CLASSIFICATION OF JIMMA COFFEE BEANS USING MORPHOLOGICAL AND COLOR FEATURES

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TESHALE LATA

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Classification Of Jimma Coffee Beans Using Morphological and Color Features

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Teshale Lata

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HARAMAYA UNIVERSITY

POSTGRADUATE PROGRAM DIRECTORATE

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Getachew Abebe (Ph.D.)	____________________	________________
Major Advisor	Signature	Date

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Name: Teshale Lata Signature: ________________

Date: June, 2024

Department: Physics

BIOGRAPHICAL SKETCH OF THE AUTHOR

The researcher was born to his father Lata Dinsa and mother Mijane Gemeda, in Oromia Regional State, Horro Guduru Wollega Zone, Jardaga Jarte Woreda, in 1991 G.C. He attended his junior school at Alibo primary school and his secondary education at Alibo Senior Secondary School. After completion of the Ethiopian University Entrances Examination (EUEE), He received B.Sc. Degree in Physics from Semera University in 2013G.C; He served as a Physics teacher at Gursum preparatory school. After serving for three years, He joined the graduate school of Haramaya University in 2016 to pursue a master degree in Physics (computational physics).

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LIST OF ACRONYMS

ANN	Artificial Neural Network
CCD	Charged Coupled Device
DIP	Digital Image Processing
ECBM	Ethiopian Coffee Buying Manual
ECX	Ethiopia Commodity Exchange
EEA	Ethiopian Economics Association
GDP	Gross Domestic product
HIS	Hue Saturation and Intensity
ISO	International Organization for Standard
ITC	International Trade Centre
MATLAB	Matrix Laboratory
RGB	Red, Green and Blue colors
JARC	Jimma Agriculture Research Center

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Classification of Jimma Coffee Beans using Morphological and Color Features

ABSTRACT

Image processing techniques have become increasingly useful in the vegetable industry, especially for applications in quality inspection and evaluation of food grains, fruits, vegetables, processed foods, and defect sorting. In this research work, we focused on the classification of Jimma coffee beans using morphological features (Limmu, Abba Buna, Yachi, and Buno wash), color, and morphological features extracted from 600 images. For each category, 150 images were captured. We used Artificial Neural Networks (ANN) to classify Jimma coffee beans based on the extracted features. Specifically, 15 color features and 8 morphological features, totaling 23 predominant features, were extracted from images of the four classes of coffee beans. We implemented a three-classification setup using color, morphology, and a combination of color and morphological datasets as inputs to the network. For the dataset considered, we allocated 70% (420 images) for training, 20% (120 images) for testing, and 10% (60 images) for validation. The accuracy of classification using color, morphology, and their combination were 74.8%, 75.0%, and 74.8%, respectively. The performance of the network was optimal for all classifications.

Keywords: Artificial neural network, Coffee bean varieties, Image processing, Feature extraction, Pattern recognition.

1. INTRODUCTION

1.1. Background of study

Coffee is the most popular soft drink in the world. Over 2.25 billion cups are consumed every day (Ponte, 2002). Its popularity and volume of consumption are growing every year, and coffee shops are the fastest growing part of the restaurant business. Today, coffee is both a part of our social experiences as well as an accepted norm for doing business. Many business managers, scientists, politicians, and people of all walks of life relax having a cup of coffee during breaks in between meetings, busy research works and routine daily activities. Economically, coffee is the second most exported commodity after oil, and employs over 100 million people worldwide (Petit, 2007).

The both local and international markets origins of coffee crop can be traced back to the Ethiopian highlands for coffee Arabica and the forest of west and central Africa for coffee Robusta (Canephor Geneva, 2002). Coffee is referred as a “green gold”, and is Ethiopia’s main source of foreign exchange earnings. Generally, the coffee produced in different regions of the country is prepared for both local and international markets.

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. 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 (Habtamu Minase, 2008).

Jimma is a zone in Oromia regional State of Ethiopia. It is bordering with Southern Nations, Nationalities and Peoples Regional state in the South, with Illubabor Zone the northwest, with East Wollaga Zone in the north and with West Shoa Zone in the northeast; while the part of its boundary with south west Shoa Zone is delineated by the Gibe River. Jimma Zone is one of coffee growing zones in the Oromia Regional State. Coffee is the major cash crop of the Zone, which is produced in the eight woredas namely, Gomma, Manna, Gera, Limmu Kossa, Limmu

Seka, Seka Chokorsa, Kersa and Dedo. Towns and cities in Jimma include Agaro, Limmu Inariya and Saqqa. The town of Jimma was separated from Jimma Zone and is a special zone now. The Central Statistical Agency (CSA) reported that 26,743 tons of coffee were produced in this zone in the year ending in 2005, based on inspection records from the Ethiopian Coffee and Tea authority. (CSA 2005). Jimma zone has 22 Woredas, the majority of these Woredas are predominantly coffee-growing areas. The coffee varieties which are dominantly being produced in Jimma zone include (Feyate, Odicha, Catimor, Mechara, Abba Buna, Yachi, Melko-CH2, Medacheriko, 741, 75227, Merdacheriko, Limmu, Wush Wush, Buno wash, 7440, Ageze, 74112, 74140,7440, 74165, 74158 and 3/70 (Demelash Teferi, 2015). Jimma coffee bean is produced, both washed and unwashed (Mengistu et al., 2020)

Classification 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 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 biases. One of such methods is image analysis or computer vision system (Maheshwari et al., 2012). Therefore, this work was initiated to model for different variety of Jimma coffee beans classification which is consistent, efficient and cost effective by exploring technology of image analysis. This work was mainly interested in classifying four Jimma coffee bean (Limmu, Abba Buna, Yachi, and Buno wash) based on their features variation like shape, size and color using image processing and analysis.

Image analysis and classification algorithms can provide a means to quantify objects and patterns in the image data and grade agricultural products. This offers two advantages over traditional or manual methods of analysis; i) human vision is biased due to many factors but automated image analysis provides an unbiased approach and ii) once an image-analysis routine is developed, it can be applied to a large number of sample images, facilitating the collection of large amounts of data for statistical analysis (Nuradin, 2016).

Therefore, it is very important to implement an automatic sorting system for quality determination in the processing industries. The processing and manufacturing sectors require automated inspection, as well as grading systems so that the losses that may incur during harvesting, production and marketing would be minimize. A cost effective, consistent, fast and accurate sorting system may be achieved using computer vision technique.

1.2. Statement of the Problem

Several coffee varieties are growing in different parts of Jimma zone. Different coffee cultivars exhibit quality parameters which differentiates one from the other. Nowadays, the quality of the coffee bean is determined by experienced technicians. However, quality determination requires high degree of accuracy to satisfy customer's needs. High-level non-destructive quality evaluation method, based on image processing was proposed by Maheshwari *et al*. (2012). Due to consistent quality requirements, image-based techniques is preferred to manual inspection of classification of agricultural products. Therefore, the implementation of imaging technology has a paramount importance to facilitate commercial activities by increasing efficiency, promoting the market and sustain dependability of customers' preference.

Coffee is not only used for consumption but also has become a lifestyle. The system for determining the quality of coffee is based on both cup and raw quality. The raw quality determination deals with the defect count of coffee and non-coffee origins. Such coffee quality parameters could be determined using images of coffee samples. Coffee quality determination is generally carried out manually, by inspecting the morphological and color parameters of coffee samples. Such practices have drawbacks in terms of consistency and accuracy and also time of execution. These constraints make it difficult to separate quality coffee beans for large production. Hence, the main objective of this research is to develop computer algorithm to classify Jimma coffee beans using image analysis. The possibility of classifying coffee beans by using their features such as color, shape, and size is employed. These features provide information about the physical alteration of coffee bean according to their varietal type. Jimma zone is considered as the source of wide varieties of coffee including: Abba buna, Yachi, Medacheriko, 741, 7440, Wush Wush, and Buno Wash which is brought forward to both national and international markets (*Mikru Tesfa*, 2018).

1.3. Objectives of the Study

1.3.1. General objective

The main objective of this thesis is to develop an appropriate computer routine algorithm that could classify four Jimma coffee bean varieties (Abba buna, Yachi, Limmu, and Buno wash), which are grown under the same and different agronomical managements based on its morphological, and color features.

1.3.2. Specific objectives

- To preprocess and segment region of interest
- To explore to extract morphological and color features
- To classify Jimma coffee bean varieties based on their color and morphological features using artificial neural network classifier algorithm**.**

1.4. Scope of the Study

This work tries to explore image analysis techniques for the classification of Jimma coffee bean in terms of color and morphological features. This place of study was selected purposively based on export potential and productivity as well as genetic diversities of coffee beans. The research work used sample coffee produced the current year in the area around Jimma. That is, our sample data drawn from coffee produced, in the name of Jimma coffee (Abba buna, Yachi, Limmu, and Buno wash) 2021/22 production year. The samples were collected from Jimma Zone and town. As variety verification, experts at Jimma Coffee and Tea authority laboratory were requested to certify the samples.

1.5. Significance of the Study

This study focuses on the development of an algorithm to classify morphological, color features of genetic variety of Jimma coffee beans prepared for export purpose, and it has contribution in overcoming the subjective way of identifying, coffee raw-quality and to increase the reliability of classification of coffee beans. Once the algorithm is developed and evaluated, it is possible to classify coffee bean automatically and apply them in beans, processing industries in Ethiopia in real-time. In addition to this, it may help to create baseline data for researchers to develop a modified system by integrating with other algorithms as one package

2. LITERATURE REVIEW

2.1. An Overview of Coffee Quality in Ethiopia

Coffee is the most important crop in the national economy of Ethiopia and the leading export commodity. Ethiopia is well known not only for being the home of Arabica coffee, but also for it is very fine quality coffee acclaimed for its aroma and flavor characteristics. The coffee types that are distinguished for such unique characteristics include Sidamo, YirgaChefe, Hararghe, Gimbi and Limmu types (Workafes and Kassu, 2000).

In recent years, different coffee producing countries have tremendously expanded their production and export volume (Behailu *et al*., 2008). According to the current context of overproduction and low prices of the coffee market, improvement of coffee quality could provide the coffee chain with a new impetus (Leroy *et al*., 2006). Production and supply of coffee with excellent quality seems more crucial than ever before for coffee exporting countries. Consequently, some countries consider assessment of coffee quality as important as disease resistance and productivity in their coffee variety development program (ITC, 2004). In view of the present situation, making effort to overcome challenges and threats only through expansion of production does not seem visible for countries like Ethiopia. Thus, it has been repeatedly mentioned at various forum that providing good quality coffee is the only way out and viable option to get into the world market and to remain competitive (Behailu *et al*., 2008).

Ethiopian coffees growing in different parts of the country can have different defects of coffee beans and they were classified based on features of coffee beans by using image analysis. The classification was done by artificial neural network of Matlab toolbox. Identification and classification of coffee beans using DIP and ANN means is possible as the result shows in the earlier sections. The classifications by using morphological and combination of morphological and color features give the best result. Therefore, the quality evaluation centers must use the imaging applications. The classification of defects of coffee beans has performed best and accurate results by color features and texture features. The lowest accuracy was obtained from classification of defects of coffee beans using morphology features, (Bedasa, 2018).

2.2. Digital Image Processing

Images are ways of recording and presenting information in visual form and, in the broadest sense, an image corresponds to any kind of two-dimensional data. The naturally occurring form of image is not suitable for processing with computers as computers cannot operate directly on pictorial data but require numerical data. Therefore, images need to be converted into numerical data referred to as digital image, to enable computer manipulation (Ertürk, 2003).

Image processing is widely used in many applications, including the film industry, medical imaging, industrial manufacturing, weather forecasting, agriculture and geo-informatics. In some of these areas, the size of the image is very large, yet the processing time has to be very small and sometimes real-time processing is required. The typical applications of digital image processing are remote sensing, medical imaging, transportation, military, agricultural area, security, industrial manufacturing and the like (Huiyu and Zhang, 2010).

The field of digital image processing refers to processing digital images by means of a digital computer. There is no general agreement among authors regarding where image processing stops and other related areas, such as image analysis and computer vision, begin. Sometimes a distinction was made by defining image processing as a discipline in which both the input and output of a process are images (Gonzalez and Woods, 2002).

2.2.1. Pre-image processing

This performs some basic tasks to render the resulting image more suitable for the job to follow. In this case, it may involve enhancing the contrast, removing noise, or identifying regions likely to contain the postcode.

2.2.2. Histogram

This refers to a graph indicating the number of times each grey level occurs in the image. It shows intensity variation. We can infer a great deal of information about the appearance of an image from its histogram. Consider the following examples:

- ✓ Dark Image: The grey levels (and hence the histogram) are clustered at the lower end.

- ✓ Uniform Bright Image: The grey levels are clustered at the upper end.
- ✓ Well-Contrasted Image: The grey levels are well spread out over much of the range.

2.2.3. Image segmentation

This refers to the partition of image into meaningful regions based on homogeneity or heterogeneity criteria. It is used to extract the particular features, which allow researchers to differentiate between objects. In short, it is the process of extracting from the image that part of it which contains just the postcode. The most commonly used techniques of segmentation are thresholding, edge detection, binary mathematical morphology and region growing and splitting (Gonzalez and Woods, 2002). Image segmentation is the important step to split the different regions with special significance in the image. These regions do not meet each other and each region should meet consistency conditions in specific regions.

2.2.4. Thresholding

This is an older, but an easy and popular method for image segmentation. Image segmentation by thresholding is a powerful approach for segmenting images having illumination objects on dark background. Thresholding technique is based on image space region, i.e., on individuality of image. Thresholding process converts a multilevel image into a binary image, i.e., it chooses a suitable threshold, T to divide image pixels into several regions and divides objects from the background. Thresholding process is used to decide as intensity value, called threshold, and threshold separates the desired module. The segmentation is gained by grouping all pixels with intensity better than the threshold into one class, and all other pixels into a different class (Saranya*et al*., 2014).

Suppose $f(x,y)$ is the input, $g(x,y)$ is the output, T is a threshold. The segmented image, $g(x,y)$, is given by:

$$g(x,y) \;= \begin{cases} 255, for\;\; f(x,y) \leq T \\ 0, \quad\;\; for\; f(x,y) > T \end{cases} \tag{2.1}$$

where $g(x,y) \;=\; 255$ for image elements of objects, and $g(x,y) \;=\; 0$ for image elements of the background (or vice versa). Thresholding is a vital part of image segmentation when one wishes to isolate objects from the background. It is also an important component of robot vision (Zhihua *et al*., 2013).

In this research work, automatic threshold method was used, which was automatically selected threshold value for each image by the system without human intervention. It usually seeks to select a value for the threshold that separates an object from its background. This suggests that the objects (coffee beans) have a different range of intensities with respect to the background.

Automatic thresholding

Algorithm for Iterative threshold selection steps are:

1. Select an initial estimate of threshold T. a good initial value is the average intensity of the image.
2. Partition the image into two groups R_1 and R_2 using the T.
3. Calculate the mean gray value μ_1 and μ_2 of the partitions R_1 and R_2.
4. Select the new threshold:

$$T = \frac{1}{2}(\mu_1 + \mu_2) \tag{2.2}$$

Repeat steps 2-4 until the mean values μ_1 and μ_2 in successive iteration do not change.

2.3. Image Feature Extraction

After segmentation of the area of interest, in the next step significant features are extracted and these features can be used to determine the meaning of a given sample. Actually, image features usually include color, shape and texture features.

2.3.1. Color feature extraction

Color is one of the most widely used visual features in content-based image retrieval. Computer can represent millions of distinct colors. In practice, even human eye can identify thousands of color shades and limited number of gray levels. Therefore, color is a powerful descriptor or feature that simplifies object identification (Acharya and Ray, 2005).

RGB color space can be, converted into another color space such as HSV and for all the converted color space values; the mean, variance, range, and standard deviation are calculated. Each bean image gives different values of mean, variance, range, and standard deviation, for classification. All visible colors can be, represented by a linear combination of the base vectors in the RGB space. In one such accepted RGB color space, a color image mathematically treated as a vector function with three components. If variations of intensities were uniform across the spectrum, then normalized RGB space was of values as given in equation 2.2 (Gonzalez and Wood, 2002).

$$r = \frac{R}{R+G+B}\ ; \quad g = \frac{G}{R+G+B}\ ; \quad b = \frac{B}{R+G+B} \tag{2.3}$$

So that they satisfy the normalization condition

$$r + g + b = 1$$

2.3.2. HSI color space

The HSI color spaces, are particularly common in the field of computer graphics. The HSI color space is often used by people who are selecting the color (e.g., of paints or inks) from a color wheel or palette, because it corresponds better to how people experience color than the RGB color space did as shown in Figure 0.1.

Hue, saturation, and intensity value are used as coordinate axes by projecting the *RGB* unit cube along the diagonals of white to black. As hue varies from 0 to 1, the corresponding colors vary from red through yellow, green, cyan, blue, magenta, and back to red, so that there are actually red values both at 0 and 1. As saturation varies from 0 to 1, the corresponding colors (hues) vary from unsaturated (shades of gray) to fully saturated (no white component). As value, or brightness, varies from 0 to 1.0, the corresponding colors become increasingly brighter.

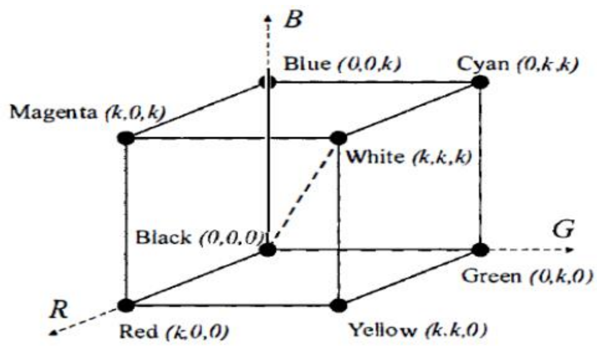

Figure 0.1. RGB color space.

The values of RGB color components are in the range [0, 1] and HSI components were extracted from these RGB components. The equations (2.3), (2.4) and (2.5) were used to evaluate H, S, and I components respectively for a given image sample.

$$\mathrm{H} \ = \begin{cases} \theta, & if\ B \leq G \\ 360° - \theta, & if\ B > G \end{cases}$$

where

$$\theta \ = \cos^{-1}\left\{\frac{0.5[(R-G)+(R-B)]}{[(R-G)^2+(R-G)(G-B)]^{1/2}}\right\} \tag{2.4}$$

$$\mathrm{S} = 1 - \frac{3}{(R+G+B)}[\min(\mathrm{R}, \mathrm{G}, \mathrm{B})] \tag{2.5}$$

$$\mathrm{I} = \ \frac{1}{3}(\mathrm{R} + \mathrm{G} + \mathrm{B}) \tag{2.6}$$

The mean, variance and range are calculated, respectively, as

$$\mu \ = \ \sum_{x}\sum_{y}\frac{p\ (x, y)}{MN} \ , \tag{2.7}$$

$$\sigma_x = \ \sum_{x}\sum_{y}\frac{(x-\mu)^2 p\ (x, y)}{MN} \quad , \tag{2.8}$$

$$R \ = \max p(x, y) - \min p(x, y) \quad , \tag{2.9}$$

where $p(x, y)$ represents the gray level value of a pixel at (x, y) within a given image $M \times N$ size of the image**.**

2.3.3. Morphological feature

Morphology is the geometric property of images. In our case, it is used to determine the size and shape characteristics of four coffee beans (Limmu, Abba Buna, Yachi, and Buno wash). It can be obtained from the analysis of binarized images. From morphology of coffee beans, the following geometric features are extracted from the binarized images as described in the previous section.

I. Surface Area (A): The area of the coffee bean will be measured by counting the number of pixels having a value of 1. It is measured by square pixels. Mathematically the area of the ith object 0_i (x, y)&, measured in pixels, is given by

$$A_i = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} O_i\,(x, y) \tag{2.10}$$

where A is the area of the object.

II. Perimeters (P): The length of the outside boundary of the region covered by a coffee bean image. The perimeter will be measured by counting the number of pixels lying on the boarder of the coffee bean. If $d_1, d_2, \cdots, d_n$ are boundary coordinates, then the object perimeter is given by:

$$P = \sum_{i=1}^{N-1} d_i \tag{2.11}$$

III. Major axis length (L_{maj}): it is the distance between (x_1, y_1) and (x_2, y_2) endpoints of the longest line that could be drawn through the image. The major axis endpoint was found by computing the pixel distance between every combination of border pixels in the image boundary and finding the pair with maximum length.

$$L_{\mathrm{maj}} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \ , \tag{2.12}$$

where (x_1, y_1) and (x_2, y_2) were the coordinates of the two ends of the major axis. Once the end points of the major and minor axis were found, their length was given by the same equation.

IV. Minor axis length (L_{min}): it was the distance between (x, y) and (x_0, y_0) ends of the shortest line that could be drawn through the object line maintaining perpendicularity with the major axis.

$$L_{\mathrm{min}} = \sqrt{(x - x_0)^2 + (y - y_0)^2} \ , \tag{2.13}$$

where (x, y) and (x_0, y_0) were the coordinates of the two ends of the minor axis. The length of the minor axis is the minimum distance in the object between two ends perpendicular to the major axis length.

V. Equivalent diameter (d_{eq}): is the diameter of the circle with the same area as the coffee bean and is expressed:

$$d_{eq} = \sqrt{\frac{4A}{\pi}} \ , \tag{2.14}$$

where A is the area of a coffee bean region in the image.

VI. Surface roundness (R_s): Measures the degree of roundness (circularity) of the shape the coffee bean. In a non-circular object is defined as the ratio of the area of the coffee bean to the area of the smallest circumscribed circle.

$$R_S = \frac{A_S}{\pi (D_{max}/2)^2} \ . \tag{2.15}$$

VII. Eccentricity (E_{cc}): the eccentricity of an object is defined as the ratio of the major and minor axes of the object.

$$\mathrm{E_{cc}} = \frac{L_{max}}{L_{min}} \quad . \tag{2.16}$$

VIII. Thinness ratio (T_{rat}): it is a measure the roundness of image.

$$T_{rat} = \frac{P^2}{4\pi A_s} \quad . \tag{2.17}$$

2.4. Related Work

Birhanu *et al* (2013) used digital image processing technique based on shape, texture and color features. He took sample coffees from four coffee bean growing regions (Kaffa, Hararghe, Wollega, and Yirgachefe). He classified different variety of Ethiopian coffee beans based on their features. On average 40 images were taken from each region, totally 160 images. He used 70% of the data for training and the remaining 30% for testing and validation, (25% for testing and 5% for validation). He used Neural Network classifiers on each classification parameters of shape and size, texture, color and the combination of them.

Faridah *et al*., (2010) used image processing to classify Indonesian coffee beans grade. The coffee beans were classified into six, from grade I to VI depending on the defect found in the beans. A visual sensor, a webcam connected to a computer was used for image acquisition of coffee bean image samples, which were placed under uniform illumination. The computer performs feature extraction from parameters of coffee bean image samples in terms of texture (energy, entropy, contrast, homogeneity) and color (R mean, G mean, and B mean) and determines the grade of coffee bean based on the image parameters by implementing neural network algorithm.

Habtamu Minessie (2008) used digital image analysis technique based on morphological and color features. He took sample coffees from six coffee growing regions (Bale, Harar, Jimma, Limmu, Sidamo and Wollega) which are popular and widely planted in Ethiopia. He tried to classify different variety of Ethiopian coffee based on their growing region. On average 56 images were taken from each region, totally around 309 which contained 4844 coffee beans. He used 80% of the data for training and the remaining 20% for testing. He compared classification approaches of Naïve Bayes and Neural Network classifiers on each classification parameters of morphology, color and the combination of two.

Biniyam *et al*. (2013) implemented automatic sorting or classification system by using artificial neural network (ANN) to identify geographical based classification of Hararge coffee beans. He used features of color, texture and shape with size in order to classify Hararge coffee beans into four main classes (Harar-A, Harar-B, Harar-C and Harar-D).

Yip and Yu (1996) presented a method for classifying coffees according to their scents using artificial neural network (ANN). They proposed methods to use genetic algorithm (GA) to determine the optimal parameters and topology of ANN. This finding deals with adaptive back propagation to accelerate the training process so that the entire optimization process can be achieved in an accelerated time. The optimized ANN has successfully classified the coffee difference using a relatively small set of training data. They compared performance of the result of optimized ANN significantly better than the ones and the methods proposed by other researchers.

3. MATERIALS AND METHODS

3.1. Description of the study area

This study aims at classification of Jimma zone coffee beans using morphological attributes. Jimma is one of Ethiopia’s research centers located in south west of Ethiopia, Oromia regional state, Jimma town that is at a distance of 350 km From Addis Ababa, capital of city Ethiopia (see Figure 3.1). The study area lies at an altitude of 1689 – 3018 meters above sea level and located at a Latitude range of $7^{o}40^{\prime}$N and longitude range of $36^{o}50^{\prime}$E. The average annual rainfall is 1200_2400mm per annum with annual minimum temperature 12 ℃ to 13 ℃ and maximum temperature of 24℃ to 27℃.

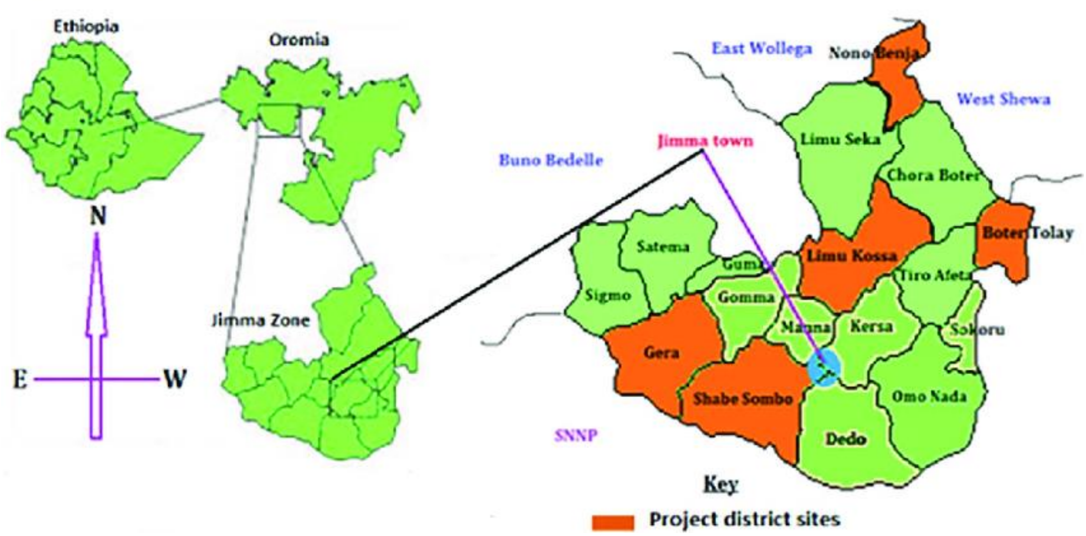

Figure 3.1. Map of Jimma zone.

3.2. Sampling Technique

Totally, 1.2kg of coffee beans samples were taken from (Abba buna, Yachi, Limmu, and Buno wash varieties) for image analysis. Sampling is one of the main procedures in coffee classification and quality assessment. Samples were collected from Jimma coffee research center. The clean coffee bean samples ware then processed for image-based analysis. One hundred fifty images were taken for each variety and totally, six-hundred coffee images were captured for the thesis work. The sample were obtained from quintals of coffee beans (the same grade coffee beans containers) 300 grams of bean samples was taken from each variety for image analysis. All sampled coffee beans were harvested of 2021/22 production year.

3.3. Methodology

A vision-based classification of Jimma zone coffee samples involves defining and measuring some specific visual characteristics like color descriptors; mean, standard deviation, and range of RGB, and HSI channels. Morphological descriptors such as; area, perimeter, major axis length, minor axes length, diameter, convex area, extent, and eccentricity were determined. In this study, quantitative details of these features were extracted from the image of Jimma coffee beans (Limmu, Abba Buna, Yachi, and Buno wash) using image-processing techniques. Automatic thresholding algorithms were employed; to segment and extract those features for classifying Jimma coffee bean varieties by using ANN. The various processing and analysis steps are summarized in the flow chat shown in Figure 3.2.

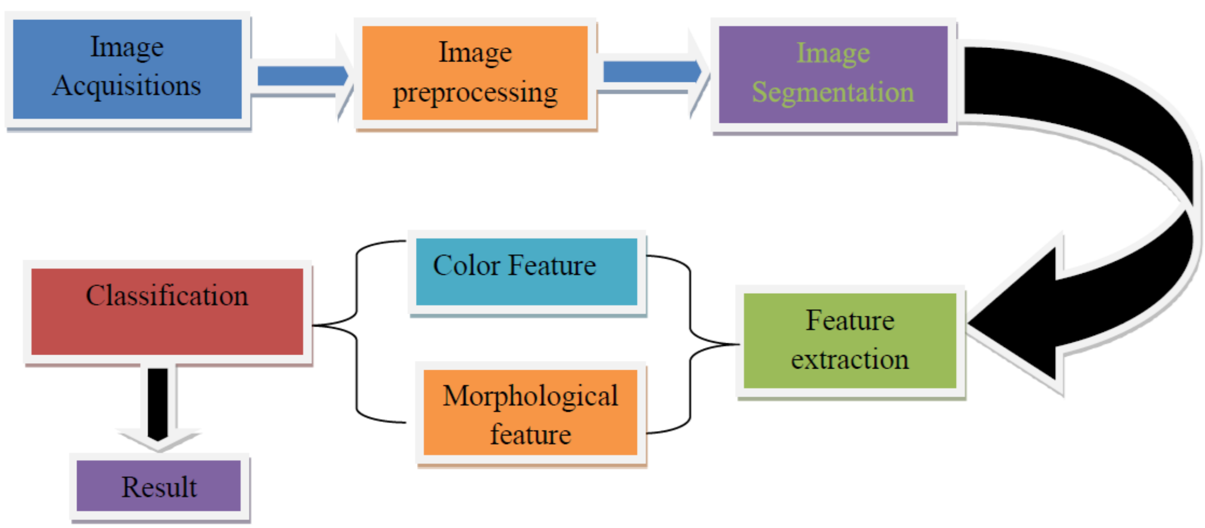

Figure 3.2. Research design.

3.4. Image Acquisition

The first step in using a machine vision system is the acquisition of a digital image. For imaging, the samples were deliberately spread on a white background tray. The samples were captured using regular digital camera with 720×1600 mega pixels of resolution. Each image was captured at the same condition, placing sample at equal distance from the camera lens normal to the plane of coffee bean, in the same light luminous and using the same camera adjustment. Variation of this condition makes the amount of light reflected from the sample reach the camera and distort the image. Then after the images were uploaded to a PC via a USB cables.

3.5. Image Pre-processing

Image preprocessing enables to improve the image in the way that increases the chances for the other process. It is common to correct unwanted signals like image noise, image distortion, blurring of image, reflection, shadow, unwanted background and the like.

In this case, noise reduction algorithms, and segmentation algorithms, were employed. Images were resized to a fixed resolution to utilize the storage capacity or to reduce the computational burden. Enhancements of image by contrast adjustment technique were used to sharpen the image, highlight the edges, improve image brightness and remove noise. The effects of noise were mitigated by employing image-filtering algorithms. Median filtering type was used.

3.6. Image Segmentation

Image segmentation refers to the process of partitioning the digital image into multiple segments to change the representation of an image into something that is more meaningful and easier to analyze i.e., to identify regions in the image that are likely to classify the variety of HCBs (Biniyam *et al*., 2013).

Image segmentation extracts objects/regions of interest from the background. These objects and regions are the focus for further identification and classification of coffee beans (He *et al.*, 2009). The image segmentation is very important to simplify feature extraction, such as color, texture, shape, and structure from images (Barakbah and Kiyoki, 2010). It is used to separate the desired objects (coffee beans) from the background. In this research work, automatic thresholding methods, which could automatically select threshold value for each image without human intervention, were used. The more advanced image processing technique of automatically segmentation is optimal thresholding. It usually seeks to select a value for the threshold that separates an object from its background. This suggests that the object (coffee bean) has a different range of intensities with respect to the background.

3.7. Features Extraction

Automated computer systems for classification, sorting and grading of agricultural products demand the extraction of relevant features that characterize the items under study. This research involved the extraction of morphological and color features from the image of sampled coffee beans. Color features of the sample coffee beans were extracted from segmented coffee bean images that resulted from histogram thresholding. Morphological features were extracted from the binary images that were produced by histogram thresholding of the gray scale images of the original coffee bean color images.

3.8. Artificial Neural Network

Artificial Neural Network (ANN) is the best-suited classifiers for pattern recognition. They arre based on the concept of biological nervous system. Pattern classification was done using a two-layer (i.e. one-hidden-layer) back propagation supervised neural networks with a single hidden layer of neurons with training functions (Zapotoczny *et al.*, 2011).

In this study, the Artificial Neural Networks (ANN) was used for recognizing the pattern and to classify color and morphological features of coffee beans which can be extracted from image processing techniques. The performance of the classifier for its specificity, sensitivity and accuracy were evaluated. The ANN topology was shown in **Error! Reference source not found.**.

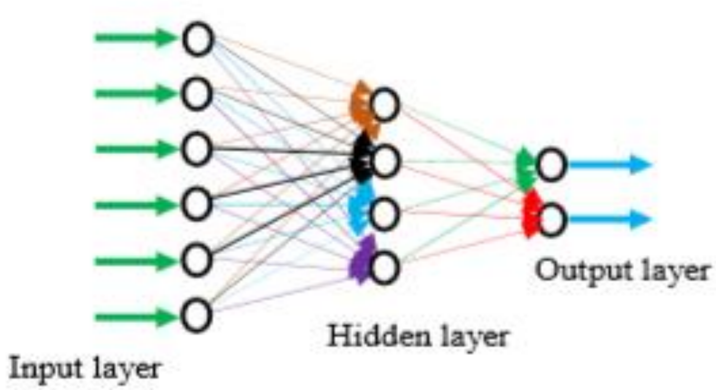

Figure 3.3. Architecture of an artificial neural network**.**

4. RESULTS AND DISCUSSION

In this chapter the classification results of Jimma coffee bean, which was obtained using pre-processing, segmentation, color and morphological features extraction and classification along with interpretation are presented

4.1. Result of Image Pre-processing

The RGB images captured were converted into intensity images for morphological features extraction. Thereafter, the images were enhanced by contrast adjustment techniques.

Figure 4.1. Original image.

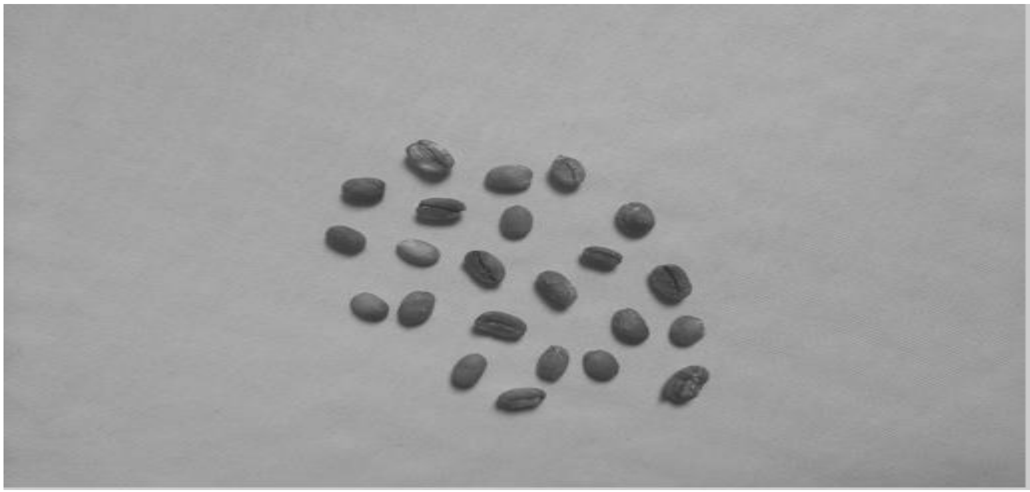

Figure 4.2. Intensity image

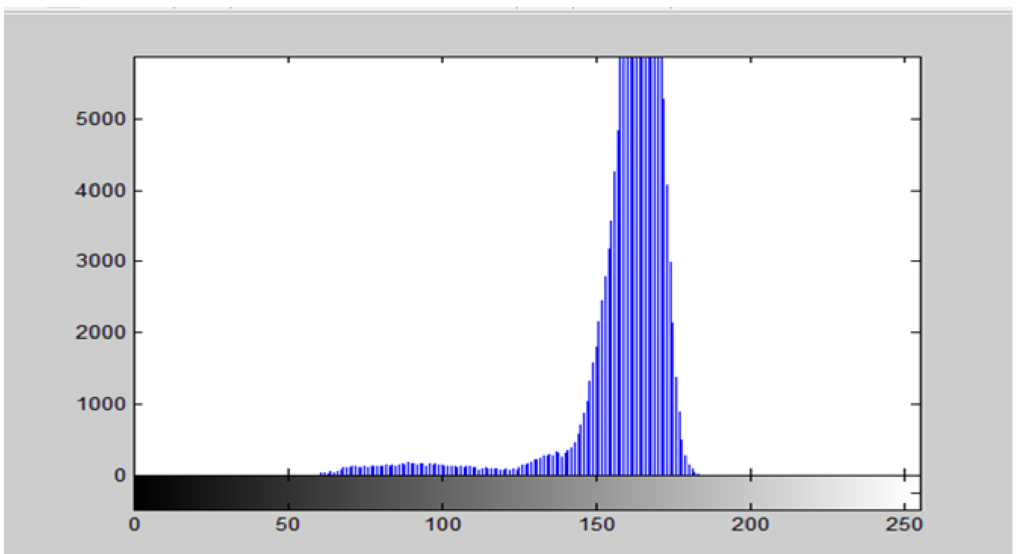

Figure 4.3. Histogram of Intensity image before adjustment.

The contrast of an image is the distribution of its dark and light pixels. A low-contrast image exhibits small differences between its light and dark pixel values. The histogram of a low contrast image is narrow (Figure 4.3). Better image could be obtained by stretching the histogram of an image using histogram equalization so that the full dynamic range of the image is filled (Figure 4.4).

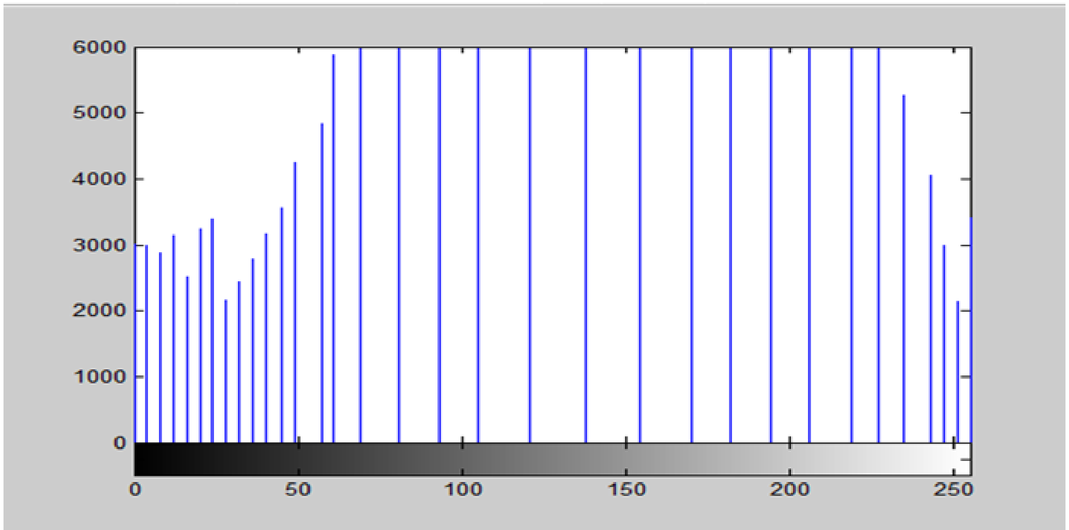

Figure 4.4. Histogram of Intensity image after adjustment

4.2. Result of Segmentation

The captured RGB images (I) were converted into gray level images (g) and then binary image (bw) to extract features. Thereafter, the images were enhanced by increasing contrast. In this work, we have used simple automatic thresholding method to segment the image from the background. Before segmentation the gray level image should be converted to binary image using *level = graythresh (g)* and *bw = im2bw (g, level);* then *L= bwlabel* (*bw, 8*); label each blob so we can make measurements of it; Matlab toolbox functions. Figure 4.5 shows the result of segmented Jimma coffee beans.

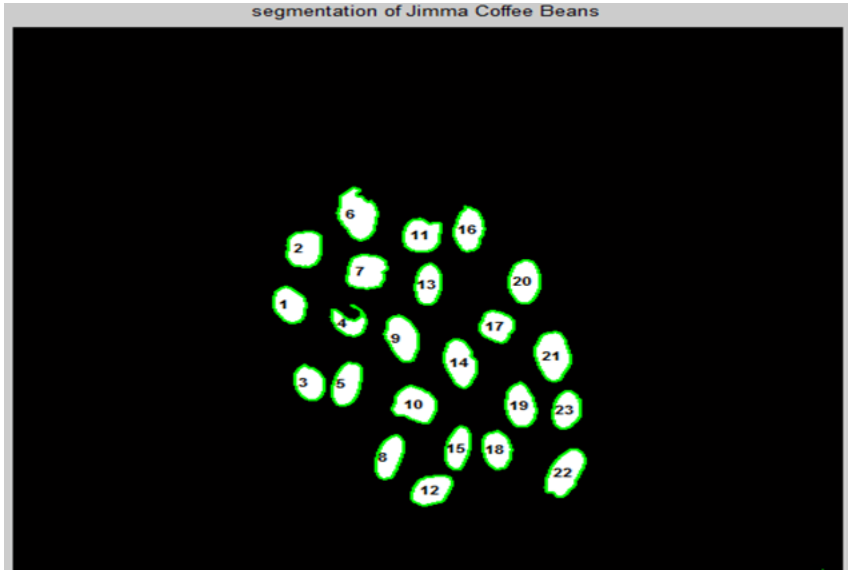

Figure 4.5. Segmented and labeled Jimma coffee beans

The objective of segmentation is to separate the object from the background so that important features for classification and object understanding can be calculated. The segmentation of coffee beans was successfully undertaken using a segmentation algorithm developed using steps listed under Appendix B.

4.3. Result of Color Features Extraction

The mean value, standard deviation and range of fifteen color components were extracted from each of RGB and HSI images, according to equations 2.3-2.9. These are mean of red, mean of green, mean of blue, mean of hue, mean of saturation, mean of intensity, Standard deviation of red, standard deviation of green, standard deviation of blue, standard deviation of hue, standard deviation of saturation, standard deviation of intensity, range of hue, range of saturation, and range of intensity) captured for colors feature extraction. Table 4.1 shows result for color feature extraction of Jimma coffee beans and algorithm was attached in Appendix C.

Table 4.1. Results for the color features extracted for the four coffee bean varieties.

A. Mean of RGB

	Limmu	Abba Buna	Yachi	Buno wash
Red	149.79	134.80	134.38	134.42
Green	153.07	156.70	157.02	156.78
Blue	162.15	192.20	193.04	191.98

B. Mean of HSI

	Limmu	Abba Buna	Yachi	Buno wash
Hue	0.55	0.61	0.60	0.59
Saturation	0.12	0.30	0.31	0.32
Intensity	0.64	0.75	0.76	0.67

C. Standard Deviation of RGB

	Limmu	Abba Buna	Yachi	Buno wash
Red	41.12	21.08	17.61	17.58
Green	44.70	24.73	20.51	19.25
Blue	49.74	30.38	25.14	22.30

D. Standard Deviation Of HSI

	Limmu	Abba Buna	Yachi	Buno wash
Hue	0.17	0.07	0.052	0.052
Saturation	0.06	0.05	0.048	0.040
Intensity	0.18	0.12	0.098	0.086

E. Range of HSI

	Limmu	Abba Buna	Yachi	Buno wash
Hue	0.98	0.98	0.98	0.98
Saturation	0.70	0.63	0.55	0.48

Intensity	0.80	0.71	0.68	0.64

The RGB values indicate the average colors of the coffee beans. According to Table 4.1, Limmu beans have the highest mean red and blue values but a lower green value compared to the other varieties. This suggests Limmu beans have a distinct color profile, potentially making them less distinguishable using mean RGB values alone. The mean HSI values provide a different perspective on the color characteristics:

- ✓ Hue: Limmu beans have a lower hue value (0.55) compared to the other varieties, indicating a slightly different color tint.
- ✓ Saturation: Limmu beans have significantly lower saturation (0.12), making them appear less vibrant.
- ✓ Intensity: Limmu beans also have lower intensity (0.64), indicating they are darker on average.

These differences in HSI values suggest that HSI might be a better indicator for distinguishing Limmu beans from the others. The standard deviation values show the variability in color. Limmu beans exhibit much higher standard deviation in all RGB channels, especially blue (49.74), indicating greater color variation within this variety. For HSI values:

- ✓ Hue: Limmu beans have the highest standard deviation (0.17), indicating more variation in hue.
- ✓ Saturation and Intensity: Limmu beans show higher variability compared to the others, particularly in intensity (0.18).

These high standard deviations might help in identifying Limmu beans based on their color variation. The range of HSI values shows the extent of color variations:

- ✓ All varieties have the same hue range (0.98), indicating a wide spread of color tones.
- ✓ Limmu beans have the highest saturation range (0.70) and intensity range (0.80), further supporting their higher color variability.

4.4. Result of Morphological Features Extraction

Morphological features were used to represent the shape, size, and boundary of objects of the images. They are eight in number, which are area, perimeter, major axis length, minor axis length, equivalent diameter, Surface roundness, thinness ratio and eccentricity. Table 4.2 shows the eight morphological features of the four objects (Limmu, Abba Buna, Yachi and Buno wash) samples of Jimma coffee beans were extracted based on equations 2.10 - 2.17. The MATLAB code Algorithm used to extract these listed features were attached in Appendix D.

Table 4.2. Result of morphological features extracted from four Jimma coffee beans

Parameters	Limmu	Abba buna	Yachi	Buno wash
A	8580	21177	14233	8444
P	127.8	299.0	200.9	120.6
L_{maj}	37.2	89.4	60.6	37.0
$L_{\min}$	36.1	89.2	60.1	36.6
d_{eq}	34.4	82.9	56.3	34.1
R_s	8984	22501	15002	9002
T_{rat}	0.97	0.99	0.96	0.95
E_{cc}	0.30	0.15	0.1	0.1

Where A: surface area, P: perimeter, L_{maj}: major axis length, $L_{\min}$: minor axis length, d_{eq}: equivalent diameter, R_s: Surface roundness, T_{rat}: thinness ratio and E_{cc}: eccentricity.

Based on Table 4.2, Abba Buna has the largest surface area (21177), followed by Yachi (14233), Limmu (8580), and Buno Wash (8444). This indicates that Abba Buna beans are significantly larger in surface area compared to the other varieties. The perimeter follows a similar trend as the surface area, with Abba Buna having the largest perimeter (299.0), followed by Yachi (200.9), Limmu (127.8), and Buno Wash (120.6). This suggests that Abba Buna beans are not only larger but also have a more extensive boundary. Abba Buna beans have the longest major (89.4) and minor (89.2) axis lengths, indicating an elongated shape. Yachi beans are the next in size (60.6 and 60.1), while Limmu and Buno Wash have similar, smaller axis lengths around 37.2 and 36.1, respectively. The equivalent diameter, which gives an idea of the average diameter of the beans, is highest for Abba Buna (82.9), followed by Yachi (56.3), Limmu (34.4), and Buno Wash (34.1).

Abba Buna beans also exhibit the highest surface roundness (22501), followed by Yachi (15002), Buno Wash (9002), and Limmu (8984). This suggests that Abba Buna and Yachi beans are rounder compared to Limmu and Buno Wash. The thinness ratio is highest for Abba Buna (0.99), indicating a nearly perfect circular shape. Limmu and Yachi have slightly lower values (0.97 and 0.96), while Buno Wash has the lowest (0.95). The eccentricity values show that Limmu beans have the highest eccentricity (0.30), indicating a more elongated shape. Abba Buna, Yachi, and Buno Wash all have lower and similar eccentricity values (0.15, 0.10, and 0.10), indicating they are more circular.

4.4. Feature Classification

Feature classification was done by using ANN of neural network particle recognition toolbox in MATLAB software. Inputs, which are 30 extracted features of color and morphological, and combination of color and morphological features their values, were found in Tables 4.1 and 4. 2, respectively, and outputs, which are the Target classes described in Table 4.3: by binary digit representation were, imported to MATLAB and were pre-specified before starting training or classification, but the weights (hidden and output neurons) in the network would be adjusted based on the classification accuracy.

The best classification point is at the point where mean squared and percent errors are, minimum or zero. Until this point was obtained, training continues by default values of both samples data training, testing and validations, and layers of neurons of hidden and outputs. The default values of samples data are 70%, 20%, and 10% for training, testing, and validations, respectively and the default values for network set-ups of hidden and output neurons of layers are 15 and 4, respectively. If the best classification result could not be, obtained on default values of data and network set-ups then it can be changed randomly until the best point is achieved.

4.4.1. Classification representations

To precede classification step objects were assigned in the binary number system. The following table shows the arrangement of classes for classification purposes in binary digit representation.

Table 4.3. Binary digit representation of four target classes for classification.

No	Sample name	Binary digit representation
1	Limmu	1000
2	Abba Buna	0100
3	Yachi	0010
4	Buno wash	0001

4.4.2. Classification result of color features

For classification of this work using color features; 15 are used as input and the four target classes or output for Limmu, Abba Buna, Yachi and Buno wash coffee beans in it. To adjust classification set-up using color features 15 inputs, 15 hidden layers and 4 output layers of a neuron of particle recognition toolbox of MATLAB software of version R2013a and 4 outputs were used as described in Figure 4.6.

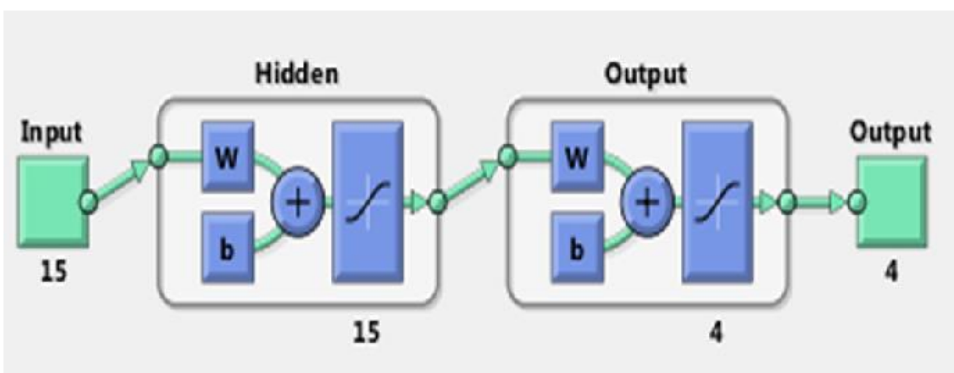

Figure 4.6. Neural Network training tool-using colors features

The confusion matrix expresses the correct classification and misclassification of the testing data set of coffee beans.

Table 4.4. Test Confusion matrix of classification using color feature.

	Limmu	Abba Buna	Yachi	Buno wash	**Total (%)**
Limmu	**29**	**0**	**0**	**0**	**100**
Abba Buna	**0**	**26**	**0**	**0**	**100**
Yachi	**0**	**0**	**0**	**0**	**0**
Buno wash	**0**	**0**	**33**	**32**	**49.2**
Total (%)	**100**	**100**	**0**	**100**	**72.5**

Table 4.4 shows that the number of samples correctly classified and misclassified. The diagonal elements of the matrix indicate the correctly classified and elements below or above the diagonal elements show misclassified. As shown in Table 4.4, the summary result of artificial neural network classifier using color features from the total test 120 samples, 72.5% (87 samples) of coffee beans were correctly classified and 26.5% (33 samples) were misclassified. This means 33 Yachi coffees beans are is misclassified to Buno wash coffee beans. The overall confusion matrix is shown in, Table 4.4 above indicates the accuracy of classification using color features as 76.8%, 72.5%, 66.7%, and 74.8% for training, testing, validation and overall (all confusion matrix), respectively.

4.4.2. Classification result of morphological features

In this section, we used a neural network with 8 input neurons, 15 hidden neurons, and 4 output neurons to classify coffee beans based on morphological features. The 4 output neurons correspond to the target classes: Limmu, Abba Buna, Yachi, and Buno Wash beans. The inputs to the network are morphological features including: Area, Perimeter, Major axis length, Minor axis length, Equivalent diameter, Extent, Roundness, and Eccentricity. Table 4.5 shows the confusion matrix, which indicates the correct classifications and misclassifications of the testing data based on morphological feature extractions.

Table 4.5. Confusion matrix of classification using morphological features.

	Limmu	Abba Buna	Yachi	Buno wash	**Total (%)**
Limmu	0	0	0	0	**0.0**
Abba Buna	0	28	0	0	**100**
Yachi	27	0	33	0	**55.0**
Buno wash	0	0	0	32	**100**
Total (%)	**0.0**	**100**	**100**	**100**	**77.5**

As shown in Table 4.5, the summary result of ANN classifier using morphological features, from the total test 120sample 77.5% (93 sample) were correctly classified and 12.5% (27 samples) were misclassified. This means 27 sample of Limmu coffee beans were misclassified to Yachi coffee beans. The overall confusion matrix shown in Appendix A, Table 2 indicates the accuracy of classification using morphological features are 73.8.8%, 77.5%, 78.3%, and 75.0% for training, testing, validation, and overall (all confusion matrix) respectively.

4.4.3. Classification result using a combination of color and morphology

This experimental setup used the combination of the two features (color and morphological). Here we used 23 numbers of neurons in the input layer and 4 number of neurons in the output layer that correspond to the expected output. The number of neurons in the hidden layer was 15 as shown in figure 4.7.

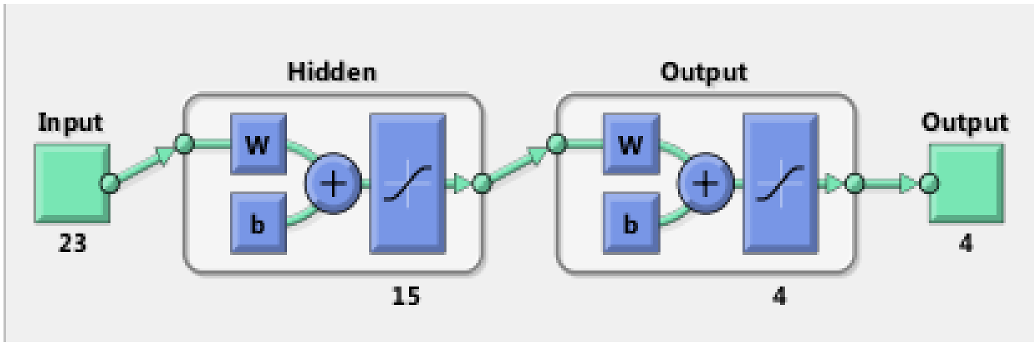

Figure 4.7. Neural Network number of neuron hidden Layer

Similar to the above two setups, out of the data set 70%, 20%, 10% were assigned for training, testing, and validation, respectively. Table 4.6 shows the confusion matrix that indicates the correct classification and misclassification of the dataset.

Table 4.6. Test confusion matrix of classification using combined features.

	Limmu	Abba Buna	Yachi	Buno wash	**Total (%)**
Limmu	29	0	0	0	**100**
Abba Buna	0	29	35	0	**45.5**
Yachi	0	0	0	0	**0.0**
Buno wash	0	0	0	27	**100**
Total (%)	**100**	**100**	**0.0**	**100**	**70.8**

As it seen in Table 4.6 test confusion matrix 29, 29, 0, and 27 instances were taken from Limmu, Abba Buna, Yachi, and Buno wash coffee beans, respectively. The summary result of ANN classifier-using combination of color, and morphological features from the total test 120, 70.8% (85 samples) coffee beans were correctly classified, and 29.2% (35 samples) were misclassified. 35 Yachi coffee beans were entirely misclassified as Abba Buna coffee beans.

The overall confusion matrix is shown in Appendix A, Table 3: indicates the accuracy of classification using a combination of color and morphological features are 75.0%, 70.8%, 81.7%, and 74.8% for training, testing, validation, and overall (all confusion matrix), respectively. It was found that the classification performance of the network was best in the case of classification using the combination of color and morphology. The analysis of neural network training performance of combination of color and morphological features classification at different classes of coffee beans is also as shown in Figure 4.8. The training generates the graph illustrated in Figure 4.8 which shows that the response of the network performance, where the error MSE decreases to obtain 25 epoch when the training was stopped for having reached a stop early avoiding the overtraining.

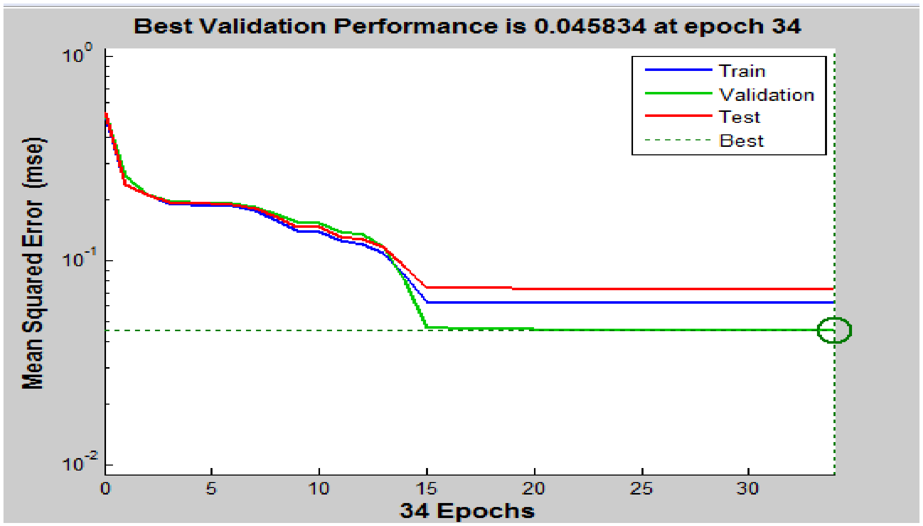

Figure 4.8. Performance result of color and morphological features.

Figure 4.8 indicates that the validations of performance increasing as the training epoch increase, the best validation was found at epoch 34 and its best validation performance was 0.045834 combination of color and morphological feature classification.

5. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1. Summary

This study focused on classifying Jimma coffee beans using their morphological and color features. Specifically, four varieties of Jimma coffee beans (Limmu, Abba Buna, Yachi, and Buno Wash) were objectively classified based on their botanical origin using image processing techniques. A total of 150 images were captured for each coffee variety, resulting in 600 images overall. These images were split into 70% (420 images) for training, 20% (120 images) for testing, and 10% (60 images) for validation.

The classification process utilized color and morphological descriptors to distinguish between the coffee varieties. Images were captured with a Galaxy A12 phone camera (48 MP, 720x1600 resolution) under controlled lighting conditions. These images underwent preprocessing (image enhancement and noise removal) using MATLAB tools. Subsequently, relevant color and morphological features were extracted, and classifications were performed using the image processing and pattern recognition toolbox in MATLAB. An artificial neural network (ANN) was employed for classification, achieving a 74.2% success rate.

5.2. Conclusion

The Jimma Zone in the Oromia Regional State is a major coffee-growing area, renowned for its diverse Arabica coffee. Despite favorable conditions and a long history of coffee production, ANN-based classification of Jimma coffee beans using morphological and color features has proven effective. The best classification results were obtained by combining color and morphological features. However, certain varieties (Abba Buna, Yachi, and Buno Wash) showed similar RGB values, making them hard to distinguish based on mean RGB alone. Limmu coffee beans, distinguished by their low blue and red values and high standard deviation in hue and intensity, stood out. The overall confusion matrix (Appendix A, Table 2) indicates classification accuracies of 73.8% for training, 77.5% for testing, 78.3% for validation, and 75.0% overall. Thus, implementing imaging applications in the industry is recommended.

5.3. Recommendations

Based on the findings of this study, several recommendations for further research and improvements are suggested. This research could inspire additional work in the field of image analysis for agricultural purposes. Future studies could explore:

- ✓ Classification of fruits using imaging systems and computer vision.
- ✓ Detection of cracks on fruits through image analysis.
- ✓ Enhancing coffee classification methods beyond traditional human inspection, which lacks scientific precision.

These avenues could expand the application of image technology in agriculture, improving the classification and quality control of various crops.

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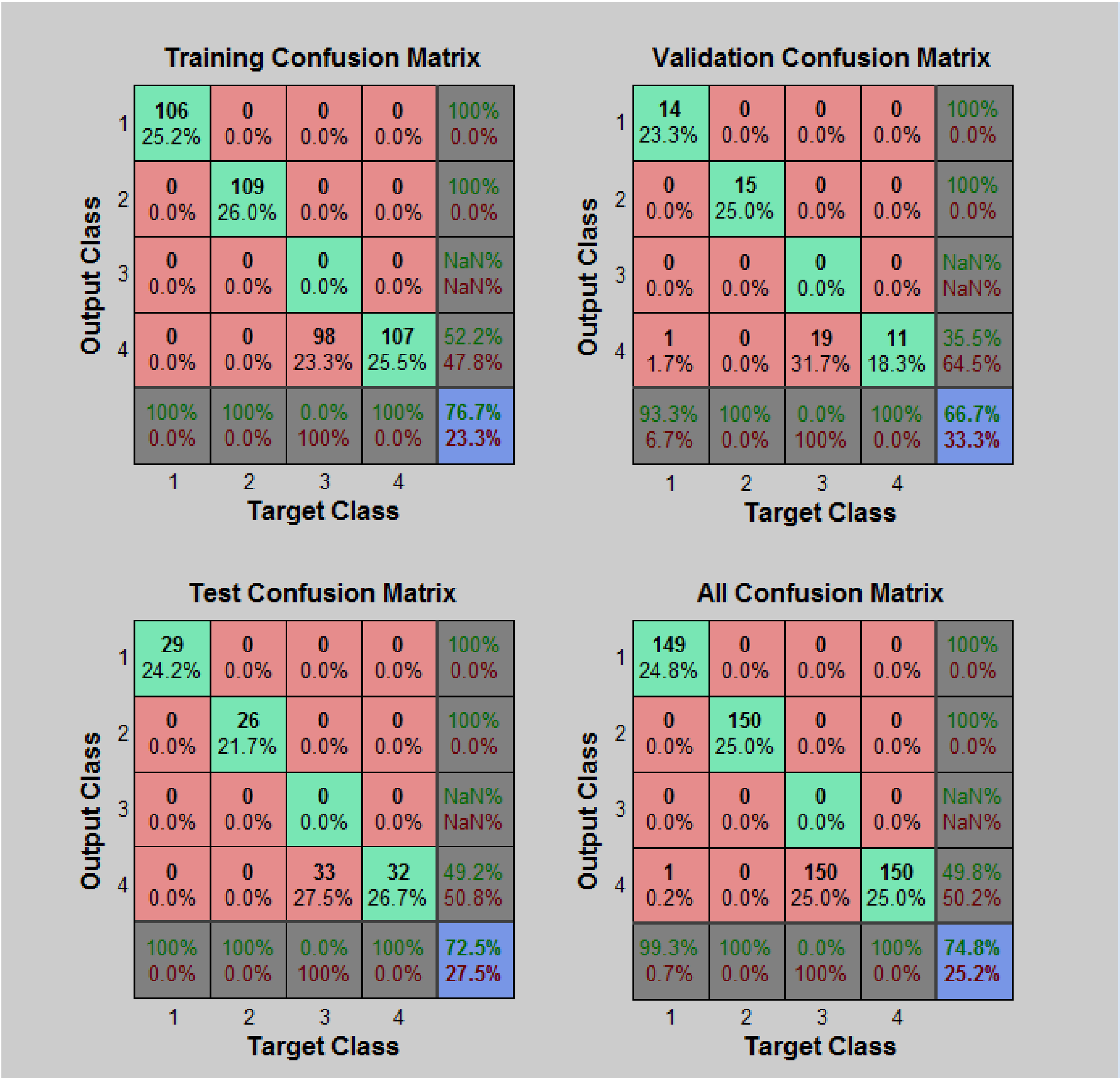
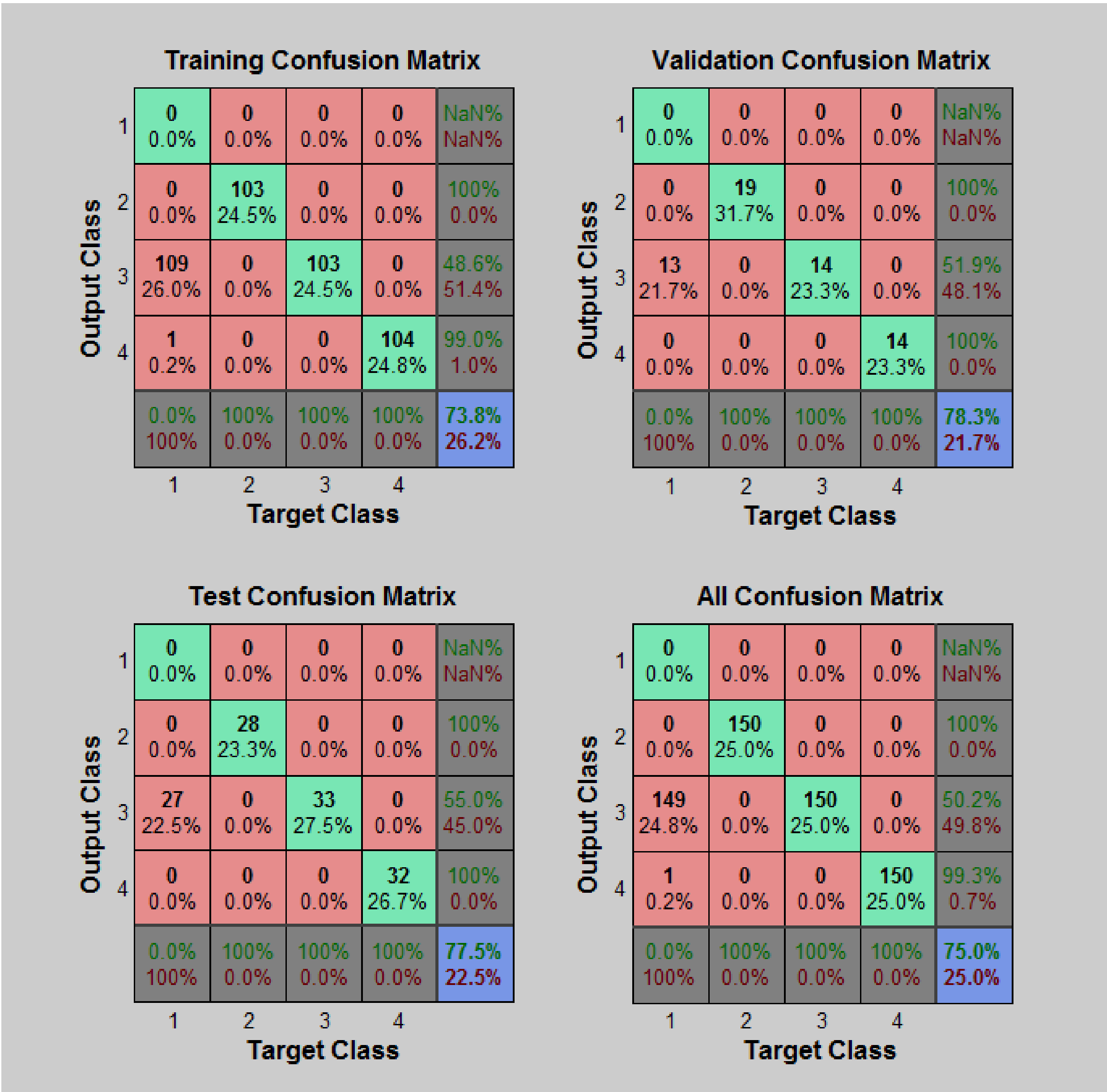
APPENDICES

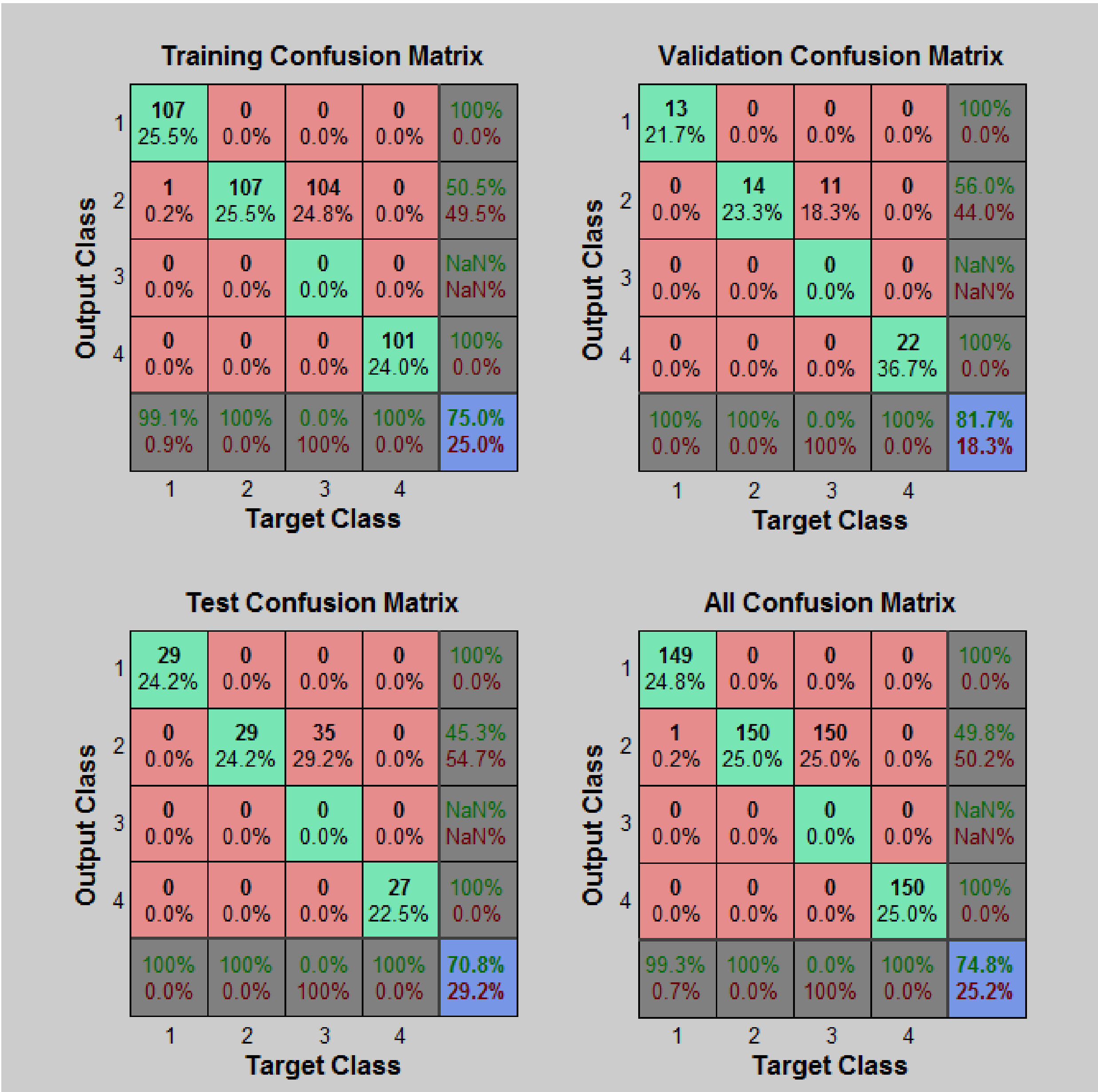
Appendix A: Table 1 confusion matrix of classification of color feature.



Appendix A: Table 2 confusion matrix of classification morphological feature.



Appendix A: Table 3 Confusion matrix of classification combination of color and morphological feature



APPENDIX B: LIST OF ALGORITHMS

Appendix B1: MATLAB code used for threshold based Image segmentation

```
clear all
close all
clc
X = imread('coffee_0071.JPG');%Read the image
A= imresize(X,[512 512]);
I=rgb2gray(A); %convert the rgb image to gray-level
g=imadjust(I,[],[],1);
figure,imshow(I), % displaying the gray level image
figure,imhist(I);% the histogram  of low contrast of intensity image
I2=histeq(I); %display yhe new equalized image
figure,imshow(I2);
figure,imhist(I2); %the histogram of high contrast of intensity image
originalImage=g;
% stretched the orginal image
rmin = min(X(:)); rmax = max(X(:));
r = 0:255;
s = zeros(size(r));
s(1:find(s==rmin)) = 0;
step = length(r(find(r==rmin):find(r==rmax)));
s(find(r==rmin):find(r==rmax)) = 0:255. /step:255-255. /step;
s(find(r==rmax)+1:end) = 255;
img2 = double(A); img2 = (img2 - min(img2(:))) ./ max(img2(:) - min(img2(:)));
I2 = rgb2gray(img2);%convert the stretched image to gray level image
a = imresize(I2,[512 512]);%%%%%%%%%%%%%%%%%%%%%%%%%
g3=imadjust(a,[],[],1);
stretcehedimage=g3;
level=graythresh(g3); %converting the image to binary using OTSU's
B=im2bw(g3,level);
figure,imshow(B); title('binary image'),
hold on;
BWc = ~ B; %complement of binary image
seD = strel('disk',1);
BWcdil = imdilate(BWc,seD);%dilate the complement binary image
% Do a "hole fill" to get rid of any background pixels inside the blobs
```

```
BWdfill = imfill(BWcdil,'holes');
boundaries = bwboundaries(BWdfill);
numberOfBoundaries = size(boundaries);
for k = 1 : numberOfBoundaries
thisBoundary = boundaries{k};
plot(thisBoundary(:,2), thisBoundary(:,1), 'g', 'LineWidth',2);
end
seD = strel('disk',1);
BWcero = imerode(BWdfill,seD);
BWfinalimage = BWcero;% final image
imshow(BWfinalimage); %Display resulting binary image
title('segmentation of Jimma Coffee Beans');% segmenting the image using water shed distance transform segmentation.
L = bwlabel(BWfinalimage, 8); % Label each blob so we can make measurements of it
s = regionprops(L, 'Centroid');
hold on;
boundaries = bwboundaries(BWfinalimage);
numberOfBoundaries = size(boundaries);
for k = 1 : numberOfBoundaries
thisBoundary = boundaries{k};
plot(thisBoundary(:,2), thisBoundary(:,1), 'g', 'LineWidth', 2);
end
fontSize = 8; % Used to control size of "coffee number" labels put atop the image.
labelShiftX = -7; % Used to align the labels in the centres of the coffee.
blobMeasurements = regionprops(L, stretcehedimage, 'all');
numberOfBlobs = size(blobMeasurements, 1);
blobECD = zeros(1, numberOfBlobs);
for k = 1 : numberOfBlobs% Loop through all blobs.
blobCentroid = blobMeasurements(k).Centroid; % Get centroid.
text(blobCentroid(1) + labelShiftX, blobCentroid(2), num2str(k), 'FontSize', fontSize,'FontWeight', 'Bold');
end
```

Appendix B2: Matlab code used to extract Color feature

```
clear all
close all
clc
A = imread('coffee_0100.jpg');%read the RGB image
```

```
RGB=imresize(A,[372 512]);%re-sized image because the image is too large to be displayed
R=RGB(:,:,1); % component of red from the image
G=RGB(:,:,2); %component of green from the image
B=RGB(:,:,3); %component of blue from the image
HSI = rgb2hsv (RGB);
H=HSI (:,:,1);
S=HSI (:,:, 2);
I=HSI (:,:,3);%\t
subplot(2,2,1), imshow(H), title('hue')
subplot(2,2,2), imshow(S), title('saturation')
subplot(2,2,3), imshow(I), title('Intensity')
subplot(2,2,4), imshow(RGB), title('RGB')
%Mean value of each channel
% display the RGB componentes
figure, subplot(2,4,1), imshow(RGB), title('Original Image');
subplot(2,4,2), imshow(RGB(:,:,1)), title('R component');
subplot(2,4,3), imshow(RGB(:,:,2)), title('G component');
subplot(2,4,4), imshow(RGB(:,:,3)), title('B component');
% segmenting the colour image by using requantization
for n=2;% number of colour levels during requantization
[I1,map2]=rgb2ind(RGB,n,'nodither');
figure,imshow(I1,map2)
figure,imshow(I1,hsv(2))
end
% converting the RGB color image to HSI color component
HSI = rgb2hsv(RGB);
H=HSI(:,:,1);% component of hue from the image
S=HSI(:,:,2);% component of saturation from the image
I=HSI(:,:,3);% component of intensity from the image
% display the HSV componentes
subplot(2,4,6), imshow(HSI(:,:,1)), title('Hue');
subplot(2,4,7), imshow(HSI(:,:,2)), title('Saturation');
subplot(2,4,8), imshow(HSI(:,:,3)), title('Intensity');
% Apply a smoothing filter to each components of RGB image and reconstruct the image
fn = fspecial('average');
RGB2r = imfilter(RGB(:,:,1), fn);
RGB2g = imfilter(RGB(:,:,2), fn);
```

```
RGB2b = imfilter(RGB(:,:,3), fn);
RGB2(:,:,1) = RGB2r;
RGB2(:,:,2) = RGB2g;
RGB2(:,:,3) = RGB2b;
figure, subplot(1,2,1), imshow(RGB), title('Original Image');
subplot(1,2,2), imshow(RGB2), title('Averaged Image');
% Filter all components of theHSVimage.
fn = fspecial('average');
HSI2h = imfilter(HSI(:,:,1), fn);
HSI2s = imfilter(HSI(:,:,2), fn);
HSI2i = imfilter(HSI(:,:,3), fn);
HSI2(:,:,1) = HSI2h;
HSI2(:,:,2) = HSI2s;
HSI2(:,:,3) = HSI2i;
figure, subplot(1,2,1), imshow(HSI), title('Original Image');
subplot(1,2,2), imshow(HSV2), title('Averaged Image');
figure, subplot(1,2,1), imshow(YIQ), title('Original Image');
subplot(1,2,2), imshow(YIQ2), title('Averaged Image');
% calculate the Mean value of each channel of each image
disp('color channel of coffee')
fprintf('mean value of \tRed \tGreen \tBlue \n');
fprintf(' \t%g \t%g \t%g \n', mean2(R), mean2(G) ,mean2(B));
% displies the mean value of R,G& B
fprintf('mean value of \thue \tsaturation \tintensity \n');
fprintf('\t%3.3g \t%3.3g \t%3.3g \n', mean2(H), mean2(S) ,mean2(I));
% displies the mean value of H,S& V
% standard divation of each channel std(u(:))
fprintf('standard divation of \tRed \tGreen \tBlue \n');
fprintf(' \t%g \t%g \t%g \n', std2(R), std2(G) ,std2(B));
% displies the standareddivation of R, G & B
fprintf('standard divation of \thue \tsaturation \tintensity \n');
fprintf(' \t%3.3g \t%3.3g \t%3.3g \n', std(H(:)), std(S(:)) ,std(I(:)));
% displies the standareddivation of H, S & I
% Range of each channel
fprintf('RANGE of \tHUE \tSATURATION \tINTENSITY \n');
fprintf('\t%3.3g \t%3.3g \t%3.3g \n', range (H(:)),range (S(:)),range (I(:)));
```

Appendix B3: Mat lab code used to extract Morphological feature

```
clear all
close all
clc
A=imread('coffee_0101.jpg');
I=imresize(A,[300 300]);% resizing the shape of the image
I2=rgb2gray(I);%converting the resized image to gray level
figure,imshow(I2) % displaying the gray level image
level=graythresh(I2);
g=im2bw(I2,level);
% segmenting the image using water shed distance transform segmentation.
gc= ~g; % compliment of the binary image
D=bwdist(gc); % distance transform of the image
M=watershed(-D); % watershed ridge lines of the negative of the distance transform.
W=M==0;
g2=g&~W; % the segmented image
% determain the number of grains of coffee in the image
[labeled,numobjects]=bwlabel(g,8);
% measure object properties in the image
disp('Jimma coffee beans')
fprintf(1,' \t A \t P \t Ma \tMi \tDi \tCoA \tEx \tEcc \n');
graindata=regionprops(labeled,'all');
% computestatical properties ofobjects in the image
A=mean([graindata.Area]);% area of the image
P=mean([graindata.Perimeter]);% perimeter of the image
Ma=mean([graindata.MajorAxisLength]);% major axis of the image
Mi=mean([graindata.MinorAxisLength]);% minor axis of the image
Ex=mean([graindata.Extent]); % extent of the image
CoA=mean([graindata.ConvexArea]); % convex area of the image
Di=mean([graindata.EquivDiameter]); % diameter of the image
Ecc=mean([graindata.Eccentricity]); % eccentricity of the image
% printing all statistical values
fprintf(1,'%d \t%8.1f\t%8.1f \t%8.1f \t%8.1f \t% 8.1f \n'...
    , A, P, Ma, Mi, Di, CoA, Ex, Ecc);
```

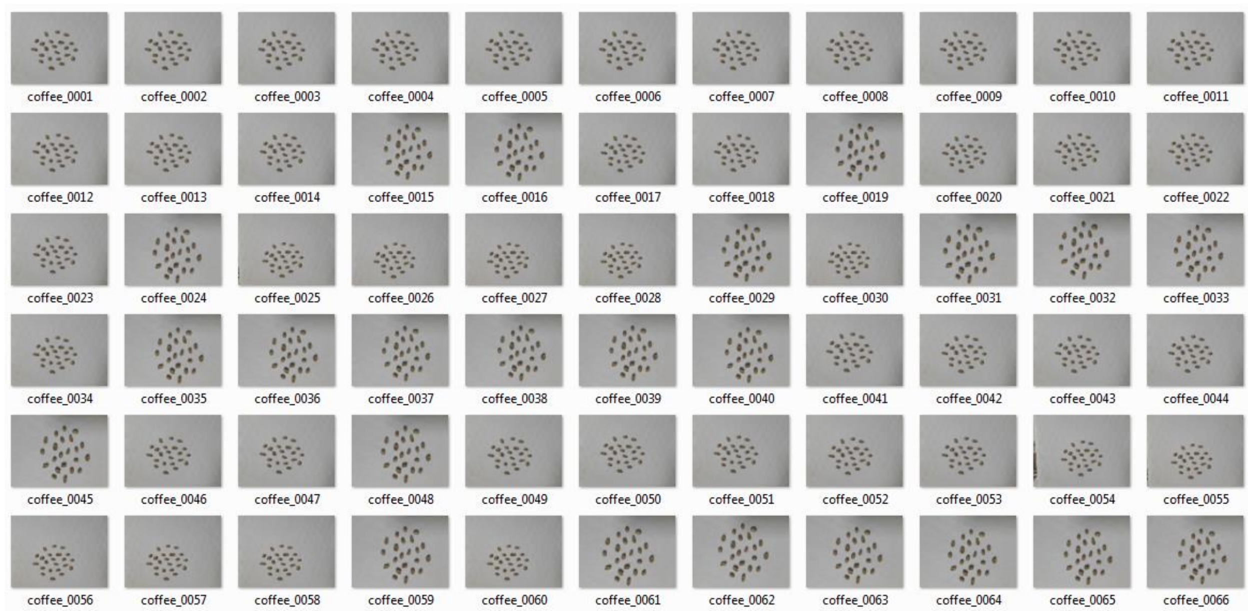
Appendix B4: MatLab code used for simulate the network

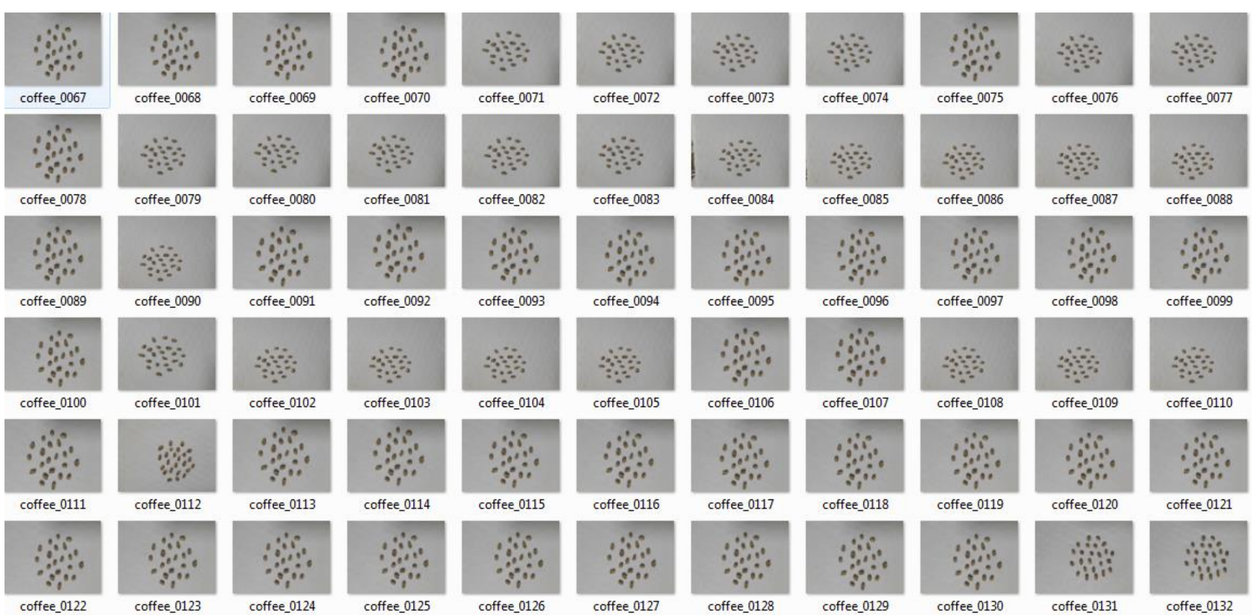
```
clear all
close all
clc

X=input;%the variable input
T=target;
set demorandstream(818339141)
net=patternnet(120);
%view(net)
[net,tr]=train(net,X,T);
nntraintool
plotperform(tr);
testX=X(:,tr.testind);%train the network
testT=T(:,tr.tesind);
testY=net(testX);
testindices=vec2ind(testY);
[C,Cm]=confusion(testT,testY);
fprintf('Percentage correct classification:%f%%\n',100*(1-C));
fprintf('percentage incorrect classification:%f%%\n',100*C);
plotroc(testT,testY);
display  End of Demo message(m file name);
size(X);
size(T);
```

APPENDIX C: LIST OF SAMPLE IMAGE

Appendix C1: Sample of different classes of coffee beans image on white background






coffee_0133
coffee_0134
coffee_0135
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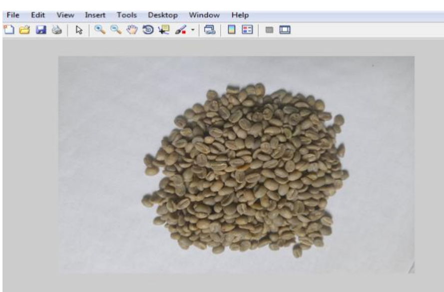
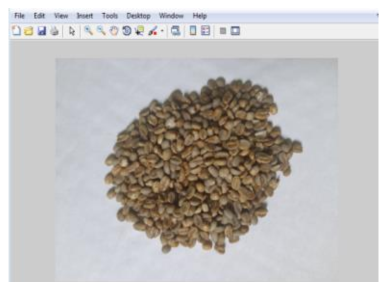
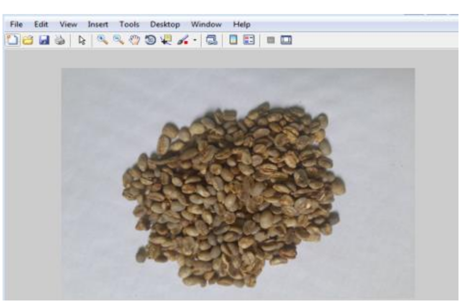


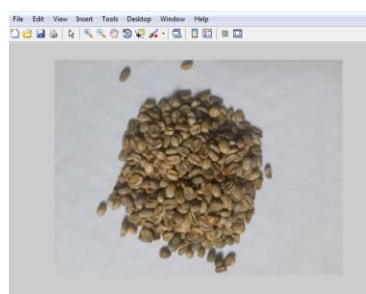
A. Sample of Limmu coffee beans



B. Sample of Abba Buna coffee beans



C. Sample of Yachi coffee beans



D. Sample of Buno wash coffee beans