ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

IMAGE ANALYSIS FOR ETHIOPIAN COFFEE CLASSIFICATION

By

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DEPARTMENT OF COMPUTER SCIENCe

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1. **Sebsibe Hailemariam, Advisor** ______________________
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DEDICATION

To GOD

For Blessing Ethiopia with Natural Coffee - Our Green Gold

To the Memory of My Brother

Yizengaw Makonnen

For His Great Inspirations in My Early Ages

To My Parents and My Beloved Fiance – Bezuyie

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Ethiopia is a homeland of coffee. Coffee is a major export commodity of Ethiopia, which has a significant role in earning foreign currency. There are different varieties of coffee in Ethiopia and they are classified based on their growing region.

In view of this, a digital image analysis technique based on morphological and color features was developed to classify different varieties of Ethiopian coffee based on their growing region. Sample coffees were taken from six coffee growing regions (Bale, Harar, Jimma, Limu, Sidamo and Welega) which are popular and widely planted in Ethiopia. On the average 56 images were taken from each region. The total number of images taken was 309 which contain 4844 coffee beans.

For the classification analysis, ten morphological and six color features were extracted from each coffee bean images. The processing type of coffee (washed or unwashed) has been also predefined during the analysis.

We have compared classification approaches of Naïve Bayes and Neural Network classifiers on each classification parameters of morphology, color and the combination of the two. To evaluate the classification accuracy, from the total of 4844 data sets 80% were used for training and the remaining 20% was used for testing. The classification system was supervised corresponding to the predefined classes of the growing regions.

It was found that the classification performance of neural networks classifier was better than Naïve Bayes classifier. It was also showed that the discrimination power of morphology features was better than color features but when both morphology and color features were used together the classification accuracy was increased. The best classification accuracies (80.7%, 72.6%, 56.8%, 96.77%, 95.42% and 69.9% for Bale, Harar, Jimma, Limu, Sidamo and Welega respectively) were obtained using neural networks when both morphology and color features were used together. The overall classification accuracy was 77.4%.

Keywords: Ethiopian coffee, Coffee Bean, Image Analysis, Classification, Neural Networks

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Coffee is an edible commodity. It is widely used as a beverage but now a days its use as input in some food processing industries is increasing [40]. For instance, it is used as a flavoring to various pastries, ice-creams, chocolate, etc.

There are different types of coffee in the world. Among different types of coffee, the major economic species are coffee Arabica and coffee Robusta. Arabica accounts 80 % of the world coffee trade, and Robusta most of the remaining 20 %. Coffee Liberica and Excelsa together supply less than 1 % [14, 30].

The origins of the coffee crop can be traced back to the Ethiopian highlands for coffee Arabica and the forest of West and Central Africa for coffee Robusta (Canephora). Coffee was well established as a beverage in Yemen by the 14th century, from where it spread to other Middle Eastern countries in the 15th century and across Arabian Sea to India. Today coffee is widely cultivated and used through out the tropics [13, 14].

Ethiopia has a suitable environment to grow all Arabica coffee varieties. Currently, only Coffee Arabica is grown in Ethiopia. Other coffee species are not cultivated yet. Ethiopia being the home of Arabica coffee, the first coffee was discovered from south-western massive highlands of Ethiopia called Kaffa, more specifically from a district called Buno. In Ethiopia, coffee production is concentrated in the Oromia and Southern regions of the country, though the majority of Ethiopian regions are still suitable for coffee growth [13, 14].

Ethiopia is not only the icon of coffee, but it thrives on coffee and people drink coffee regularly in every part of the country. Coffee is closely associated with the Ethiopian culture. Most people in the country start their day by taking a cup or two of coffee in the morning. Coffee ceremony, the tradition of serving coffee in Ethiopia is unique.

Ethiopian Economy is highly dependent on agriculture. Among the agricultural production, coffee sub-sector plays a major role in the economy of the country. Coffee is the biggest source of foreign currency earning and has a major contribution to Gross Domestic Product (GDP) [15].

Coffee production for international market in the country goes through many processes in order to be competitive to the world market. Due to this, the government has given serious monitoring and care to preserve the inherent coffee quality characteristics to satisfy customer preferences. Accordingly, every coffee produced have to go through the monitoring of the institute of Ethiopian Coffee Quality Inspection and Auction Center, in Addis Ababa or Dire Dawa, to certify that the supplied coffee has met the minimum requirement of national standard for export [14, 31, 40].

Processing coffee is the method of converting the raw coffee fruit (cherry) into the commodity green coffee (coffee bean). In Ethiopia, there are two ways of coffee processing. They are wet method (washed coffee) and dry method (natural coffee). The wet method is used in regions where there is plentiful supply of water. It involves more capital outlay and more care than the dry method. The dry method is simple. It is all done with exposure to the sun. The wet method involves removing the pulp from the bean within 12 hours while the dry method takes at least three to five weeks. In general, the coffee produced by wet method is usually of better quality but commands higher prices [40].

From the total coffee production of Ethiopia, the highest proportion accounts for natural coffee. That is, dry processed coffee is supplied to the market [15, 31]. Relatively, a small portion of coffee production is washed coffee. The coffee supplying areas for washed and unwashed coffee include Yirgacheffe, Sidamo, Limu and Bebeka. Mainly unwashed coffees are from Harar, Jimma, Bale, Wellega and Illubabor. Coffee in each area has specific physical and chemical properties which attributes to distinct characteristics of the region.

Coffee is graded for export with the objective of producing the best cup quality and there by securing the best price possible. However, there is no universal grading system. Each producing country has its own national standard which fulfills the minimum export quality requirement suggested by the market [14, 15, 31].

In Ethiopia, coffee grading is conducted through the combination of two methods [31]. They are green coffee (raw bean) analysis and cup tests (liquoring). Green coffee analysis involves visual inspection of physical characteristics of coffee bean. This includes screen analysis which makes size assessment, defect count, appearance or color test and shape which usually refers to the structure of beans. Cup test is based on roasted coffee analysis (chemical process) by which aroma, acidity, and other flavor components are tested. From the over all grading of coffee, green analysis accounts 40% and cup test accounts 60% in the quality inspection process.

Coffee grown in a given area has a peculiar taste and physical characteristics due to different climatic condition of the place. In order to preserve the distinct flavors, considerable emphasis is placed on keeping consignment from different regions. The Ethiopian Coffee Quality Inspection and Auction Center, which is under the ministry of Agriculture and Rural Development, is responsible for regulating the quality of export coffee.

1.2 Motivation

The technology of image analysis is relatively young and its origin can be traced back to the 1960s. It has experienced tremendous growth both in theory and application. It was applied in areas such as medical diagnosis, industrial automation, aerial surveillance (biometrics), remote sensing (satellite observation of Earth) and in the automated sorting and grading of agricultural products [33, 34].

Until a few years ago, constant problems affected image analysis and prevented their widespread adoption. Since its start, image processing has appeared as a computationally intensive and almost intractable field because its algorithms require high speed processors and large memory size. Even the input–output of high-resolution images was traditionally a bottleneck for common computing platforms such as personal computers and workstations. In recent years, however, faster microprocessors, faster and larger memories, and faster and wider buses have made computer vision affordable on a wide scale [33, 36].

Technological advancement is gradually finding applications in different problem domains as mentioned before and very recently in the agricultural and food industries. Efforts are being geared towards the replacement of human operator with automated systems, as human operations are usually inconsistent and non-efficient. Automated systems in most cases are faster and more precise. However, there are some basic infrastructures that must necessarily be in place in automation [33].

In Ethiopia, a large segment of the population is involved in the coffee industry due to the importance placed on the sector. The Coffee sector is privileged with the advantage of receiving government support for research, infrastructure improvement, financial and manpower contributions, quality control systems, and publicity. The creation of the Coffee and Tea Authority proves this fact and one of its objectives is to support the production and trade of coffee as well as research efforts [14].

In Ethiopia, technologies of image analysis or computer vision have not been explored in a significant manner in the development of automation in agricultural and food industries. Particularly, Ethiopian coffee quality inspection is based on traditional ways of classification and grading system [31].

Therefore, the implementation of imaging technology in the sector will have a paramount importance to facilitate commercial activities by increasing efficiency, to sustain dependability of customer preferences and to promote the market.

1.3 Problem Statement

There are different varieties of coffee that are growing in different regions of Ethiopia. These coffee varieties of Ethiopia are sorted into different types of classes and grades. Coffee is classified in-order to get uniform end product. For instance, the uniformity in coffee bean size is important because it is difficult to roast large beans together with very small beans or broken beans because the smaller beans over roast or completely burn before the larger beans are roasted. Therefore, classification and grading of coffee is an industry requirement.

In line with this, coffee variety identification is very useful in encouraging good quality coffee production, ensuring dependable and competent exporters as well as creating lasting business relationship with overseas clients. In addition, sorting and packing has a significant role for the market of commercial goods. There is a need for automated inspection, as well as identification systems so that the abuses during distribution and marketing can be minimized. The need arises to pack the goods in a consistent and acceptable manner to gain and maintain market share. With these, a coffee has to be classified by region of origin, then graded and gets packed in some reliable system for market.

In Ethiopia, the method of coffee variety identification is through traditional inspection and previous experiences which is subjective and non efficient. The basis of coffee variety identification is often subjective with attributes color, size, shape and flavor frequently examined by human inspectors [15, 31]. It is also found that human perception could easily be biased [4]. As a result, objective discrimination of coffee varieties and quality determination is necessary which is consistent, non-destructive and cost effective for commercial purposes.

In light of these, it is pertinent to explore the possibilities of adopting faster systems which saves time and is more accurate in classification of coffee by reducing observer effects of biases pertaining to the quality standard that enhances the commercial needs. One of such methods is image analysis or computer vision system.

Therefore, this thesis work will initiate a model for Ethiopian coffee variety classification which is consistent, efficient and cost effective by exploring the technology of image analysis.

1.4 Scope of the Research

The purpose of this thesis work is to explore image analysis techniques and approaches on Ethiopian coffee variety identification based on their growing region.

The research work is based on coffee production of the current period. That is, our sample data is from coffee produced in Ethiopia in the production year of 2006/07. Another assumption is that two or more coffee from different areas or growing regions are not mixed.

In general, this research work was based on dry fruit or a coffee bean physical property grown in Ethiopia. In this activity, neither roasted nor milled or boiled coffee was analyzed.

1.5 Objective

The main objective of this research is to design an appropriate classification model of Ethiopian coffee varieties with respect to their growing region or area of plantation by using image analysis techniques.

In light of this general theme, the specific objectives of the research are the following.

i. Exploring morphological characteristics of Ethiopian coffee varieties such as shape, size and other important properties of a coffee bean like color in a particular area which is an identity of the bean in the production region.
ii. Extracting features from a coffee bean image that suits to a classification of different varieties of Ethiopian coffee.
iii. Identifying a coffee variety or growing region from a digital image of coffee beans.
iv. The performance of the proposed classification model will also be measured from the prototype implementation or experimentation.

1.6 Methodology

In order to accomplish the objectives of the research, literatures on contemporary development of image analysis related to cereal or fruit classification will be reviewed. From these insight reviews of image analysis techniques and tools that were employed on agricultural products variety identification and that were pertinent to this work will be selected. These image analysis techniques are selected based on the performance they had on the current related works.

The methods and tools that will be used in this research work are described in the following sections.

1.6.1 Materials and methods

A digital camera model DSC- S650, SONY 7.2 Mega Pixel, was used to record coffee bean images. When images were taken, the camera was mounted on a stand which provides easy vertical movement and stable support for the camera. The camera was fixed at a distance of 130mm from the sample table in-order to get clear images of coffee beans.

Samples were arranged on a white background table during image recording. The coffee beans were scattered on the table, each making no contact with another. The separation between coffee beans was kept in order to make image segmentation easier.

To obtain uniform lightning or balanced illumination, an incandescent lamp whose light source was 100W with a rated voltage of 220V was used in all experiments. The lighting system was switched on for about 5 minutes prior to acquiring any images for its stabilization. In-order to reduce the influence of surrounding light, we took the samples in a controlled room. The images were taken at resolution of 1632x1224 pixels.

1.6.2 Sampling Techniques

Sampling is one of the main procedures in coffee classification and quality assessment. In the current practice of the manual system, the sample drawer draws a ‘representative’ sample of 3kg per 10 tons of a truck, which is an average carrying capacity of a truck, on its arrival. From this 3kg, 300g is used for green analysis. The remaining was used for cup test and other references. We will take coffee bean samples from these sampled data because we need certified coffee for our research work [31, 40].

In view of this, from each coffee growing region, we have taken five different 100 grams of coffee bean which were from the same but that were transported to the quality inspection center at different times. Hence, some portion of these 500 grams of coffee bean image was captured from a given region.

In this regard, we have taken 309 images in which the images contain 4844 coffee beans. From these samples, 80% were used for training and 20% were used for testing purposes.

The samples of coffee beans were obtained from Ethiopian Coffee Quality Inspection and Auction Center (ECQIAC) which is under the Ministry Agriculture and Rural Development. All samples were certified coffee beans by domain experts of the laboratory of ECQIAC.

1.6.3 Tools

Some image processing, image analysis and classification tools and application development environment for the implementation of the proposed model will be required for the study.

Hence, for image processing and analysis of coffee bean images, ImageJ on windows platform was used. ImageJ is a public domain Java image processing program inspired by National Institute of Health [32]. It is open source software freely available on the Web[1]. It was designed with an open architecture in-order to provide extensibility via Java plugins. Therefore, for the purpose of displaying, editing, processing and analyzing coffee bean images, we will use ImageJ application software.

For neural network classification, NeuroSolustions version 5.0 was used. It is a proprietary application software of NeuroDimension, Inc. The evaluation copy of NeuroSolustions is available on the Web[2]. NeuroSolutions is neural network simulation software. It is based on object orientated modeling. It enables a graphical user interface (GUI) icon based construction of networks in the design of neural network model. Therefore, the system simplifies the

[1] http://rsb.info.nih.gov/ij/download.html
[2] http://www.neurosolutions.com/download.html

design of neural network model and also makes the output of the classification also easy to manage and understand.

Similarly, for Naïve Bayes Classification Weka 3.4 was used. Weka is a machine learning software, written in Java, and developed at the University of Wiakato in New Zealand. It is open source software which is freely available on the Web[3].

1.6.4 Classification Approaches

To implement the proposed model for the classification of coffee by their growing region, Naïve Bayes and neural network classification approaches were compared. For the neural network classification, feed forward multilayer neural network model was used. The classification systems were supervised because classes were predefined that correspond to the selected growing regions. See section 2.2.4 for detail descriptions about the classifiers.

1.7 Layout of the Thesis

The remaining part of the thesis is organized as follows:

The basic theory and concepts of digital images analysis and other relevant topics of image classification that are required for better understanding of the research domain are reviewed in chapter two. A general overview characteristic of Ethiopian coffee beans is also provided in the same chapter. Finally, this chapter reviews related research works that has been done on the classification of agricultural products using image analysis.

Chapter three gives a detail description of the classification model of Ethiopian coffees based on regions of origin (growing regions).

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[3] **http://www.cs.waikato.ac.nz/ml/weka**

Chapter four presents the implementation of the classification model and experiment results. In this chapter the experiment results of two classification approaches are also compared.

Finally, the conclusions drawn from the study and recommendations and possible future works are given in chapter five.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Ethiopian Coffee

Ethiopia is a homeland of coffee. There are different varieties of Arabica coffee that are growing in different regions of the country. Coffee in different regions has got distinct bean characteristics due to their climatic differences [13, 31, 39].

These coffee bean varieties are sorted in different types of classes and grades. The major coffee sorting attributes are size and shape. Coffee is sorted by size in-order to get uniform end product. The uniformity in bean size is important because it is difficult to roast large beans together with very small light beans or broken beans. The smaller beans tend to over roast, as they require less roasting than large beans. Very small pieces of beans may even burn completely [9, 14, 31, 39].

Hence, coffee in a specific growing region is classified based on its physical and chemical characteristics. The physical characteristics are size, shape and color. Based on size, coffee bean can be grouped in to pea berry (very small), small bean, medium bean, bold bean, large bean, extra large bean and very large (elephant) bean. Based on shape, coffee beans have different structures. They can be round, oval, elongated, flat, etc. A well-processed coffee also has an attractive raw color. The color of coffee can be bluish, grayish, greenish, faded or brownish [31, 39, 40].

2.1.1 Coffee Processing

Coffee processing is a method of converting the raw fruit of the coffee into commodity green coffee. There are two types of coffee processing methods. They are dry coffee processing method (natural or unwashed) and wet processing method (washed) [40].

The washed processing method is used in regions where a plenty of fresh water is available. This method gives high quality end product. It also minimizes the drying time needed but the method has running costs, which needs investment [39, 40].

The unwashed processing method is not as complicated as that of the washed processing. It is dried with the help of natural sunlight but it takes longer time than the washed method to dry the coffee beans. In Ethiopia unwashed coffee production accounts 80% of the total production [39, 40].

2.1.2 Coffee Grading

The primary issues of coffee grading are country (region) of origin, physical characteristics and sensory standards (taste). There is no universal coffee grading system except the recommended standards. Each producing country has their own national standard of grading scheme [14, 39].

In Ethiopia, there are two major components of coffee quality inspection. They are green analysis (visual test) and liquor analysis (cup test). These two methods are universally acceptable methods in both coffee producing and consuming countries tailored to the quality control system of respective countries [39, 40]. From the total grading of a coffee, the weight of green analysis is 40% and the remaining 60% is by cup test.

The green analysis is based on human sense of sight (eye) and with the help of other techniques to identify and classify coffee. This method inspects the physical properties of coffee like shape, size, color, uniformity or irregularity and defect count of the coffee bean [9, 39, 40].

In coffee grading, the parameters moisture content and bean size are preliminarily tested. The upper limit of moisture content is 11.5%. The lower limit of screen size for Ethiopian coffee bean is 14 units [31, 40], where 1 unit is 1/64 of inch. If these two conditions are not fulfilled, the coffees are considered as inferior quality so that further analysis of grading will not carried out. For the case of moisture content, it is recommended to reprocess the coffees to minimize the moisture content.

Screen size analysis is done by the help of sieve like apparatus to check the size of each coffee bean. The analysis is carried out by adding 300g of coffee bean to the apparatus and after repeatedly shaking the beans on the equipment, the amount of coffee beans passed through the holes are weighted in-order to check the proportion of the coffee bean under the specified screen size. The coffee bean screen size is usually reported as 14 to 20. The numbers indicate the dimension of the holes of the sieve, which is 1/64 of an inch. For example, Screen size 14 means the diameter of the hole is 14/64 of an inch [39]. The picture of the apparatus is shown in Figure 2-1.

Figure 2-1: Screen Size Analysis Apparatus

After the beans are passed the preliminary tests, other parameters will be evaluated with regard to their processing type. Washed coffee is graded by using the parameters shape, odor and color. Color, odor and shape parameter accounts 15%, 10% and 15% respectively from the total weight of grading by green analysis which is 40%. Similarly, the parameters of unwashed coffee are defect count and odor and their contribution is 30% and 10% from the total weight of grading by green analysis which is 40% [31, 40].

The other component of grading is cup test. It is based on human sense of test (tongue) to identify and classify coffee. It investigates the chemical properties of coffee. The parameters of cup test are acidity, body and flavor. Acidity is a primary coffee taste sensation created as the acids in the coffee combine with the sugars to increase the over all sweetness of the coffee. Body is the texture and sensation of coffee in the mouth; for example, coffee may feel light or heavy. Flavor is an aroma or the smell perception of the elements present in roasted coffee. Each of these parameters accounts 20% of the total weight of grading by cup test which is 60% [31, 40].

In summary, Ethiopian coffee is graded by evaluating green analysis out of 40% and cup test out of 60%. From the overall test value of each parameter with regard to either unwashed or washed coffee, the final grade is set based on the national standard of Ethiopian coffee grading system. For instance if the cumulative value from both visual test and cup test is from 81-100%, it is a grade one coffee. The grades are set specific to the growing region.

2.2 Digital Image Analysis

In common usage, an image or picture is an artifact that reproduces the likeness of some physical object. They are typically produced by optical devices such as cameras. They are rich in information and convey different implications.

Image technology is relatively a young technology which has got wide applications in different disciplines such as medical diagnosis, multimedia system, security – biometrics, geographic information system (GIS)- remote sensing, industrial automation- robot control, and very recently sorting of agricultural products [33,36].

In its early time, image-processing algorithms were computationally intensive. They require high processing speed and large memory size but in current trends of digital technology, computer capacity is increasing from time to time. For instance, there are faster microprocessors, larger memory size and faster and wider buses. This advancement of technology made image analysis affordable.

Image analysis is concerned with the extraction of measurements, data or information from an image by using image processing techniques. In the literature, this field has been called computer vision, image data extraction, scene analysis, image description, automatic photo interpretation, image understanding and a variety of other names [34].

Image analysis is distinguished from other types of image processing, such as segmentation and enhancement, in that the ultimate product of an image analysis system is usually numerical output rather than a picture. Image analysis also diverges from classical pattern recognition in that analysis systems are not limited to the classification of scene regions to a fixed number of categories, but rather are designed to provide a description of complex scenes [33, 34].

There are different stages of image analysis [34]. The first step towards designing an image analysis system is digital image acquisition using cameras. Sometimes we may receive noisy images that are degraded by some degrading mechanism. One common source of image degradation is the optical lens system in a digital camera that acquires the visual information. If the camera is not appropriately focused then we get blurred images. In such cases, we need appropriate techniques of refining the images so that the resultant images are of better visual quality, free from aberrations and noises.

After the enhancement of the image to the desired quality, the next step is the identification or segmentation of objects of interest within the image. Segmentation is the process that subdivides an image into a number of uniformly homogeneous regions. Each homogeneous region is a constituent part or object in the entire scene. In other words, segmentation of an image is defined by a set of regions that are connected and non-overlapping, so that each pixel in a segment of the image acquires a unique region label that indicates the region it belongs to.

After identifying each segment, the next task is to extract a set of meaningful features such as texture, color and shape. These are important measurable entities which give measures of various properties of image segments. Some of the texture properties are coarseness, smoothness, regularity, etc., while the common shape descriptors are length, aspect ratio, area, perimeter, circularity, etc. Each segmented region in an image may be characterized by a set of these features.

Finally based on the set of these extracted features, each segmented object is classified to one of a set of meaningful classes. For example, Ethiopian coffees from predefined growing region like Harar coffee, Sidamo coffee, Jimma coffee, etc. The classification is done using pattern classifiers. The pattern classifier can be statistical classifiers or neural network.

In the next sections we will describe the representation of images in computer system and some of the different stages of image analysis as mention before such as image processing, feature extraction and pattern classification.

2.2.1 Image Representation

An image is a set of points in a plane, each with its own luminance or color. One can think of any image as consisting of tiny, equal areas, or picture elements, arranged in regular rows and columns. The position of any picture element, or pixel, is determined on a plane. They can be binary (having only two distinct luminance values), grey-value (monochrome) images or color images [33]

In a computer vision system, the camera does the task of an eye and the computer acts as the brain by processing the information perceived by the camera. Hence, signals generated by the camera are stored in the computer as a digital image [33-36].

An image is a complex object rich in content. As a result, its representation is also complex unlike traditional data. The output of most sensors is a continuous voltage waveform whose amplitude and spatial behavior are related to the physical phenomenon being sensed. To create a digital image, we need to convert continuous sensed data into digital form. This involves two processes: sampling and quantization [19, 33, 34].

An image captured by a sensor or a camera is expressed as a continuous function f(x,y) defined on continuous variables x and y. And the function value refers to the amplitude at that point (x, y) [19]. To convert such image to digital form, we have to sample the continuous image in both coordinates and the amplitude. Digitizing the coordinate values x and y is called sampling that provide the set of pixels. Digitizing the amplitude, which is the gray level, is called quantization. Quantization involves the conversion of continuous gray-level (amplitude) into discrete quantities [19, 33].

In general, the transformation process of sampling and quantization is shown in Figure 2-2.

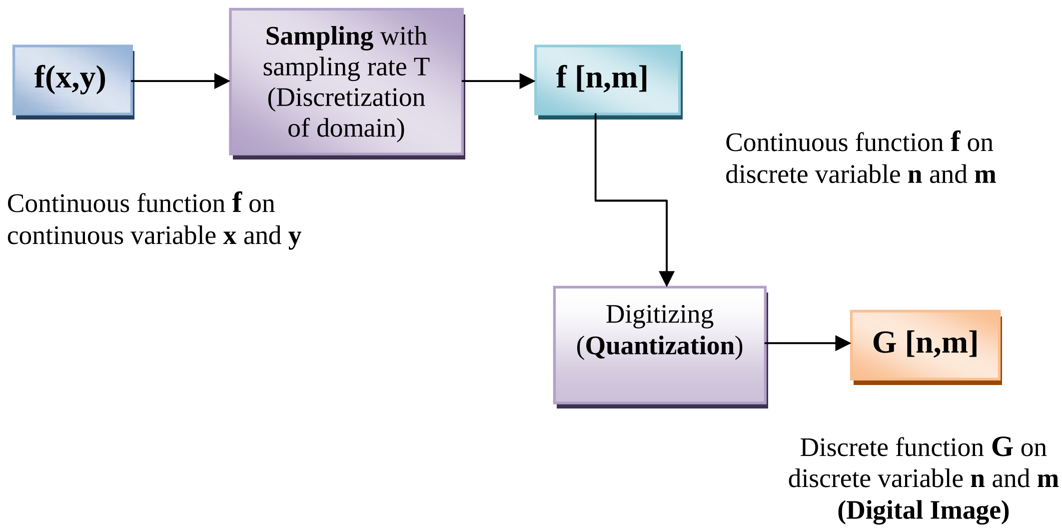


Figure 2-2: Sampling and Quantization Process

A discretized and quantized image can be represented by an MxN matrix as shown below. Each point in the matrix is a sample point.

$$
G[n, m] = \begin{pmatrix} G(0,0) & G(0,1) & \cdots & G(0, N-1) \\ G(1,0) & G(1,1) & \cdots & G(1, N-1) \\ \vdots & & & \\ G(M-1,0) & G(M-1,1) & \cdots & G(M-1, N-1) \end{pmatrix}
$$

G is a function that assigns a gray-level value to each discrete coordinates (quantization). The number of bits required to store a digital image is: b = **M**x**N**x**k,** Where k is an integer such that 2^k is the number of gray-levels. Such an image is called a "k-bit" image. Therefore, an image with 256 possible gray level values is called an 8-bit image [19, 33, 37]. From the representation, it is clear that image data has huge storage requirement.

NB: A color image will have grey level (intensity) for each of the basic color components Red, Green and Blue.

2.2.2 Image Processing

Image processing is defined as manipulating images in various ways, in order to reduce distortion or noise, enhance an image and extract information from the image. Hence, image processing is used for improving the visual appearance of images to a human viewer and preparing images for measurement of the features and structures present.

In the following sections, we will see some image processing techniques that include image acquisition, image enhancement, and image segmentation.

2.2.2.1 Image Pre-processing

This refers to the initial processing of the raw image. The images captured or taken are transferred onto a computer and are converted to digital images. Digital images though displayed on the screen as pictures, they are digits which are readable by the computer and are converted to tiny dots or pixel (picture elements) representing the real objects. In some cases pre-processing is done to improve the image quality by suppressing undesired distortions referred to as noise or by the enhancement of important features of interest.

Recent technology has the adoption of digital camera, which eliminates the additional component required to convert images taken by photographic charge coupled device (CCD) cameras or other sensors to readable format by computer processors. Images taken by digital camera maintain the features of the images with little noise due to its variable resolution. In this study digital camera was used to capture images as described in section 1.7.1.

2.2.2.2 Image Segmentation

Image segmentation is an essential component of image analysis technique that determines the quality of the final result. Segmentation involves partitioning an image into a set of homogeneous and meaningful regions, such that the pixels in each partitioned region possess an identical set of properties or attributes**.** These sets of properties of the image may include gray levels, contrast, spectral values, or textural properties. The result of segmentation is a number of homogeneous regions, each having a unique label. An image is thus defined by a set of regions that are connected and non-overlapping, so that each pixel in the image acquires a unique region label that indicates the region it belongs to. The set of objects of interest in an image, which are segmented, undergoes subsequent processing, such as object classification and scene description [33]. The image is usually subdivided until the region of interest is isolated from the background.

Many images can be characterized as containing some object of interest of reasonably uniform brightness placed against a background of differing brightness. For such images, luminance is a distinguishing feature that can be utilized to segment the object from its background. If an object of interest is white against a black background, or vice versa, it is a trivial task to set a mid gray threshold to segment the object from the background. Practical problems occur, however, when the observed image is subject to noise and when both the object and background assume some broad range of gray scales. Another frequent difficulty is that the background may be non-uniform [33].

As presented in [34], image segmentation is described as follows. A complete segmentation of an image **R** involves identification of a finite set of regions (R_1, R_2, R_3, . . . , R_N) such that :

i. $R = R_1 \cup R_2 \cup \ldots R_N$ – The union of all the sub regions gives the original region
ii. $R_i \cap R_j = \phi \quad \forall i \neq j$ - The sub-regions don't have an intersection

Segmentation algorithms are based on one of the two basic properties of gray-level values. One is based discontinuity of gray-level values; the other is based on the similarity of gray-level values

In the gray level values discontinuity, we partition an image based on abrupt changes in gray level. The principal areas of interest within this category are the detection of lines and edges in an image. Thus if we can extract the edges in an image and link them, then the region is described by the edge contour that contains it. From this point of view, the connected sets of pixels having more or less the same homogeneous intensity form the regions. Thus the pixels inside the regions describe the region and the process of segmentation involves partitioning the entire scene in a finite number of regions.

The second approach is similarity in the gray levels. It is based on the similarity among the pixels within a region. While segmenting an image, various local properties of the pixels are utilized. There are different types of well-established segmentation techniques. Among these, here we will describe histogram-based thresholding and edge detection [33].

A) Histogram Based Thresholding

Gray level thresholding techniques are computationally inexpensive methods for partitioning a digital image into mutually exclusive and exhaustive regions. The thresholding operation involves identification of a set of optimal thresholds, based on which the image is partitioned into several meaningful regions [33].

Thus, gray level thresholding is based on the analysis of the histograms of an image. The analysis of the histogram depends on the number of its peak values. Figure 2-3 shows a typical histogram of a single coffee bean image.

Figure 2-3: Histogram of a Coffee Bean Image

For example, in bi-level thresholding, the object and background form two different groups with distinct gray levels. When, the shapes of the histogram with peaks corresponding to the object and background regions and a valley in between, the valley point is usually chosen as the threshold. In bi-level thresholding, all gray values greater than threshold T are assigned the object label and all other gray values are assigned the background label, thus separating the object pixels from the background pixels. Thresholding thus is a transformation of an input image A into a segmented output image B as follows [33, 34]:

(a) $b_{ij} = 1$ for $a_{ij} > T$.

(b) $b_{ij} = 0$ for $a_{ij} < T$, where T is the threshold

Here $b_{ij} = 1$, for the object pixels and $b_{ij} = 0$, for the background pixels.

A simple iterative algorithm for threshold selection in a bi-level histogram image is presented as follows.

i. Choose an initial threshold $T \leftarrow T_0$
ii. Partition the image using T in two regions – background and foreground (object)
iii. Compute mean gray value μ_1 and μ_2 of background and object regions respectively.
iv. Compute the new threshold $T \leftarrow \dfrac{\mu_1 + \mu_2}{2}$
v. Repeat steps 2 to 4 until there is no change of T.

In Figure 2.4, we have shown the image thresholding of a coffee bean image which was developed by using ImageJ [32]. The minimum and maximum threshold values were 0 and 213 respectively. Hence, all the pixels with value greater than 213 were assigned the value 0, and all pixels with value less than or equal to 213 were assigned to the value 1. The level 0 area was the background, and the level 1 area was the coffee bean region. In other words, the coffee bean region was changed to black and the background region was changed to white, where in this case 1 represents black and 0 represents white.

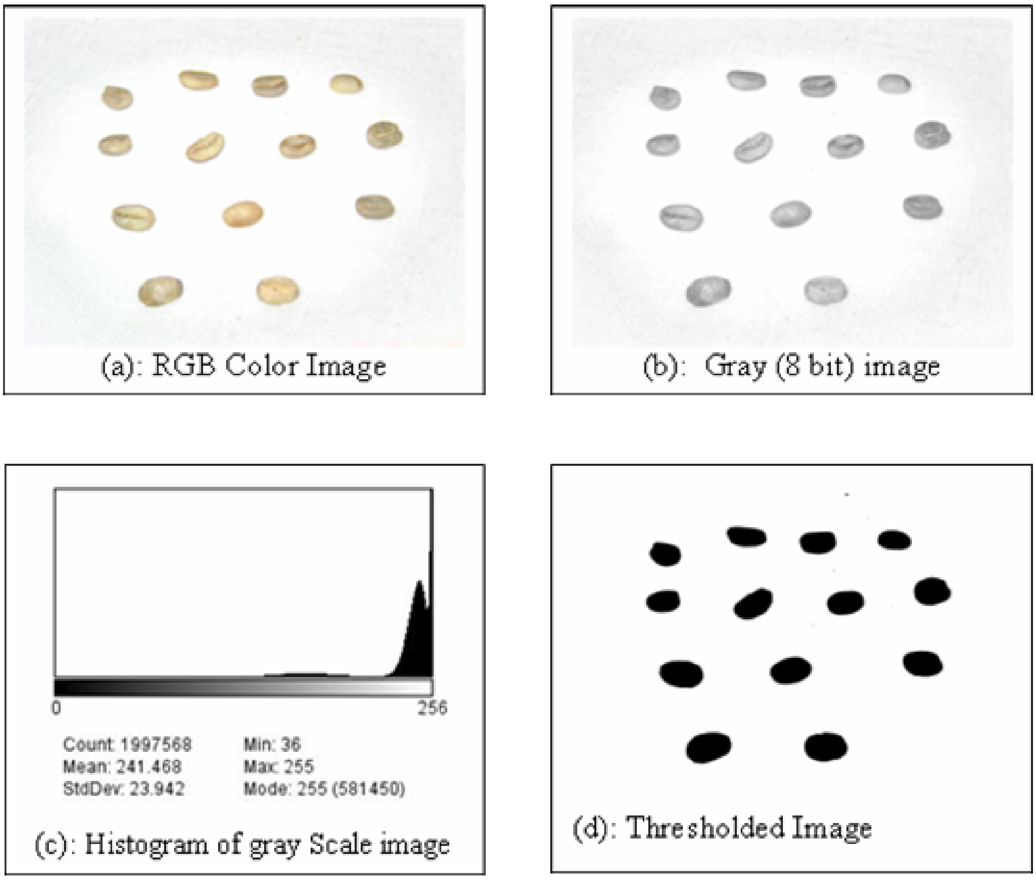


Figure 2-4: Image Segmentation by Histogram-based Thresholding

B) Edge Detection

Edges, lines, and points carry a lot of information about the various regions in the image. These features are usually termed as local features, since they are extracted from the local property alone. Though the edges and lines are both detected from the abrupt change in the gray level, yet there is an important difference between the two. An edge essentially demarcates between two distinctly different regions, which means that an edge is the border between two different regions. A line, on the other hand, may be embedded inside a single uniformly homogeneous region. For example, a thin line may run between two plots of agricultural land, bearing the same vegetation. A point is embedded inside a uniformly homogeneous region and its gray value is different from the average gray value of the region in which it is embedded [33].

The edge detection operation is essentially an operation to detect significant local changes in the intensity level in an image. The change in intensity level is measured by the gradient of the image [33]. Since an image f(x,y) is a two dimensional function, its gradient is a vector

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{df}{dx} \\ \frac{df}{dy} \end{bmatrix}.$$

The magnitude of the gradient may be computed in several ways. One way of computing magnitude of the gradient is

$$[G(f(x,y))] = \sqrt{G_x^{\ 2} + G_y^{\ 2}}.$$

The direction of the gradient is

$$\theta(x,y) = \tan^{-1}(G_y / G_x).$$

Gradient operators compute the change in gray level intensities and also the direction in which the change occurs. This is calculated by the difference in values of the neighboring pixels, i.e., the derivatives along the X-axis and Y-axis. In a two-dimensional discrete image the gradients are approximated by:

$$G_x = f(i+1, j) - f(i, j)$$

$$G_y = f(i, j+1) - f(i, j)$$

A number of edge detectors based on a single derivative have been developed by various researchers. In each of these operator-based edge detection strategies, we compute the gradient magnitude in accordance with the formula given above. If the magnitude of the gradient is higher than a threshold, then the presence of an edge detected.

For instance, Sobel edge detection strategy is a **3** x **3** neighborhood based gradient operator. The convolution masks for the Sobel operator are defined by the two kernels shown in Figure 2.5. The result of an edge detection generated by the Sobel operator is shown in Figure 2.6. The two masks are separately applied on the input image to yield two gradient components G_x, and G_y, in the horizontal and vertical orientations respectively [33, 34].

A mask is a set of pixel positions and corresponding values called weights. Each mask has an origin, which is usually one of its positions. The application of a mask to an input image yields an output image of the same size as the input.

1	2	1
0	0	0
−1	−2	−1

(a) Gradient G_x

1	0	−1
2	0	−2
1	0	−1

(b) Gradient G_y

Figure 2-5: Sobel Masks

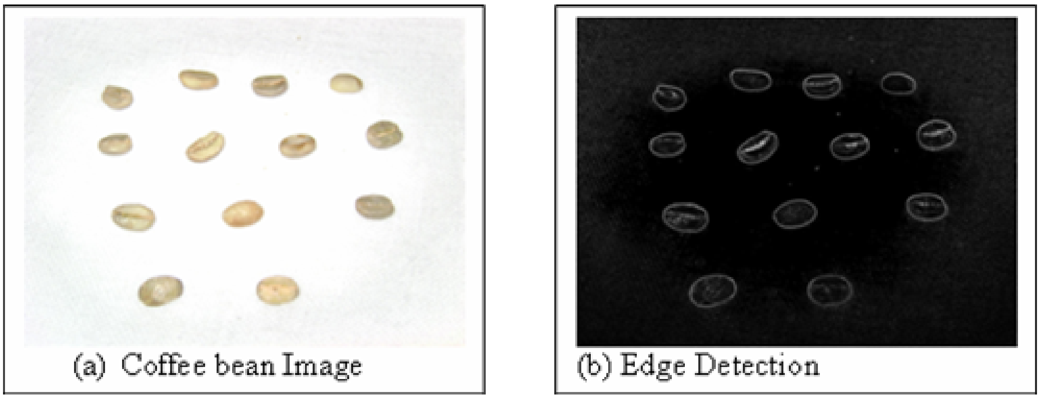


Figure 2-6: Sobel Edge Detection

In summary, thresholding is an important part of image segmentation to create binary images. Binary image analysis is useful for image feature extraction. For example, it simplifies the computation of geometrical features of an image. Hence, for this research work, we have used histogram-based image thresholding as it is simple and computationally inexpensive.

2.2.3 Feature Extraction

An image feature is a distinguishing primitive characteristic or attribute of an image. One of the key factors of image analysis is the extraction of sufficient information that leads to a compact description of an examined image. Owing to the immense size of the digital images, it can be very time-consuming if an image is to be analyzed in its original form. To make the process of image analysis simple and less time consuming, some quantitative information is extracted from the objects to be analyzed in the image. By extracting region of interests, the computational cost of object recognition is greatly reduced, thus improving the recognition efficiency [37].

Image features have a major importance in image classification. There are several types of image features that have been proposed for image classification. Morphology, color and texture are some of the basic image features [33-36].

Morphological features are the geometric property of an image like shape and size. They are physical dimensional measures that characterize the appearance of an object. For instance, area and perimeter are some of the most commonly measured size features and similarly circularity measures the shape of image compactness.

Image geometrical measurements are computed from binary images [34]. For example, consider a discrete binary image containing one or more objects, where O(i,j)=1 if a pixel is part of the object and O(i,j) =0 for all non-object or background pixels. The perimeter of each object is the count of the number of pixel sides traversed around the boundary of the object starting at an arbitrary initial boundary pixel and returning to the initial pixel. That is, to compute the perimeter of an object, we identify the boundary object pixels covering an area. Then, perimeter is defined by the sum of these boundary object pixels. The area of each object within the image is simply the count of the number of pixels in the object for which O (i,j)=1. Mathematically, the area of a binary object is given by $A = \sum_i \sum_j O(i, j)$, where O (i,j) represents the object pixels (binary 1). The area is thus computed as the total number of object pixels in the object.

In line with this, circularity or roundness is a typical measure of image shape compactness. It is defined as $C = \frac{4\pi A}{P^2}$, where ***A*** is the area of the polygon and **P** is its perimeter. If the shape is circular, its compactness will be equal to 1. However, if the space is a very thin and long bar, its compactness will be close to 0.

Figure 2-7 shows an example for a 2x2 pixel square of a binary image. The object area is A=4 and the object perimeter is P=8. The circularity is 0.79 by using the above formulas. The gray color indicates the boundary of the image, which is the perimeter of the image and the black region or the pixel values of 1, indicates the area of the object.

0	0	0	0	0	0
0	0	0	0	0	0
0	0	1	1	0	0
0	0	1	1	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Figure 2-7: Example of Perimeter and Area Computation

Morphological features are widely used in automated grading, sorting and detection of objects in industry. In certain applications such as classification of cereal grains, these features, alone, are not sufficient for a high-performance inspection process and thus need to be combined with other features. Color and textural features are extracted from the properties of pixels inside the object boundary [2, 3, 6, 8, 23, 24, 28, 29].

In addition to geometrical features, color is one of the most widely used features for image classification. In an image, each pixel records a numeric value that is often the brightness of the corresponding point in the image. Several such values can be combined to represent color information. The most typical range of brightness values is from 0 to 255 (8 bit range), but depending on the type of camera, scanner or other acquisition device a large range of 10 or more bits, up to perhaps 16 (0 to 65,535) may be encountered. However, in most cases these images are still stored with a set of discrete integer grey values because it is easier to manipulate such arrays and convert them to displays [35]. In line with this, the statistical values of color features like mean, mode, standard deviation, etc. are used for image classification.

Therefore, image features such as morphology, color and texture are used as inputs to a pattern classifier that discriminates objects, coffee in our case, into different categories.

2.2.4 Pattern Classifiers

Pattern classification is an area of science concerned with discriminating objects on the basis of information available about these objects. The objective is to recognize objects in the image from a set of measurements of the objects. Each object is a pattern and the measured values are the features of the pattern. A set of similar objects possessing more or less identical features are said to belong to a certain pattern class [33,38].

Hence, the aim of pattern recognition is the design of a classifier, a mechanism which takes features of objects as its input and which results in a classification or a label or value indicating to which class the object belongs. This is done on the basis of the learning set- a set of objects with a known labeling. The classifiers performance is usually tested using a set of objects independent of the learning set, called the test set [33-38].

A number of pattern classification techniques have been used for the recognition of patterns. Classification methods are mainly based on two types. They are supervised learning and unsupervised learning [33].

In supervised classification, the classifier is trained with a large set of labeled training pattern samples. The term labeled pattern samples means that the set of patterns whose class memberships are known in advance.

In unsupervised case, the system partitions the entire data set based on some similarity criteria. This results in a set of clusters, where each cluster of patterns belongs to a specific class.

In the following sections, we will describe a statistical classifier and neural network classifier.

2.2.4.1 Bayesian Classification

Bayesian classification is a statistical classifier developed by Thomas Bayes. It is a prediction of class membership probabilities. The Bayesian classification approach is described as follows [33].

Assume that there are N classes of patterns $C_1, C_2, \ldots, C_N$, and an unknown pattern x in a d-dimensional feature space $x = [x_1, x_2, \ldots, x_d]$. Hence the pattern is characterized by d number of features. The problem of pattern classification is to compute the probability of belongingness of the pattern x to each class C_i, $i = 1, 2, \ldots, N$. The pattern is classified to the class C_k if probability of its belongingness to C_k is a maximum.

While classifying a pattern based on Bayesian classification, we distinguish two kinds of probabilities. They are priori probability and posteriori probability [33]. The priori probability indicates the probability that the pattern should belong to a class, say C_k, based on the prior belief or evidence or knowledge. This probability is chosen even before making any measurements, i.e., even before selection or extraction of a feature. Sometimes this probability may be modeled using Gaussian distribution, if the previous evidence suggests it. In cases where there exists no prior knowledge about the class membership of the pattern, usually a uniform distribution is used to model it. For example, in a four class problem, we may choose the priori probability as 0.25, assuming that the pattern is equally likely to belong to any of the four classes.

The posteriori probability $P(C_i/x)$, on the other hand, indicates the final probability of belongingness of the pattern x to a class C_i . The posteriori probability is computed based on the feature vector of the pattern, class conditional probability density functions $P(x/C_i)$ for each class C_i and priori probability $P(C_i)$ of each class C_i.

Bayesian classification states that the posteriori probability of a pattern belonging to a pattern class C_k is given by

$$P(C_k/x) = \frac{P(x/C_k)P(C_k)}{\sum_{i=1}^{N}\left(P(x/C_i)P(C_i)\right)}$$

The denominator $\sum_{i}^{N} P(x/C_i)P(C_i)$ in the above expression is the scaling term which yields the normalized value of the posteriori probability that the pattern x belongs to class C_i. Hence, x belongs to class C_p when $P(C_p|x) = \max\{P(C_1|x), P(C_2|x), \ldots, P(C_N|x)\}$.

2.2.4.2 Artificial Neural Network

Artificial neural networks (ANN) are highly distributed interconnections of adaptive nonlinear processing elements. In other words, they are large set of interconnected neurons, which execute in parallel to perform the task of learning. Hence, ANN resembles human brain in two respects. The first property is that knowledge is acquired by the network through a learning process. The other is interneuron connection strengths known as weights are used to store the knowledge, i.e., the weights on the connections encode the knowledge of a network. The neurons are modeled after the biological neurons and hence they are termed as neural networks [33, 37].

In connection with this, the ANN features of distributed processing, adaptation and nonlinearity are the hallmark of biological information processing systems. Therefore, ANNs are working with the same basic principles as biological brains. That is, ANNs mimic biological brains [37].

Distributed computation of ANN has the advantages of reliability, fault tolerance, high throughput (division of computation tasks) and cooperative computing. The adaptation is the ability to change a system's parameters according to some rule (normally, minimization of an error function). Adaptation enables the system to search for optimal performances. The ANN property of nonlinearity is also important in dynamic range control for unconstrained variables and produces more powerful computation schemes when compared to linear processing. However, it complicates theoretical analysis tremendously [33].

Unlike more analytically based information processing methods, neural computation effectively explores the information contained within input data, without further assumptions. Statistical methods are based on assumptions about input data ensembles (i.e. a priori probabilities, probability density functions, etc.). Neural networks, on the other hand build relationships in the input data sets through the iterative presentation of the data and the intrinsic mapping characteristics of neural topologies, normally referred to as learning.

There are two basic phases in neural network operation. They are training or learning phase and testing - recall or retrieval phase. In the learning phase, data is repeatedly presented to the network, while weights are updated to obtain a desired response. In testing phase, the trained network with frozen weights is applied to data that it has never seen.

Although there exists many models and representations of ANNs, each one of these networks possesses four tuple attributes $< Nc, W, \sigma, \delta >$, where Nc is a finite set of highly interconnected neurons with outputs $n_1, n_2, \ldots, n_k$; W denotes a finite set of weights which represents the strength w_{ij} of the interconnection between neurons n_i and n_j; σ is a propagation rule which shows how the input signals to a neuron n_i propagates through it. A typical propagation rule may be $\delta(i) = \Sigma n_j w_{ij}$ and δ is an activation function which is usually a nonlinear function like sigmoid function [33].The most popular neural network model is the rnultilayer perceptron (MLP), which is an extension of the single layer perceptron proposed by Rosenblatt [37]. Multilayer perceptrons, in general, are feedforward network, having distinct input, output, and hidden layers. The architecture of multilayered perceptron with error backpropagation network is shown in Figure 2.8 [33].

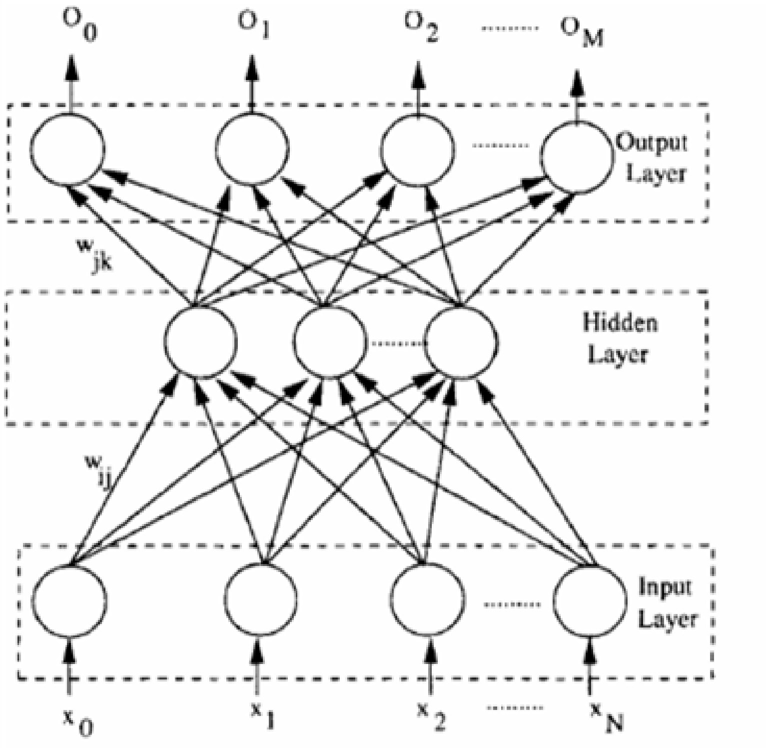


Figure 2-8: Architecture of a Backpropagation Neural Network

In an M-class problem where the patterns are N-dimensional, the input layer consists of N neurons and the output layer consists of M neurons. There can be one or more middle or hidden layer(s). Figure 2-8 shows a single hidden layer case, which is extendable to any number of hidden layers. The output from each neuron in the input layer is fed to all the neurons in the hidden layer. No computations are performed at the input layer neurons. The hidden layer neurons sum up the inputs and pass them through the sigmoid non-linearity and fan-out multiple connections to the output layer neurons.

In feed forward activation, neurons of the first hidden layer compute their activation and output values and pass these on to the next layer as inputs to the neurons in the output layer, which produce the networks actual response to the input presented to neurons at the input layer. Once the activation proceeds forward from the input to the output neurons, the network's response is compared to the desired output corresponding to each set of labeled pattern samples belonging to each specific class, there is a desired output. The actual response of the neurons at the output layer will deviate from the desired output, which may result in an error at the output layer. The error at the output layer is used to compute the error at the hidden layer immediately preceding the output layer and the process continues [33].

In view of the above, the net input to the j^{th} hidden neuron is expressed as

$$I_j^h = \sum_{n=1}^{N} x_n w_{ij}^h + \theta_j^h$$

The output of the j^{th} hidden layer neuron is

$$O_j = f_j^h\left(I_j^h\right) = \frac{1}{1+e^{-I_j^h}} \qquad ,$$

Where $x_1, x_2, \ldots, x_n$ is the input pattern vector, weights w_{ij} represents the weight between the hidden layer and the input layer, and θ_j^h is the bias term associated with each neuron in the hidden layer. These calculations are known as forward pass. In the output layer, the desired or target output is set as T_k and the actual output obtained from the network is O_k. The error (T_k - O_k) between the desired signal and the actual output signal is propagated backward during the backward pass. The equations governing the backward pass are used to correct the weights. Thus the network learns the desired mapping function by back propagating the error and hence the name error backpropagation. The average error E is a function of weight as shown below:

$$E(W_{jk}) = \frac{1}{2}\sum_{k=1}^{M}(T_k - O_k)^2$$

To minimize the error E we have to find the root of the partial derivatives

$$\sum_{k=1}^{M}\frac{\partial E}{\partial W_{jk}} = 0$$

Hence, from this we can obtain the value of updated weights as follows

$$W_{jk}^{(new)} = W_{jk}^{(old)} + \eta\delta_j O_j \,,$$

where η is the learning rate of the hidden layer neurons.

In summary, artificial neural networks can be regarded as an extension of many classification techniques, which have been developed over several decades. These networks are inspired by the concept of the biological nervous system, and have proved to be robust in dealing with the ambiguous data and the kind of problems that require the interpolation of large amounts of data. Instead of sequentially performing a program of instructions, neural networks explore many hypotheses simultaneously using massive parallelism. Neural networks have the potential for solving problems in which some inputs and corresponding output values are known, but the relationship between the inputs and outputs is not well understood or is difficult to translate into a mathematical function [33, 37]. These conditions are commonly found in tasks involving grading and classification of agricultural products [6].

2.3 Related Works

The classification and grading of seeds or fruits are essential activities contributing to the final added value in the crop production. Image analysis studies are performed at different stages of the production process, including the seed varieties classification, the cereal grading for industrialization or commercialization purposes, during scientific research for improvement of species, etc. In traditional system, specialized technicians do this works manually. In most cases these methods are slow and possess a degree of subjectivity, which is hard to quantify, both in their commercial as well as in their technological implications. This indicates a major technical and economical importance of new methods like image analysis for reliable and fast identification and classification of seeds. Like the manual identification work, the automatic classification should be based on knowledge of seed size, shape, color and texture. Numerous image analysis algorithms are available for such descriptions, which make computer vision a suitable candidate for such tasks [4, 24].

In connection with this, it was shown that the basis of quality assessment is often subjective with attributes such as appearance, smell, texture and flavor frequently examined by human inspectors [20]. Human perception could also be easily biased as indicated in the report of [21]. So, it is pertinent to explore the possibilities of adopting faster systems, which are fast and accurate in sorting of crops. One of such reliable method is the automated computer vision system, which is motivated by imaging technology [33, 34].

In general, the main motivation behind the application of image analysis or computer vision system on agricultural products is due to the drawbacks of manual classification and grading systems such as subjectivity, tediousness, labor requirements, cost and inconsistency, as reported by many researchers [1 - 12].

In the next section, we present some related research works that have been done on classification of agricultural products by using image analysis.

2.3.1 Image Analysis Application on Agricultural Products

Image analysis techniques have been increasingly applied in the area of agriculture and food industries. For instance, identification of varieties of seeds, grading of fresh products, detection of defects such as cracks, dark spots and bruises on fresh fruits and seeds are some of the applications [2, 16, 17, 18, 25].

Advances in computer technology have produced a surge of interest in image analysis during the last decade. The potential of this technique for the classification, grading and other quality control in agricultural and food processing industries have been recognized [21]. Series of studies have been conducted in recent years to investigate the application of computer vision technology in classifying and grading of fresh agricultural products. For instance, in [21], a simple digital imaging method for measuring and analyzing color of food surfaces was used and found that the method allows measurements and analysis of the color of food surfaces that are used to detect the defects in food products. Other investigations have been conducted to separate wheat from non-wheat components (weed seeds and stones) [29], discrimination of wheat class and varieties [3, 18, 22, 28], etc.

In Midwestern United States, pathogenic prediction and grading of soybean seeds was developed using color image analysis of seed varieties [27]. In this study, the color image analysis is based on a set of values representing Red, Green and Blue (RGB) to identify color variations. RGB histograms were collected on regions of each seed and used to evaluate seed color and sensitivity and response of the sensor to color variations. The classification accuracy for symptomatic soybean seeds with highest probability of occurrence ranged from

83 to 93%. The classification accuracy for linear and quadratic functions ranged from 67 to 81% for test samples with all seed types included.

In Japan, machine vision grading of fruit vegetables was developed using neural network [26]. The developed system enabled to evaluate different kinds of fruit vegetables by learning their corresponding extracted shape characteristics. In the judging experiments, 4 varieties of strawberry, Reiko, Toyonoka, Nyoho, Akihime and 1 variety of green-pepper Sadowarahikari super were used. The results showed that the judging accuracy for strawberry ranged from 94 to 98% while 89% for green pepper.

In Canada, digital image analysis technique has been applied to discriminate wheat classes and varieties [3, 28]. In this works, a computer vision algorithm was developed to distinguish the kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye. These research works were based on morphological and color features to classify the cereal grains. For morphological feature, area, perimeter, length of major axis, length of minor axis and aspect ratio were taken for shape and size analysis of a kernel. For color feature, mean, median, mode and standard deviation of the grey-level values of the objects in the image were taken. In [28], the classification accuracies of 100, 94, 93, 99, and 95% were obtained for CWRS wheat, CWAD wheat, barley, oats, and rye, respectively. In [3], best classification accuracies of 98.7, 99.3, 96.7, 98.4, and 96.9 for barley, CWRS wheat, CWAD wheat, oats and rye, respectively were obtained using probabilistic neural networks.

Barley malt grain size is an important factor regarding the uniformity of malting process in brewery industries. For this purpose an image analysis system was built for the evaluation of grain malt size [1, 10]. In these studies, color images of bulk grain samples of five grain types, namely barley, oats, rye, wheat, and durum wheat. A back propagation neural network based classifier for classification of various types of cereal grains using color and textural features extracted from images of bulk grain samples. The classification accuracies of over 98% were obtained for all grain types.

In China, an image analysis technique to identify rice seed varieties was developed recently [2]. A neural network model was used for pattern classification. In recording the images, one rice seed image was taken at a time. In this work, color and morphological features were used as classification parameters. They used MATHLAB 6.5 programming language to extract color and morphological features of individual seeds. From color features of the mean and variance of RGB components were calculated. Six varieties (ey795, syz3, xs11, xy5968, xy9308, z903) rice seeds, which are widely planted in Zhejiang Province of china, were considered for the research work. The experimentation result indicated that the classification accuracies are 90.00%, 88.00%, 95.00%, 82.00%, 74.00%, 80.00% for ey7954, syz3, xs11, xy5968, xy9308, z903 respectively.

In summary, the above studies showed that morphological (shape and size), color and texture features of a seed were used for image analysis of agricultural products. In comparison to shape and size analysis of seed image, the color of seed image is highly affected by the illumination of light intensity. As a result, morphological feature have got more classification performance than color. It was also shown that the texture feature has less discriminating power than the two [24]. But when different features were combined the classification accuracy was increased [2, 3, 24].

In addition to this, as shown by many researchers current works, neural network is widely in use due to its high performance in the classification accuracy of agricultural products than other classification techniques like statistical classifiers. The classification accuracies were high when features are distinctly different among tested varieties. In the case where there was a high similarity among groups to be discriminated, the classification accuracies were not as high as distinct varieties. According to the scholars view, such a problem can be improved when neural network model is used.

Hence, as most Ethiopian coffee beans appearance looks homogeneous, the implementation of artificial neural network model sounds appropriate.

CHAPTER THREE

3. DESIGN OF ETHIOPIAN COFFEE CLASSIFICATION

Ethiopia has a suitable environment to grow different varieties of Arabica coffee. As described in section 2.1, coffee growing in different regions of Ethiopia has distinct characteristics. These coffee varieties are distributed to the market separately. Considerable emphasis was placed on keeping consignment from different regions in order to maintain the distinct essence of each region.

In this section we describe the classification of Ethiopia coffee design process based on growing region using image analysis.

3.1 Overview of Coffee Classification

The task of classification occurs in wide range of human activity. The problem of classification is concerned with the construction of a procedure that will be applied to differentiate items, in which each new item must be assigned to one of a set of pre-defined classes on the basis of observed attributes or features.

Accordingly, image analysis or computer vision is used in the classification of Ethiopian coffee to pre-defined classes. The pre-defined classes are the growing regions (origin of the coffee). The feature or attributes are computed from coffee bean images. These observed features of coffee bean were used to decide the class or the place where the coffee was grown. The logical view of the classification problem is shown in Figure 3-1.

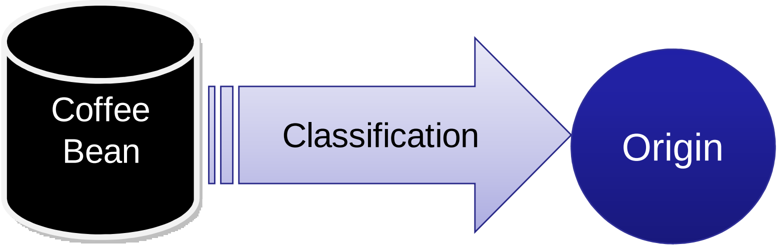


Figure 3-1: Logical View of Coffee Classification

As indicated in Figure 3-1, images of coffee beans are taken from different regions of the country. Some attributes of the images are used as input to the classification process. Then, the classification process gives the growing region (region of origin) of the indicated coffee bean.

Hence, in this research our interest is to address the classification problem of Ethiopian coffee bean varieties by using image analysis that is growing in different regions of the country. The schematic representation of coffee classification procedure is described in Figure 3-2.

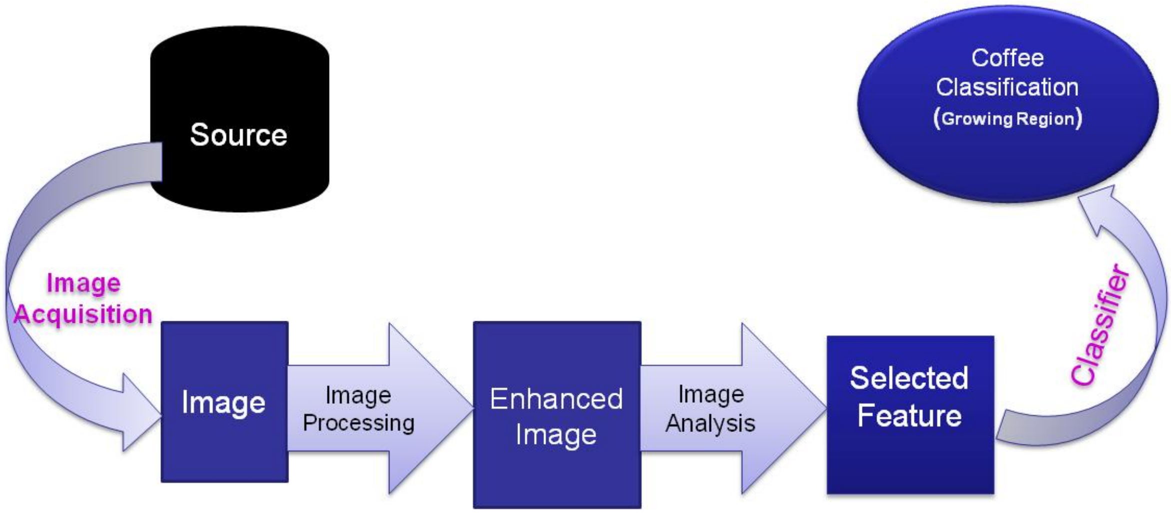


Figure 3-2: Schematic Representation of Coffee Classification Procedure

As depicted in Figure 3-2, classification process of Ethiopian coffee involves the following activities.

i. Image acquisition of a coffee bean from each growing region
ii. An image processing techniques is applied on the acquired image to enhance the quality of image so as to remove noises.
iii. Appropriate features are extracted from the enhanced image by using image analysis techniques that are used to classify a coffee.
iv. The classification model of training and testing data of Ethiopian coffee will be developed
v. Finally, suitable pattern classifiers are selected to classify Ethiopian coffee beans to the predefined classes of the growing region

In the following sub-sections, we describe in detail each of these activities.

3.2 Image Acquisition

Image analysis starts with image acquisition. As described in section 1.6.1, this involves all aspects that have to be addressed in order to obtain images of the objects of interest. The selection of radiation (light) sources and sensors (such as cameras) has to be considered very carefully. The geometry of the viewing situation, i.e., the relative positioning of sources and camera with respect to the objects of interest, usually also has a major impact on the contrast between these objects and their background. Therefore, image acquisition is the most critical factor for the success of image analysis application.

For this study, images have been taken from six major coffee export producing regions of Ethiopia. They are Bale, Harar, Jima, Limu, Sidamo and Welega. Coffees from these regions are the most widely planted and popular coffee brands of the country so that they were selected for this research.

The samples were obtained from Ethiopia Coffee Quality Inspection and Auction Center, which is under the Ministry of Agriculture and Rural Development. The classes (growing region) of the sampled coffee beans were certified by the domain experts in the institution's laboratory. All sampled coffee beans were the products of 2006/07 production year. The samples have been taken in October 2007.

The coffee beans images were taken after different lightening and viewing situations were tried in-order to record clear image with minimal noises. As described in section 1.6.1, the camera was adjusted under the following conditions, which enabled us to record clear images of the coffee beans.

- Coffee beans were scattered on white background
- The camera was mounted on stand to ease vertical movement and to capture stable image
- The distance between the sample table and the camera was 130 mm
- The coffee beans were scattered within the field view of 10cm x 10 cm and the lens of the camera was focused at the center of this field view vertically downward.
- For all images, the same incandescent lamp light source of 100W was used
- All images were taken at resolution of 1632x1224 pixels
- All the captured images were in JPEG (Joint Photographers Expert Groups) file format
- All images were taken in the same controlled environment of a in-order to avoid external effects of sunlight and other environmental conditions.

The picture that represents the camera setup of image recording environment is shown in Figure 3-3.

Figure 3-3: Sample Image Shot Environment

The total number of images taken from the six regions, Bale, Hrarar, Jimma, Limu, Sidamo and Welega, were shown in Table 3-1. Images of a single coffee bean that were acquired by the digital camera are shown in Figure 3-4.

Region	Number of images	Total number of Beans	Processing Type
Bale	46	791	Unwashed
Harar	52	722	Unwashed
Jima	49	824	Unwashed
Limu	54	850	Washed
Sidamo	49	810	Washed
Welega	59	847	Unwashed
Average	**56**	**807**	
Total	**309**	**4844**	

Table 3-1: Coffee Image Data Taken from Different Regions

Figure 3-4: Typical Coffee Bean Images from Each Region

3.3 Image Processing

Image processing is a technique that focuses on the manipulation of images in various ways in-order to enhance image quality. The input and the output of image processing are both images. It is the analysis of image-to-image transformation that is used for image enhancement - to selectively increase contrasts, for image restoration - to correct for geometrical distortions and non-uniform lighting in the image acquisition and for feature extraction [33].

Image processing is started from rendering of images on computer screen and storing images on hard disks or other media for further processing. As described in section 2.2.2, it includes all tasks in image pre-processing, image segmentation and removal of noises.

Image segmentation is one of the most important tasks in image processing. It is the process of dividing an image into different homogeneous regions such that the pixels in each partitioned region possess an identical set of properties or attributes. The result of segmentation is a number of homogeneous regions, each having a unique label. Image segmentation is basically used to isolate region of interest from the background noise.

For image processing, we have used ImageJ [32] which is a public domain java image processing program inspired by National Institute of Health (NIH). ImageJ can be used to display, edit, process and analyze many formats and types of images. We have selected ImageJ for the following reasons.

i. ImageJ is open source software, which is available freely on the Web[4].
ii. ImageJ was designed with an open architecture that provides extensibility via Java plugins. Custom acquisition, analysis and processing plugins can be developed using

[4] http://rsb.info.nih.gov/ij/downloads.html

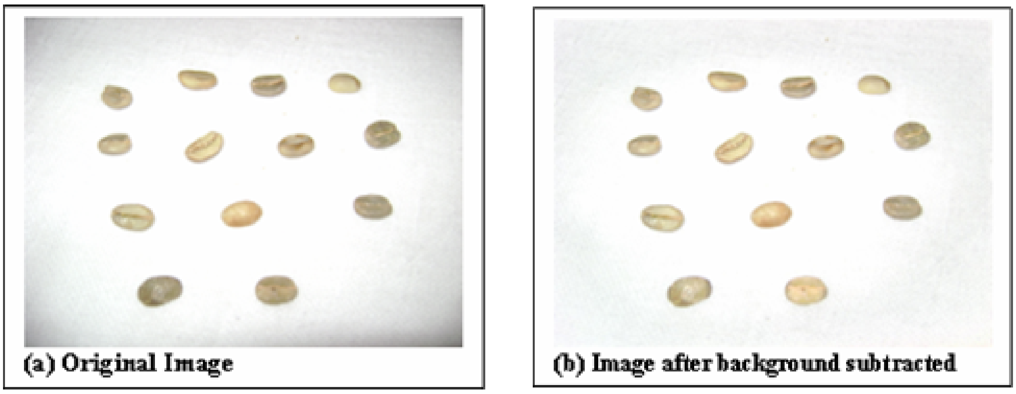
ImageJ's built in editor and Java compiler. User-written plugins make it possible to solve almost any image processing or analysis problem.

iii. It supports stacks, a series of images that share a single window. For instance, it enables us to process and analyze simultaneously the coffee bean images of a region that were taken at different times.

iv. It is multithreaded, so time-consuming operations such as image file reading can be performed in parallel with other operations.

Hence, ImageJ was used for image processing tasks of coffee bean images to enhance the quality of image and to change images to binary for feature extraction purposes.

From the original coffee bean images, the background is subtracted in-order to avoid blurs, light distortions and other noises that are formed due to illumination effects. The enhancement of original image by subtracting the background was shown in Figure 3.5.



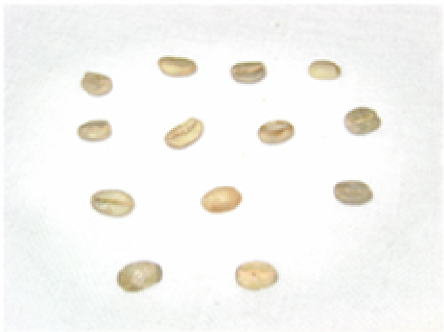
(a) Original Image

(b) Image after background subtracted

Figure 3-5: Image Enhancement

After the enhancement of the image, images were segmented by using histogram based thresholding technique as described in section 2.2.2.2. Thresholding is an important part of image segmentation. The threshold value of the upper and lower limit is set based on the histogram analysis of each coffee bean in the image. The result of the thresholded image is a binarized image. A binarized image is an image whose pixel values are changed into zero and ones or black and white. That is, based on the threshold pixel values of image within a region of interest (the coffee bean) are set to zero and the remaining (the background) is set to pixel value of 1. The pixel value of 0 indicates black (coffee) and pixel value of 1 indicates white (background).

Finally we have obtained each coffee bean in the image has been isolated from the background and labeled in-order to ease image analysis from the binarized image. An example of a segmented image was shown in Figure 3-6.


(a) Original image

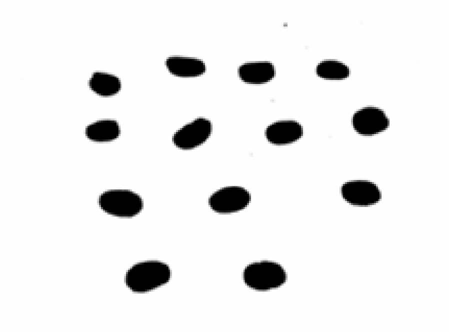

(b) Binary Image

Figure 3-6: Image Segmentation

3.4 Feature Extraction

As described in section 2.2, image analysis is the process of extracting meaningful information from images that are used for classification of images to different categories. For image analysis of Ethiopian coffee, two classification parameters are identified. They were morphological features and color features. We have considered these two features because their structural forms like shape and size and also their visual color differences identify coffee varieties growing in different regions by human vision in the traditional system. Hence, the classification system proposed was based on morphology and color analysis, which considers an assessment of human visual inspection as starting point.

3.4.1 Morphological Features

Morphology is the geometric property of images. In our case it is the size and shape characteristics of coffee beans. It can be obtained from the analysis of binarized images. From morphology of coffee beans the following geometric features were extracted from the binarized images as described in the previous section.

i. **Area (A):** The number of pixels inside the region covered by a coffee bean, including the boundary region. It is measured by square pixels.

ii. **Perimeter (P):** The length of the outside boundary of the region covered by a coffee bean.

iii. **Length:** It is the length of the smallest rectangle enclosing a coffee bean.

iv. **Width:** It is the width of the smallest rectangle enclosing a coffee bean

v. **Major Axis Length (Major):** It is the distance between the end points of the longest line that could be drawn through the coffee bean. The major axis end points are found by computing the pixel distance between every combination of border pixels in the coffee bean boundary and finding the pair with the maximum length.

vi. **Minor Axis Length (Minor):** It is the distance between the end points of the longest line that could be drawn through the coffee bean while maintaining perpendicularity with the major axis.

vii. **Aspect Ratio (Elongation):** The ratio of the length of the major axis to the length of the minor axis (Elongation =Major/Minor)

viii. **Rectangular Aspect Ratio(RecAspecRatio):** The ratio of length to width of the bounding rectangle (**RecAspecRatio** =length/width)

ix. **Roundness(R):** Measures the degree of roundness (circularity) of the shape the coffee bean. It is calculated as $R = \frac{4\pi A}{P^2}$, where A is the area of a coffee bean region in the image and P is the perimeter. The value of R is between 1 and 0. If the value of *R* is equals to 1, it is a perfect circle and if the value of R is equal to 0, it corresponds to a region without area.

x. **Feret Diameter (D):** It is the diameter of a circle having the same area as the area a coffee bean and computed as: $D = \sqrt{\frac{4A}{\pi}}$, where A is the area of a coffee bean region in the image.

3.4.2 Color Features

Natural color images incorporate three sensors that are spectrally sensitive to the red, green and blue portions of the light spectrum which are collectively described as RGB images. Graphics file formats store RGB images as 24-bit images, where the red, green, and blue components are 8 bits each [33].

In relation with RGB colors, there are three common perceptual descriptors of a light sensation. They are intensity (I), Saturation (S) and hue (H). Intensity is a measure of the brightness of a given image while saturation describes the amount of whiteness of a light source in a given image. The hue is also an attribute of light that distinguishes one color from the other, for example a red color from green or yellow color [33]. The mathematical formula that converts RGB color space to HSI [33] is given as follows.

$$I = \frac{1}{3}(R + G + B)$$

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

$$H = \arccos\{\frac{[(R-G)+(R-B)]/2}{[(R-G)^2 + (R-B)(G-B)]^{1/2}}\}$$

Hence, the color features are extracted by computing the mean values of RGBs and HSIs of coffee bean images. That is, the mean value of red, mean value of green, mean value of blue, mean value of hue, mean value of saturation and mean value of intensity are computed from each component.

In summary, some of the sixteen features (ten morphological and six color features) will be used for the classification of Ethiopian coffee beans by the growing region.

3.5 Classification Model

Image classification is a fundamental problem in pattern recognition. As described in section 2.2.4, pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest, make sound and reasonable decisions about the categories of the patterns. Patterns are any entity or object. For example, coffee bean images are patterns.

In classification, the objective is to categorize objects in the scene (coffee bean images) from a set of measurements of the objects. The measured values are the features of the pattern. A set of similar objects or patterns possessing more or less identical features are said to belong to a certain category called classes.

The image classification model has three main components. They are representation of image features, learning and testing process for semantic categories using these representations and the classifier. As described in section 2.2.4, a classifier is a program that takes input feature vectors and assigns it to one of a set of designated classes.

3.5.1 Feature Representation

Features or attributes are values measured from coffee bean images. As we described in the previous section, we have two basic features of coffee bean images, namely morphological features and color features. We have identified ten morphological features and six color features for the classification of Ethiopian coffee beans by growing region. Among Ethiopian coffee growing regions, six major coffee growing regions (Bale, Harar, Jimma, Limu, Sidamo and Welega) were selected for this research. Hence, we have six categories or classes. The tabular representation of features or attributes was shown in Table 3-2. In the table E (.) indicates the mean value of the color features. For example E(R) is the mean value of red.

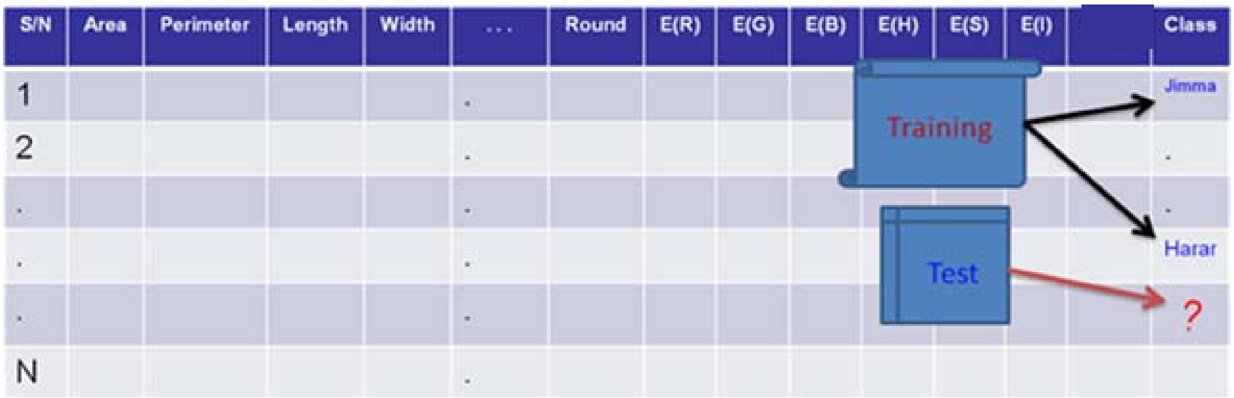


Table 3-2: Attributes Tabular Representation

As indicated in Table 3-2, we will compute the feature values of each coffee bean in all images in the sample. In our case, N=4844 which is the total number of data sets. In the training process the class values will be provided because we will use supervised learning. In-order to test the classification accuracy of the system, feature data sets that are not in the training data set will be used. In the classification process, the total data set is partitioned to 80% for training and 20 % for testing.

The class labels corresponding to names of the growing region of a coffee are categorical data. Hence, we need to represent these values by using binary numbers to simplify the representation that is appropriate to the pattern classifier program. The input and output vector representation of the features is shown in Figure 3-7.

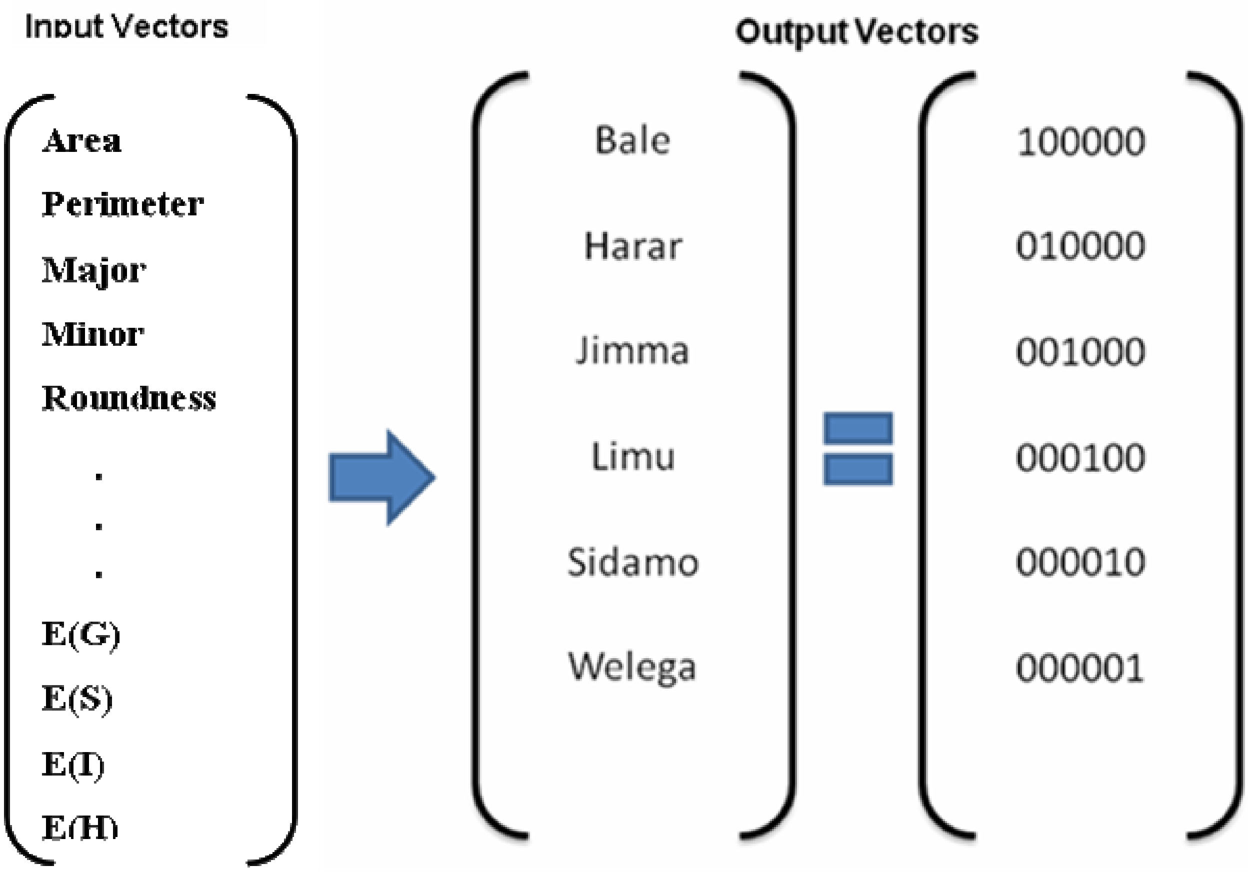


Figure 3-7: Vector Representation of Input and Output Features

As indicated in Figure 3-7, the output vectors (classes) are represented by using the binary numbers 0 and 1. Since we have six classes that correspond to the predefined growing regions, we need to uses 6 bit binary numbers. Each bit refers whether that feature belongs to a region represented at that bit position. As shown in Figure 3-7, first, second, third, fourth, fifth and the sixth bit represent Bale, Harar, Jimma, Limu, Sidamo and Welga respectively. The bit value indicates whether the feature data set is the member of that class or not. If the value of the column is 1, the feature data set is the member of the class. If the value of the column vector is 0, it indicates that the feature data set is not the member of the class.

3.5.2 Overview of Training and Testing Process

The second major components of classification are learning and testing processes that use the previously described representations of input and output vectors. We describe the training and testing process separately. The training process is shown in Figure 3-8.

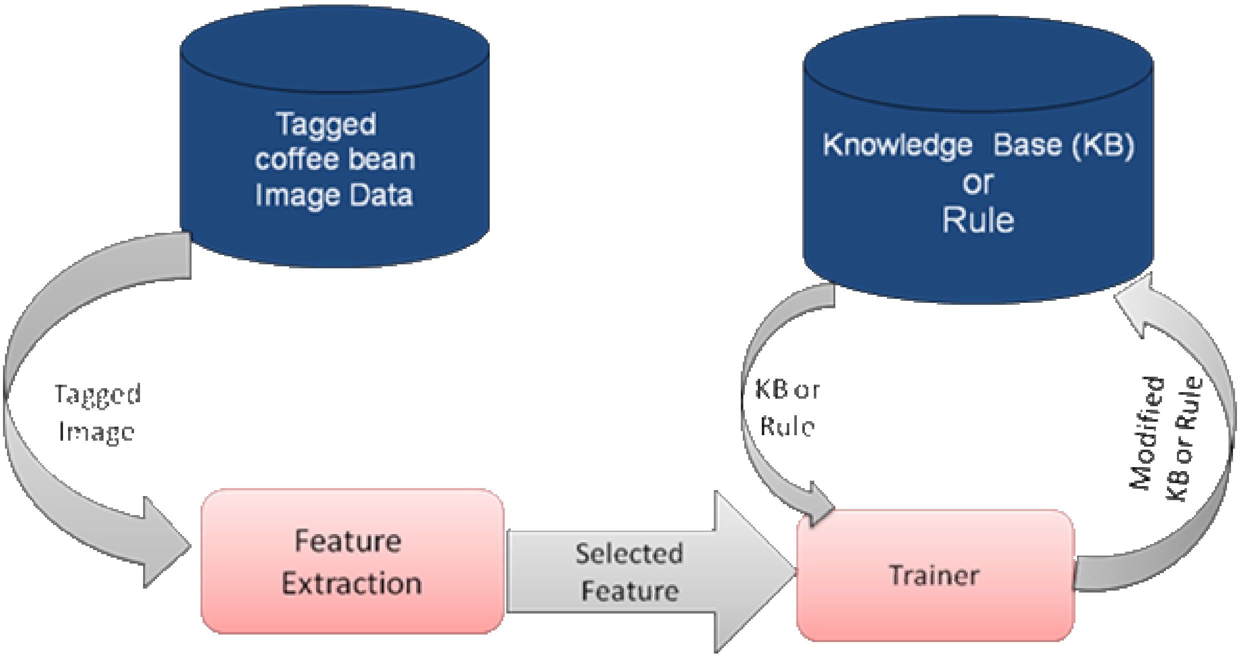


Figure 3-8: Training Process

In the training process, as indicated in Figure 3-8, to classify a coffee bean image, first each coffee bean image is taken from a particular growing region and labeled or tagged with the name of its growing region. For example, coffee grown in Harar is tagged as Harar category or class. Therefore, we will have tagged imaged data to be analyzed. Then, features are extracted from tagged images by using image analysis as described in the previous section.

In relation with the extracted features, we will select features that are used as input to the pattern classifier and then the system is trained by the classifier from the available information or knowledge source.

The process finally generate a knowledge base which is the primary input for any decision making process at testing phase.

Hence, the knowledge base will be used to test the accuracy of the classifier. The testing process is shown in Figure 3-9.

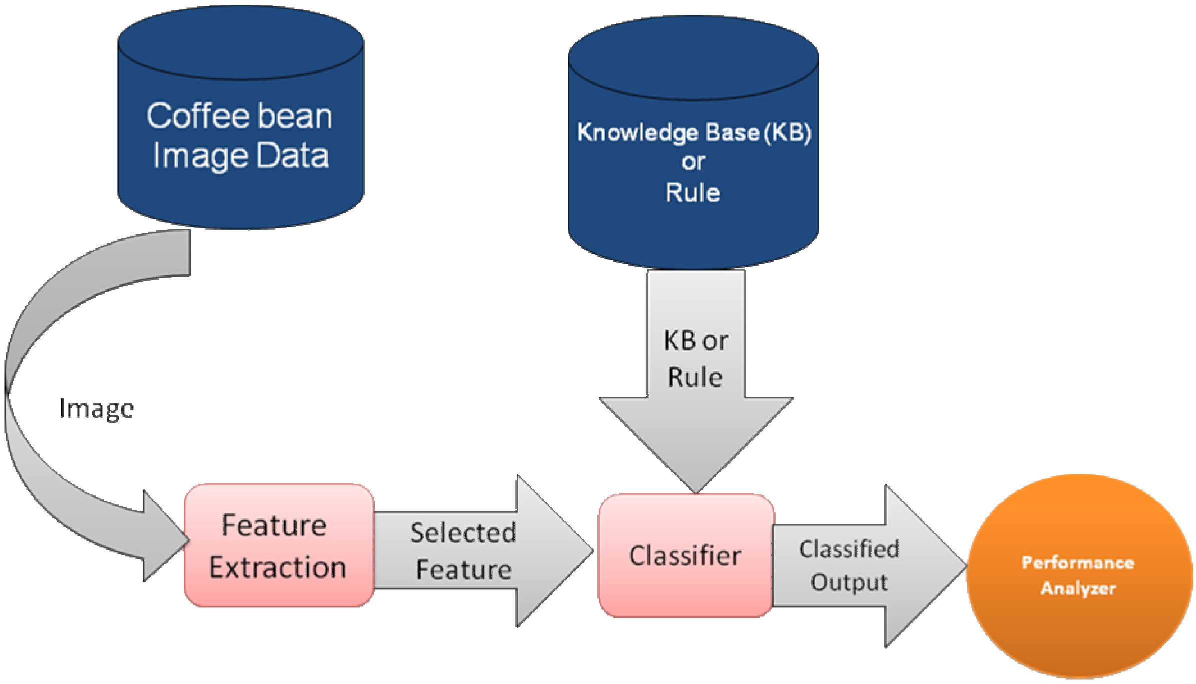


Figure 3-9: Testing Process

As described in Figure 3-9, an image of coffee bean that is not in the training data set is used in the testing process. The images do not need to be tagged. It is the task of the pattern classifier to decide the class or category of the coffee bean image by using the knowledge developed in the training process.

The feature extraction and selection of the testing process is done in the same way as the feature selection and extraction of the training process. The selected features are used as input to the pattern classifier. The pattern classifier uses the knowledge or rule obtained in the training process to test the classification accuracy of the system. The classifier produces class tags and the analyzer generates the performance of the classifier. The analyzer also investigates the classified output by checking patterns classified correctly and misclassified.

3.5.3 Classifier

The last component of classification model is the selection of pattern classifier. As described in section 2.2.4, a pattern classifier is software that is used to train, test and analyze a problem based on the training and testing model of the classification algorithm.

As clearly stated in the previous sections, the classification problem that we need to address provides complete information about the number of classes and their labels. Hence it is supervised.

In this view, we have selected two classifiers to analyze their generalization capability. The two classifiers were Naïve Bayes classifier and artificial neural network (ANN). See their detail description in section 2.2.4.

In the case of ANN, we need to select appropriate topology and learning algorithm that best fits to the proposed classification model. Hence, its basic components are described as follows.

- **Learning Paradigm**: It is a model of the environment in which the neural network operates to learn or train the system. Based on the type of learning process, the networks can be supervised or unsupervised. In supervised learning, the desired output is available for all of the samples needs to be trained. In unsupervised learning, the system must determine the classes structure mainly the optimal numbers of classes and their properties.
- **Architecture**: It is the topology of the network that describes the pattern of connections between neurons. In our case, we will use feed forward multilayer perceptron (MLP)

model. A feed-forward multilayer ANN is a topology in which neurons are arranged in layer and has the following properties.

- The first layer gets the input data from the environment and is called input layer.
- The last layer generates output class and is called output layer.
- Layers other than input and output layers are called hidden layers.
- The i^{th} layer gets input from each of the neurons in the $i^{th} - 1$ layer weighted by some weight factor for $1 < I \leq N$. A feed forward multilayer perceptron with 2 hidden layers was shown in Figure 3-10. In our case N=4, and is called 3 layer perceptron.

- **Learning algorithm:** Learning in ANN indicates the methods used to determine the adaptation of weights between the connections of two neurons. A MLP feed-forward network uses back propagation learning algorithm for adapting its weights to a sequence of training samples during a learning phase. A back propagation algorithm is a supervised learning algorithm that propagates classification errors from the output layers back toward to the input layers and modify the weight to minimize the total error.
- **Activation function:** It is the processing logic that computes the neuron's final output state. Back propagation requires continuous and differentiable activation function. Hence, sigmoid function was used in order to provide smooth control of the input-output relationship. The equation of the activation function is shown below.

$$F(x) = \frac{1}{1+e^{-x}}$$

In Figure 3-10, X is a P dimensional vector that indicates the input features. The matrix W_{ij} indicates the weight or synaptic strength of connected neurons and Y is the output vector which has equal number of dimensions as the number of output classes.

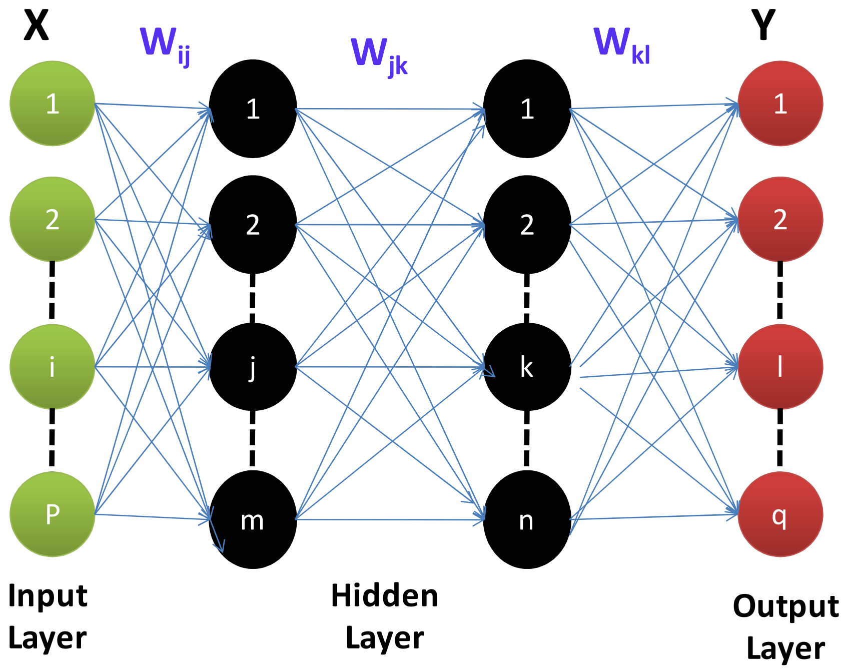


Figure 3-10: Multilayer Perceptron Model with 2 hidden Layers

In summary, as shown in Figure 3-10, we will use feed forward multilayer perceptron with 2 hidden layers in addition to the input and output layers. The input features are the morphological and color features that we have identified in the previous section. Depending on the selected features and the scenario of the experiment that will be conducted, the value of **p** (number of inputs) can be between one and the maximum number of selected features, sixteen in our case. Since we have considered six coffee growing regions, we will have six as the dimension of Y- the output.

CHAPTER FOUR

4. IMPLEMENTATION OF COFFEE CLASSIFICATION

This chapter describes the implementation of the classification process of Ethiopian coffee, which was specified in detail in the previous chapter. As described in section 3.1, the classification of Ethiopian coffee varieties has four components. They were image acquisition, image segmentation, feature extraction and classification.

Image acquisition is the process of recording images. Coffee bean images were taken from six regions, Bale, Harar, Jimma, Limu, sidamo and welega, as specified in section 3.2. The number of recorded images from each region was shown in Table 3.1.

Next to image acquisition, image segmentation techniques were applied on the recorded images. Segmentation was used to separate each coffee bean image from the background, which usually resulted in binarized image.

From the segmented images appropriate features were extracted. As described in section 3.4, some morphological and color features were identified. These features are used to classify a given coffee bean to its growing region.

The following sections describe the detail implementation of image segmentation, feature extraction and classification processes.

4.1 Development Environment

The development of full-fledged classification system of coffee varieties by integrating image analysis techniques needs a lot of money to invest. Starting from image acquisition, we need high quality digital camera and well established and controlled environment to record the images. In addition to this, image-processing techniques are resource intensive. They need powerful computers with high processing speed, larger memory and disk capacity.

Our system is developed and tested on a PC of Intel® Pentium® IV CPU with 2.40GHZ speed, 256 MB of RAM, 40GB of hard Disk capacity, with Microsoft Windows XP Professional operating system.

4.2 Image Binary Analysis

A binary image is an image whose pixel values were changed to 0 and 1 or black and white. In this work the black indicates the object of interest or the coffee region on the image and the white indicates the background. As mentioned in section 3.3, we have used a public domain java image processing program, ImageJ 1.38 bundled with java 1.6 [32], for image segmentation and feature extraction. It was designed with an open architecture that provides extensibility via Java plugins. Hence, we customized the system to our interests by using macros and java plugins.

ImageJ is a useful tool to analyze and process images. The beauty of this tool in relation to our work is that it supports an image stack that helps to process and analyze image of the same size and type stored in the same folder at the same time. In other words, we can import and load a sequence of images stored in one folder as a single image. As an example, Figure 4.1 shows 52 images were loaded by using importing facility of imageJ on one slide window. These 52 images were taken from Harar region. Since, these images are of the same type and size; they were imported as a sequence of images and loaded as stack. We can navigate through each slice of the images by using the slide window.

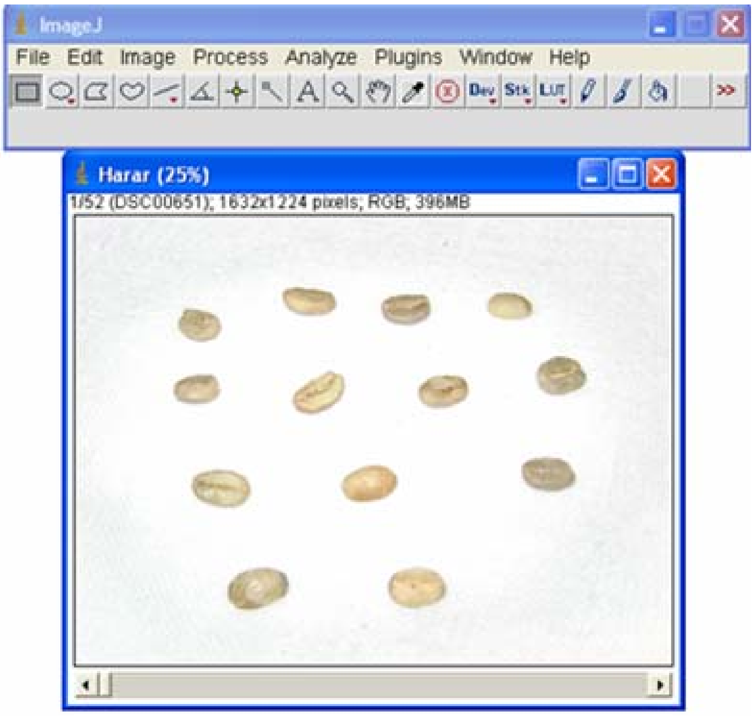
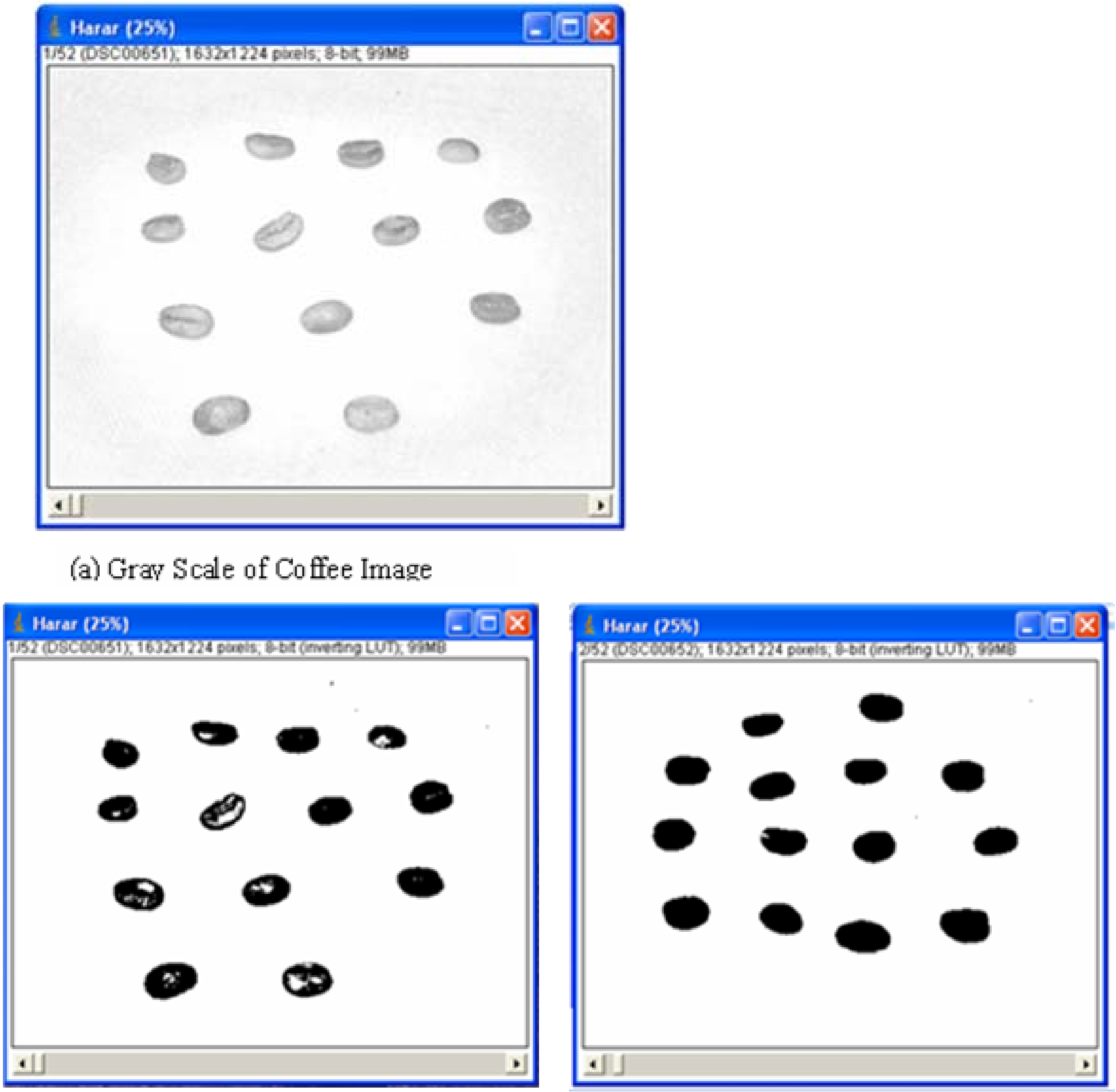


Figure 4-1: Screen Shot of Sequence of Images Loaded to ImageJ

On the image stack, we applied image segmentation to separate each coffee bean image from the background by using thresholding technique which was described in section 3.3. First, the RGB color image stack in Figure 4.1 was changed to gray scale (8 bit) image stack. Then, the gray scale image was changed to binary image by setting threshold value which is based on histogram analysis. The threshold value was 213.



(a) Gray Scale of Coffee Image

(b) Binary Image

(C) Binary Image - Holes filled

Figure 4-2: Screen Shot of Image Binarization

Hence, as shown in Figure 4-2(a), the gray scale image was segmented with threshold value of 213 by using histogram analysis as described in Figure 2-3. With this threshold value the binary image indicated in Figure 4-2 (b) was obtained but due to some defects on the surface of the coffee or due to over drying of the coffee processing, there exists white color surface which resulted as holes. These holes were filled with their neighboring pixels or changed to the black. The image of binary image with holes was filled as shown in Figure 4-2(c).

Finally, by specifying the region of interest (ROI) on the segmented image, features of each coffee bean in the image stack were calculated from its binary image.

4.3 Morphology Analysis

Morphology is the size and shape characteristics of a coffee bean. As mentioned in section 3.4.1, we have identified ten morphological features. They were area, perimeter, length and width of a rectangle bounding a coffee bean, major and minor axis length, feret diameter, rectangular aspect ratio, elongation and circularity or roundness of a coffee bean. These features were computed from the image binary analysis described in the previous section.

Figure 4-3 shows a region of interest on the image or the region of each coffee bean that we were interested to compute its morphological features.

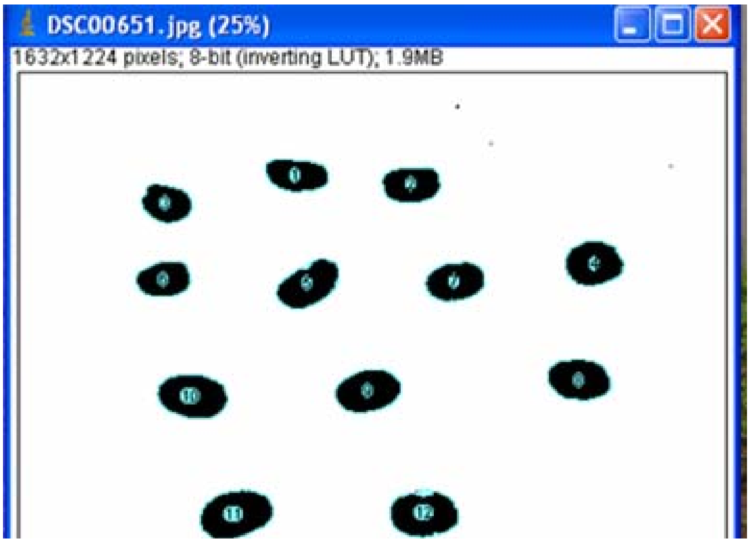
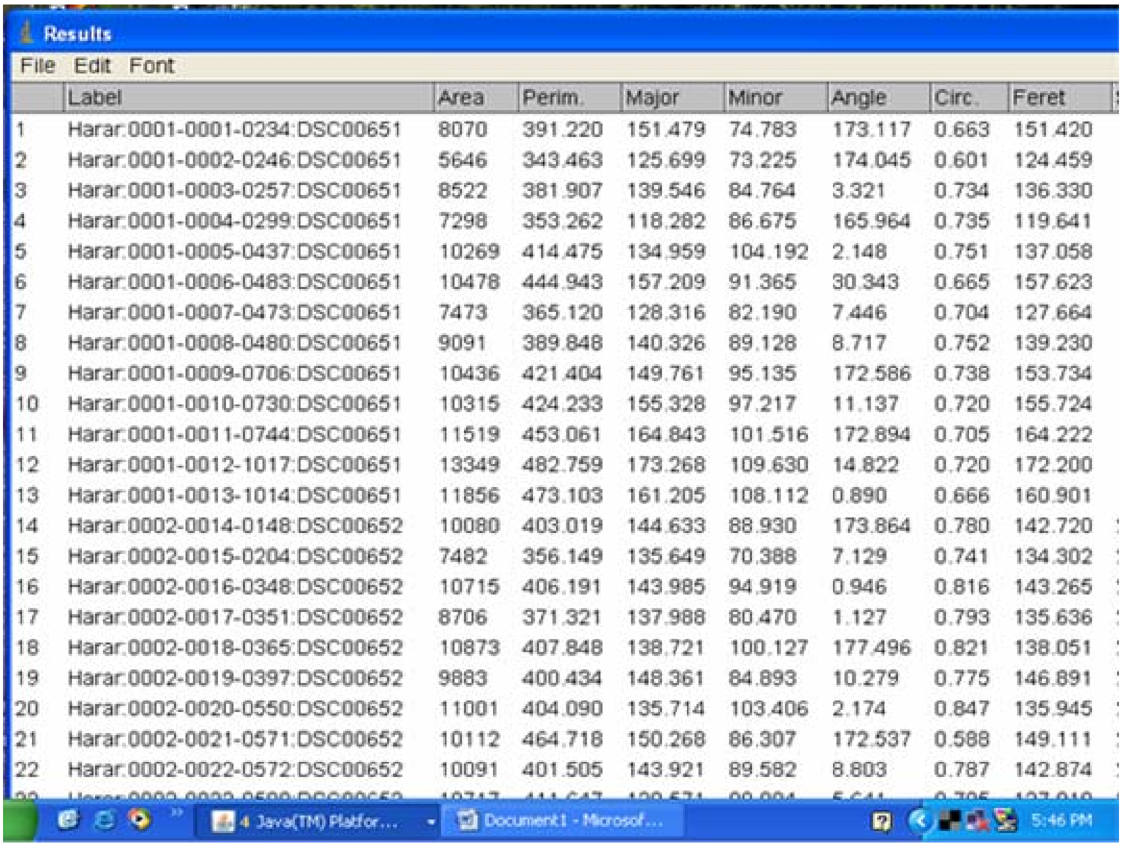


Figure 4-3: Screen Shot of Labeling and Specifying Region of Interests

From the labeled region of interests as shown in Figure 4-3, morphological features were computed by using particle analysis method of imageJ. The results were shown in Figure 4-4. The measured values were in pixels.


Results

File Edit Font

	Label	Area	Perim.	Major	Minor	Angle	Circ.	Feret
1	Harar:0001-0001-0234:DSC00651	8070	391.220	151.479	74.783	173.117	0.663	151.420
2	Harar:0001-0002-0246:DSC00651	5646	343.463	125.699	73.225	174.045	0.601	124.459
3	Harar:0001-0003-0257:DSC00651	8522	381.907	139.546	84.764	3.321	0.734	136.330
4	Harar:0001-0004-0299:DSC00651	7298	353.262	118.282	86.675	165.964	0.735	119.641
5	Harar:0001-0005-0437:DSC00651	10269	414.475	134.959	104.192	2.148	0.751	137.058
6	Harar:0001-0006-0483:DSC00651	10478	444.943	157.209	91.365	30.343	0.665	157.623
7	Harar:0001-0007-0473:DSC00651	7473	365.120	128.316	82.190	7.446	0.704	127.664
8	Harar:0001-0008-0480:DSC00651	9091	389.848	140.326	89.128	8.717	0.752	139.230
9	Harar:0001-0009-0706:DSC00651	10436	421.404	149.761	95.135	172.586	0.738	153.734
10	Harar:0001-0010-0730:DSC00651	10315	424.233	155.328	97.217	11.137	0.720	155.724
11	Harar:0001-0011-0744:DSC00651	11519	453.061	164.843	101.516	172.894	0.705	164.222
12	Harar:0001-0012-1017:DSC00651	13349	482.759	173.268	109.630	14.822	0.720	172.200
13	Harar:0001-0013-1014:DSC00651	11856	473.103	161.205	108.112	0.890	0.666	160.901
14	Harar:0002-0014-0148:DSC00652	10080	403.019	144.633	88.930	173.864	0.780	142.720
15	Harar:0002-0015-0204:DSC00652	7482	356.149	135.649	70.388	7.129	0.741	134.302
16	Harar:0002-0016-0348:DSC00652	10715	406.191	143.985	94.919	0.946	0.816	143.265
17	Harar:0002-0017-0351:DSC00652	8706	371.321	137.988	80.470	1.127	0.793	135.636
18	Harar:0002-0018-0365:DSC00652	10873	407.848	138.721	100.127	177.496	0.821	138.051
19	Harar:0002-0019-0397:DSC00652	9883	400.434	148.361	84.893	10.279	0.775	146.891
20	Harar:0002-0020-0550:DSC00652	11001	404.090	135.714	103.406	2.174	0.847	135.945
21	Harar:0002-0021-0571:DSC00652	10112	464.718	150.268	86.307	172.537	0.588	149.111
22	Harar:0002-0022-0572:DSC00652	10091	401.505	143.921	89.582	8.803	0.787	142.874

Figure 4-4: Screen Shot of Morphological Features Computation

4.4 Color Analysis

As described in section 3.4.2, we have identified six color features. They were the mean value of RGBs (Red, Green and Blue) components and the mean value of HSIs (Hue, Saturation and Intensity) components.

Therefore, to compute the mean value of each component of these color spaces we need to split each component to separate image stack. To do these, we have added two java class plugins to ImageJ. They were RGB_Stack_Splitter.java and HSB_Stack_Splitter.java. The Java codes of these two plugins were shown in Appendix A.

By using the plugin of RGB stack splitter, the RGB color image stack was split to red, green and blue components. As an example, the case of Harar coffee bean images was shown in Figure 4-5.

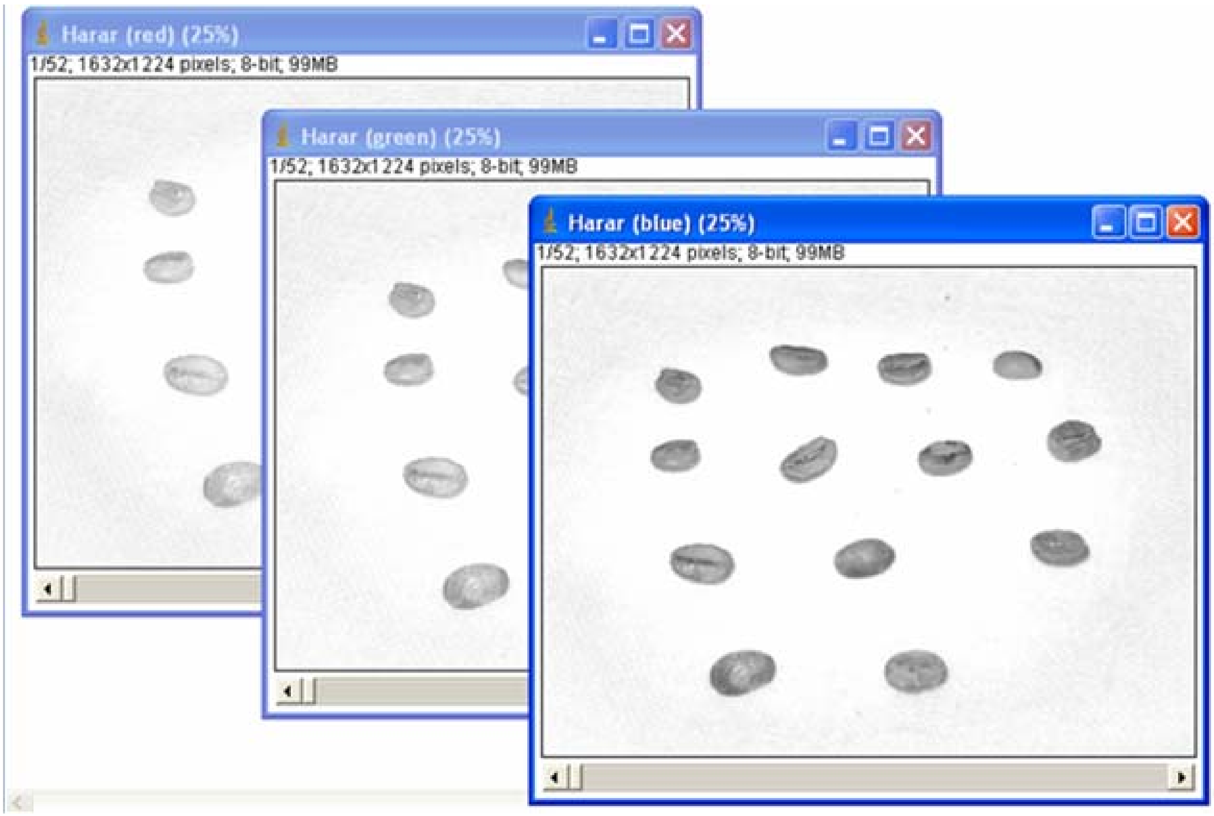


Figure 4-5: Screen Shot of RGB Color Image Split

Similarly, by using the plugin of HSB stack splitter, the RGB color image stack was split to hue, saturation and brightness (intensity) stack image components. As an example, the case of Harar coffee bean images was shown in Figure 4-6.

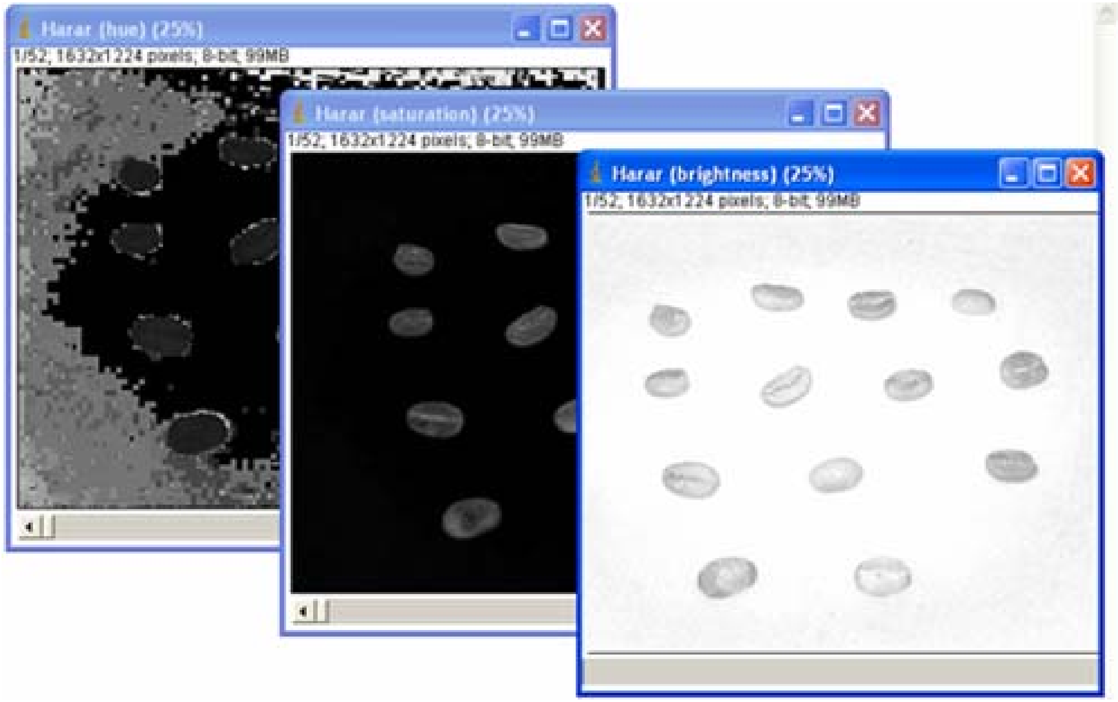
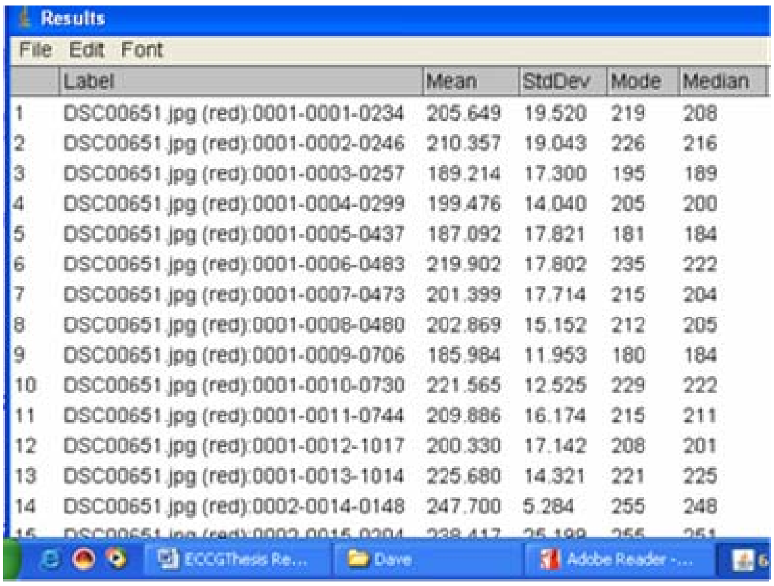


Figure 4-6: Screen Shot of HSB Color Image Split

After each color space was split, the mean values of each component were computed by ImageJ particle analyzer method similar to the morphology features based on the specified ROI shown in Figure 4-3. As an example, the results of red color feature component were shown in Figure 4-7.



	Label	Mean	StdDev	Mode	Median
1	DSC00651.jpg (red):0001-0001-0234	205.649	19.520	219	208
2	DSC00651.jpg (red):0001-0002-0246	210.357	19.043	226	216
3	DSC00651.jpg (red):0001-0003-0257	189.214	17.300	195	189
4	DSC00651.jpg (red):0001-0004-0299	199.476	14.040	205	200
5	DSC00651.jpg (red):0001-0005-0437	187.092	17.821	181	184
6	DSC00651.jpg (red):0001-0006-0483	219.902	17.802	235	222
7	DSC00651.jpg (red):0001-0007-0473	201.399	17.714	215	204
8	DSC00651.jpg (red):0001-0008-0480	202.869	15.152	212	205
9	DSC00651.jpg (red):0001-0009-0706	185.984	11.953	180	184
10	DSC00651.jpg (red):0001-0010-0730	221.565	12.525	229	222
11	DSC00651.jpg (red):0001-0011-0744	209.886	16.174	215	211
12	DSC00651.jpg (red):0001-0012-1017	200.330	17.142	208	201
13	DSC00651.jpg (red):0001-0013-1014	225.680	14.321	221	225
14	DSC00651.jpg (red):0002-0014-0148	247.700	5.284	255	248

Figure 4-7: Screen Shot of Red Color Feature Computation

4.5 Experimental Results

In the previous section, the computation of morphological and color features were described in detail. Sixteen features (ten morphology and six color features) were identified as described in section 3.4. In addition to these features, the processing type of a coffee – washed or unwashed- was used as input to differentiate the two coffee products. Hence, the total input features were seventeen. These features were used to classify different varieties of Ethiopian coffee based on their region of origin.

In line with this, we have designed three experimental scenarios to test the classification performance of different set of features. That is the classification was tested by using color features, morphological features and the combination of both morphological and color features. Each of these three scenarios was conducted under the two classifiers mentioned before in-order to compare their generalization capabilities.

In-order to train the classifiers, a set of training coffee beans was required, and the growing regions of the varieties were predefined. As shown in Table 3-1, 4844 coffee beans were taken from the predefined six regions of Bale, Harar, Jimma, Limmu, Sidamo and Welega.

There are two basic phases of pattern classification. They are training and testing phases. In the training phase, data is repeatedly presented to the classifier, while weights are updated to obtain a desired response. In testing phase, the trained system is applied to data that it has never seen to check the performance of the classification. Hence, we need to design the classifier by partitioning the total data set into training and testing data set. From the total data set of each region, 80% was used to build training and the remaining 20% of the total was used for testing data. Hence, from the total of 4844 data sets, 3875 were used for training and 969 were used for testing.

In general, a classier has some input features based on the scenario of the designed experiment and some output features. In this study, there were six output classes, because the predefined growing regions of the coffee were six. The total numbers of exemplas or patterns were 4844. This exemplas were normalized with mean 0 and variance 1.

4.5.1 Naïve Bayes Classifier

As we described in section 2.2.4.1, a Bayesian classifier is a statistical classifier, which is based on probability distribution. It classifies an object into the class to which it is most likely to belong based on the observed features.

The experimentation of coffee classification by Bayesian classifier has been made by using Weka 3.4. Weka is a machine learning or data mining software written in Java. It is open source software freely available on the Web[5]. The experimentation was conducted under the following three scenarios.

i) Scenario 1- using morphological features

In this experimentation, the ten morphological features described in section 3.4.1, together with the processing type were used as input to the classifier. Hence, the there were eleven input features. There were also six output classes that correspond to the six predefined coffee growing regions. As mentioned before, 80% of the data set was used for learning and 20% was used as testing data set.

The classification result of Naïve Bayes classifier using the selected morphological attributes was shown in Table 4-1.

---

[5] **http://www.cs.waikato.ac.nz/ml/weka**

Actual Class / Predicted Class	Bale	Harar	Jima	Limu	Sidamo	Welega
Bale	75	21	29	5	0	43
Harar	24	56	40	0	5	25
Jimma	28	42	54	5	4	37
Limmu	3	0	0	150	7	0
Sidamo	4	0	0	16	139	0
Welega	30	30	34	3	0	60
Total	164	149	157	179	155	165
Percent correct	**45.7**	**37.6**	**34.4**	**83.8**	**89.7**	**36.4**

Table 4-1: Summary Result of Naïve Bayes Classifier Using Morphology Features

The summary result of Table 4-1 was obtained from 969 instances (testing data) which were 20% of the total data set. The confusion matrix of the table shows that the correctly classified and misclassified instances of each class. The elements of the table show the number of test examples whose actual class was the row heading and whose predicted class was the column heading. The diagonal elements show instances that were correctly classified. Other elements showed misclassified instances in relation to the corresponding row and column labels.

In general, the over all classification of Naïve Bayes classifier on the selected morphological feature showed that from the total test examples of 969 instances, 534 (55.1%) were correctly classified and 435 (44.9%) were misclassified.

Analysis of the Result

The result of Naïve Bayesian classification using morphology feature showed that the classification accuracy of Bale, Harar, Jimma, Limu, Sidamo and Wellega coffees were 45.7, 37.6, 34.4, 83.8, 89.7 and 36.4 respectively(in percent).

Bale coffee was misclassified more to Wellega coffee (18.3%) and Welega coffee was more misclassified to Bale coffee (26.1%). This shows that there is strong morphology relationship between Bale and Welega coffee beans. A closer look at the morphological structure of these coffee been shows their relative bigger size from other beans. Moreover, they have elongated shape. There is also a significant misclassification of Bale and Welega coffee bean instances to Jimma (17.1% and 22.4% respectively) and Harar (14.6% and 15.2% respectively) coffees since the structure and bean shapes of these coffees were correlated. These coffees were relatively less misclassified to Limu and sidamo coffees because they were washed coffees and the size of these coffee beans is small.

Harar coffee was misclassified more to Jimma coffee (28.2%) and Jimma coffee was more misclassified to Harar coffee (25.5%). This shows that an existence of strong morphology relationship between Harar and Jimma coffee. They have relatively similar size which is smaller to medium. Harar and Jima coffees were also significantly misclassified to Welega (20.1% and 21.7% respectively) and Bale (14.1% and 18.5% respectively) coffees because the structure and shape of these coffee beans are correlated. Harar and Jimma coffee beans were not misclassified to Limu and Sidamo which are washed coffees.

Limu coffee was more misclassified to Sidamo coffee (8.9%) and Sidamo coffee was more misclassified to Limu coffee (4.5%) because they have relatively similar size. Limu coffees were relatively less misclassified to Bale (2.8%), Jimma (2.8%) and Welega (1.8%). And Sidamo coffees were misclassified to Harar (3.2%) and Jimma (2.6%) mostly due to their similarity in size and shape of the beans and in addition the processing type of these coffees was unwashed coffees.

The analysis of Naïve Bayes classification using morphology feature that shows the correlation of the different coffee varieties of the six regions was indicated as bar chart in Figure 4-8.

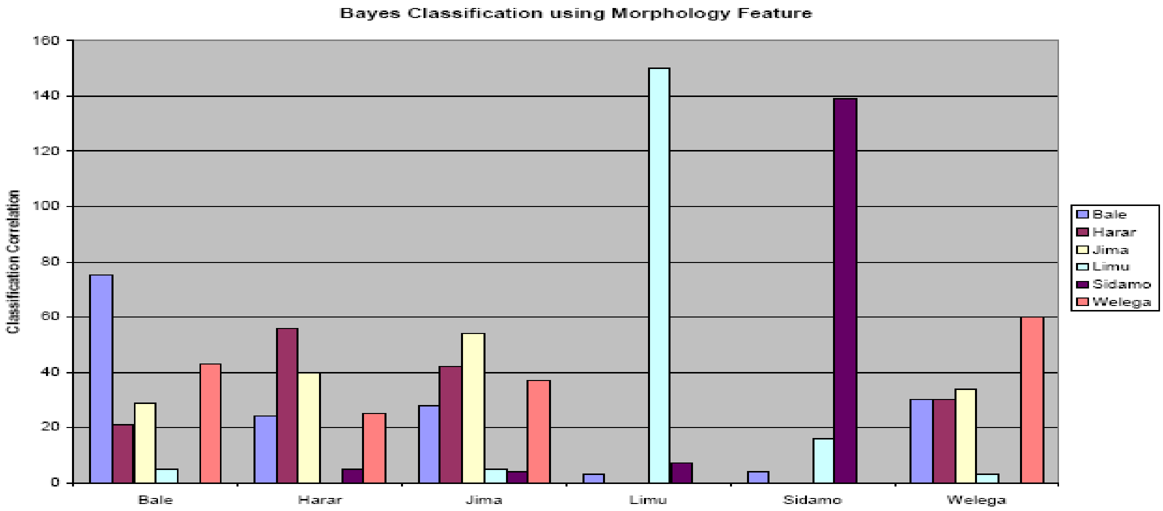


Figure 4-8: Bayes Classification Using Morphology Feature - Confusion Matrix Bar chart

ii) **Scenario 2 – Using Color Features**

Here, the number of input features was seven corresponding to the six color features described in section 3.4.2, as well as the processing type. And similar to all, there were six output classes. The classification result was shown in Table 4-2.

Actual Class / Predicted Class	Bale	Harar	Jima	Limu	Sidamo	Welega
Bale	68	13	37	0	0	38
Harar	10	80	34	0	0	29
Jimma	36	40	47	0	0	40
Limmu	0	0	0	112	53	0
Sidamo	0	1	0	67	102	0
Welega	50	15	39	0	0	58
Total	164	149	157	179	155	165
Percent correct	**41.5**	**53.7**	**29.9**	**62.6**	**65.8**	**35.2**

Table 4-2: Summary Result of Naïve Bayes Classifier Using Color Features

As indicated in Table 4-2, the summary result of Naïve Bayes classifier on the selected color feature alone showed that from the total test examples of 969 instances, 467 (48.2%) were correctly classified and 502 (51.8%) were misclassified.

Analysis of the Result

The result of Naïve Bayesian classification using color feature showed that the classification accuracy of Bale, Harar, Jimma, Limu, Sidamo and Wellega coffees were 41.5, 53.7, 29.9, 62.6, 65.8 and 35.2 respectively(in percent).

Bale coffee was misclassified more to Wellega coffee (30.5%) and Welega coffees were more misclassified to Jimma coffee (24.2%). Jimma coffee was more misclassified to Welega coffee (24.8%) and Harar coffee is also more misclassified to Jimma coffee (26.8%). Limu coffee was more misclassified to Sidamo coffee (37.4%) and Sidamo coffee to Limu (34.2%). In addition there is a significant misclassification among each region. There is no regular pattern regarding color feature classification because there is slight difference among the color of each coffee bean regions. Mostly the significant color difference can be observed between washed and unwashed coffees.

The analysis of Naïve Bayes classification using color feature that shows the correlation of the different coffee varieties of the six regions was indicated as bar chart in Figure 4-9.

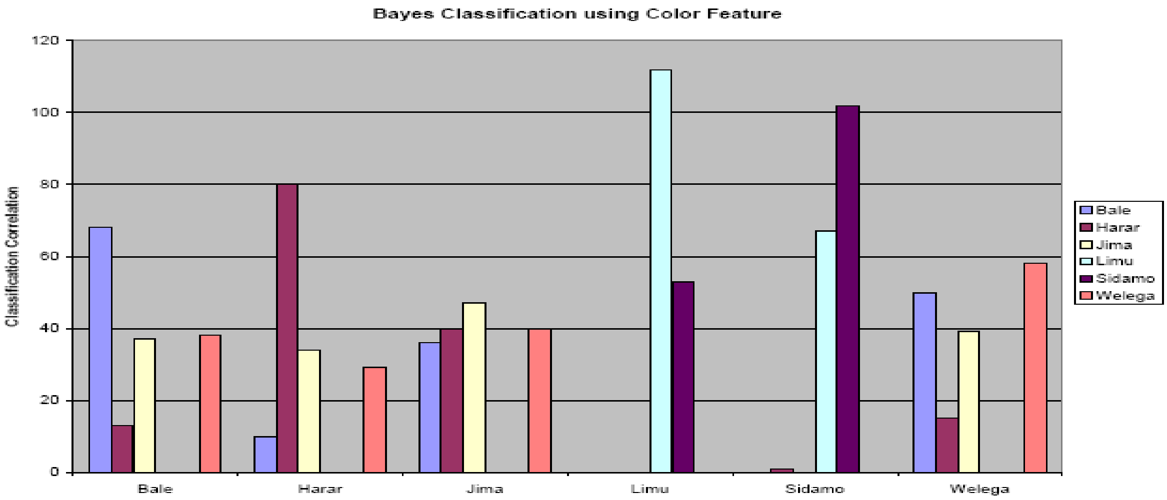


Figure 4-9: Bayes Classification Using Color Feature - Confusion Matrix Bar chart

iii) Scenario 3 – Using both Features

In this scenario, the classification input features were seventeen corresponding to the ten morphological features and the six color features described in section 3.4, as well as the processing type. There are also six output classes. The classification result was shown in Table 4-3.

Actual Class / Predicted Class	Bale	Harar	Jima	Limu	Sidamo	Welega
Bale	90	10	17	3	0	49
Harar	14	85	39	0	0	21
Jimma	19	35	69	2	1	26
Limu	3	0	0	155	5	0
Sidamo	4	0	0	17	149	0
Welega	34	19	32	2	0	69
Total	164	149	157	179	155	165
Percent correct	**54.9**	**57.0**	**43.9**	**86.6**	**96.1**	**41.8**

Table 4-3: The Result of Naïve Bayes Classifier Using Morphology and Color Features

As indicates in Table 4-3, the summary result of Naïve Bayes classifier using both morphology and color feature showed that from the total test examples of 969 instances, 617 (63.7%) were correctly classified and 352 (36.3 %) were incorrectly classified.

Analysis of the Result

The result of Naïve Bayesian classification using morphology and color feature showed that the classification accuracy of Bale, Harar, Jimma, Limu, Sidamo and Wellega coffees were 54.9, 57.0, 43.9, 86.6, 96.1, and 41.8 respectively (in percent).

In this scenario, even though the classification accuracy was increased, it reflects the property of morphology feature. The analysis result of this experiment is similar to the analysis of scenario (i) of Naïve Bayes Classification.

The analysis of Naïve Bayes classification using morphology and color features that shows the correlation of the different coffee varieties of the six regions was indicated as bar chart in Figure 4-10.

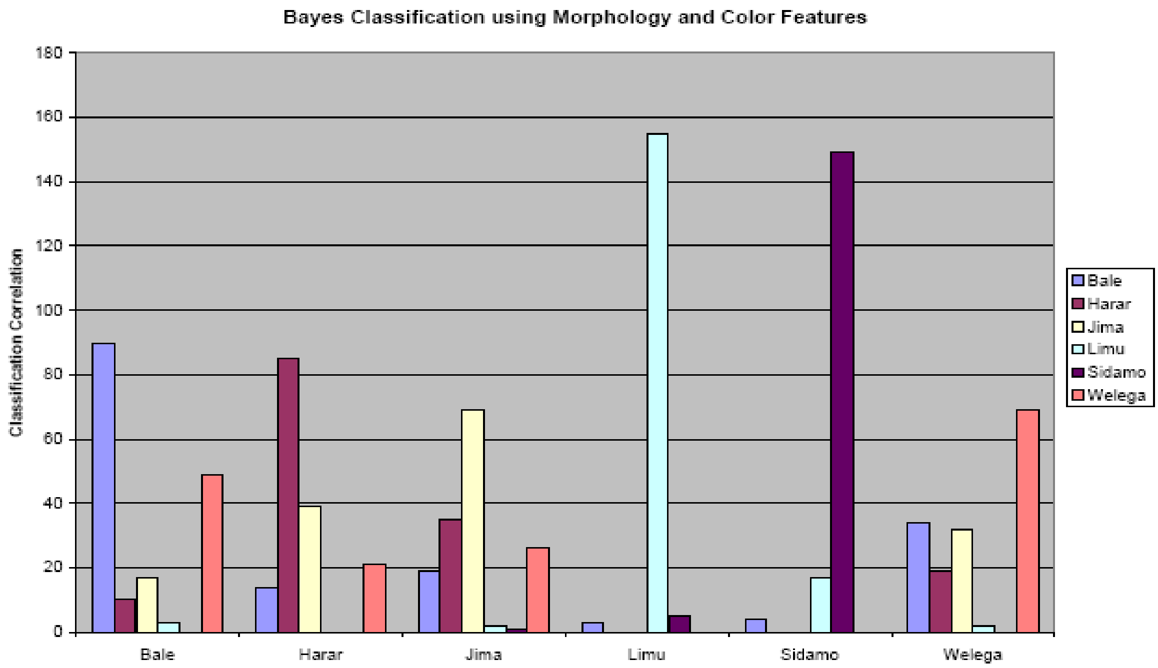


Figure 4-10: Bayes Classification Using Both Features - Confusion Matrix Bar chart

4.5.2 Neural Network Classifier

A neural network is an adaptable system that can learn relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data [37]. They are a large set of interconnected neurons, which execute in parallel to perform the task of learning. As described in section 3.5.3 we have used feed forward multilayer perceptron (MLP) model with back-propagation learning rule which is based on supervised learning.

In relation to this, as described in Figure 3-10, a three-layer (2 hidden and 1 output layers) network was used. The activation function of the hidden layer was tan-hyperbolic function. In the output layer, sigmoid transfer function was selected because its output (0 to 1) was fit for the classification. The network was trained to output 1 in the correct class of the output vector and to fill the rest of the output vector with 0 as described in Figure 3-7.

When the network was trained, the neuron number of the input layer depends on the selected features as indicated in the experimentation scenarios. And the neuron numbers of hidden layers were eighteen and thirteen for the first hidden layer and the second hidden layer neurons respectively. Trial and error approach was used to find a suitable number of the hidden layer that provided good classification accuracy based on the data input to the neural network. The neuron number of the output layer was six based on the number of predefined coffee growing regions that were considered for the study.

During training, the connection weights of the neural network were initialized with some random values. The training samples in the training set were input to the neural network classifier in random order and the connection weights were adjusted according to the error back-propagation learning rule. This process was repeated until the mean squares error (MSE) fell below a predefined tolerance level or the maximum number of iterations is achieved. When the network training was finished, the network was tested with test dataset which was 20% of the total data set.

As described in section 1.6.3, NeuroSolutions 5.0 application software was used as neural network simulation program. Similar to the Naïve Bayes classification, the experiment was conducted under three scenarios as shown below.

i) Scenario 1 – Using Morphology Features

In this scenario, the ten morphological features and the processing type of coffee were used as input to the network as described in section 3.4.1. Hence, the neuron numbers of the input layer were eleven. The output neurons were six that corresponds to the six predefined coffee growing regions considered in this study. The numbers of neurons in the hidden layers were eighteen and thirteen for the first hidden layer and the second hidden layer respectively as mentioned before.

The network was trained by 80% of the total data set. Then, the performance of the trained network was tested by using 20% of the total data set. The classification result was shown in Table 4-4. The table shows the confusion matrix that indicates the correct classification and misclassification of 969 instances of the testing data.

Actual Class / Predicted Class	Bale	Harar	Jimma	Limmu	Sidamo	Welega
Bale	92	20	31	0	0	46
Harar	12	61	35	0	0	23
Jimma	19	38	80	0	0	35
Limmu	0	0	0	180	6	0
Sidamo	0	0	0	6	147	0
Welega	27	16	23	0	0	72
Total	150	135	169	186	153	176
Percent Correct	**61.3**	**45.2**	**47.3**	**96.77**	**96.08**	**40.9**

Table 4-4: Summary Result of Neural Classifier Using Morphology Features

As indicated in Table 4-4, the summary result of neural classifier using morphology feature alone showed that from the total test examples of 969 instances, 632 (65.2%) were correctly classified and 337 (34.8 %) were misclassified. The percentage of correctly classified instances for each class was shown in the last row of Table 4-4.

Analysis of the Result

The result of Artificial Neural Network (ANN) classification using morphology feature showed that the classification accuracyof Bale, Harar, Jimma, Limu, Sidamo and Wellega coffees were 61.3, 45.2, 47.3, 96.77, 96.08 and 40.9 respectively (in percent).

The same to the naïve Bayes classification of morphology, Bale coffee was misclassified more to Wellega coffee (18.0%) and Welega coffee was more misclassified to Bale coffee (26.1%). This shows that there is strong morphology relationship between Bale and Welega coffee beans. As mentioned in the case of Naïve Bayes morphology classification, a closer look at the morphological structure of these coffee been shows that their relative bigger size from other beans. Moreover, they have an elongated shape. There is also a significant misclassification of Bale and Welega coffee bean instances to Jimma (12.7% and 19.9% respectively) and to Harar (8.0% and 13.1% respectively) coffees since the structure and bean shapes of these coffees were correlated. These coffees were not misclassified to Limu and sidamo coffees because they were washed coffees and the size of these coffees beans is small.

Harar coffee was misclassified more to Jimma coffee (28.1%) and Jimma coffee was more misclassified to Harar coffee (20.7%). This shows that an existence of strong morphology relationship between Harar and Jima coffee. They have relatively similar size which is smaller to medium. Harar and Jimma coffees were also significantly misclassified to Welega (11.6% and 13.6% respectively) and to Bale (14.8% and 18.3% respectively) coffees because the structure and shape of these coffee beans was correlated. Harar and Jimma coffee beans were not misclassified to Limu and Sidamo which are washed coffees.

Limu coffee was more misclassified to Sidamo coffee (3.2%) and Sidamo coffee was more misclassified to Limu coffee (3.9%) because they have relatively similar size. Limu and Sidamo coffees were not misclassified to the unwashed coffees.

In general, the morphological classification pattern of Naïve Bayes and Artificial Neural Network classifiers was the same but the performance accuracy was increased in Artificial Neural Network case.

The analysis of ANN classification using morphology feature that shows the correlation of the different coffee varieties of the six regions was indicated as bar chart in Figure 4-11.

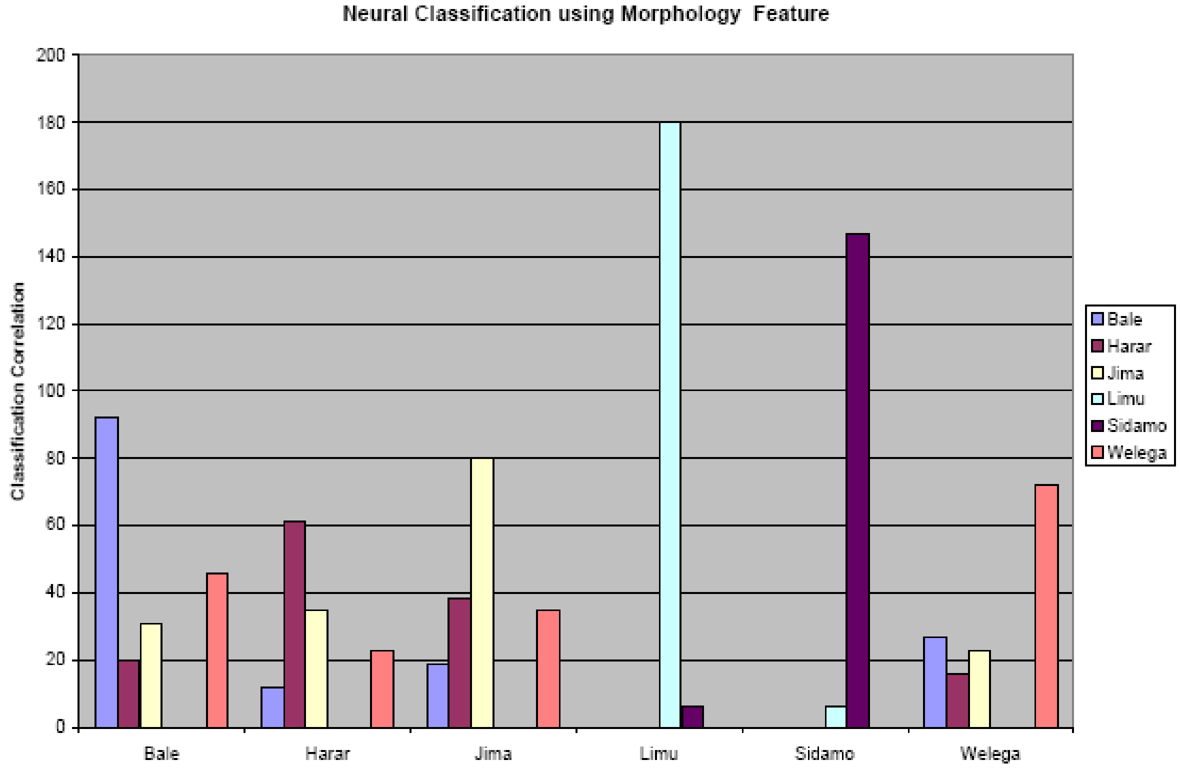


Figure 4-11: ANN Classification Using Morphology Feature - Confusion Matrix Bar chart

ii) **Scenario 2 – Using Color Features**

In this experimentation the six color features and the coffee processing type were used as input to the neural network. Hence, the neuron numbers of the input layer were seven. Similar to other scenarios, the output neurons were six corresponds to the six predefined coffee growing regions considered for this study. The numbers of neurons in the hidden layers were also eighteen and thirteen for the first hidden layer and the second hidden layer respectively as mentioned before.

After the network was trained by 80% of the data set, the test summary result of 20% of the data set was shown in Table 4-5. The table shows the confusion matrix that indicates the correct classification and misclassification of 969 instances - the testing data.

Actual Class / Predicted Class	Bale	Harar	Jimma	Limmu	Sidamo	Welega
Bale	81	15	27	0	0	50
Harar	21	87	50	0	0	23
Jimma	17	20	54	0	0	26
Limmu	0	0	0	129	71	0
Sidamo	0	0	0	57	82	0
Welega	31	13	38	0	0	77
Total	150	135	169	186	153	176
Percent Correct	**54.0**	**64.4**	**32.0**	**69.4**	**53.6**	**43.8**

Table 4-5: Summary Result of Neural Classifier Using Color Features

As indicated in Table 4-5, the summary result of neural classifier using color feature alone showed that from the total test examples of 969 instances, 510 (52.6%) were correctly classified and 459 (47.4 %) were incorrectly classified. The percentage of correctly classified instances for each class was shown in the last row of Table 4-5.

Analysis of the Result

The result of ANN classification using color feature showed that the classification accuracy of Bale, Harar, Jimma, Limu Sidamo and Wellega coffees were 54.0, 64.4, 32.0, 69.4, 53.6 and 43.8 respectively (in percent).

Bale coffee was misclassified more to Wellega coffee (20.7%) and Welega coffees were more misclassified to Bale coffee (28.4%). Jimma coffee was more misclassified to Harar coffee (29.6%) and Harar coffee is also more misclassified to Jimma coffee (14.8%). Limu coffee was more misclassified to Sidamo coffee (30.6%) and Sidamo coffee to Limu (46.4%). In addition there is a significant misclassification among each region. There is a better classification pattern than Naïve Bayes color feature classification and also a better classification performance was obtained in most regions than the Naïve Bayes color classification though there is slight color difference in each coffee variety.

The analysis of ANN classification using color feature that shows the correlation of the different coffee varieties of the six regions was indicated as bar chart in Figure 4-12.

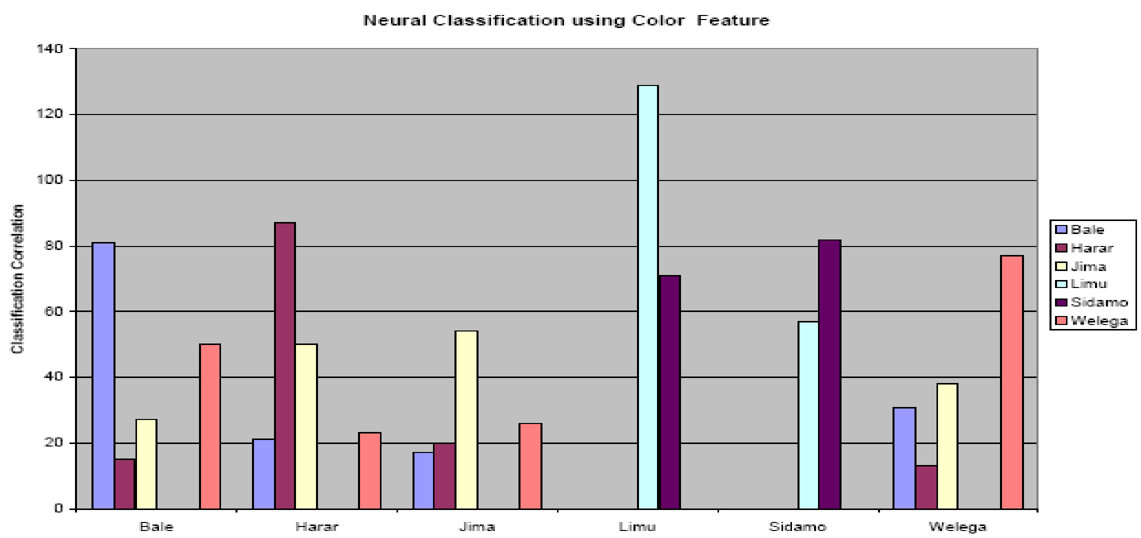


Figure 4-12: ANN Classification Using Color Feature - Confusion Matrix Bar chart

iii) Scenario 3– Using Both Features

In this scenario, seventeen features corresponding to ten morphological features, six color features and processing type of coffee were used as input to the neural network as described in section 3.4. Hence, there were seventeen neuron numbers for the input layer. The same to others, this experimentation has six output classes corresponding to the predefined coffee growing regions. The numbers of neurons in the hidden layers were also eighteen and thirteen for the first hidden layer and the second hidden layer respectively as mentioned before. After the network was trained using the training data set, the result of the test data set was shown in Table 4-6.

Actual Class / Predicted Class	Bale	Harar	Jimma	Limmu	Sidamo	Welega
Bale	121	8	22	0	0	37
Harar	9	98	30	0	0	10
Jimma	7	17	96	0	0	20
Limmu	0	0	0	180	7	0
Sidamo	0	0	0	6	146	0
Welega	13	12	21	0	0	109
Total	150	135	169	186	153	176
Percent Correct	**80.7**	**72.6**	**56.8**	**96.77**	**95.42**	**61.9**

Table 4-6: Summary Result of Neural Classifier Using Morphology and Color Features

As indicated in Table 4-6, the summary result of neural classifier using both morphology and color feature showed that from the total test examples of 969 instances, 750 (77.4%) were correctly classified and 219 (22.6%) were misclassified. The percentage of correctly classified instances for each class was shown in the last row of Table 4-6.

Analysis of the Result

The result of ANN classification using morphology and color feature showed that the classification accuracy of Bale, Harar, Jimma, Limu Sidamo and Wellega coffees were 80.7, 72.6, 56.8, 96.77, 95.42, and 61.9 respectively (in percent).

In this scenario and the same to the Naïve Bayes Classifier, even though the classification accuracy was increased, it reflects the property of both features. The analysis result of this experiment is similar to the analysis of scenario (i) of ANN classification.

The analysis of ANN classification using morphology and color features that shows the correlation of the different coffee varieties of the six regions was indicated as bar chart in Figure 4-13.

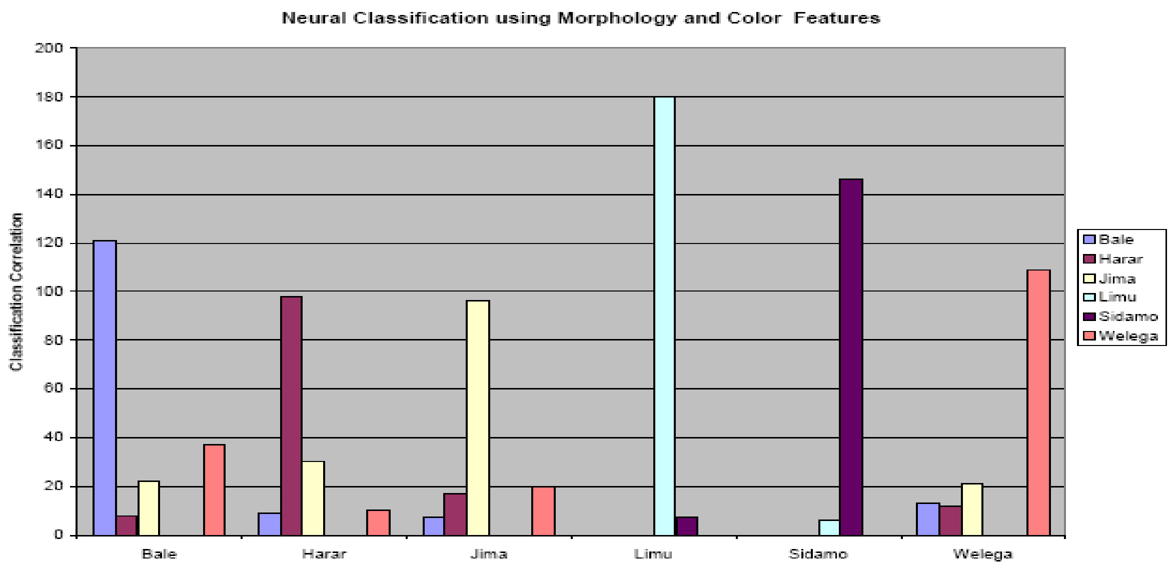


Figure 4-13: ANN Classification Using Both Features - Confusion Matrix Bar chart

4.6 Discussion

As we have presented in detail in the previous section, the experiments were conducted under three scenarios by using feature sets of morphology and color separately, and combining the two feature sets. Then, the experiment results were compared the performance of the Naïve Bayes classifier and neural network classification over the three scenarios.

The total number of data sets is 4844. Out of these, 80% were used for training and the remaining 20% were used for testing. There were ten morphology features, six color features and a processing type. In total there were seventeen attributes. Following standard practice, the data sets were normalized with mean 0 and variance of 1 and prepared in randomized order, prior to presentation to the classifiers.

The discriminating power of the different set of features in relation to Naïve Bayes and neural network classifiers generalization capabilities were shown in Table 4-7 and Table 4-8 respectively. The values indicate the percentage of correctly classified coffee beans of each region.

Feature	**Unwashed Coffee**				**Washed Coffee**		**overall**
	Bale	**Harar**	**Jimma**	**Welega**	**Sidamo**	**Limu**	
Morphology	**45.7**	**37.6**	**34.4**	**36.1**	**89.7**	**83.8**	**55.1**
Color	**41.5**	**53.7**	**29.9**	**35.2**	**65.8**	**62.6**	**48.2**
Morphology + Color	**54.9**	**57.0**	**43.9**	**41.8**	**96.1**	**86.6**	**63.7**

Table 4-7: Naïve Bayes Classifier Performance Summary

Feature	Unwashed Coffee				Washed Coffee		overall
	Bale	**Harar**	**Jimma**	**Welega**	**Sidamo**	**Limu**	
Morphology	**61.3**	**45.2**	**47.3**	**40.9**	**96.08**	**96.77**	**65.2**
Color	**54.0**	**64.4**	**32.0**	**43.8**	**53.6**	**69.4**	**52.6**
Morphology + Color	**80.7**	**72.6**	**56.8**	**61.9**	**95.42**	**96.77**	**77.4**

Table 4-8: Neural Classifier Performance Summary

A quick look at both Tables 4-7 and 4-8, shows the large discriminating power of the morphological features. As anticipated, color is not as good as morphology because many varieties of coffee have more or less similar color [40].

From unwashed coffees, the discriminating power of color feature for Harar coffee was better than others. This was because by its nature, Harar coffee mostly characterized by a unique color called amber color [31, 40]. In addition, color feature classification result for washed coffees of Limu and sidamo also indicates relatively a better discrimination power than that of unwashed coffees. As mentioned in section 2-1, this confirms to the manual system in which color is used as a parameter of classifying and grading of washed coffees [40].

The classification accuracy result of Jimma and Welega coffee were less discriminated than others. From the predefined classes (growing regions) the size of Bale and Welega are bigger. The size of Harar and Jimma are small to medium as indicated in Figure 3-4. This resulted in that most of the coffee beans of Jimma were misclassified as Harar coffee. Similarly, most coffees of Welega were misclassified as Bale as shown in Table 4-6. In other words, there is an ambiguity of classification between Bale and Welega Coffee beans and also between Harar and Jimma Coffee beans.

In general, the over all result showed that morphology features have more discriminating power than color features and the discrimination power increases when morphology and color features were used together. The classification performance of artificial neural network is by far better than Naïve Bayes classifier.

4.7 Limitations

The classification accuracy was acquired below laboratory settings, so it had some limits. The quality of the camera, the image acquisition environment and other imaging factors may affect the result.

In addition to this, the production period of Ethiopian coffees are from August to January. The new products are available to market starting from the end of December. Our samples were taken in November which was a slack time. There was shortage of most the coffees varieties during this period. Hence, at this period there is the possibility of one to be mixed with the other due to the shortages. This property was what observed on the experimentation results.

Climatic condition changes may affect the production of a coffee. Hence, this may also cause the product of a coffee bean to deviate from its normal signature.

Therefore, these factors have to be investigated which were the potential causes for the misclassification of coffee in some regions.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Coffee is a commercial commodity that plays a major role in earning foreign currency among export commodities of Ethiopia. The sub-sector is getting governmental and non-governmental attention due its significance in commercial activities. The brand patent creation of each coffee variety based on region of origin was an issue in current periods. For example, the recent controversy over Yirgacheffe coffee brand by Starbucks was one of this issues [31]. Hence, coffee growing in each regions of Ethiopia has to be identified in some consistent manner.

In line with this, to discriminate different varieties of Ethiopian coffee, we have selected an image analysis technology which has been got recently its application in classification and variety identification of agricultural products [6].

In the classification problem of Ethiopian coffee based on growing region, morphological and color features were extracted from a coffee bean images taken from six regions of Ethiopia – Bale, Harar, Jima, Limu , sidamo and Welega – by using image analysis techniques. Some of these selected features were used as input to the classification model.

To test the classification accuracy of each selected feature set, Naïve Bayes and neural network classifiers were compared. The experiment was conducted under three scenarios of the features data set such as morphology, color and both morphology and color features.

The experimental results showed that morphological features have more discriminating power to classify coffee based on growing regions than color features in both Naïve Bayes Classification and neural network classification. But the classification accuracy of coffee increases when the morphological and color features were used together which shows the importance of color feature in discriminating coffees of different regions in addition to morphological features.

The result of the experimentation also showed that different varieties of coffees growing in different regions of Ethiopia has been classified more accurately by neural network than by using Naïve Bayes classifier.

In general, Ethiopian coffees growing in different regions can be classified by using image analysis. The best classification accuracy was obtained using neural networks when morphology and color features were used together. The six regions, Bale, Harar, Jimma, Limu, Sidamo and Welega, were identified with the classification accuracy of 80.7%, 72.6%, 56.8%, 96.8%, 95.4% and 61.9% respectively by using neural network classification with morphological and color features parameters. In this case the overall performance was 77.4%.

5.2 Recommendations

Ethiopian economy is mainly based on agriculture. Image analysis technology has a paramount importance in the variety identification of agricultural products such as cereal crops, fruits, vegetables etc as reported by many researchers [4, 6]. In Ethiopia, no research has been conducted in this direction to support the sector. Hence, the research may pave the way and initiate researchers to work more in the area.

The image analysis for the classification of Ethiopian coffee by growing regions can be further investigated. The work can also be seen in depth and researched by the different characteristics of its physical and chemical attributes in connection to image technology.

In light with this, the following recommendations are made for further research and improvements.

- Identification of coffee varieties from mixed components of coffee beans
- Coffee classification by using image analysis of roasted coffee
- Computer vision for coffee defect identification and counting
- Coffee grading by using computer vision system.

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APPENDIX A – RGB COLOR SPLITTER JAVA CODE

```
// RGB_Stack_Splitter.java

import ij.*;
import ij.plugin.filter.PlugInFilter;
import ij.process.*;
import ij.gui.*;
import java.awt.*;

/** Splits an RGB image or stack into three 8-bit grayscale images or stacks. */

public class RGB_Stack_Splitter implements PlugInFilter {
   ImagePlus imp;

   public int setup(String arg, ImagePlus imp) {
      this.imp = imp;
      return DOES_RGB+NO_UNDO;
   }

   public void run(ImageProcessor ip) {
      splitStack(imp);
   }
   public void splitStack(ImagePlus imp) {
       int w = imp.getWidth();
       int h = imp.getHeight();
       ImageStack rgbStack = imp.getStack();
       ImageStack redStack = new ImageStack(w,h);
       ImageStack greenStack = new ImageStack(w,h);
       ImageStack blueStack = new ImageStack(w,h);
       byte[] r,g,b;
       ColorProcessor cp;
       int n = rgbStack.getSize();
       for (int i=1; i<=n; i++) {
          IJ.showStatus(i+"/"+n);
          r = new byte[w*h];
          g = new byte[w*h];
          b = new byte[w*h];
          cp = (ColorProcessor)rgbStack.getProcessor(1);
          cp.getRGB(r,g,b);
          rgbStack.deleteSlice(1);
          //System.gc();
          redStack.addSlice(null,r);
          greenStack.addSlice(null,g);
          blueStack.addSlice(null,b);
          IJ.showProgress((double)i/n);
      }
      String title = imp.getTitle();
      imp.hide();
      new ImagePlus(title+" (red)",redStack).show();
      new ImagePlus(title+" (green)",greenStack).show();
      new ImagePlus(title+" (blue)",blueStack).show();
   }
}
```

// HSB_Stack_Splitter.java

```
import ij.*;
import ij.plugin.filter.PlugInFilter;
import ij.process.*;
import ij.gui.*;
import java.awt.*;

/** Splits an RGB image or stack into three 8-bit grayscale images or stacks (hue,
saturation and brightness). */

public class HSB_Stack_Splitter implements PlugInFilter {
   ImagePlus imp;

   public int setup(String arg, ImagePlus imp) {
      this.imp = imp;
      return DOES_RGB+NO_UNDO;
   }

   public void run(ImageProcessor ip) {
      splitStack(imp);
   }

   public void splitStack(ImagePlus imp) {
       int w = imp.getWidth();
       int h = imp.getHeight();
       ImageStack hsbStack = imp.getStack();
       ImageStack hueStack = new ImageStack(w,h);
       ImageStack satStack = new ImageStack(w,h);
       ImageStack brightStack = new ImageStack(w,h);
       byte[] hue,s,b;
       ColorProcessor cp;
       int n = hsbStack.getSize();
       for (int i=1; i<=n; i++) {
          IJ.showStatus(i+"/"+n);
          hue = new byte[w*h];
          s = new byte[w*h];
          b = new byte[w*h];
          cp = (ColorProcessor)hsbStack.getProcessor(1);
          cp.getHSB(hue,s,b);
          hsbStack.deleteSlice(1);
         //System.gc();
          hueStack.addSlice(null,hue);
          satStack.addSlice(null,s);
          brightStack.addSlice(null,b);
          IJ.showProgress((double)i/n);
      }
      String title = imp.getTitle();
      imp.hide();
      new ImagePlus(title+" (hue)",hueStack).show();
      new ImagePlus(title+" (saturation)",satStack).show();
      new ImagePlus(title+" (brightness)",brightStack).show();
   }
}
```

Declaration

I, the undersigned, declare that this thesis is my original work and has not been presented for a degree in any other university, and that all source of materials used for the thesis have been duly acknowledged.

Declared by:

Name: ________________________________

Signature: _____________________________

Date: _________________________________

Confirmed by advisor:

Name: ________________________________

Signature: _____________________________

Date: _________________________________

Place and date of submission: Addis Ababa, January 2008.