely used in image classification compared to other two. MLP network it has been proven that this method has highly successful in training of multilayered neural network (Islam, 2010). Due to this reason, this research will apply MLP with back propagation algorithm for training and testing purposes.

CHAPTER THREE
METHODOLOGY

This chapter discusses in more details on the methodology and system design for modeling Malaysia's flower image classification. This research is divided into two phases which are image processing and classification modeling which involves training and testing activities. Initially A total of1800flowerimageswere taken around the UUM, Changlun and Jitra.

3.1 Introduction

This research focuses on finding ways to develop a classification model for Malaysia’s flowers classification based on colour and texture features found in the flower image. All images of flowers that have been recorded together with its features such as colour and texture are extracted and stored in the database.

3.2 Methodology

A number of activities was carried out in certain phases in which two methodologies are involved namely Methodology for Image Processing and methodology for Classification modeling. In the image processing phase, the methodology used was adapted from Siraj *et al*. (2006) whereby the process undergo several sub-processes in image processing such as image filtering, image segmentation, image detection and image extraction while for the classification phase, the methodology adapted by Kaastra and Boyd (1996) was applied. This methodology involve straining and testing processes using AI classifiers such as Neural Networks, Logistic Regression and

Decision Tree. Figure3.1 shows theoretical framework used in this research which involves activities such as:

a) Image Capturing
b) Image Processing
c) Training and Testing
d) Classification

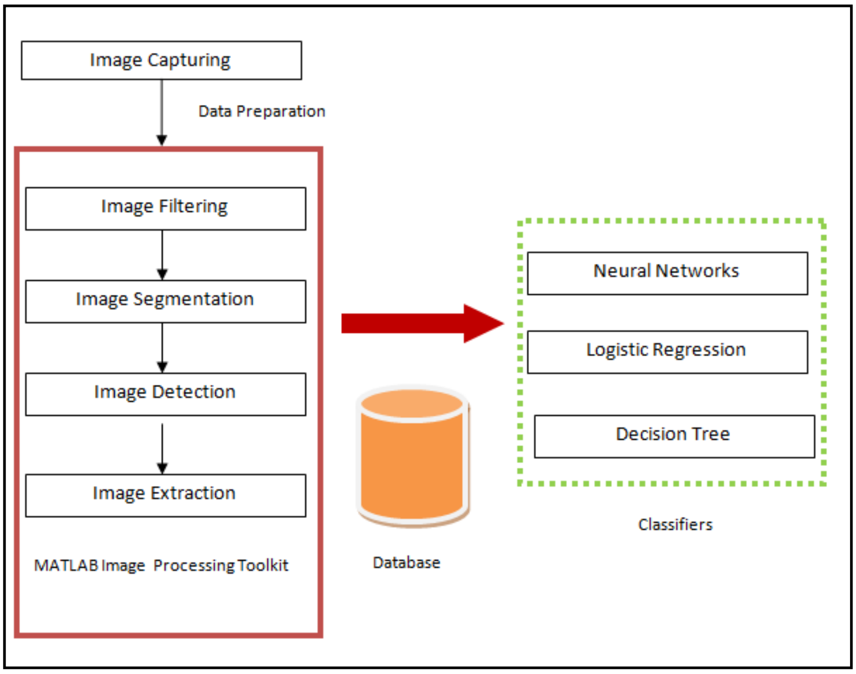


Figure 3.1: Theoretical framework of the research(Adapted from Siraj et al.,2006; Kaastra & Boyd, 1996)

In conjunction with the theoretical framework, the research framework for this study is outlined in Figure 3.2 which comprises of Phase 1 to Phase 6. Since this study involves experimental type of research, the CRISP Data Mining phases are outlined and matched with the research framework. The phases involved are stated in Table 3.1 and a detail of these phases is shown in Figure 3.2.

Table 3.1: Research Framework

Phase	Description
Phase 1	Business Understanding
Phase 2	Data Understanding
Phase 3	Data Preparation
Phase 4	Modeling
Phase 5	Evaluation
Phase 6	Deployment

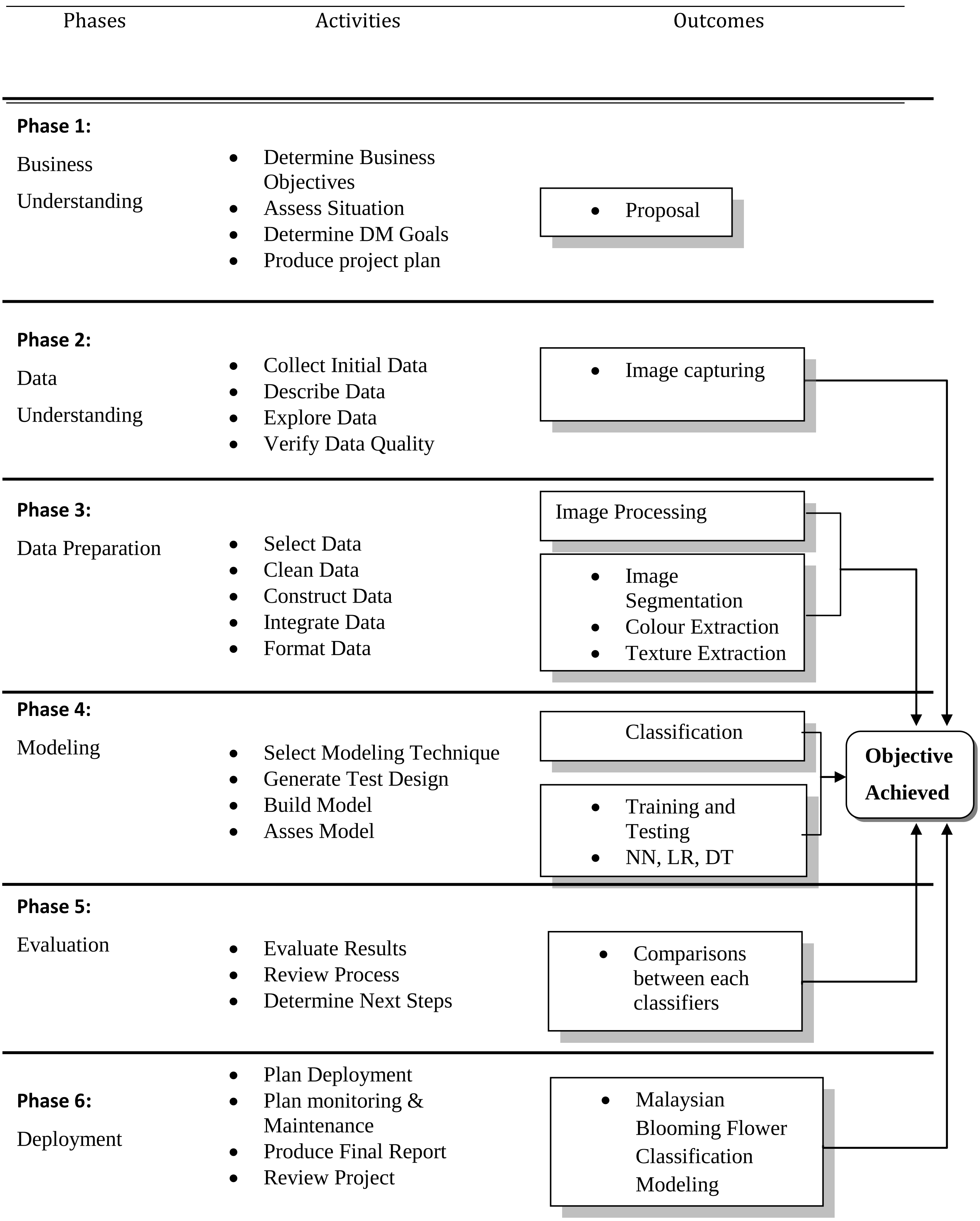


Figure 3.2: Theoretical Framework

3.2.1 Phase 1: Business Understanding

This is the first phase which is focusing on the research objectives, transforms it into a data mining problem description and a groundwork preparation was designed to complete the objectives. At the end of this phase, a proposal was produced.

3.2.2 Phase 2: Data Understanding

This phase starts with an initial data collection in order to get familiar with the data, discover data quality problems, find out first insights into the data and identify interesting subsets to form hypotheses for hidden information

In this phase, flower images were captured in image capturing activity. The capturing technique was adapted from Saitoh, Aoki and Kaneko(2004). Based on this technique, flower as the target object being focused on the center of camera display with defocused background. A Panasonic Lumix DMC-F2 digital camera was used to capture flower's image into the system. The display sensor was set to 1024x768 with 5.0 Megapixels of resolution. Images are recorded and saved in JPEG (Joint Picture Expert Group) format.

Each image that has been recorded are taken without using camera's flashlight due to the illumination emitted from flash light can disrupt the structure of colour and texture of object and this will lead to inaccurate readings (Warhade *et al.,* 2008). Figure 3.3 shows the samples of flower image taken.

Figure 3.3: Samples of flower image taken

Surrounding environment also can affected the image quality whereby is intensity and direct illumination from sun varies with time. Intensity of sunlight's volume emitted during morning time is not as same as noon .Therefore, the time of each recording is set uniform every day, which is between 10 am until 11 am daily.

Overall, a total of1820pieces of images from30different types of flowers varies in colours and texture was recorded where 60images were taken for each type of flower. All recorded images were labeled and stored in a folder before the next process is the process of image processing carried out.

3.2.3 Phase 3: Data Preparation

Data preparation phase covers all activities to create the final dataset from the initial raw data. Data preparation tasks were performed in several processes. Main outcome in this data preparation phase is Image Processing. Several activities were involved in image processing such as image filtering, image segmentation, region detection, and feature extraction. The whole process is done completely in by using an engineering software namely MATLAB r2008b.

MATLAB r2008b is software that has a high ability in handling the work related to technical computing. To carry out the process of image processing, a special tool namely Matlab Image Processing Toolbox is required. By using this toolbox, image intensity are stored in a single matrix. This matrix stores data in matrix form [0, 1] with a range of data [0, 255]. Each element in this matrix represent the range of intensity where 0 representing black and 255 representing the intensity of a white. The explanation of each step described in the next subsection.

Image Filtering

The main objective of image filtering is to improve the image quality compared to original image and can best way for specific purposes. It is a technique applied to remove noises present in an image. If noises present in an image, it will be lead to low quality reading (Saha & Udupa, 2001). According to Seitz and Dyer (1997) three types of image noises has been found namely Salt and pepper noise(random occurrences of both black and white pixels), Impulse noise (random occurrences of white pixels only) and Gaussian noise(dissimilarities of intensity derived from a Gaussian normal allocation) .

In any images, noises were usually appears during the image recording process such as wrong exposure and ISO setting on the camera. Thus to remove any noises in appears in images captured before, the adaptive filtering algorithm called *"wiener2"* was implemented Lim (1990). The equation of "wiener2" algorithm is shown in Eqn. 2.2 and 2.3.

$$\mu = \frac{1}{NM} \sum_{n_1, n_{2 \in n}} a(n_1, n_2)$$

and

$$\sigma^2 = \frac{1}{NM} \sum_{n_1, n_{2 \in n}} a^2(n_1, n_2) - \mu^2 \quad (2.2)$$

where

n : the N x M local neighborhood for each pixel appears in image.

`wiener2` function creates a pixel wise filter using algorithm in Eqn. 2.3.

$$b(n_1 n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(a(n_1, n_2) - \mu) \quad (2.3)$$

where v^2 is noise.

Image Segmentation

Image Segmentation is a process to Identify Region of Interest (ROI) of any objects. Main objective of image segmentation is to create an image representation of the object selected into an easier an understandable form for analyzing purposes by following to certain rules (Chakraborty *et al.*,1996; Sural *et al.*,2002 and Sjoberg, 2006). During image capturing activities, unnecessary background images such as leaves and soil were captured too. Since just flower images is needed, therefore background image have to eliminate.

To done this, colour segmentation was used to eliminate those unwanted background by dividing flower and the background (Liu *et al*. 2005).

To perform colour segmentation, each image must be transform into a binary form. In order to create binary form image, images must undergo an RGB to HSV colour space conversion and then that HSV image being converted to grayscale form as shown in Figure 3.4.

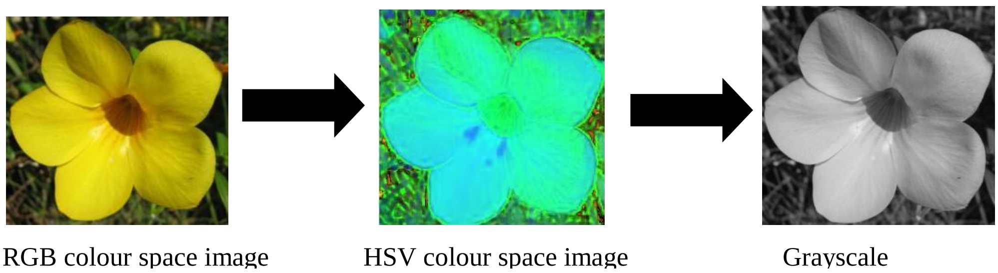


Figure 3.4: RGB colour space to HSV colour space to gayscale colour space

Based on grayscale image, the next step is a process called *Image Thresholding*. This step capture threshold of the global image by choosing the threshold which reduces the intra-class variance of the black and white pixels. The value of the threshold level has to be identified to perform this process. The Otsu's (1979) method was applied at this stage in to compute global threshold that can later be employed to convert image’s intensity to a binary image. The Otsu’s equation is shown in Eqn. 2.4.

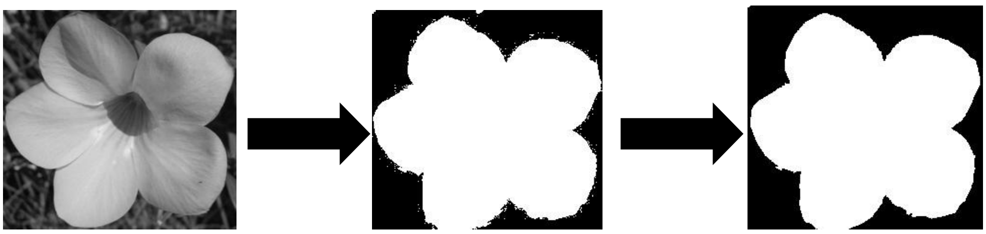
$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \tag{2.4}$$

Where

ω_i : Probabilities of the two classes separated by a threshold (t)

σ_i^2 : Classes variances.

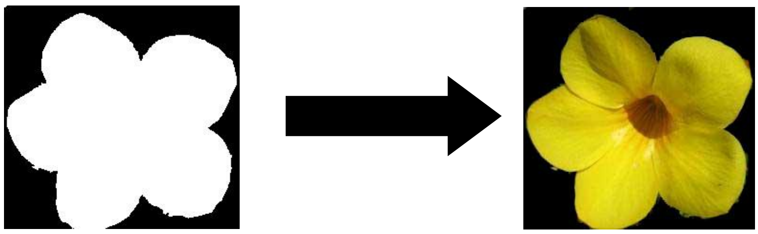
In image thresholding, the flower's ROI has been detected in white space. The obtained ROI generally got some noises especially noises surrounding the boundary. The morphology process was applied to overcome this problem by remove noises that appear surrounding binary image. There are few morphology techniques taken out in this phase namely '*opening morphology'* (to remove noise), '*closing morphology'* (smoothing boundary of the object) and '*cleaning morphology'* (cleaning flower's boundary for better segmentation outcome). The results for image thresholding and image morphology are exhibited in Figure 3.5.



Grayscale image Image Thresholding Morphing

Figure 3.5: Image Thresholding and Image morphology

The last process of this phase is to bring back flower's image that has been hide from view in the thresholding process. For this purpose, the *imfill* function was applied to produce flowers without the background image as illustrated in Figure 3.6. The image reconvert to RGB colour space for colour and texture extraction purposes.



Binary Image   Flower image without background

Figure 3.6: Flower image without background

Region Detection

This step will find the ROI of objects using *bwboundaries* method. This step is vital for calculating the colour and texture features.

Feature Extraction

Feature extraction is a process to locate an outstanding part, pixels, quality or characteristic involves in an image (Lester, 1998). The main objectives of feature extraction are to taken out the important attributes of the patterns and its returns information about the composition of an image into a form that can be understands by human (Tsang & Tsang, 1998).

Every region distinguished in image processing step is belonging to one of several groups. Colour and texture features were extracted from each flower region. The characteristics of the flowers were collected and stored in numerical form based on a mathematical formula. Next subsection discuss about colour and texture extraction.

Page1	Page 2

image=imread('flower's_name.jpg');
image_resize = imresize(image, [300 300]);
imGray=rgb2gray(image_resize);
imGray=im2double(imGray);
imH=rgb2hsv(image_resize);
level=graythresh(imH(:,:,1))
 	
% figure,imshow(imH(:,:,1)>level);
se=strel('disk',5);
I=(imH(:,:,1)>0.53);
 	
% figure,imshow(I),title('I');
Io=imopen(I,se);
%figure,imshow(Io),title('Io');
Ic=imclose(Io,se);
 	
%figure,imshow(Ic),title('Ic');
Iclean=BWmorph(Ic,'clean');
 	
%figure,imshow(Iclean),title('Iclean');
%figure,imshow(Ic),title('Iclean');
 	
Idilate=BWmorph(Iclean,'dilate');
Ifill=imfill(Idilate,'holes');
figure,imshow(Ifill),title('Ifill');
	%figure,imshow(Idilate),title('Idilate');
	%[lab,num]=bwlabel(Idilate);
	%[lab,num]=bwlabel(Iclean);
	
	[lab,num]=bwlabel(Ifill);
	num
	%figure,imshow(lab/12);
	colormap(jet);
	a=hist(lab(:),num+1);
	[cnt objLabel]=max(a(2:num+1))
	flower=lab==objLabel;
	
	%figure,imshow(flower);
	flowerOnly(:,:,1)=im2double(image(:,:,1)).*im2double(flower);
	flowerOnly(:,:,2)=im2double(image(:,:,2)).*im2double(flower);
	flowerOnly(:,:,3)=im2double(image(:,:,3)).*im2double(flower);
	figure,imshow(flowerOnly);
	imwrite(flowerOnly,'flower's_name_crop.jpg');

Figure 3.7: MATLAB code for feature extraction

Colour extraction

All the images that have been undergoing segmentation process are saved in RGB colour space. Since RGB colour space is easily being influenced by intensity and illumination from sun or camera flashlight and leads to imbalanced perception of colour dissimilarity, thus a transformation to HSV colour space is needed (Jeong, 2001). Among the reasons of choosing HSV are stated as below;

i. HSV is much closer to human's eye perception in by showing astonishing performance in object recognition of images (Lucchese and Mitra, 2001).
ii. It' a nonlinear transformation of the RGB colour space with high capability of inversion without difficulty (Smith, 2002).
iii. Be able to minimize the consequence from illumination variations from lighting condition in outdoor scene (Nilsback and Zisserman, 2006).

HSV must be normalized to obtain the correct value representation for the images. The RGB to HSV conversion formula is depicted as in Table 3.2 and the collected data gather from the conversion stored as shown in Table 3.3.

Table 3.2: RGB to HSV conversion formula

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	$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)]$
Luminance	$V = \frac{1}{3}(R+G+B)$

Table 3.3: Example of HSV colour space value

Flower's Name	HSV Colour Space		
	Hue	**Saturation**	**Luminance**
Turnera	0.393	0.178	0.82
Marigold	0.13	0.149	0.711
Periwinkle	0.863	0.186	0.885
Hibiscus	0.47	0.494	0.619

Texture extraction

The texture appears in images was analyzed using the gray-level co-occurrence matrix (GLCM). The purpose of GLCM is to calculate approximately of image properties related to surface's pattern order by measuring the intensity of pixels in selected region (Krishnapuram *et al.*,2004). Each pattern has their own vector and each vector are denoted as (*i,j*). GLCM match ups the number of occurrences of the pair of gray levels *i* and *j* which are a distance (d) apart in the original image (Partio *et al.*, 2002).

Guru, Sharath and Manjunath (2010) added that GLCM is in *N x N* form. *N* represent the number of gray levels occurs in images where the of p (i, j, d, θ) in GLCM where relative frequency denoted as p, I is gray level of the pixel (p) in coordinate (w, y) meanwhile j is grey level that located at distance (d) from (p) in orientation of θ. GLCM is based on replicated occurrence of some configurations of pixels intensity in an image (Ian *et al.*,2008). To transform the image into the co-occurrence matrix space, the nearest pixels in one of the eight angles are calculated. Generally, there are four angles can be implemented to calcute GLCM; 0°, 45°, 90°, and 135° (Lee, Jeon, & Kwon, 2004).

There are about 14 features can be calculated from each GLCM (Haralick, Shanmugam & Dinstein, 1973) but for this research, only four (4) features such as Contrast, Correlation, Energy and Homogeneity are used for texture calculations which was adapting from Zhang, Yoo and Ha (2007) . The formula is depicted in Table 3.4 and collected data of GLCM stored as shown in Table 3.6.

Table 3.4: Equation for Contrast, Correlation, Energy and Homogeneity of GLCM

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

Table 3.5: Examples of Contrast, Correlation Energy and Homogeneity datasets

Flower's Name	Gray Level Co-occurrence Matrix Value			
	Contrast	**Correlation**	**Energy**	**Homogeneity**
Turnera	0.07	0.973	0.265	0.966
Marigold	0.046	0.959	0.332	0.977
Perwinkle	0.084	0.942	0.294	0.96
Hibiscus	0.079	0.959	0.322	0.963

```
input=imread('flower's_name.jpg');
i=rgb2gray(input);
glcm=graycomatrix(i);
statContrast=graycoprops(glcm,'contrast')
statCorrelation=graycoprops(glcm,'correlation')
statEnergy=graycoprops(glcm,'energy')
statHomogeneity=graycoprops(glcm,'homogeneity')
```

Figure 3.8: Texture extraction using MATLAB

The entire flower's data representation have been extracted and converted into numerical form. This dataset were stored in database which means each flower will have 7 attribute to represent each flowers. All 7 attributes were used as input data in each classifier. Table 3.6 shows how flower's data representation being recorded.

Table 3.6: Colour and Texture extraction values

Colour Extraction			Texture Extraction				Target (Flower name)
Hue	**Saturation**	**Luminance**	**Contrast**	**Correlation**	**Energy**	**Homogeneity**	
0.393	0.178	0.82	0.07	0.973	0.265	0.966	Turnera
0.13	0.149	0.711	0.046	0.959	0.332	0.977	Marigold
0.863	0.186	0.885	0.084	0.942	0.294	0.96	Periwinkle
0.47	0.494	0.619	0.079	0.959	0.322	0.963	Hibiscus

3.2.4 Phase 4: Modeling

In this phase, various modeling techniques were selected and in general, there are few techniques were carried out for the same types of data mining problem. Some techniques may have specific requirements on the form of data. To have an actual model, a quality procedure needs to be tested and validated. The dataset were separated into training and testing set and the model build based on train set.

Neural Networks, Logistic Regression and Decision Tree were among classifiers used to develop the Malaysian flowers modeling classification. The information obtain from feature extraction phase were gathered in one data set. Each data has been classified to their class and has been represented by a label. Data from the data preparation phase will be trained, validated and tested and then the accuracy percentage was recorded.

As for training, data preparation for Neural Network, Decision Tree is different from data preparation of Logistic Regression. Normally Artificial Intelligence algorithm requires data to be scaled within the range 1 and 0 or between -1 and 1.

The steps in carrying out the experiment for Neural Networks, Logistic Regression and Decision Tree are adapted from Siraj, Omer and Hasan (2012) as shown in Figure 3.9.

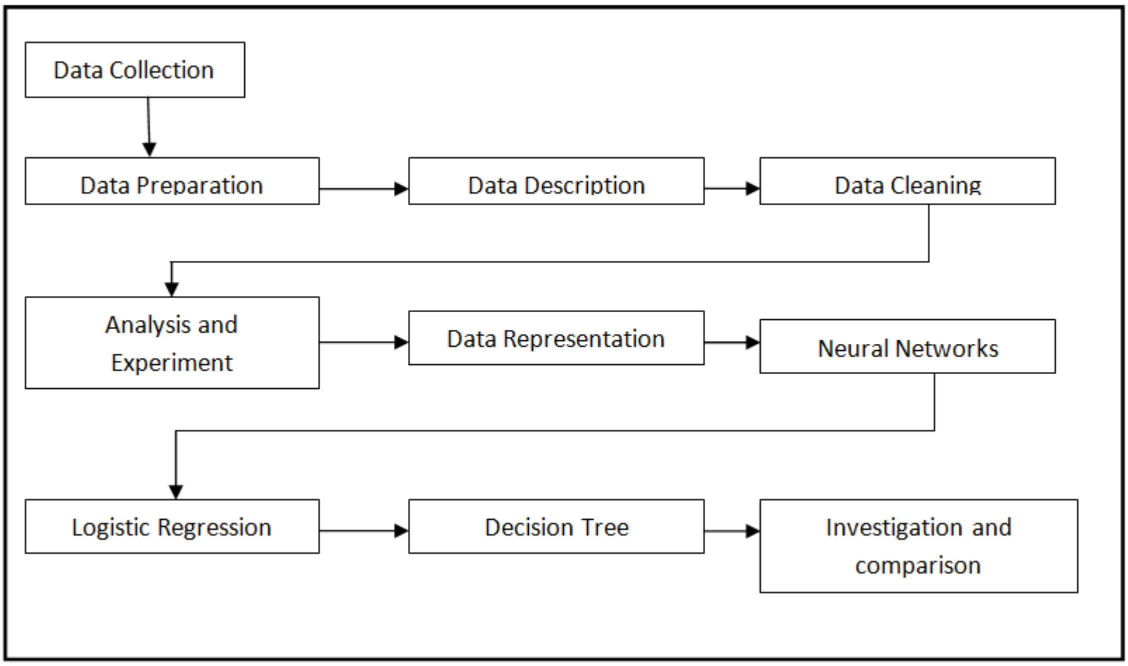


Figure 3.9: Steps in carrying out the experiment (Adapting from Siraj, Omer & Hasan, 2012)

At the initial stage, the performance of Neural Networks is lower than 50% accuracy. Several possibilities of data representation has been explored in order to increase the performance of Neural Networks. Following Siraj and Patridge (2002) the data representation has been explored using the whole original dataset. The original dataset has been split into easy to learn and hard to learn patterns as shown in Figure 3.10.

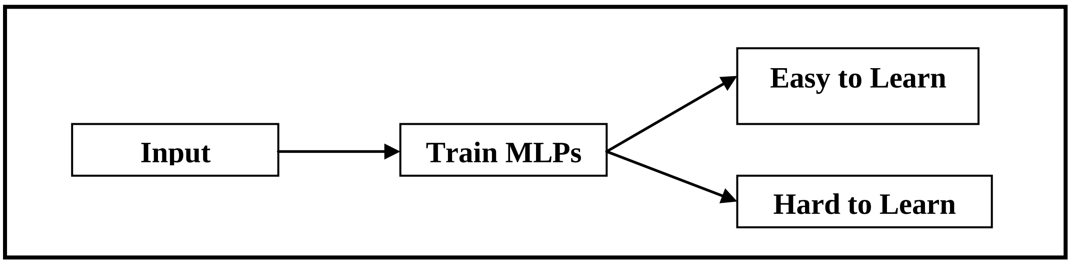


Figure 3.10: Original dataset has been split into Easy to Learn and Hard to Learn patterns.

To further investigate the impact of hard to learn patterns on the accuracy of Neural Networks, these patterns are presented two (2) and three (3) to Neural Networks as suggested by Siraj and Sheik Osman (2010).

Testing

During this phase, validation and test sets were carried out to determine the accuracy of the classification model. The test set was used to assure that the training produces the best test result with no indication of over fitting. Flower image classification can be used if classification model was established after the testing process.

3.2.5 Phase 5: Evaluation

This phase review which of the model has meets the research objectives. Before move to model's final deployment, it is important to evaluate thoroughly the model and review the steps executed to construct the model to be certain it properly achieves the research objectives. The main objective is to determine if there is some important research issue that has not been sufficiently considered. The accuracy of Malaysian flower classification is tested in several experiment using different classifiers. The comparison processes of each classifier were taken.

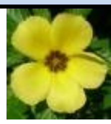
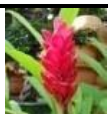
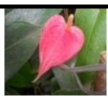
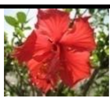
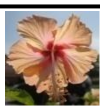
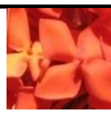
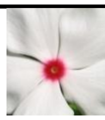
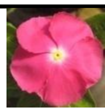
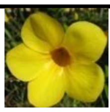
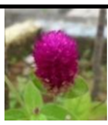
CHAPTER FOUR
RESULTS

In order to develop a suitable model from the flower image dataset, this chapter describes the results and comparison among three techniques that are used in this study including Backpropagation Neural Networks (BPNN), Logistic Regression (LR) and Decision Tree (DT). Several experiments were carried out to monitor the classification performance with different dataset allocation. The analysis focuses on test result as well as training patterns that could possibly explain as to why some flower images are difficult to learn by NN.

4.1 Preliminary Study Using NN

A total of 1800 flower images have been captured in several flower nurseries around Changlun and Jitra. For this study, a total of 30 types of flowers were captured, each of them is represented by 60 images. Table 4.1 exhibits the flower types captured in this study. As mentioned in the previous chapter, the flower images were captured between 10 a.m to 11 a.m daily up to one month. In some of the images, shadow appears and such noise would affect the precision of the image. This also may lead to inaccurate data representation during feature extraction.

Table 4.1: Flower types and images

No.	Name	Image	No.	Name	Image
1	Bellis Perennis		16	Turnera Ulmifolia (Yellow)	
2	Alpine Purpurata		17	Turnera Ulmifolia (White)	
3	Sinningia Speciosa		18	Phalaenopsis Orchid (Purple)	
4	Pink Wind Flower		19	Phalaenopsis Orchid (Peach)	
5	White Wind Flower		20	Marigold (Yellow)	
6	Authurium Andreanum		21	Marigold (Orange)	
7	Ipomoea Cairica		22	Anthurium (Red)	
8	Hibiscuss (Red)		23	Cana Generalis	
9	Hibiscuss (Orange)		24	Corngea	
10	Hibiscuss (Peach)		25	Javanese Ixora	
11	Bougainvillea (Purple)		26	Spider Lily	
12	Euphorbia Milii (Red)		27	Periwinkle (White)	
13	Euphorbia Milii (Peach)		28	Periwinkle (Pink)	
14	Allamanda (Yellow)		29	Periwinkle (Red)	
15	Gomphrena Globosa L		30	Rose (Red)	

Initially, the number of hidden unit for flower classification problem is investigated. Two learning algorithms associated with BPNN, namely Scale Conjugate Gradient (SCG) and Gradient Descent (GD) are explored. In addition, difference data allocations are also investigated as this may indicate the number of sample images to be used for each type of flowers. Based on Prechelt (1994)the data allocation is set to 60:20:20, 70:20:10 and 80:10:10.

For preliminary experiments, each type of flower is represented by 60 images. The number is set based on Ehsan (2007) that indicated the number of images that representing each type of flowers influences the accuracy of NN. To prepare the data for NN training, Nilsback (2009) approach has been adopted such that each flower is classed based on their unique appearance. As an example, the flower images extracted from Nilsback is shown in Figure 4.1.

Figure 4.1: Flower dataset example by Nilsback (2009)

For 10 images of each flower type, the accuracy of NN obtained is between 60-70%. Based on such findings, this study represents each type of flower by 60 images.

Hence, for 30 type of flower, 1800 images are extracted and form a dataset for this initial experiment. The results are exhibited in Table 4.2.

Table 4.2: Results of Hidden layer with 1800 flower images

Data Allocation	No. of Hidden Unit	Scale Conjugate Gradient			Gradient Descent		
		Training	Validation	Testing	Training	Validation	Testing
Allocation 60:20:20	1	4.3%	7.0%	2.9%	4.3%	.0%	3.9%
	2	4.6%	2.3%	4.2%	5.3%	3.9%	4.7%
	3	4.9%	5.7%	1.7%	4.7%	6.2%	4.7%
	4	6.7%	4.8%	2.7%	5.2%	1.5%	2.5%
	5	6.3%	12.9%	2.7%	5.8%	5.1%	6.0%
	6	5.2%	1.7%	.0%	6.6%	4.4%	2.3%
	7	7.7%	1.6%	3.8%	7.5%	3.4%	6.9%
	8	8.4%	7.5%	3.3%	6.7%	1.2%	2.9%
	9	7.2%	4.5%	4.5%	9.2%	5.1%	2.8%
	10	9.5%	7.8%	4.3%	7.1%	1.8%	8.1%
Allocation 70:20:10	1	3.8%	2.1%	3.1%	3.8%	3.3%	1.3%
	2	6.0%	2.2%	8.3%	3.7%	6.8%	1.4%
	3	3.5%	2.3%	3.8%	4.8%	2.3%	3.6%
	4	5.8%	2.7%	5.8%	5.6%	2.4%	1.3%
	5	5.8%	2.8%	8.6%	7.0%	3.0%	8.3%
	6	6.3%	2.1%	11.2%	5.8%	5.9%	3.0%
	7	6.9%	2.9%	5.3%	6.3%	4.0%	1.0%
	8	9.1%	4.7%	3.3%	8.5%	3.3%	3.5%
	9	9.3%	1.9%	4.3%	6.9%	2.5%	2.6%
	10	8.8%	2.8%	4.5%	8.6%	4.7%	4.9%
Allocation 80:10:10	1	3.7%	3.4%	8.7%	3.8%	3.3%	3.8%
	2	4.5%	2.0%	1.9%	4.4%	4.4%	3.6%
	3	4.3%	3.0%	2.3%	5.0%	4.3%	4.7%
	4	4.6%	1.8%	3.8%	5.2%	2.0%	11.1%
	5	5.2%	3.2%	6.8%	5.2%	3.7%	5.8%
	6	5.6%	1.8%	3.2%	4.4%	3.3%	3.7%
	7	6.5%	7.1%	3.4%	6.8%	3.5%	4.3%
	8	7.1%	1.9%	13.8%	6.0%	6.9%	5.2%
	9	5.7%	2.0%	6.0%	7.9%	7.4%	4.1%
	10	6.8%	6.8%	4.7%	5.9%	5.8%	4.0%

Note that, a total of three nets obtained accuracy higher than 10%. Two of the nets are those that use SCG (11.2% for 70:20:10 and 13.8% for 80:10:10). One of the net uses GD with accuracy of 11.1% (80:10:10).

Closer inspection on the training patterns for SCG and GD are shown in Table 4.3 and Table 4.4.

Table 4.3: Scale Conjugate Gradient Training Result Architecture (Data Allocation: 80:10:10; Accuracy: 9.5%)

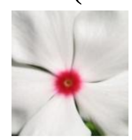
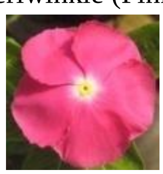
Class	Type of Flowers	Euphorbia Milli (Red)	Euphorbia Milli (Peach)	Turnera Ulmifolia (Yellow)	Turnera Ulmifolia (White)	Phalaenopsis Orchid (Purple	Phalaenopsis Orchid (Peach)	Marigold (Yellow)	Marigold (Orange)	Periwinkle (White)	Periwinkle (Pink)	Periwinkle (Red)	Wind Flower (Pink)	Wind Flower (White)	Hibiscuss (Red)	Hibiscuss (Orange)	Hibiscuss (Peach)
1	Euphorbia Milli (Red)	0	0	0	0	0	0	0	0	4	0	0	0	4	1	0	2
	Euphorbia Milli (Peach)	0	0	0	0	0	0	0	0	0	0	0	1	8	0	0	1
2	Turnera Ulmifolia (Yellow)	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0
	Turnera Ulmifolia (White)	0	0	0	0	0	0	1	0	2	0	0	0	1	0	0	1
3	Phalaenopsis Orchid (Purple	0	0	0	0	0	0	0	0	1	0	0	1	3	0	0	3
	Phalaenopsis Orchid (Peach)	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	1
4	Marigold (Yellow)	0	0	0	0	0	0	1	0	1	0	0	1	0	0	2	0
	Marigold (Orange)	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	3
5	Periwinkle (White)	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	2
	Periwinkle (Pink)	0	0	0	0	0	4	0	0	0	0	0	0	1	1	0	1
	Periwinkle (Red)	0	0	0	0	0	0	1	0	2	0	0	0	5	0	0	0
6	Wind Flower (Pink	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2
	Wind Flower (White)	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0
7	Hibiscuss (Red)	0	0	0	0	0	0	0	0	0	0	0	1	4	0	0	3
	Hibiscuss (Orange)	0	0	0	0	0	0	1	0	0	0	0	0	5	0	0	1
	Hibiscuss (Peach)	0	0	0	0	0	0	2	0	1	0	0	0	0	1	0	14

Table 4.4: Gradient Descent Training Result Architecture (Data Allocation: 80:10:10; Accuracy: 4.1%)

Class	Type of Flowers	Euphorbia Milli (Red)	Euphorbia Milli (Peach)	Turnera Ulmifolia (Yellow)	Turnera Ulmifolia (White)	Phalaenops is Orchid (Purple	Phalaenops is Orchid (Peach)	Marigold (Yellow)	Marigold (Orange)	Periwinkle (White)	Periwinkle (Pink)	Periwinkle (Red)	Wind Flower (Pink	Wind Flower (White)	Hibiscuss (Red)	Hibiscuss (Orange)	Hibiscuss (Peach)
1	Euphorbia Milli (Red)	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0
	Euphorbia Milli (Peach)	0	4	0	0	0	0	0	0	0	0	48	0	0	0	0	0
2	Turnera Ulmifolia (Yellow)	0	1	0	0	0	0	0	0	0	0	44	0	0	0	0	0
	Turnera Ulmifolia (White)	0	1	0	0	0	0	0	0	0	0	50	0	0	0	0	0
3	Phalaenopsis Orchid (Purple	0	3	0	0	0	0	0	0	0	0	43	0	0	0	0	0
	Phalaenopsis Orchid (Peach)	0	6	0	0	0	0	0	0	0	0	45	0	0	0	0	0
4	Marigold (Yellow)	0	1	0	0	0	0	0	0	0	0	50	0	0	0	0	0
	Marigold (Orange)	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0
5	Periwinkle (White)	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0
	Periwinkle (Pink)	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0
	Periwinkle (Red)	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0
6	Wind Flower (Pink	0	4	0	0	0	0	0	0	0	0	40	0	0	0	0	0
	Wind Flower (White)	0	1	0	0	0	0	0	0	0	0	45	0	0	0	0	0
7	Hibiscuss (Red)	0	4	0	0	0	0	0	0	0	0	43	0	0	0	0	0
	Hibiscuss (Orange)	0	2	0	0	0	0	0	0	0	0	45	0	0	0	0	0
	Hibiscuss (Peach)	0	4	0	0	0	0	0	0	0	0	43	0	0	0	0	0

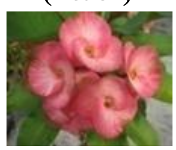
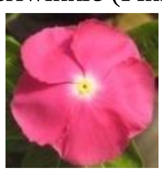
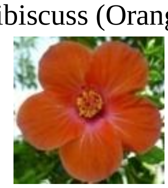
For NN training using SCG, the red and peach Euphorbia Milii misclassified as Wind Flower and Periwinkle of white colour (Table 4.5). Based on misclassification images, both Euphorbia Milii (red and peach) and Hibiscus (red and orange) are classified as white Wind Flower.

Table 4.5: Original image and Misclassified image
(Training; Data Allocation: 80: 10: 10, Accuracy: 9.5%)

Training	Original Image	Misclassified Image	
Scale Conjugate Gradient (Data Allocation: 80:10:10)	Euphorbia Milii (red) 	Wind Flower (white) (4) 	Periwinkle (white) (4) 
	Euphorbia Milii (Peach) 	Wind Flower (white) (8) 	
	Periwinkle (Pink) 	Phalaenopsis Orchid (Peach) (4) 	
	Hibiscuss (Red) 	Wind Flower (white) (4) 	
	Hibiscuss (Orange) 	Wind Flower (white) (5) 	

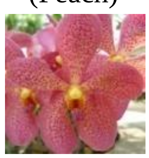
The test result also reveal that Euphorbia Milii (red) is misclassified as Wind Flower (white) as depicted in Table 4.6.

Table 4.6: Original image and Misclassified image
(Testing; Data Allocation: 80: 10: 10 Accuracy: 10.2%)

Testing	Original Image	Misclassified Image
Scale Conjugate Gradient (Data Allocation: 80:10:10)	Euphorbia Milii (red) 	Wind Flower (white) (1) 
	Euphorbia Milii (Peach) 	
	Periwinkle (Pink) 	
	Hibiscuss (Red) 	
	Hibiscuss (Orange) 	

On the other hand, training using GD shows that both Euphorbia Milii (peach) and Hibiscus (red or peach) misclassified as the image of red Periwinkle (Table 4.7). Hence, when GD is used for training, it is difficult for NN to classify flowers with Peach, Pink and Red. In fact, NN recognized those colours as Red or Peach. The assumption the value HSV colour of Red and Peach are close to each other.

Table 4.7: Original image and Misclassified image (Training; Data Allocation: 80: 10: 10, Accuracy: 4.1%)

Training	Original Image	Misclassified Image	
Gradient Descent (Data Allocation: 80:10:10)	Euphorbia Milii (Peach) 	Periwinkle (Red) (48) 	
	Phalaenopsis Orchid (Peach) 	Periwinkle (Red) (45) 	Euphorbia Milii (Peach) (6) 
	Wind Flower (Pink) 	Periwinkle (Red) (43) 	Euphorbia Milii (Peach) (4) 
	Hibiscuss (Red) 	Periwinkle (Red) (43) 	Euphorbia Milii (Peach)(4) 

	Hibiscuss (Peach) 	Periwinkle (Red) (43) 	Euphorbia Milii (Peach) (2) 

Similar observation is also revealed in GD's testing result as shown in Table 4.8.

Table 4.8: Original image and Misclassified image
(Testing; Data Allocation: 80: 10: 10 Accuracy: 8.6%)

Testing	Original Image	Misclassified Image	
Gradient Descent (Data Allocation: 80:10:10)	Euphorbia Milii (Peach) 	Periwinkle (Red) (2) 	
	Phalaenopsis Orchid (Peach) 	Periwinkle (Red) (3) 	
	Wind Flower (Pink) 	Periwinkle (Red) (2) 	
	Hibiscuss (Red) 	Periwinkle (Red) (2) 	Euphorbia Milii (Peach) (1) 

Result exhibited in Table 4.4 indicates that most flowers that do not learn considered the type of flower as Periwinkle. Some of them are wrongly classified as Euphorbia Milii (peach). For GD, most colours (peach, pink or red) are misclassified as red or peach colour. Note that flower such as hibiscus, regardless of its colour, the flower is classified as Euphorbia Milii (peach). As the aim of the research is to study the classification model of flower images, to this end, the same flower with different colours is classified as the same type of flowers. Hence the reduction of data set is depicted in Table 4.9.

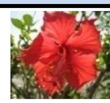
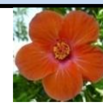
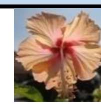
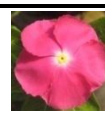
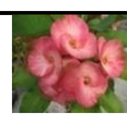
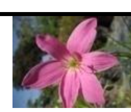
Table 4.9: Reduction of flower dataset

No.	Name	Frequency
1	Bellis Perennis	60
2	Alpine Purpurata	60
3	Sinningia Speciosa	60
4	Wind Flower (Pink)	60
5	Wind Flower (White)	60
6	Authurium Andreanum	60
7	Ipomoea Cairica	60
8	Hibiscus (Red)	60
9	Hibiscus (Orange)	60
10	Hibiscus (Peach)	60
11	Bougainvillea (Purple)	60
12	Euphorbia Milii (Red)	60
13	Euphorbia Milii (Peach)	60
14	Allamanda	60
15	Gomphrena Globosa L	60
16	Turnera Ulmifolia (Yellow)	60
17	Turnera Ulmifolia (White)	60
18	Phalaenopsis Orchid (Purple)	60
19	Phalaenopsis Orchid (Peach)	60
20	Marigold (Yellow)	60
21	Marigold (Orange)	60
22	Anthurium (Red)	60
23	Cana Generalis	60
24	Corngea	60
25	Javanese Ixora	60
26	Spider Lily	60
27	Periwinkle (White)	60
28	Periwinkle (Pink)	60
29	Periwinkle (Red)	60
30	Rose (Red)	60
	Total	1800

No.	Name	Frequency
1	Wind Flower	120
2	Hibiscus	180
3	Euphorbia Milii	120
4	Turnera Ulmifolia	120
5	Phalaenopsis Orchid	120
6	Marigold	120
7	Periwinkle	180
	Total	960

To get some understanding about the classification error, a few examples of image classification are taken. To end this, all 30 types of flower images were filtered to reduce the number of images by adapting Nilsback and Zisserman's (2006) technique whereas all the same types of flowers were grouped in same flower type. As an example, hibiscus flower with 3 different colours were put into hibiscus group. In this study, from 30 flower image were taken, only 16 of them have their own group (same flower type) with overall images is 960 were formed. The images were grouped into 7 classes of flowers type and arranged as shown in Table 4.10.

Table 4.10: The 7 groups of flowers

No.	Name	Flower image	Flower image	Flower image
1	Hibiscus			
2	Periwinkle			
3	Phalaenopsis Orchid			
4	Marigold			
5	Turnera Ulmifolia			
6	Euphorbia Milii			
7	Wind Flower			

4.2 Experimental Results

Initial experiments are focused on the impact of number of hidden units, data allocation and data representation on the performances of NN. Following the same previous procedures, the newly formed dataset is used for training, validation and testing in the following data allocation 60:20:20, 70:20:10 and 80:10:10. The experimental results are shown in Table 4.11.

Table 4.11: Experimental results various hidden units and data allocation

Data Allocation	No. of Hidden Unit	Scale Conjugate Gradient			Gradient Descent		
		Training	Validation	Testing	Training	Validation	Testing
Allocation 60:20:20	1	66.2	62.4	73.8	76.7	69.1	74.5
	2	100	100	100	100	100	51.3
	3	100	95.7	100	100	97.8	98.9
	4	99.8	100	100	100	97.8	97.7
	5	99.4	98.9	100	100	100	99.1
	6	100	100	100	100	100	100
	7	100	100	100	100	100	100
	8	100	100	100	100	100	100
	9	100	100	100	100	100	100
	10	100	100	100	100	100	100
Allocation 70:20:10	1	64.5	98.9	57	65.1	62.9	69.5
	2	97.7	100	99	98.5	98.2	91
	3	99.2	96.7	100	99.7	97.7	99.1
	4	99.5	95	97.9	68.6	91.8	97.9
	5	99.2	96.2	99.1	98.8	98.2	99
	6	99.5	97.9	98.1	99.7	100	99
	7	99.9	100	99.1	99.9	100	98
	8	100	100	96.5	98	96.7	95
	9	98.7	98	97.9	99.9	98.3	98.3
	10	99.7	100	99.1	99.3	97.9	99.1
Allocation 80:10:10	1	62.4	54.4	66.7	54.9	53.7	48.9
	2	47	45.4	34.8	52.7	54.7	89.5
	3	59.9	54.9	56.8	65.4	59.3	95.2
	4	67.1	65.5	56.6	70.7	71.8	96.5
	5	74.3	72.5	70.2	75.3	69.9	100
	6	73.4	68.5	100	76.2	74.9	96.8
	7	73.4	67.9	100	73.4	76.4	100
	8	75.5	69.7	74.5	73	74.3	94.3
	9	74.1	70.5	100	79.6	70.2	100
	10	76.1	74.7	72.8	79.2	70.9	98.3

Note that data allocation 60:20:20 with hidden unit 6 to 9 obtained 100% test results for both SCG and GD learning algorithm. Test accuracy of 100% can be obtainedin data allocation of 70:20:10 with SCG. Nonetheless, several nets for data allocation 80:10:10 achieved 100% in testing.

Following Siraj and Partridge (2002), the flower images were duplicated and fed into Neural Networks to investigate whether duplication of data leads to better computation. The analysis continues with double repeated of hard pattern to learn. For this experiment, total numbers of difficult to learn patterns from training are duplicated whether this will lead to better computation.

Based on Table 4.12, distribution data allocation between 60:20:20 give highest accuracy for flower classification. The other allocation (70:20:10 and 80:10:10) also did not have much differences compare to the original dataset. Even though the percentage look quite low, but it’s not too obvious.

Table 4.12: Results of Hidden layer for Double repetition of hard pattern to learn

Data Allocation	No. of Hidden Unit	Scale Conjugate Gradient			Gradient Descent		
		Training	Validation	Testing	Training	Validation	Testing
Allocation 60:20:20	1	64.1	71.7	67.6	77.8	79.8	76.4
	2	99.8	98.9	100	100	100	100
	3	99.5	96.4	99	99.5	98.9	97.9
	4	100	97.7	100	100	100	100
	5	99.8	100	98.8	100	99	100
	6	100	100	100	100	100	98
	7	99.5	100	98.8	100	100	100
	8	100	98.9	100	100	98	100
	9	100	100	100	100	98	100
	10	100	100	98.8	100	97	100
Allocation 70:20:10	1	65	47.9	60.6	70	64.2	77
	2	98.9	95.9	96.3	96.5	89.8	94
	3	99.7	98.5	100	98.9	98	95.2
	4	99.3	94.7	99	99.3	100	96.6
	5	99.4	100	97.3	98.4	95.6	97.2
	6	99.2	98.2	99.1	98.6	98	93.8
	7	99	98	99.1	99.9	100	99
	8	99.2	100	100	99.7	98.2	97.8
	9	98.2	96.2	94.1	99.9	100	100
	10	98.9	98.4	100	99.5	98.1	97.9
Allocation 80:10:10	1	63	46.7	68.6	61.9	58.9	63.3
	2	95.2	94.8	91.8	96.3	93.2	92.5
	3	93.4	86.3	85.7	96	86	87
	4	97.9	98.3	98.1	97.4	96.3	98.2
	5	96.8	88.5	95.8	99.1	96.8	98.3
	6	99.6	95.2	98.2	96	92.2	90.7
	7	96.7	90.4	96.6	99.6	100	97
	8	97.9	93.7	96.6	93	83.1	87.3
	9	99	96.4	96.5	96.4	90.2	96.8
	10	97.7	95.6	92.7	99.6	100	98.5

Triple repetition of hard pattern to learn

In this experiment, the original data are numbers are increase to three time repetition.

Table 4.13: Results of Hidden layer for Triple repetition of hard pattern to learn

Data Allocation	No. of Hidden Unit	Scale Conjugate Gradient			Gradient Descent		
		Training	Validation	Testing	Training	Validation	Testing
Allocation 60:20:20	1	56.3	58	61.7	64.2	68.3	64
	2	88.3	88.5	85.4	88.1	84.1	80.2
	3	92.8	90.8	88.1	84.7	88.6	90.7
	4	97.3	97.4	94.5	88.4	79.9	84.3
	5	95.5	92.5	93	96.3	95	94.8
	6	90.3	89	84.9	87.1	83.7	85.9
	7	97.6	95.8	95.2	96.7	95.7	95
	8	91.9	88.3	91.4	99.2	96.2	97.9
	9	94.9	93.3	94.9	98.1	96.5	96.7
	10	98.5	97.2	97.9	96.3	97.7	96.8
Allocation 70:20:10	1	40.2	43.1	42.3	61.1	64.9	61.8
	2	86.8	78.1	79.6	80.3	75.8	79.3
	3	90.5	82.5	85.8	92.2	93.4	90.2
	4	97	94.7	96	92.7	83.8	91.3
	5	88.8	86.1	89.5	94.8	90.4	90.1
	6	96.4	95.6	95.4	83.1	73	76.4
	7	98.1	94.4	95.6	84.4	78.2	83.7
	8	86.1	90.4	84.8	98.8	98.1	97.3
	9	96.7	87.1	94	97.2	94.6	94.9
	10	95.8	93.1	95.4	81.8	73.7	83.3
Allocation 80:10:10	1	55.6	57.5	53.9	56.2	55.1	57.8
	2	74.6	60.4	76.8	86.7	83.3	77.9
	3	83.4	81.4	83.9	78.5	73.9	69.3
	4	95.7	92.2	88.1	78.4	68.9	80.8
	5	94.3	89.3	95.1	97.5	97.3	99
	6	97.2	96	95.5	98.2	94.1	96.2
	7	97.3	92.6	94.1	89.9	88.1	92.5
	8	92.8	95.6	91.4	98.4	98.1	97.9
	9	84.3	79.8	85.6	96.7	95.4	93.7
	10	88	81.3	86.2	79.4	70.9	77.1

When data was copied three times and being trained by using NN, the overall classifications are decreased.

Hidden Layer against Flower types

Next is finding what hidden unit that produces most accurate flower recognition. In data allocation of 60:20:20, 100% accuracy was obtained from Marigold (hidden layer 1 and 2) and Turnera flower (Hidden Layer 9).

Table 4.14: 60:20:20 scale conjugate

No. of Hidden Unit	Hibiscus	Periwinkle	Orchid	Marigold	Turnera Ulmifolia	Euphorbia milii	Windflower
1	59.5	88.6	0.0	100.0	0.0	0.0	0.0
2	62.5	65.1	62.5	100.0	95.0	0.0	0.0
3	80.0	45.9	63.6	76.2	84.2	0.0	0.0
4	88.0	76.0	65.2	90.9	97.1	20.0	36.4
5	75.8	79.5	71.4	87.0	88.9	36.7	36.7
6	68.6	67.9	75.0	93.3	0.0	16.1	33.3
7	75.8	70.6	66.7	83.3	81.5	61.5	18.2
8	88.1	77.3	63.6	72.4	76.2	58.3	47.6
9	70.7	69.8	60.0	84.6	100.0	78.6	76.0
10	74.4	83.3	64.3	64.3	87.9	44.4	50.0

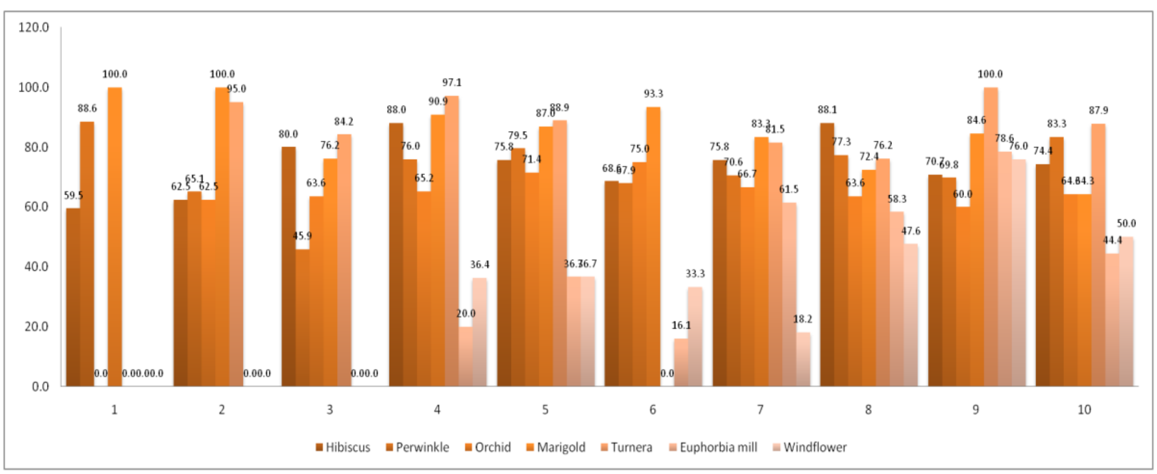


Figure 4.2: Data Allocation 60:20:20 (Scale Conjugate)

When GD learning algorithm was applied to data allocation 60:20:20, the highest accuracy was obtained from Hibiscus (97.1%) in hidden layer 3.

Table 4.15: 60:20:20 Gradient Descents

No. of Hidden Unit	Hibiscus	Perwinkle	Orchid	Marigold	Turnera	Euphorbia milii	Windflower
1	63.2	84.1	0.0	90.9	7.4	0.0	0.0
2	71.4	80.0	0.0	71.0	93.3	5.9	0.0
3	97.1	76.6	57.1	62.5	64.0	11.5	25.0
4	80.0	72.7	64.0	92.0	96.3	34.8	44.4
5	86.7	74.3	48.8	87.5	94.7	47.8	16.7
6	75.9	64.3	40.7	0.0	0.0	0.0	50.0
7	78.9	81.4	65.4	88.9	85.7	57.9	24.0
8	71.1	82.8	65.6	80.6	80.0	66.7	50.0
9	84.4	75.6	72.7	93.3	85.7	37.0	43.5
10	72.2	80.0	64.3	85.7	90.9	62.5	38.1

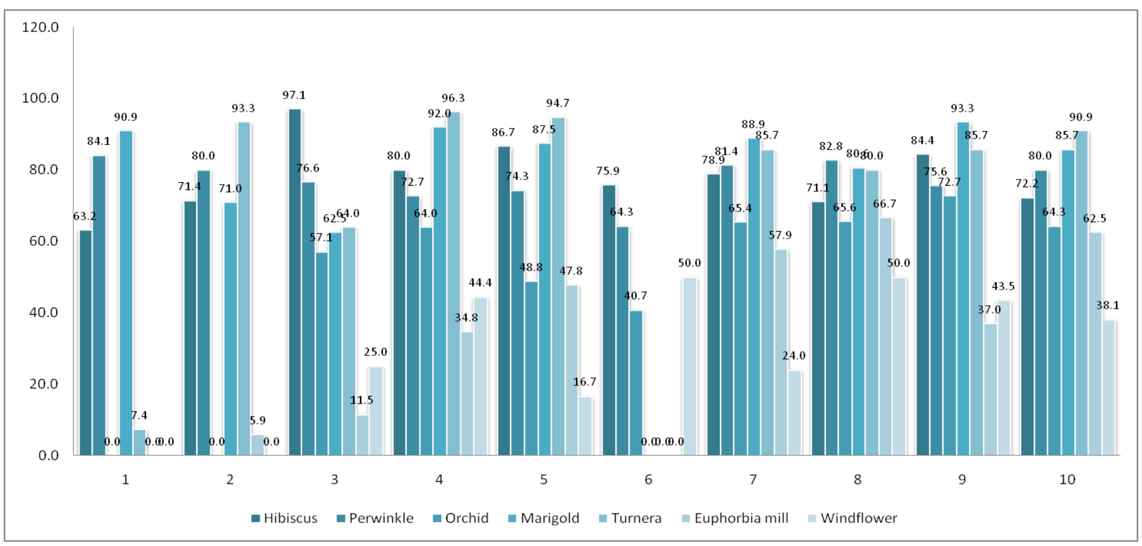


Figure 4.3: Data Allocation 60:20:20 (Gradient Descents)

4.3 Logistic Regression

Logistic regression is among the common models used in pattern classification and recognition purposes.It's have the ability to create the possibility for multivariate analysis and could be used in interprets relationships by examining the relationships between a set of conditions and the probability of an occur event (Mojsilovic, 2005).

Once the analysis on Logistic Regression is performed, the model summary is obtained as shown in Table 4.16.

Table 4.16: Logistic Regression Case Processing Summary

	Single Datasets		Double Datasets		Triple Datasets	
Flower Name	**N**	**Percentage**	**N**	**Percentage**	**N**	**Percentage**
Hibiscus	180	18.80%	207	20.00%	342	20.30%
Periwinkle	180	18.80%	189	18.30%	302	18.00%
Orchid	120	12.50%	126	12.20%	206	12.20%
Marigold	120	12.50%	116	11.20%	178	10.60%
Turnera	120	12.50%	116	11.20%	186	11.10%
Euphorbia Milii	120	12.50%	143	13.80%	234	13.90%
Wind Flower	120	12.50%	136	13.20%	234	13.90%
Total	**960**	**100.00%**	**1033**	**100.00%**	**1682**	**100.00%**

A more useful measure to assess the utility of a logistic regression model is classification accuracy (Table 4.17), which compares predicted group membership based on the logistic model to the actual, known group membership, which is the value for the dependent variable.

Based on the results shown in Table 4.17, the accuracy for overall flower of Original flower image dataset is 60.5%, Double repetition hard pattern to learn (57.6%) and Triple repetition of hard to learn pattern (52.8%).

Table 4.17: Logistic Regression Classification Result

Dataset	Observed	Predicted							
		Hibiscus	Periwinkle	Orchid	Marigold	Turnera	Euphorbia Mill	Wind Flower	Percent Correct
Original	Hibiscus	136	10	4	3	8	13	6	14.2%
	Periwinkle	10	121	19	2	6	3	19	12.6%
	Orchid	25	26	56	0	2	5	6	5.8%
	Marigold	7	0	0	95	10	0	8	9.9%
	Turnera	0	1	0	6	106	0	7	11.0%
	Euphorbia Mill	58	15	4	3	3	22	15	2.3%
	Wind Flower	4	30	18	10	9	4	45	4.7%
	Overall Percentage	25.0%	21.1%	10.5%	12.4%	15.0%	4.9%	11.0%	60.5%
Double Repetition	Hibiscus	141	7	3	4	7	33	12	13.6%
	Periwinkle	11	103	27	2	10	11	25	10.0%
	Orchid	9	35	53	3	0	18	8	5.1%
	Marigold	5	0	0	99	5	0	7	9.6%
	Turnera	0	0	0	3	104	0	9	10.0%
	Euphorbia Mill	58	9	4	10	0	46	16	4.5%
	Wind Flower	12	48	10	10	2	4	50	4.8%
	Overall Percentage	22.8%	19.6%	9.4%	12.7%	12.4%	10.8%	12.3%	57.6%
Triple Repetition	Hibiscus	244	19	4	5	15	42	13	14.5%
	Periwinkle	24	157	32	2	10	28	49	9.3%
	Orchid	40	58	85	0	4	7	12	5.1%
	Marigold	23	0	0	117	20	1	17	7.0%
	Turnera	3	1	1	7	150	1	23	9.0%
	Euphorbia Mill	120	25	3	5	4	46	31	2.7%
	Wind Flower	13	62	34	20	11	7	87	5.2%
	Overall Percentage	27.8%	19.1%	9.5%	9.3%	12.7%	7.8%	13.8%	52.8%

When the difficult pattern to learn dataset is duplicated, the percentage of accuracy reduces by 2.9% from original dataset (60.5%). Similarly, when the triple dataset (duplicated three times), the accuracy of logistic regression is reduce to 52.8% compare to original dataset classification accuracy.

The classification accuracy of each type of flower is further illustrated in Figure 4.5a, Figure 4.5b and Figure 4.5c. For Hibiscus, its classification accuracy decrease by 0.6% for Double repetition of data. When the number of hard to learnt pattern is repeated three times, the accuracy is increasing by 0.3% instead of decreasing. By comparison, the classification also decreases for other flowers such as Periwinkle (2.6%), Phalaenopsis Orchid (0.7%), Marigold (0.3%) and Turnera (1%).

For double repetition dataset, the classification of Euphorbia Milii increases by 2.2% while Wind Flower by 0.1%. However, flowers such as Hibiscus, Periwinkle, Orchid, Marigold and Turnera decrease their accuracies within the range of 0.3% and 1%.

The same types of flowers increase their classification accuracy by 0.4% for Euphorbia Milii and 0.6% for Wind Flower for Triple dataset. However another flower known as Hibiscus, the classification accuracy improves by 0.3%.

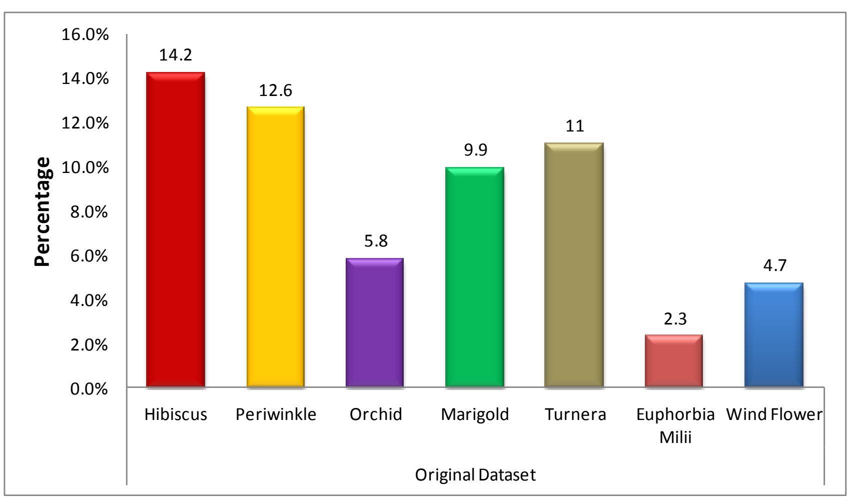


Figure 4.4a: Flower Accuracy Percentage using Logistic Regression (Original)

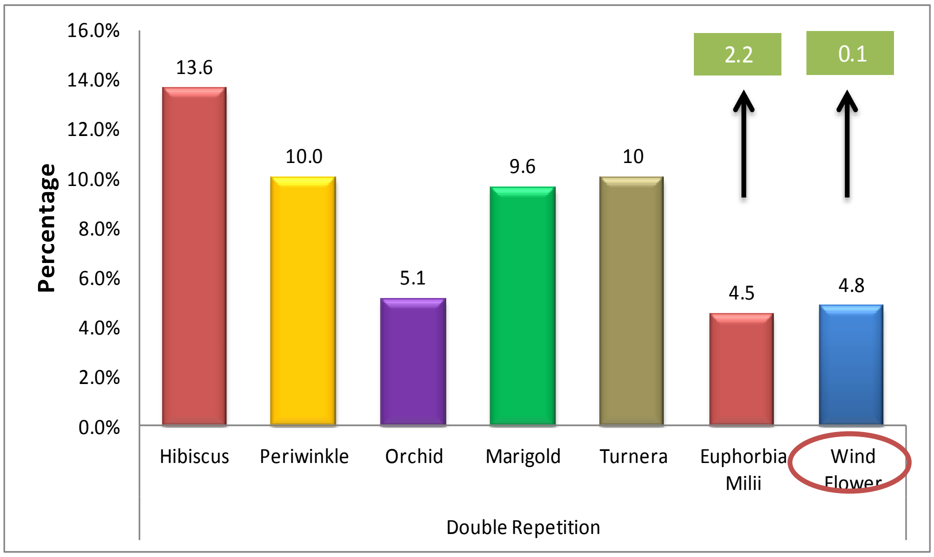


Figure 4.4b: Flower Accuracy Percentage using Logistic Regression (Double repetition)

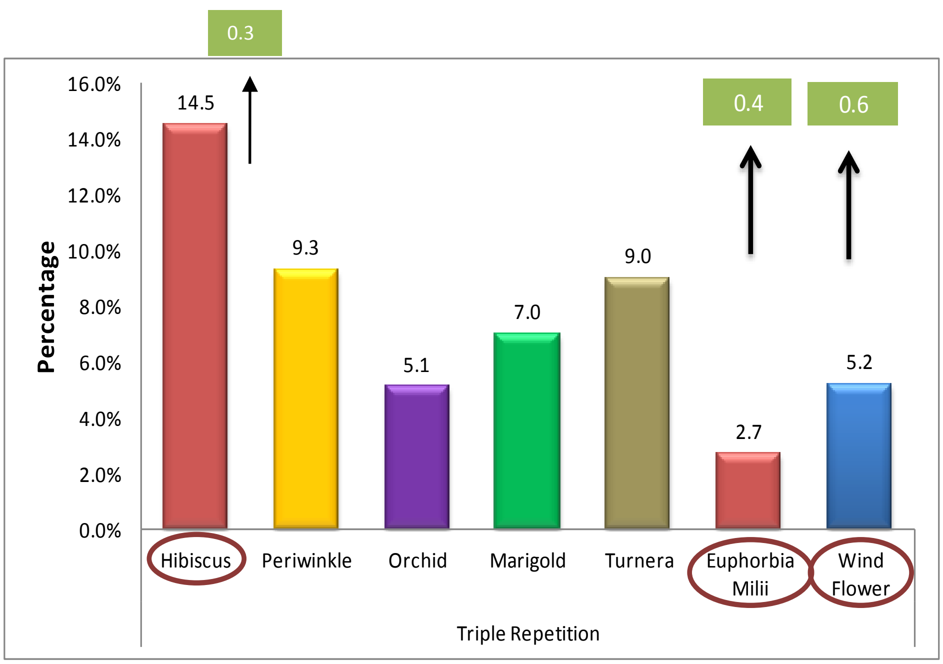


Figure 4.4c: Flower Accuracy Percentage using Logistic Regression (Triple repetition)

To Test the Significance of the Chi Square

Having performed the comparison between the performance of single, double and triple dataset, the results in Table 4.18 indicate that there is significance different between the performances amongst the three datasets. Further investigation is carried out in the next experiment.

Table 4.18 : Model Fitting Information

		Single Dataset		Double Dataset		Triple Datasets	
Model		Intercept Only	Final	Intercept Only	Final	Intercept Only	Final
Model Fitting Criteria	**-2 Log Likelihood**	3.70E+03	3.21E+03	3.97E+03	2.86E+03	6.46E+03	4.93E+03
	Chi-Square	495.861		1.11E+03		1.53E+03	
Likelihood Ratio Tests	**Sig.**	0.001		0.001		0.001	

Table 4.19: Goodness of Fit

	Single Datasets		Double Datasets		Triple Datasets	
	Chi-Square	Sig.	Chi-Square	Sig.	Chi-Square	Sig.
Pearson	1.172E+102 (df= 5694)	0.001	1.812E+56 (df= 3978)	0.001	1.256E+71 (df= 5694)	0.001
Deviance	3204.732 (df= 5694)	1	2860.173 (df= 3978)	1	4926.148 (df= 5694)	1

Pseudo R-Square is an Aldrich and Nelson's coefficient which serves as an analog to the squared contingency coefficient, with an interpretation like R-square. Its maximum is less than 1. It may be used in either dichotomous or multinomial logistic regression.

Table 4.20: Pseudo R-Square

	Single Dataset	Double Dataset	Triple Datasets
Cox and Snell	0.403	0.658	0.597
Nagelkerke	0.412	0.673	0.611
McFadden	0.134	0.279	0.237

Among the three Pseudo R-Square, Nagelkerke obtained the highest accuracy. While logistic regression does compute correlation measures to estimate the strength of the relationship (pseudo R square measures, such as Nagelkerke's R^2), these correlations measures do not really tell us much about the accuracy or errors associated with the model.

Similar to Linear Regression of R^2 value, theCoz & Snell R Square and Nagelkerke R-Square and McFadden R-Square are obtained. Comparing the two methods, Negelkerke R-Square obtained higher accuracy (60.3%) than Cox & Snell R (45.1%). While logistic regression does compute correlation measures to estimate the strength of the relationship (pseudo R square measures, such as Nagelkerke's R^2), these correlations measures do not really tell us much about the accuracy or errors associated with the model.

The likelihood ratio is a function of log likelihood and is employed in significance testing in Normal Regression (NOMREG). Likelihood is a probability that the observed values of the dependent which may be forecasted or predicted from the observed values of the independents. Likelihood varies from 0 to 1. The log likelihood (LL) is its log and varies from 0 to minus infinity (it is negative because the log of any number less than 1 is negative). LL is calculated through iteration, using maximum likelihood estimation (ML). Log likelihood is the basis for tests of a logistic model. Because -2LL has approximately a chi-square distribution, -2LL can be used for assessing the significance of logistic regression, analogous to the use of the sum of squared errors in OLS regression.

Table 4.21: Likelihood Ratio Tests

	Effect	Model Fitting Criteria	Likelihood Ratio Tests		
		-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Single Dataset	Intercept	2.23E+03	.	6	.
	V1	3.23E+03	27.583	6	0
	V2	2.50E+03	.	6	.
	V3	2.78E+03	.	6	.
	V4	2.06E+03	.	6	.
	V5	4.01E+03	806.172	6	0
	V6	3.10E+03	.	6	.
	V7	2.05E+03	.	6	.
Double Dataset	Intercept	2.49E+03	.	6	.
	V1	2.54E+03	.	6	.
	V2	3.02E+03	161.293	6	0
	V3	3.07E+03	207.983	6	0
	V4	2.34E+03	.	6	.
	V5	2.95E+03	94.263	6	0
	V6	3.04E+03	177.394	6	0
	V7	2.35E+03	.	6	.
Triple Dataset	Intercept	4.06E+03	.	6	.
	V1	5.27E+03	340.021	6	0
	V2	4.53E+03	.	6	.
	V3	4.99E+03	65.748	6	0
	V4	3.82E+03	.	6	.
	V5	4.86E+03	.	6	.
	V6	4.90E+03	.	6	.
	V7	3.80E+03	.	6	.

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model.

The null hypothesis: All parameters of the effects from the final model are 0.

This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom**.** Based on results exhibited in Table 4.22, the significant values of independent variables from Hibiscus to Wind flower are less than 1.0.

Table 4.22: Parameter Estimates

		B	Wald	df	Sig.
Single Dataset	Intercept	52.071	0.155	1	0.694
	Hibiscus	0.024	50.035	1	0
	Periwinkle	-0.006	2.175	1	0.14
	Orchid	-0.017	11.707	1	0.001
	Marigold	-34.615	0.292	1	0.589
	Turnera	-4.294	0.856	1	0.355
	Euphorbia Mill	0.646	0.189	1	0.663
	Wind Flower	-49.363	0.136	1	0.712
Double Dataset	Intercept	15.235	0.013	1	0.91
	Hibiscus	0.023	56.351	1	0
	Periwinkle	-0.002	0.244	1	0.622
	Orchid	-0.02	14.583	1	0
	Marigold	-19.944	0.092	1	0.762
	Turnera	-14.72	7.277	1	0.007
	Euphorbia Mill	-0.523	0.12	1	0.729
	Wind Flower	-1.824	0	1	0.989
Triple Dataset	Intercept	-549.697	33.652	1	0
	Hibiscus	0.023	91.008	1	0
	Periwinkle	-0.007	4.684	1	0.03
	Orchid	-0.016	20.469	1	0
	Marigold	259.503	32.791	1	0

	Turnera	-9.437	4.586	1	0.032
	Euphorbia Mill	-0.064	0.003	1	0.958
	Wind Flower	557.93	33.478	1	0

4.4 Decision Tree

A decision tree is a special tree structure constructed to help with making decisions in complex problem-solving (Quinlan, 1996). Decision tree is a graph or model of conditions and their possible consequences. Typically a decision tree can be learned by dividing the data source or rules into subset(s) which was based on specific attribute value (Papagelis and Kalles, 2001). This process is repeated on each resulting subsets in a recursive way where each recursion is completed when all data or rules involved in the subset(s)keep up a correspondence to the same decision, or when no values being added to the predictions (Yuan and Shaw, 1995)

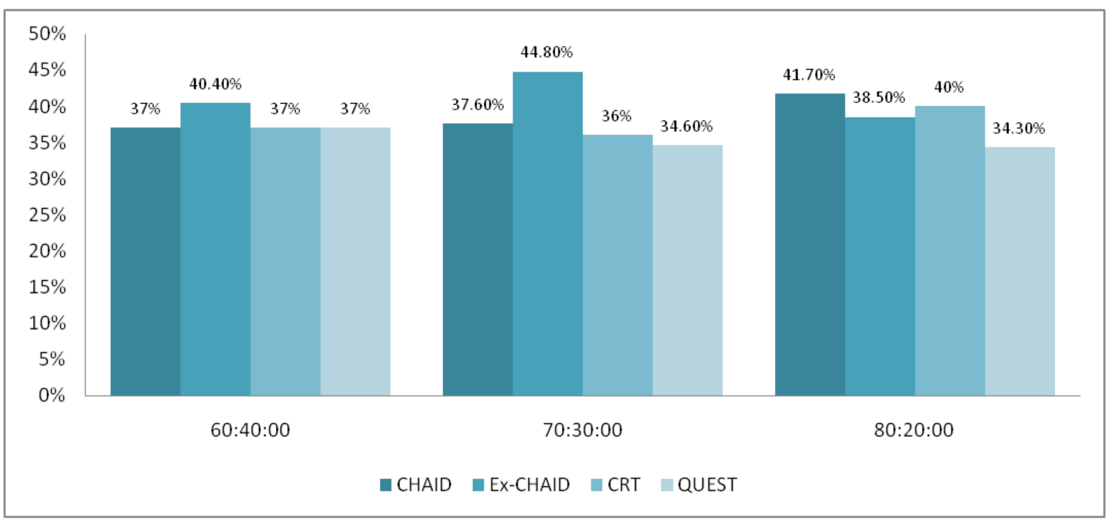


Figure 4.5: Decision Tree with Original dataset of hard pattern to learn

For original data set with allocation of 60:40, Ex-CHAID achieved the highest test result (40.4%). Similarly with data allocation 70:30, Ex-CHAID obtained the highest test result (44.8%). The third data allocation reveals that CHAID scores the highest test result (41.7%). The result exhibited in Figure 4.4.1 indicates that Ex-CHAID and CHAID obtained the highest accuracy. Note that test result with data allocation 60:40 yields 37% for CRT, Quest and CHAID. The failures can be further analyzed and the results are shown in **Table 4.22:**

Table 4.23: Decision Tree with original dataset of hard pattern to learn.

Cross Validation			Split Sample Validation					
Growing Method	**No. of Sample folds**	**Predicted Classification**	**60 : 40**		**70 : 30**		**80 : 20**	
			Train	**Test**	**Train**	**Test**	**Train**	**Test**
CHAID	25	46.4%	42.50%	37%	40.60%	37.60%	41.80%	41.70%
Ex-CHAID	25	49%	42.20%	40.40%	44.10%	44.80%	43.60%	38.50%
CRT	25	43.9%	41%	37%	41.20%	36%	42.90%	40%
QUEST	25	37.3%	43.10%	37%	38.80%	34.60%	42.30%	34.30%

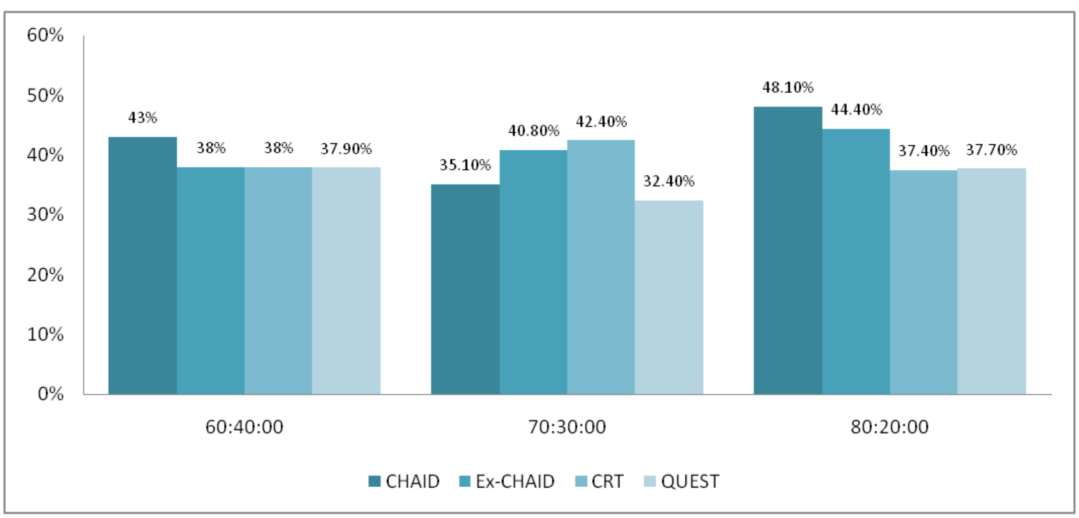


Figure 4.6: Decision Tree with double repetition dataset of hard pattern to learn

For double data set with allocation of 80:20, CHAID achieved the highest test result (48.1%). But for data allocation of 70:30, CRT obtained the highest test result (42.4%).

The failures can be further analyzed and the results are shown in Table 4.24. Results exhibited in Table 4.24 indicate that CHAID method obtained the highest test accuracy consistency with different data allocation. Both CRT and QUEST obtained test accuracy between 37% - 42%.

Table 4.24: Cross Validation and Split Sample Validation

Cross Validation			Split Sample Validation					
Growing Method	**No. of Sample folds**	**Predicted Classification**	**60 : 40**		**70 : 30**		**80 : 20**	
			Train	**Test**	**Train**	**Test**	**Train**	**Test**
CHAID	25	48.7%	42.30%	43%	40.80%	35.10%	45.50%	48.10%
Ex-CHAID	25	49.5%	45.10%	38%	45%	40.80%	43.50%	44.40%
CRT	25	49.8%	39.50%	38%	45.50%	42.40%	40. 6%	37.40%
QUEST	25	41.8%	38.80%	37.90%	34.70%	32.40%	43.40%	37.70%

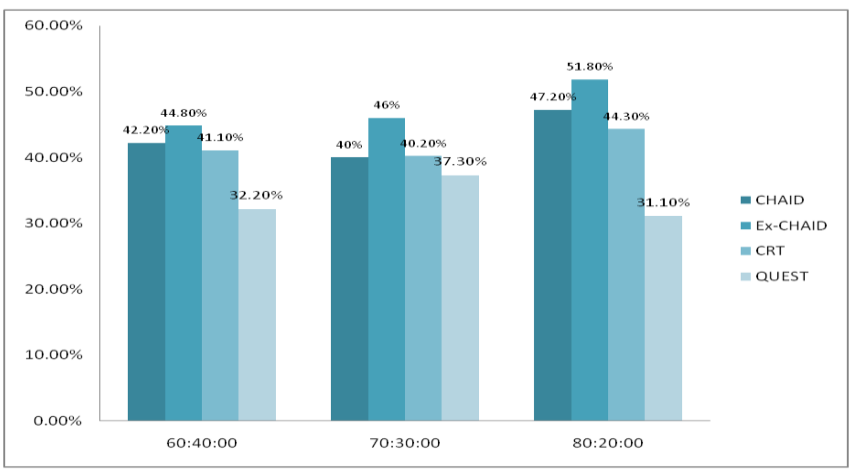


Figure 4.7: Decision Tree with Triple repetition dataset of hard pattern to learn

Similar observation is also shown by EX-CHAID when the hard to learn pattern is repeated.

Table 4.25: Decision Tree with double repetition dataset of hard pattern to learn

Cross Validation			Split Sample Validation					
Growing Method	**No. of Sample folds**	**Predicted Classification**	**60 : 40**		**70 : 30**		**80 : 20**	
			Train	**Test**	**Train**	**Test**	**Train**	**Test**
CHAID	25	52%	46.30%	42.20%	47.60%	40%	49.30%	47.20%
Ex-CHAID	25	53.6%	44.20%	44.80%	46.20%	46%	48.60%	51.80%
CRT	25	52.4**%**	39.40%	41.10%	45%	40.20%	46. 5**%**	44.30%
QUEST	25	44.5**%**	32.60%	32.20%	40.50%	37.30%	39.90%	31.10%

Analysis Decision tree by flower type

For the original flower dataset, Marigold shows the highest accuracy (95.5%) with data allocation 60:40. However, for data allocation 80:20, Euphorbia Mill shows the highest accuracy (83.3%).

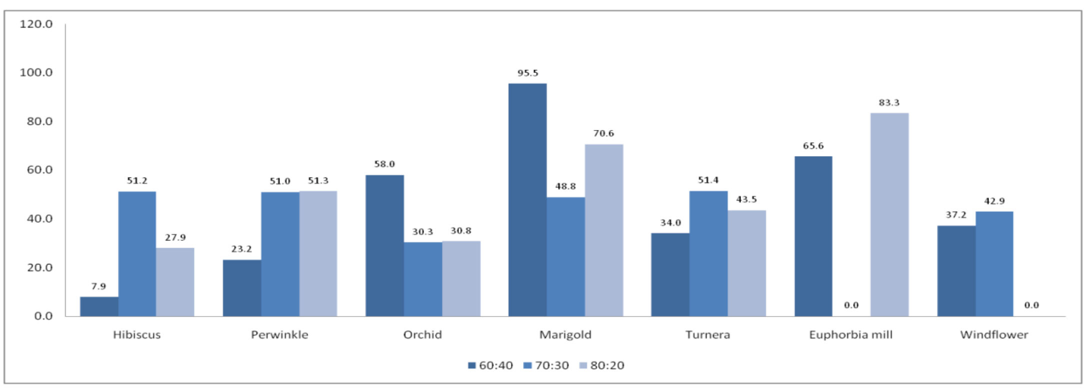


Figure 4.8: Decision Tree EX CHAID original flower dataset

Table 4.9 for double repetition flower, Hibiscus and Perwinkle obtained the highest accuracy while in Table 4.10 indicated the average accuracy for triple repetition which appear more stable than the rest. Marigold shows the highest accuracy for data allocation 60:40. The performance for rest of the flowers such as Hibiscus, Perwinkle and Euphorbia Mill are quite consistent with various data allocation.

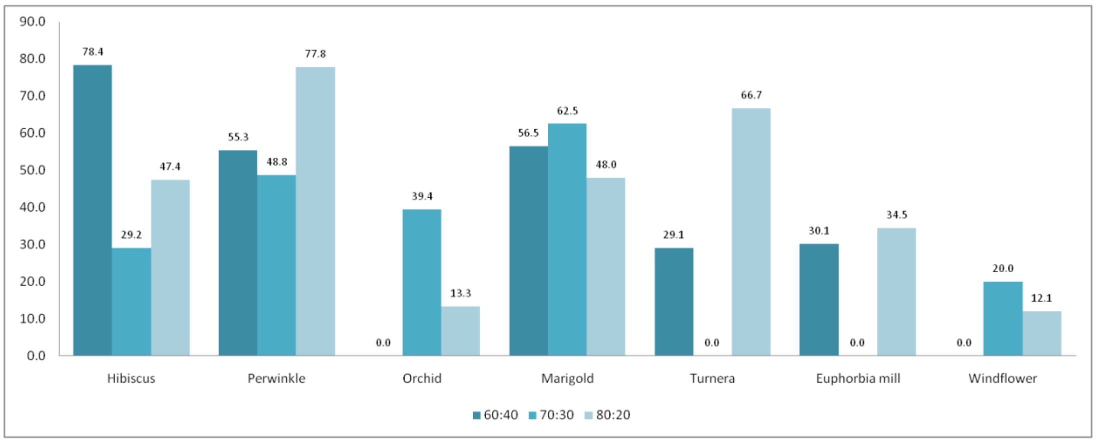


Figure 4.9: Decision Tree EX CHAID double repetition flower dataset

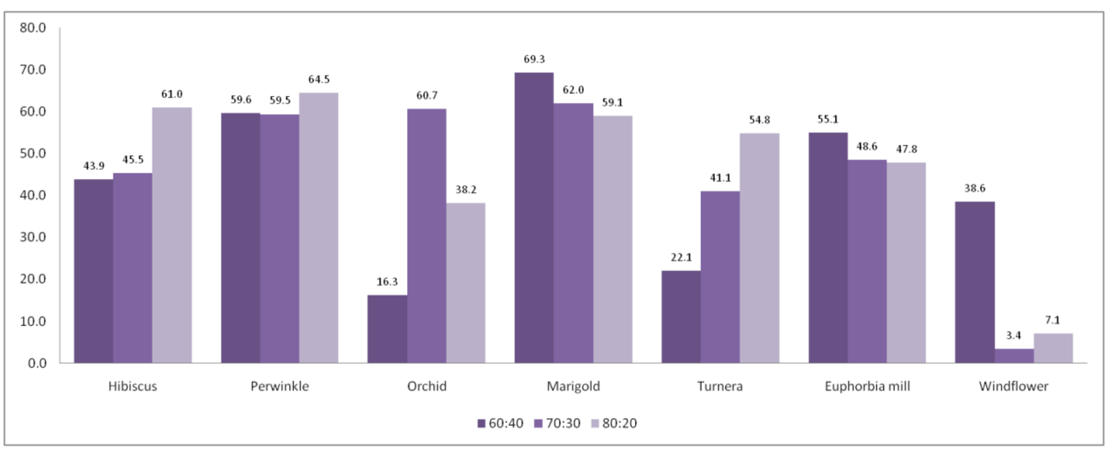


Figure 4.10: Decision Tree EX CHAID Triple repetition flower dataset

4.5 Summary

A total of 1800 images have been extracted from 30 Malaysian flowers (60 images per flower) and trained using Multilayer Perceptron with backpropagation algorithm. Classifications of flowers were based on seven (7) attributes which including Hue, Saturation, Value, Contrast, Correlation, Energy and Homogeneity. These values were generated from MATLAB Image Processing Toolbox based on ROI chosen for each flower image. The performance of neural networks was evaluated based on classification accuracies of empirical results.

In this study, NN has shown its potential in building Malaysian flower model. Since NN has shown its potential in building Malaysian flower model, therefore in future, dataset built in this study can be extended to increase the classification accuracy. Varieties sample of images can be captured for a particular flower with various colours. Shape features of flowers can be included as one of the important attribute in order to improve the classification accuracy as well. This indirectly enhances the NN algorithm sensitivity and leads to a higher 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.

CHAPTER FIVE
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

As mentioned in the previous chapters, there are minimum numbers on image processing and image classification for flower imagesin Malaysia and South East Asian region has been conducted (Aulia, (2005); Ehsan (2008); Suppaiboonvong, (2010); Pornpanomchai *et al*. (2011) and Tan, Koo & Lim (2012)). In this study a method to develop a classification model for Malaysian flowers based on colours and texture feature has been proposed. There are 1800 flower images have been selected to represent the whole dataset used in this experiment. 60 samples for each flower have been collected to represent each category. Classifications of flowers were based on colour and texture feature with seven characteristics which including Hue, Saturation, Luminance, Contrast, Correlation, Energy and Homogeneity. All attribute for each images then being trained and tested using three different data mining classifiers; Neural Networks, Logistic Regression and Decision Tree classifier. The outcome results were proved successful classification whereby classification by using Neural Networks classifier give the best classification result compare to Logistic Regression and Decision Tree.

The flower model developed in this study can be used to develop a recognition and retrieval system such as Malaysian Blooming Flower Recognition System in the future.

5.2 Recommendations

To improve the classification results for Malaysian Blooming flowers in future study, some examples are proposed as below:

5.2.1 Increase the number of Malaysian flowers datasets

The accuracy of Neural Networks can be improved by extending dataset built and includes more images of each flower type or by increasing the class of targets. Varieties sample of images can be captured for a particular flower with various colours.

5.2.2 Include shape feature

Shape features of flowers can be included as one of the important attribute in order to improve the classification accuracy (Miao, Gadelin and Yuan (2006)*;* Hiremath and Pujari (2007); Du, Wang and Zhang (2007) and Hashim etal. (2010). There are two methods to define object's shape which are based on its region and based on its contour (El-ghazal, Basir and Belksim, 2008).

Most of the researchers working in flower image classification prefer to extract flower's shape based on contour using numerous methods for instance intelligent scissor (Mortensen & Barret, 1995), Route Tracing (Saitoh et al., 2003), CAVIAR (Zou & Nagy, 2004) and OBJ CUT(Kumar, Torr & Zisserman, 2005). The shape features that have been extracted can be calculated by using any of intelligent descriptors' for example Centroid Contour-Distance, Angel Code Histogram (Hong *et. al.*, 2004), Fourier Descriptors (Kauppinen, Seppanen & Pietikainen, 1995), wavelet descriptors (Chuang and Kuo, 1996), contour displacement (Adamek and O'Connor, 2004) and curvature based Fourier descriptor (El-ghazal, Basir and Belkasim, 2008).

5.2.3 Environment

In this study, all the pictures were taken at flower nurseries around Changlun and Jitra in uncontrolled environment. In this kind of environment, there are few outside factors such as the volume of light emitted by sun, weather and existence of clutter background can affect the information in images taken. This will lead to inaccurate readings. Thus there is a need to have the flower's image in a controlled environment like a mini studio which have been carried out by Suppaiboonvong (2010). The results obtained from controlled environment later can be compared with uncontrolled environment and analysis to see which of the environment giving most accurate result.

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APPENDIX

MLP with original flower datasets

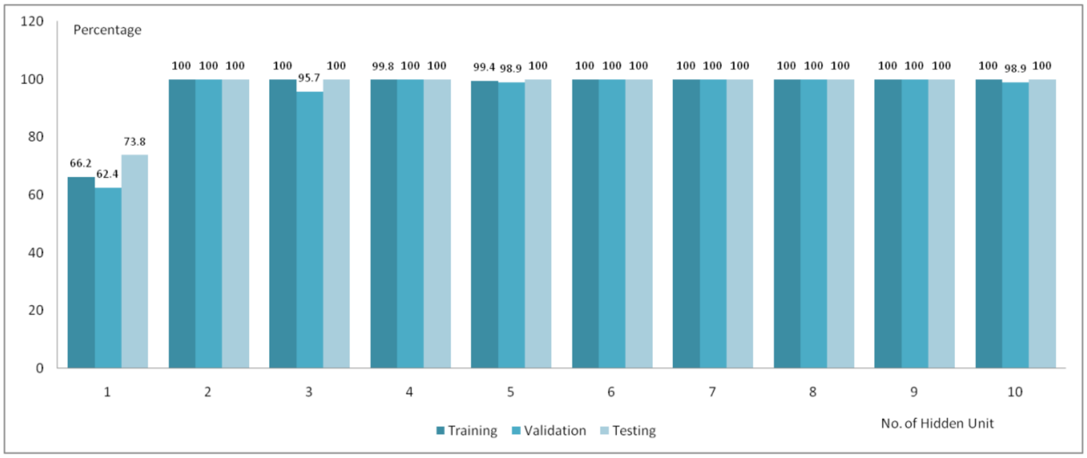

Figure 1: MLP Original Dataset 60:20:20 Scale Conjugate Gradient

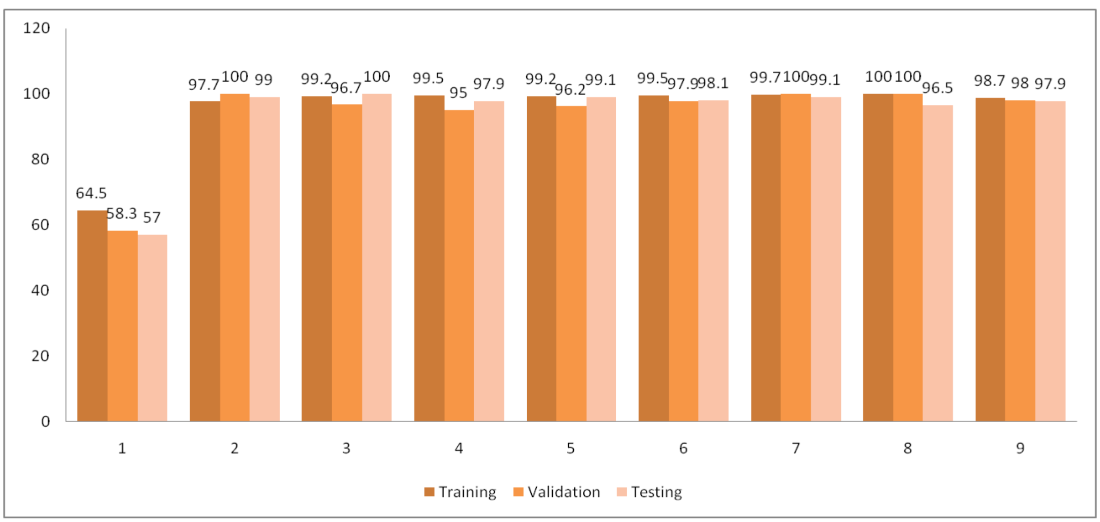

Figure 2: MLP Original Dataset 70:20:10 Scale Conjugate Gradient

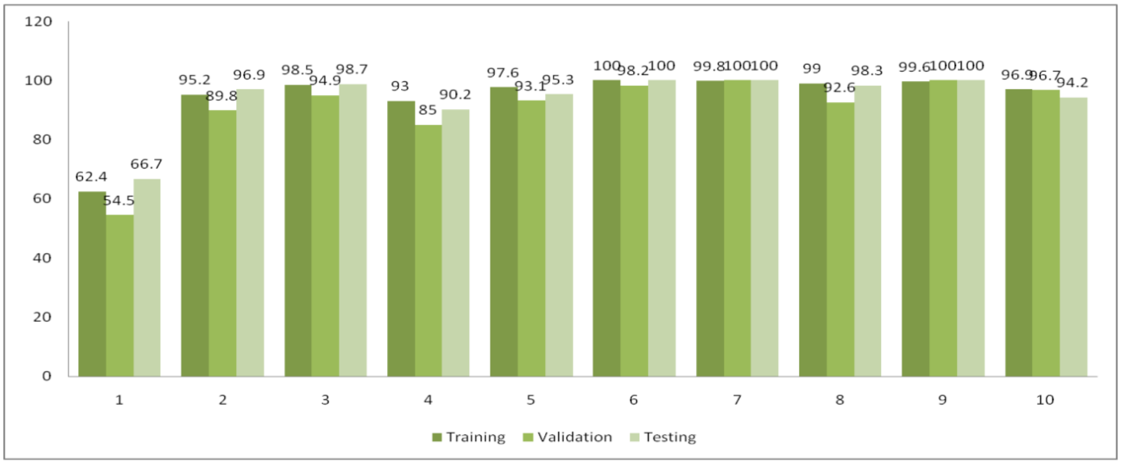

Figure 3: MLP Original Dataset 80:10:10 Scale Conjugate Gradient

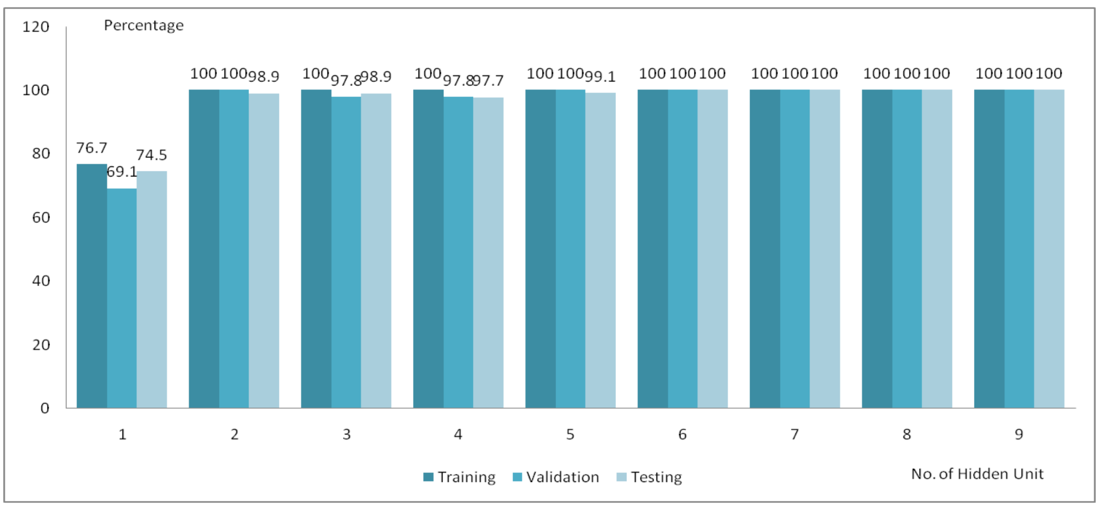

Figure 4: MLP Original Dataset 60:20:20 Gradient Descents

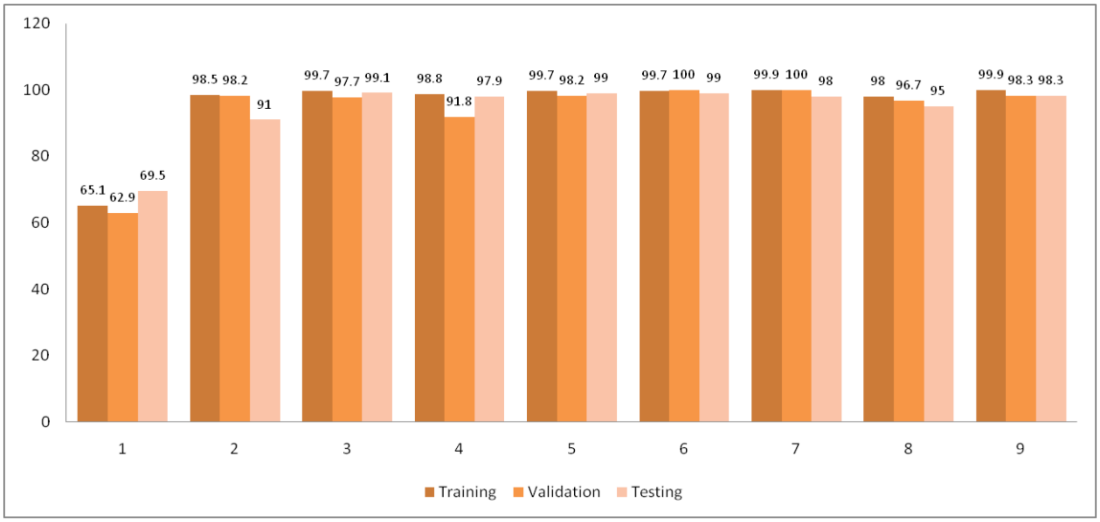

Figure 5: MLP Original Dataset 70:20:10 Gradient Descents

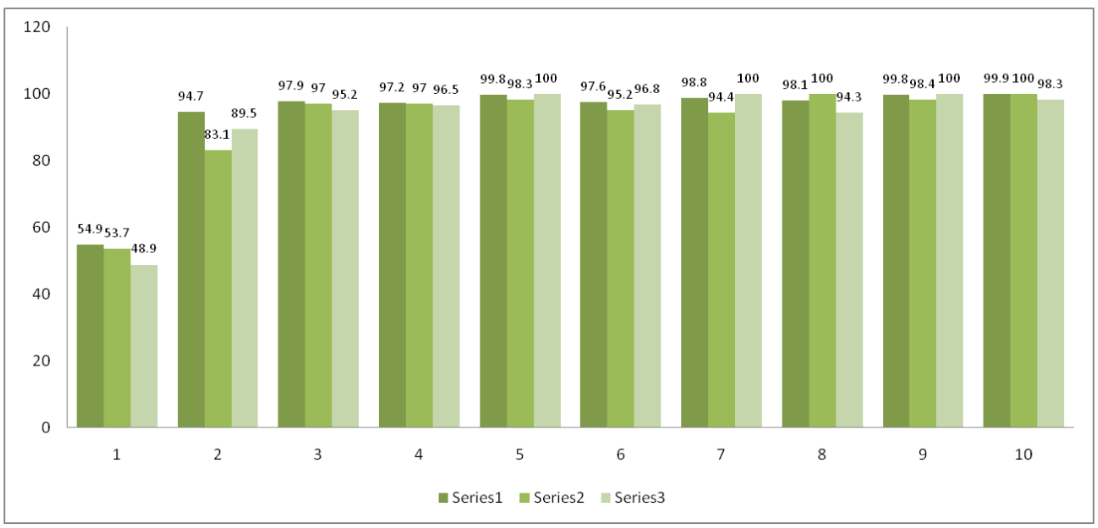

Figure 6: MLP Original Dataset 80:10:10 Gradient Descents

MLP with double repetition flower datasets

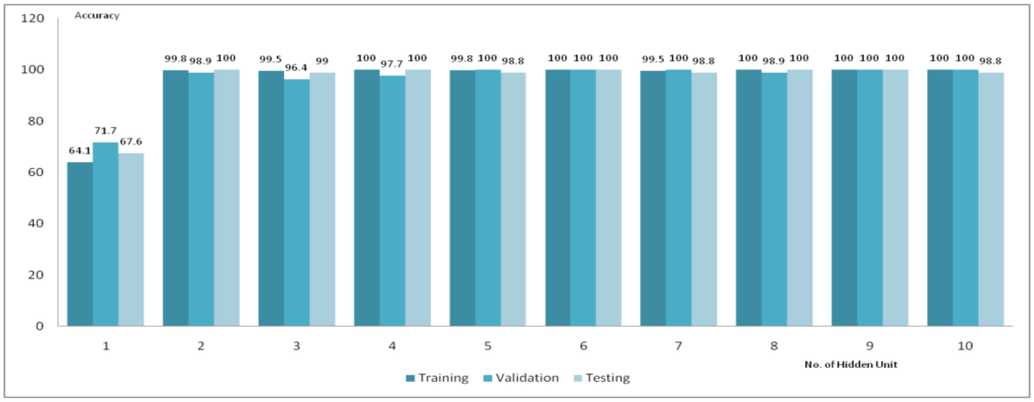

Figure 7: MLP Double Dataset 60:20:20 Scale Conjugate Gradient

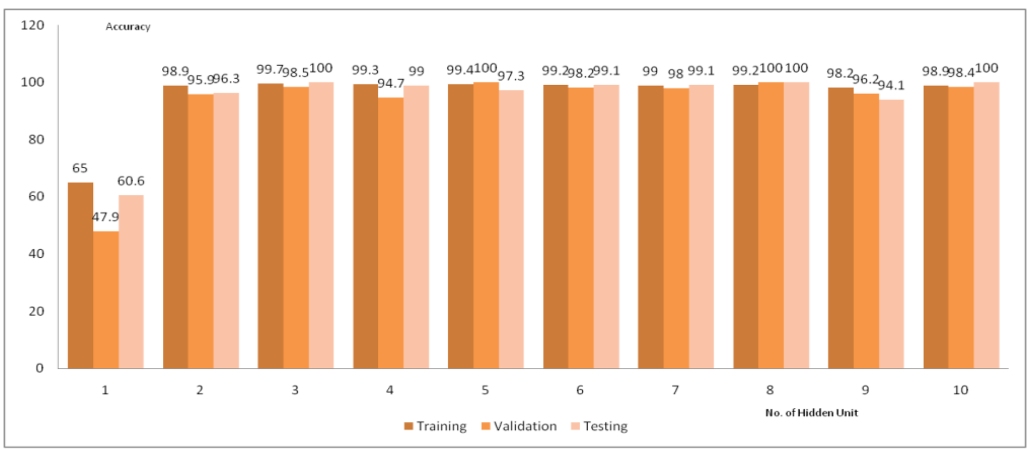

Figure 8: MLP Double Dataset 70:20:10 Scale Conjugate Gradient

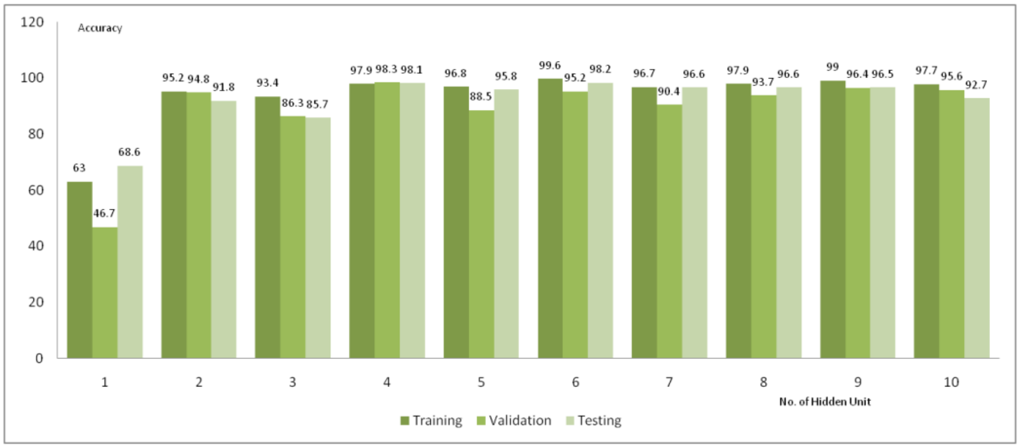

Figure 9: MLP Double Dataset 80:10:10 Scale Conjugate Gradient

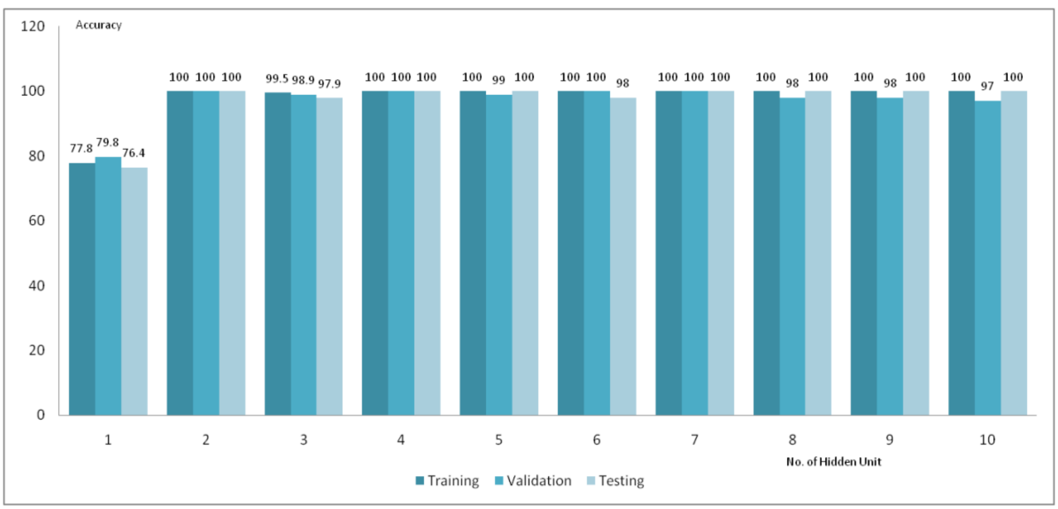

Figure 10: MLP Double Dataset 60:20:20 Gradient Descents

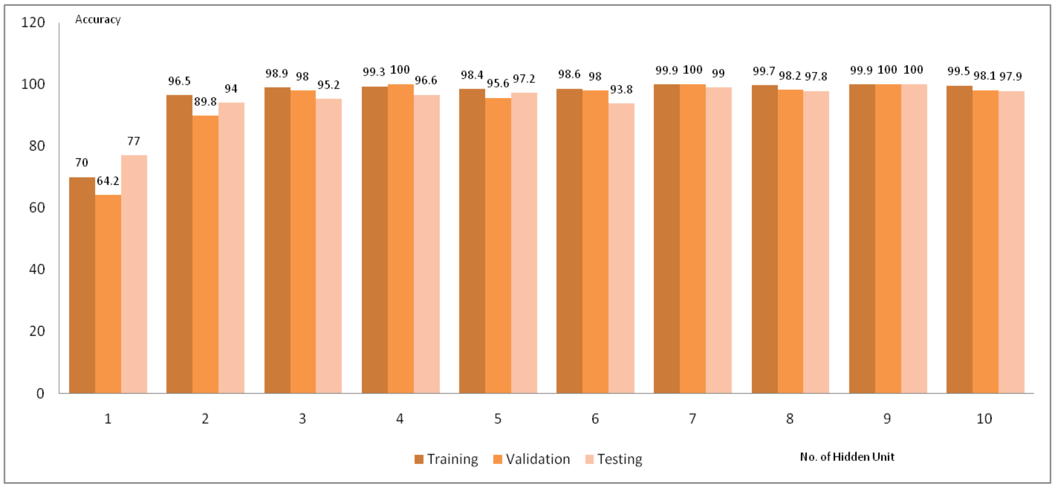

Figure 11: MLP Double Dataset 70:20:10 Gradient Descents

Figure 12: MLP Double Dataset 80:10:10 Gradient Descents

MLP with Triple repetition flower datasets

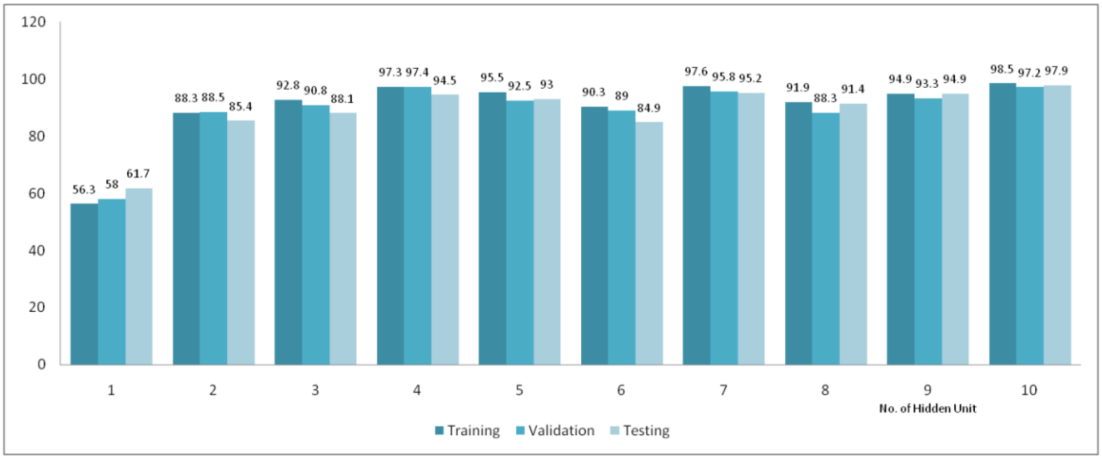

Figure 13: MLP Triple Dataset 60:20:20 Scale Conjugate Gradient

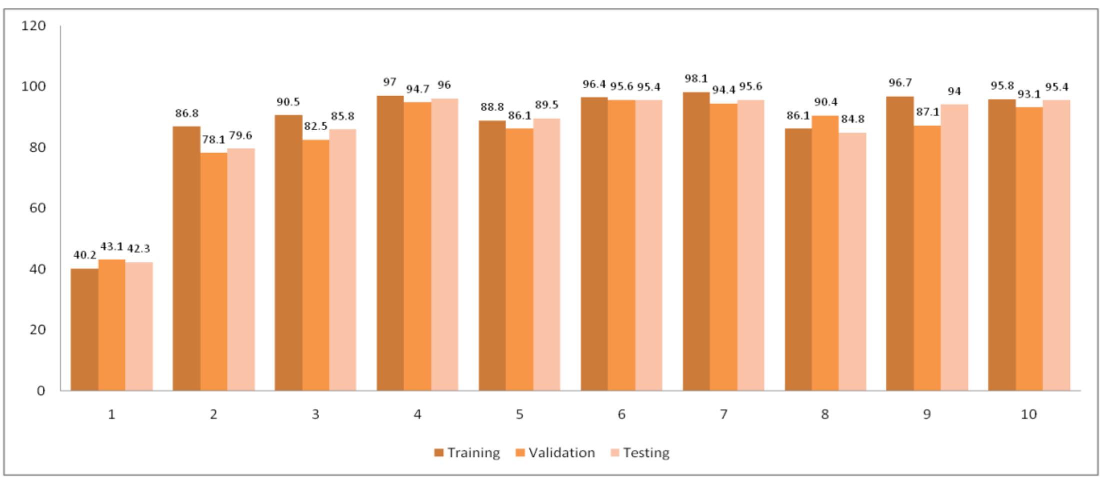

Figure 14: MLP Triple Dataset 70:20:10 Scale Conjugate Gradient

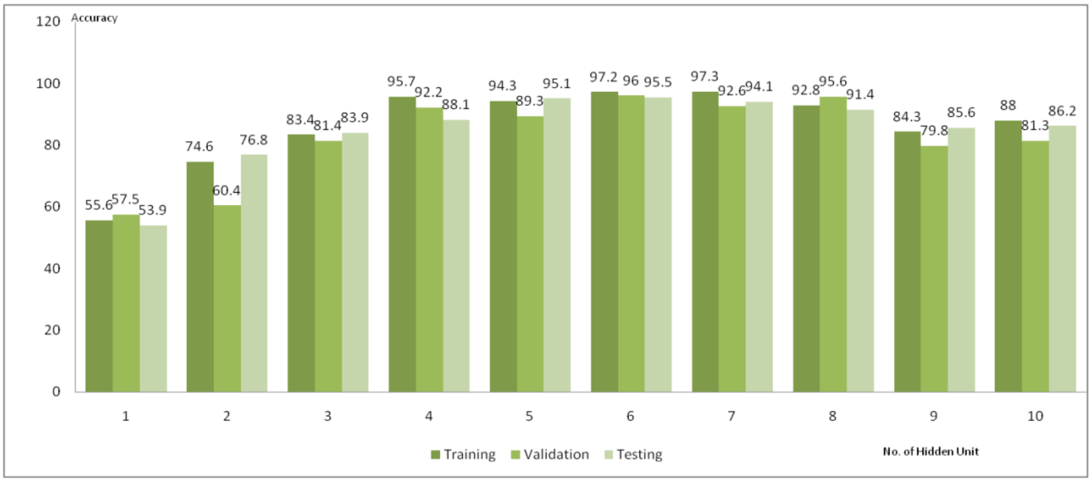

Figure 15: MLP Triple Dataset 80:10:10 Scale Conjugate Gradient

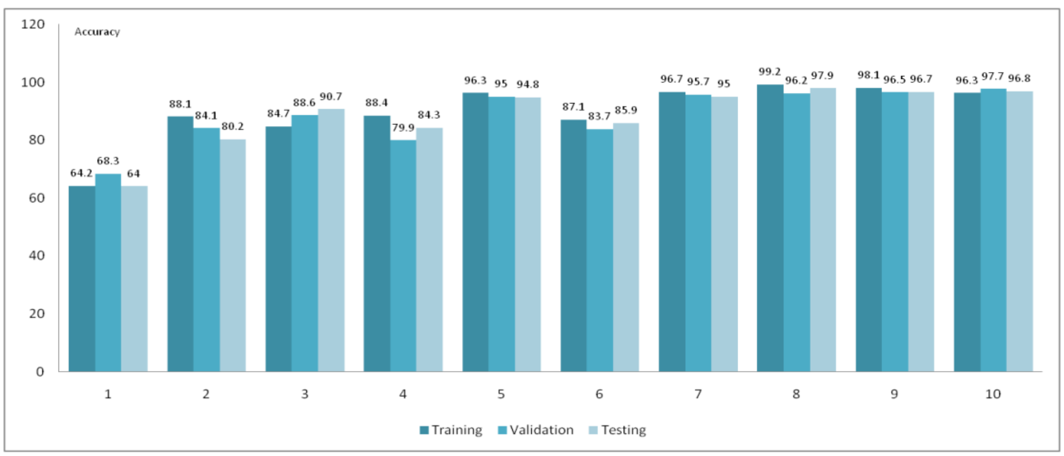

Figure 16: MLP Triple Dataset 60:20:20 Gradient Descents

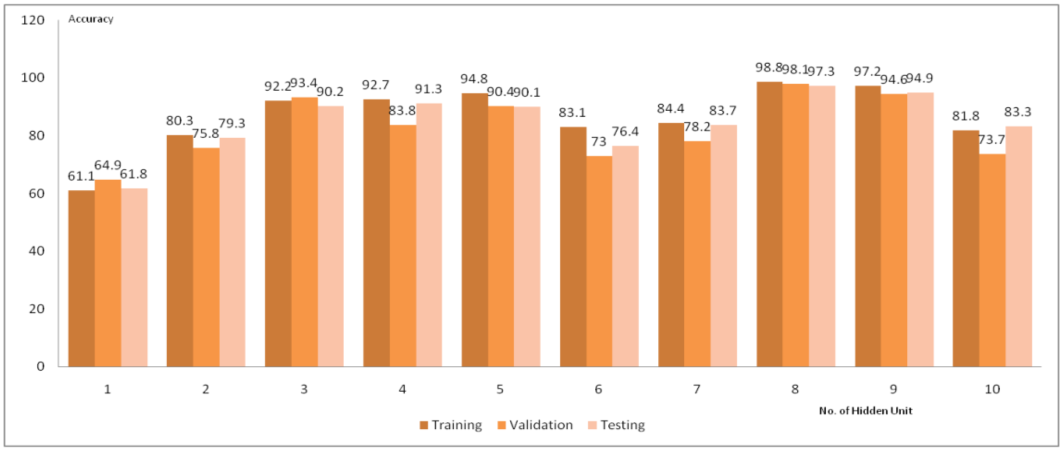

Figure 17: MLP Triple Dataset 70:20:10 Gradient Descents

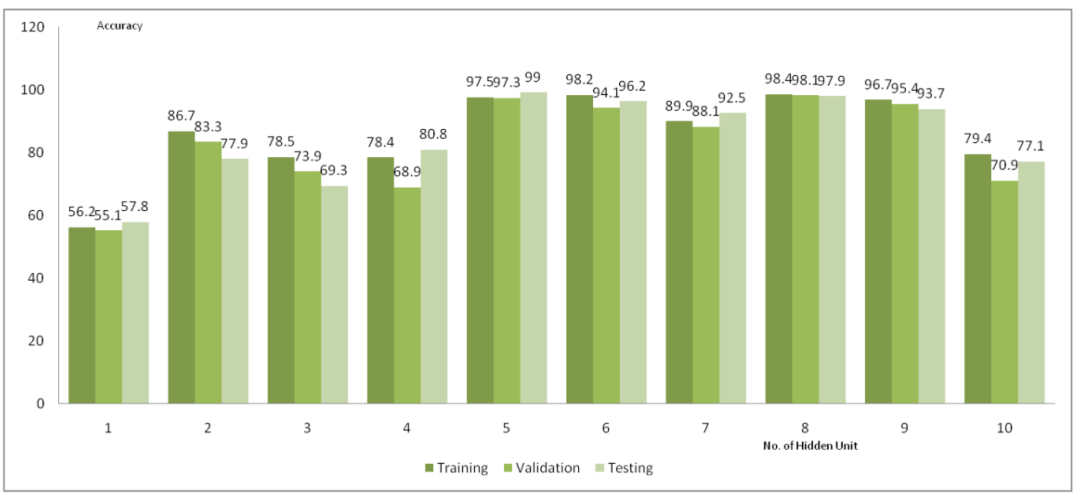

Figure 18: MLP Triple Dataset 80:10:10 Gradient Descents