JIMMA UNIVERSITY

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

INFORMATION SCIENCE PROGRAM

MASTERS PROGRAM IN INFORMATION SCIENCE (IKM)

SCALING ETHIOPIAN COFFEE RAW QUALITY USING IMAGE PROCESSING TECHNIQUES

BY: MUKTAR BEDASO

OCTOBER, 2019

JIMMA, ETHIOPIA

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FACULTY OF COMPUTING AND INFORMATICS

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A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR DEGREE OF MASTERS OF SCIENCE (MSc) IN INFORMATION SCIENCE (IKM)

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As members of the Board of examining of the MSc. research defense examination of the above title, we members of the board (listed below), read and evaluated the thesis and examination.

Name	Title	signature	Date
________________________	Chair Person	_____________	_________
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Declaration

I declare that this thesis is my original work and it has not been presented for a degree in any other Universities. All the material sources used in this work are scientifically acknowledged.

Mukthar Bedaso

October, 2019

This thesis has been submitted to the department of Information Science for examination with our approval as University Advisors:

Principal Advisor: Dr. Million Meshesha (PhD)………sign…………Date……………

Co-Advisor: ChalaDiriba (Assistant Professor)……sign………..Date ………………

DEDICATION

- *This work has been dedicated to my HERO MOTHER (Shamsia Bosone) and all MOTHERS over the world. "MOTHERS deserve more. Your mother is my mother and my mother is yours!! Let us respect and stand behind our mothers. It is painful to see mothers suffering for our lack of respect and support for them."*
- *To my Father, all of my Brothers and Sisters for their contribution on my academic success.*

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List of Acronyms and Abbreviations

ANN	Artificial Neural Network
BB	Boundary to Boundary
CB	Center to Boundary
DN	Digital Numbers
ECX	Ethiopian Commodity Exchange
FFT	Fast Fourier Transform
GA	Genetic Algorithm
GDP	Growth Domestic Product
HSB	Hue Saturation Brightness
ICO	Initial Coin Offering
KNN	K-Nearest Neighbor
LCD	Liquid Crystal Display
MLP	Multiple layer preceptors
RERB	Research and Ethical Review Board
RGB	Red Green Blue
SRM	Structural risk Minimization
SVM	Support Vector Machine

Abstract

Coffee is a beverage obtained from cherry, the fruit of coffee plant. Scaling or grading serve as a process for controlling the quality of an agricultural commodity so that buyer and seller can do business without personally examining every lot sold. This study attempts to apply digital image processing techniques towards sample coffee raw quality value scaling[1]. More specifically, this study focuses in the extraction and selection of the decisive coffee bean features that are useful for the purpose of classification of the raw quality sample coffee beans by designing, analyzing and testing an automated image processing model.

The research design employed in this study is experimental research which involves dataset preparation, designing classification model and evaluation. To facilitate experimentation image processing steps are followed, including image acquisition, image preprocessing (image filtering and attribute selection), image analysis (segmentation, feature extraction and classification), and image understanding for raw quality image scaling. ImageJ tool and Matlab programming language were used.

Techniques and algorithms were used in this study. For image preprocessing, methods like Gaussian filter to remove noise, contrast enhancement method to enhance the quality of coffee bean image, Normalization and Binarization by thresholding 8 bit images algorithm to separate image into region in image segmentation process were used. A total of 145 image datasets and 10,000 coffee beans were used from different grade of coffee fromECX Jimma center. Comparison of classification approaches of Artificial Neural Network, support vector machine and K-Nearest neighbor classifiers on each classification parameters of morphology, color and the combination of the two has been made. For the purpose of computing the grading accuracy of datasets, 80% were used for training and the remaining 20% for testing.

Experimental result shows that Artificial Neural Network classifier yielded the highest performance of 89.45%accuracy as compared to support vector machine (with 83.75%) and K-

[1]*The terms Scaling, grading and ranking has been used in this study interchangeably.*

Nearest neighbor classifier (with 77.85%).The major challenges during conducting this study are keeping the best quality control environment when acquiring images, extracting best features of HSB color feature and the homogeneity of coffee bean color features. Hence, appropriate selection of image processing and classification modules paves the way for higher accuracy in the higher level process for decision making.

Keywords: *Ethiopian coffee, Image Analysis, Classification, Artificial Neural Networks, Support Vector Machine, K-Nearest Neighbor, Scaling Coffee Raw Quality*

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Coffee is a beverage obtained from cherry, which is the fruit of coffee plant [1]. Coffee is an edible commodity. It is widely used as a beverage but nowadays it is also used as input in some food processing industries. Coffee can be used as a flavoring to various pastries, ice-creams, chocolate, etc. The coffee plant refers to several species of the genus coffee of the madder family, which is actually a tropical evergreen shrub [1]. There are different types of coffee in the world. Among different types of coffee, the major economic species are coffee Arabica and coffee Robusta [2]. Coffee Arabica accounts for 80% of the world coffee trade, and coffee Robusta accounts the remaining 19.5%. Coffee ***Liberica***and***Excelsa*** together supply less than 1% [2].From various coffee types, Ethiopia produces only coffee Arabica, which was originated in the country [2]. Coffee Arabica is a wild crop that grows in the forests of south-western parts of the country, which contain an important source of genetic resources for the world coffee industry [1].

Coffee is an indigenous plant to Ethiopia and also the major export commodity of the country which is contributing a great role in the country`s income and taking the lion's-share of the Growth Domestic Product (GDP) of the country [2]. According to the data collected in 2007 by Asfaw [5], coffee exports were generating about more than two-thirds of the foreign exchange earnings of the Ethiopian economy. Coffee is believed to be the major cash crop of the country and is frequently claimed to provide a livelihood for about 25 percent of the country's population [2]. From the total yearly, production of around 250,000 tons of coffee, about half is consumed in the country [3]. Ethiopia is not only the icon of coffee, but also coffee is cultural beverage 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 [4].

Ethiopian coffee is globally recognized with excellent quality and flavor. Nowadays Ethiopia stands the biggest coffee producer and exporter country in Africa and amongst the leading in the world [5]. Ethiopia is the oldest exporter of coffee in the world ranking sixth largest coffee producer after Brazil, Colombia, Vietnam, Indonesia and India, and the seventh largest exporter worldwide, in 2005, when exports were recorded to amount 2.43 million bags, comprising 2.82% of world trade in coffee beans according to (Initial Coin Offering) ICO statistical database [6]. From different world`s countries, the Ethiopian exports dominantly reach Japan, Germany and Saudi Arabia [1]. In World`s coffee market, Ethiopian`s coffee shows seasonal intra-annual variability in the price of coffee. There are different reasons for the fluctuations. Those are domestic supply, the periodic trends of the global coffee demand and supply and the variations between different varieties and grades of coffee [2].

According to the agreements reached between coffee importer and exporter countries[7], the production of Coffee for international market should pass through several processes in order to be strong competitive at the world market. For this reason, Ethiopian government has given serious evaluation and monitoring guidelines to keep the coffee quality characteristics to satisfy customers' preferences. Accordingly, every arrival of coffee produced has to go through the monitoring of Ethiopian Commodity Exchange (ECX) to certify that the supplied coffee has met the minimum requirement of national standard for domestic and international markets. ECX offers an integrated warehouse system from the receipt of coffee on the basis of industry accepted grades and standards for each traded coffee by type to the ultimate delivery. Arrival coffee is deposited in warehouses operated by ECX in major surplus regions of the country [8]. Coffee is ranked for export with the objective of producing the best quality and there by securing the best price possible.

The process of classifying coffee and controlling quality are very useful activities in encouraging, and enforcing good quality coffee production or provision. Such activities will also help in securing and ensuring dependable and competent exporters. Scaling serve as a process for controlling the quality of an agricultural commodity so that buyer and seller can do business without personally examining every lot sold. The term coffee scaling shows varied and obscure set of terms at the various coffee growing countries, and few are distinguished by logical clarity [9].

Figure 1.1: Raw quality coffee scaling process (image taken during data collection, Jimma ECX center laboratory experts)

In Ethiopia, coffee scaling is conducted through the combination of two methods. The scaling is done on the basis of points assigned to the sample for its Raw Quality (see figure 1.1) or green analysis which accounts 40% of total evaluation that is measured using physical appearance of the coffee beans and Liquor Value (see figure 1.2)which accounts for 60% [2].

Figure 1.2: Cup test coffee scaling process (image taken during data collection, Jimma ECX center laboratory)

The scaling system conducted by ECX is done by taking manually representative samples of 3kg coffee beans per each arriving truck from suppliers and 300g from each sample is used for raw quality evaluation analysis [2]. The rest 2700gm will be classified for roasting, reference and for clients' display. The classified samples from each truck will be tagged uniformly for future identification and processing. Coffee arrived at the center should fulfill the prerequisite to be marketable and standardized**.** Before the scaling process starts the moisture level of each coffee sample is evaluated which should not exceed the preset maximum moisture level is set to 11.5%. In addition, the coffee beans screen size should not be less than the standard Ethiopian coffee screen size, 14 units. If the sample coffee beans do not meet the above two conditions, the coffee will not be scaled, rather it will be rejected [8].

According to ECX standardization [2], a minimum of three experts should participate in the scaling activity for both the raw quality and liquor value scaling decisions. Each of experts work independently on the same sample coffee beans and finally put their results together for final evaluation of their points for each attribute. If there is a difference on one of the points, they will convince one another and elaborate their reason to let their respective points come up to uniform final decision. The final grade of coffee will be given by an overall agreement of all the experts. There is also one supervisor who responsibly follows the experts grading task [2].

Most of the time, manual scaling process is poor in producing reliable and consistent result. There is no training at higher educational institution or school level in the country for producing experts in grading of coffee and other agricultural products. Most of the time plant science professionals and traditionally coffee growers were preferred and selected for this scaling and grading process. Such demands of the experts are fulfilled by providing on the job training at the center which could extend from three months to three years, by experienced experts of the center. Few experts and a number of technical assistants participate in the classification, sorting, grading and evaluation of the coffee bean samples at the ECX. This number of staff for such a big task is insufficient, in particular at the time when the centre is decentralizing these practices of grading and classification to various regions of the country [8].

This automating of coffee raw quality scaling and grading activity is done by applying image processing techniques. Image processing is a set of technologies, in which an image data analysis and processing algorithms as well as tools are applied to improve the interpretation of data image that can yield information more useful for determining values and providing decisions [8]. Image processing allows the extraction of useful information from different parameters, and increases the likelihood of determining the scaling of different products based on their quality more accurately. Image processing is a rapidly growing area of computer science. Its growth has been fueled by technological advances in digital imaging, computer processors, and mass storage devices. Fields which traditionally used analog imaging are now switching to digital systems, for their flexibility and affordability [10]. Digital image processing has an expanding area with applications in our daily life. Many image processing and analysis techniques have been developed to aid the interpretation of data images and to extract as much information as possible from the image that can help us in making decision on the quality of agricultural products [10]. Image processing uses various techniques such as image acquisition, preprocessing, segmentation, feature extraction and classification to improve the quality of images and assists in understanding and interpreting detail of agricultural product images. Different scholars used various image processing techniques and focus on specific one for improving the determination of scale of agricultural products [10].

Image Classification is an important task in various fields such as biometry, remote sensing, medical images and scaling of agricultural products [11]. In a typical classification system, image is captured by a camera and consequently processed. In Supervised classification, first of all training took place through labeled image data set. The trained classifier model is used to classify new images. The Unsupervised classification uses the properties of the images to group them by similarity measures and these groups are known as cluster and the process is called clustering [11]. The cluster size is decided by experts in the area. When labeled training data set is not available the unsupervised classification is used for labeling them. Popular classification algorithms include Bayesian, Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Conventional Neural Network (CNN) and Support Vector Machine (SVM) [12].

Computer vision is the science that develops the theoretical and algorithmic basis by which useful information can be automatically extracted and analyzed from an observed image using computation made by computers [12]. The application of the computer vision to carry out task for quality inspection, sorting, and automatic processes in agricultural industry is increasing due to advantages such as economy, accuracy, and objectivity in term of their ability to provide numerical data with features such as size, shape, color, and texture [12]. However, these features are not represented by a unique mathematical function for many agricultural products. The natural variability of these products makes the task of identification and classification extremely challenging and computationally intensive because of the need to have a large number of classification features [13]. The implementation of artificial neural network as automation decision algorithm in computer vision has evident advantage in classification process. The development of computer vision in classification of agriculture products by using artificial neural network could be found in several researches [13]. The aim of this study is to design a prototype for scaling raw quality coffee bean using digital image processing techniques.

1.2 Motivation of the study

The origin of image processing can be traced back to the 1960s [14]. Since then it has experienced a number of advancements both in theory and application. It was applied in areas such as medical diagnosis, industrial automation, aerial surveillance or biometrics, remote sensing or satellite observation of Earth and in the automated sorting and grading of different agricultural products. Nowadays, efforts are required towards the support of human labor with artificially intelligent systems; because manual human inspection operations are inconsistent, costly and less efficient at various aspects of human tasks in different geographical area [8]. Automated intelligent system allows the accomplishment of an action aiming to control a process at optimum efficiency as controlled by a system that operates using sets of commands that have been programmed into it or response to some activities [15]**.**

Advancements in computer technologies have produced motivation in image analysis during the last decade (2000s) and the advantages behind this technique for the assistance or control of agricultural and food industrial processes have been recognized by different scholars [8]. A number of studies have been conducted in recent years to explore the application of computer vision technology like image processing, to provide scaling and grading of agricultural products, especially in fruit. Human labor requiring manual processes that are less accurate, less efficient and effective are becoming the main reasons for growing need of automated systems in the control of the agricultural products in the developing countries [16]**.**

The implementation of imaging technology in the sector have a numerous significance to moderate commercial activities by increasing efficiency, to sustain dependability of customer preferences and to promote the global market.

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.

In recent decades, image processing has become an inevitable area in agricultural sector as it acts as an expert system with decision support system [17]. Input image taken in real time is processed and transformed into useful information as an output to support farmers. In short, the main purpose of image processing is to enhance the image quality for human perception and to analyze the image for autonomous machine perception [17]. Major modules in image processing are classified as image acquisition, image preprocessing, image segmentation, feature extraction and classification. There are challenges in each of these modules. There are many computational challenges in image processing. These include issues such as the handling of image uncertainties including various sorts of information that is incomplete, noisy, imprecise, fragmentary, not fully reliable, vague, contradictory, deficient, and overloading. Extracting necessary information from region of interest after segmenting foreground from background on image require some technical skill which are challenges in today`s imaging technology [17].

1.3 Statement of the problem

Coffee is more than commodity for Ethiopians. It is a strong weapon for strengthen their social interaction and living togetherness behind taking lion`s share of Ethiopian economy [5]. Even though, coffee is contributing a great role in Ethiopia`s Growth Domestic Product (GDP), quality ranking of this product is not supported by technology rather it is performed using traditional and manual procedures. In Ethiopia, Coffee ranking based on quality is performed through the integration of two methods. The scaling is done on the basis of points assigned to the sample for its Raw Quality or green analysis and Liquor Value or cup test [18]. Raw quality or green analysis is computed out of forty percent (40%) which is measured using physical appearance of the coffee beans and Liquor Value is computed out of sixty percent (60%) which is cup test. Raw Quality assesses parameters of shape and make out of fifteen percent (15%), Color out of fifteen percent (15%) and odor out of ten percent (10%). Liquor Value assesses Cup Cleanness which is out of fifteen percent (15%), Acidity out of fifteen percent (15%), and Body (15%) and Flavor/ Character (15%). The added results of these parameters will determine the scale of coffee which is controlled by coffee and tea quality control and liquoring center of Ethiopian Commodity Exchange (ECX) [8]. This method uses visual and manual methods of inspection of the major properties used, such as appearance, shape, texture, size, color and odor of coffee beans. Manual and traditional methods of human inspection play a great role in exposing the ranking assessment to inconsistent results and subjectivism. This activity is also time-consuming, very expensive, less efficient and less effective which generate less descriptive reason and biased information for quality control and other innovative improvement activities from time to time and from individual to individual[5].

Coffee is classified in to different class in-order to get uniform end product [5]. The uniformity in coffee bean size is important because it is difficult to roast large beans together with very small beans or broken beans. This is due to the fact that, the smaller beans over roast or completely burn before the larger beans are roasted. Therefore, classification and scaling of coffee is a global market requirement. 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. For these reasons, it is critical to adopt faster systems which saves time and is more accurate in scaling of coffee by reducing observer effects of biases determining the quality standard that enhances the commercial needs which done by applying computer vision system[9].

Meftah and Rashid [9] concluded that, lack of a specialized field of study and qualification at country level for classifying and controlling quality of agricultural product plays a role in affecting the reliability, efficiency and consistency of the scaling practice even in manual inspection methods. The cost required to fulfill this gap at various scales of trainings to generate capable experts is also significant. This is a serious problem when observed from the perspective of extending and decentralizing the scaling activities to many other areas of the country by human labor. For this reason, supporting of the human inspection methods with the consistent result, nondestructive, superior speed, precise and cost effective computerized system of coffee quality scaling and grading is necessary for such agricultural products which is generating a huge amount of income to the country [19]**.**

The machine vision scaling and grading system reduces possible and potential human error and bias in the process. Even the application of this computer vision inspection technique can be applied in many and diverse areas like food industries and other agricultural sector to help the inspection and grading of various fruits and vegetables in a non-subjective way. System`s speed and accuracy able to meet the ever-increasing production and quality requirements, and promoting the development and expansion of totally automated processes.

Some attempts have been done in order to reduce the gap observed above by different local and foreign scholars. But, still the observed problem is not fully answered. The research work of Asma Redi [17] investigated classification of Ethiopian coffee using image processing techniques from Wollega region. The study raised a number of issues related to determining the classes of coffee bean based on the information extracted by using image processing techniques. However, the main focus of the study was on segmentation and feature extraction of coffee beans like width of beans, length of beans, and circularity. This shows that, there is a gap in representing the features of coffee beans in Asma's study. This study is, however concentrate on feature extraction of coffee beans and design an effective classification model that can determine the scale of coffee raw quality with better performance.

Therefore, this study focuses on designing an effective Ethiopian raw quality scaling model using digital image processing technique which is consistent, efficient and cost effective by using image processing technology.

To this end, this study attempts to investigate and answer the following research questions.

- What are the optimal features of physical characteristics of coffee bean?
- What are the suitable classification algorithms to use for scaling coffee raw quality?
- To what extent the prototype model determines the scale of Ethiopian coffee bean?

1.4 Objective of the study

1.4.1 General objective

The general objective of this study is to design an effective Ethiopian raw quality scaling model using digital image processing technique.

1.4.2 Specific objectives

To achieve the general objective of thisstudy, the following specific objectives are formulated:

- To identify the determinant parameters of physical characteristics of coffee bean which can used to scale coffee bean.
- To apply image filtering, image resolution, noise reduction, normalization and Binarization techniques on images to improve quality of coffee bean images.
- To extract coffee bean features which help us to scale them.
- To identify suitable classification algorithms to use for scaling coffee raw quality.
- To develop a model for scaling and determining the raw quality value of sample coffee, using results gained by the analysis of digital coffee bean images.
- To conduct user acceptance and measure performance of the developed grading models

1.5 Scope and limitation of the study

The tedious and time-consuming human operator visualization activity for scaling and determining the quality of this high value product is very expensive, less efficient and less effective which generate less descriptive reason and biased information for quality control and other innovative improvement activities. Although some studies have been done around coffee classification based on geographical area coverage and classification of coffee raw quality, there is a gap in emphasizing on decisive feature extraction of coffee beans.

This study is mainly focused on washed coffee bean produced in the production year 2018/19, from Jimma Zone only. Grades 1-4were under consideration for the purpose of the research as the only samples during the data collection phase, where samples ranging from 1 to 3 are available for gathering from each grade, summing up to 12 coffee bean samples, each weighing 300gms. It is on the basis of this dataset that the physical property of Ethiopian coffee bean has been studied for modeling different scale level and raw quality value computation systems using computer vision systems. The main reason for selecting Jimma Coffee is due the historically existence and emergence of Arabica coffee in the Zone and other factors that can help the researcher by being here.

The prototype limit the modeling tasks to utilize only the raw quality value of the coffee grading system rather than using liquor quality which is Cup test value evaluation techniques. Image preprocessing, image filtering, image resolution, image segmentation and image feature extraction has been employed under this research study. Feature extraction technique was the core approach area focused on under this study based on different expert`s recommendation.

There are some limitations and constraints the researcher had faced during conducting this study. Some of the constraints are lack of enough reference resources especially on Matlab tool and classifiers; there was skill gap, and other time dependent challenges. This constraints influence the research to complete this study with some limit. Lack of skill on Conventional neural network classifier (CNN) was the first study limitation that should be future work for others because CNN is considered as best classification algorithms for homogenous data like coffee bean images.

1.6 Significance of the study

The beneficiaries of this study are Farmers, agricultural experts, coffee exporters and researchers. Farmers are beneficiaries by taking input from the result obtained that can be used for further decision making on how to improve quality production of coffee. Also, if their product is ranked well without bias, they can be productive and encouraged to produce high quality coffee. Agricultural experts are facing challenge during classification and determination of quality scale of coffee beans. They are employing human inspection technique for determining the scale of raw quality coffee. However, there are a number of spectroscopic techniques which can be used for classification, scaling, and inspection of agricultural products. An imaging process is preferable to classify, rank, and inspect agricultural products. In this research, an imaging technique is employed to classify Ethiopian raw quality coffee beans. This model has many advantages over the traditional ones due to its effectiveness, objectivity, and efficiency for agricultural experts. Developing an automated computer vision system play a great role in establishing the technological and innovative approaches towards sample coffee bean raw quality value grading by extracting the relevant coffee bean features.

Coffee exporters are the beneficiaries of this research, because the model developed could help them in selecting quality coffee from the center. Nowadays in our country, Ethiopia, coffee is the first and backbone of foreign income. But exporters are facing challenge in providing quality coffee that can make them competitive exporters before world`s trade market because of lack of intelligent inspection method of scaling raw quality coffee. This research can play a great role in reducing the problem occurred during human inspection scaling system. This machine vision system, have addressed the identified gaps of the subjective and inefficient manual scaling mechanisms of one of the most important agricultural products in Ethiopia, coffee. Beyond the above described benefits, the output of this research can be an input for other further studies to be done locally as well as globally, as per the recommendation made in this study.

1.7Methodology of the study

Methodology is the procedural sequences of conducting a study [20]. There is a step by step procedure in conducting this study. Methodological procedures are followed in order to make the research scientific, reproducible and unbiased, in order to conduct studies objectively, to have a standard artistic work as well as to have a research report that fit the standard [20].The current study focuses on coffee produced in Oromia regional state, Jimma zone, which is 345 km far from Addis Ababa south-west of Ethiopia.

1.7.1 Research design

This study follows experimental research design. According to Goodwin [20], experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand causal process. In conducting experimental research design there are three major procedures followed, such as dataset preparation, model building/implementation, and prototype development and testing. To facilitate experimental research in the image domain, we applied image processing steps, such as image acquisition, image preprocessing, segmentation, feature extraction, classification and evaluation.

1.7.2 Data source and sampling technique

A sample of coffee beans for this research has been obtained from Ethiopian Commodity Exchange (ECX), Jimma branch. These samples used are certified coffee beans by domain experts of the center at international level.

The target populations of this study are domain experts of ECX (Ethiopian commodity Exchange) at Jimma branch specifically professionals on coffee and tea quality control and liquoring center team. Document analysis and interview were conducted to acquire additional knowledge. The domain experts are individuals who are performing visual inspection of grading coffee.

In this study purposive sampling technique was used to select domain experts for the purpose of acquiring knowledge and to collect dataset of previous coffee bean images. The selection criterion of domain experts for the study was based on the professions, educational qualification, years of experience on grading practice. A total of 5 domain experts are purposively selected for interview from ECX Coffee grading team, Jimma branch. For this study a total sample of 145 images and 10,000 datasets of scaled coffee bean were used.

A sample amount of washed coffee bean has been taken from the various grade levels of coffee from Jimma Zone, as scaled by the centre. In addition, samples from washed coffee were the only available resources for the purpose of the research. Necessary attributes and statistical data regarding the various samples were recorded from the tagged coffee bean packages in to the system`s database, processed by the ECX experts during the manual grading activities.

Grades 1 to5 of the Jimma coffee were there and for the purpose of this research samples ranging from grade 1 to 4 are available for gathering from the center, summing up to 1250 coffee bean sample coffee beans in one sample, each weighing 300gms. Clarity and visibility of each coffee bean and sound spacing between each coffee bean is an important task to be considered while taking the images for further processing and analysis purposes. This enforces re-sampling of each of the 1250 samples into 29 sub-samples. A total of 145 image datasets and 10,000 coffee beans were used from different grade of coffee (2150 of Grade I, 2655 of Grade II, 3043 of Grade III and 2152 of Grade IV) from ECX Jimma center. All the sampled coffee beans of the region were harvested during the 2018/2019 production year.

1.7.3 Dataset preparation

The procedures followed during dataset preparation in this study were discussed below.

1.7.3.1 Image acquisition

The data acquisition technique in this research is crucial concern to generate clear, unbiased and simplified digital coffee bean sample database for further analysis and processing. Images of coffee bean were taken in to the system by capturing image by using external CANON camera. The images captured using a digital camera are transferred into a computer, displayed on a screen and stored on the hard disk in PNG format as digital color images.

Image analysis starts with image acquisition which involves all aspects that have to be addressed in order to obtain images of the objects of interest. The selection of radiation sources and sensors such as cameras has to be considered very carefully. The geometry of the viewing situation, 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 [5].

For this study, images are taken from one major coffee export producing region of Ethiopia which is Oromia. This region is the most widely planted and popular coffee brands of the country then Jimma Zone is selected from this region for this research.

The samples were obtained from Ethiopia Commodity Exchange, Jimma branch. The classes of the sampled coffee beans were certified by the domain experts in the center`s laboratory. All sampled coffee beans are the products of 2018/19 production year.

When acquiring images from the environment, experts can use different resolution pixels. Images can be acquired at 1200 x 1200, 1456 x 1544, 696x514 and others. But experts such as Rafael Gonzalez [21]decided taking images from the environments at resolution of 1240x 800and 600x600 is better for good resolution and less memory requirement. So, all images were taken at resolution of 1240x 800 pixels. Coffee beans are scattered on white background. The camera is mounted on stand to ease vertical movement and to capture stable image. The distance between the sample table and the camera is 0.5 m. For all images, the same incandescent lamp light source of 100W is used. All the captured images were in PNG file format. PNG image file format is selected because of its lossless behavior for preserving image data.

1.7.3.2 Image preprocessing

The capturing and quality of brightness has impact on digitizing activities using computer vision systems as with the human eye. The performance of the brightness system greatly influences the quality of an image and plays an important role in the overall efficiency and accuracy of the system, underlining the need for manipulation of the illumination system specifications like type, angle and the use of constant light. So, it need to digitize the system with uniform lightning or balanced illumination. Adjustments of the imaging environment with the provision of a suitably uniform light and prohibition of the interference of external lighting sources will help attainment of a uniform and balanced illumination for capturing the sample coffee bean images [5].

Image processing is started from rendering of images on computer screen and storing images on hard disks or other media for further processing. Image preprocessing techniques are employed in order to improve the quality of acquired images. Image preprocessing techniques used in this study were image filtering, image quality enhancement, normalization and Binarization. Image filtering is used for the purpose of reducing noises from the acquired image data. So for many practical purposes Gaussian blur can be successfully implemented with simpler filters. Specifically Gaussian blur filtering was used for coffee beans image filtering purpose because of its best performance over the other filtering algorithms like mean and median filtering. Smoothing quality enhancer techniques was also employed for enhancing the quality of images for better understanding of images. Images were normalized and converted in black-white space for further processing and analysis of images. Dynamic range expansion in the image is usually to bring the image into a range that is more familiar or normal to the senses. ImageJ was used for the purpose of preprocessing images before further analysis. With the aid of **Process component of ImageJ** all proposed image preprocessing tasks has been done successfully.

1.7.3.3 Image segmentation

Image 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 [22].

In this study, after the image is enhanced and converted in to 8 bit, images were segmented by using histogram based thresholdingtechnique. The threshold value of the upper and lower limit is set based on the histogram analysis of each coffee bean in the image acquired. The result of the threshold image is a form of image converted in to binary number value. 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 bean) and pixel value of 1 indicates white (background of coffee bean images).

Finally, it was obtained each coffee bean in the image is isolated from the background and labeled in order to ease image analysis from the binarized image. 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, Image was partitioned 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 extraction is possible, 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 used is histogram-based thresholding and edge detection [33].

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, histogram-based image thresholding was used as it is simple and computationally inexpensive. The task of segmenting background from foreground was done by ImageJ.

1.7.3.4 Image feature extraction

Image feature extraction is the process of extracting meaningful information from images that are used for classification of images to different categories. For image analysis of Ethiopian raw value coffee grading system, two classification parameters are used, which are morphological features and color features. This research involves the extraction of morphological and color features from digitized images of sampled coffee beans to generate a useful input database for raw quality value scaling. Color features of the sample coffee beans were extracted from segmented coffee bean images resulting from histogram thresholding. Morphological features have been extracted from the binary images produced by histogram thresholding of the gray scale images of the original coffee bean color images. Additionally, the feature of coffee bean extracted for each coffee scale level are stored in system`s database and used for comparison purpose.

Features are used as inputs to the algorithms for classifying the objects into different categories. Pattern recognition can be done by analyzing the morphology (shape and size), color, texture (spatial distribution of color), or a combination of these features of the images. **Particle analyzer** method of ImageJwas used to extract morphological and color features of the sample coffee beans from the previously processed and analyzed binary and tresholded images. ImageJ conducted the calculation of the features for each coffee bean from the region of interest with in the concern image by giving a unique label for each bean.

1.7.3.5 Image classification

Image classification is a fundamental problem in pattern recognition. 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 such as coffee bean images [23].

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. Classifier is a program that takes input feature vectors and assigns it to one of a set of designated classes [23]. Artificial neural network (ANN), K nearest neighbor (KNN) and Support Vector Machine (SVM) are experimented to select the best algorithm for classification in this study. GUI Matlab R2018a is used for developing model by using the above three classifier.

1.7.4. Implementation tools

All sample coffee bean images were acquired using CANON color digital camera model number EOS 5D Mark III with specification of 26.1 mega pixels, 2.7'' LCD screen, Carl Zeiss VarioTessar lens with wide-angle lens of 30mm, optical zoom 4x, full HD 1080. The camera is mounted over the illumination chamber on a stand which provides easy vertical movement.

Selecting the appropriate image processing, classification and regression tools is vital. The best and important tool for this purpose is the ImageJ program [24], which runs for processing and analysis of coffee bean images, particularly for activities of pre-processing, segmenting images, and feature extraction. It is designed with an open architecture in-order to provide extensibility via Java plugins. It assists to display, edit, process, and analyze coffee bean images in the process of coffee scaling and grading. In general for tasks such as image preprocessing, image segmentation and feature extraction ImageJ was used. The extracted features, parameters and their respective values were generated on excel and used by Matlab for training and developing model and finally for testing trained model.

Matlab with graphical user interface is used for the purpose of developing model and determining the scale of coffee. Based on the model stated, the system could compare for the image taken/uploaded with the image within the database to determine the quality of coffee and will tell us its scale. Finally, the model could determine to what cluster/category the sample coffee bean canbe classified. The main reason for using Matlab R2018a is GUI Matlab is recommendable platform for imaging operation and support simple Object oriented user interface [19].

1.7.5. System evaluation

The model was evaluated by running a test dataset on the classifier built using the training dataset. The performance of the system is evaluated as an output that contains performance matrices and percentage accuracy measures for each grade obtained by from the system with comparison to experts, and summarized into a confusion matrix. Confusion matrix is a kind of a contingency table, used to drive true positives, true negatives, false positives and false negatives indicating the correct/incorrect values of samples into their respective classes. The system performance is evaluated by measuring accuracy rate [19].

$$\text{Accuracy rate} = \frac{Total\ number\ of\ samples\ correctly\ classified * 100\%}{Total\ number\ of\ samples\ used\ for\ testing} \ldots\ldots (1.1)$$

Experts were selected from office of Ethiopian Commodity exchange at Jimma branch to test the developed prototype.

User acceptance testing is also performed by client to certify the system with respect to the requirements that was proposed and agreed upon. During testing the users acceptance, the applicability of the prototype is evaluated by potential users of the system mainly experts working on scaling of coffee bean raw quality [Annex 1]. The ISO standard for user acceptance was applied for testing user acceptance. The 5E’s (Efficiency, Effectiveness, Error tolerance, easy to learn and easy to use) are the widely used ISO standard [25].

1.8 Ethical consideration

Approval letter of ethical clearance is obtained from the Research and Ethical Review Board (RERB/IRB) of Jimma institute of Technology, Jimma University for Ethiopian commodity Exchange. Confidentiality was ensured during the data sample preparation and sample collection and interview of domain expert; thus sample image was used only for the research purpose.

1.9Organization of the study

This thesis is divided into five chapters. The first chapter mainly focuses on the introduction parts and methodological procedures followed to conduct the study. The contents under this chapter are background of the study, the statement of the problems, and research questions of the study, general and specific objectives of the study, scope and limitations of the study, significance of the study, and the methodology that the researcher used to conduct this study.

The second chapter discussed about conceptual and review of related works to this study. In this chapter, the researcher addressed about Ethiopian coffee, overview of machine vision system, scaling method of coffee beans, agricultural image processing, image processing techniques, and the steps of digital processing techniques and related works which are relevant for this study.

In chapter three, the methods and algorithms used for developing Ethiopian raw quality coffee scaling model including the system`s architecture were discussed. Moreover, GUI implementation and the results of the all steps of scaling system were discussed.

In chapter four, discussion of each and every result and the experimental result was discussed. It also includes development environment, binary image analysis, feature analysis, experimental results and discussion. Finally, chapter five includes conclusion and recommendation; as well as the future research work.

CHAPTER TWO

LITERATURE REVIEW

2.1Overview

The technological integration of a camera and a computer, which is called machine vision system, provides an alternative to the manual inspection of biological products. Human inspections of agricultural products using morphological and color features that correlate with quality are being supported by machine inspection systems in different industries with their acceptance in recent years [26].

Any tasks of visual inspection such as defect detection, dimensional measurement, orientation detection, scaling, sorting and counting, could be conducted with such automated inspection techniques. Machine vision includes several advantages over the manual methods of inspection. Some of the advantages are capability of being compatible with other on-line processing tasks, taking dimensional measurements more accurately and consistently than a human being, and provision of measure of color and morphology of an item objectively than subjectively. More importantly, the absence of physical contact involved makes this method more needed and the possibility of damage during inspection to homogenous biological products is very low [27]. Besides, computer vision system is non-destructive, in addition to its attractive feature; it can be used to create a permanent record of any measurement at any point in time [28].

2.2 Digital Image Processing

An image is defined as a two-dimensional function, f (a, b), where a and b are spatial or geographical coordinates. The amplitude of **f** at any pair of coordinates (a, b) is also called the intensity of the image at that point [21]. When a, b, and the amplitude values of an image f are all finite, discrete quantities, the image is a digital image. In general, as noted by Gonzalez [19], a digital image is an array of numbers representing spatial distribution of a certain appearance parameters such as reflectivity of electromagnetic radiation, emissivity, temperature or some geophysical or topographical elevation. A digital image is composed of a finite number of elements, each of which having a particular location and value [21].

Digital image consists of discrete picture elements called pixels [29]. Associated with each pixel is a number represented as DN (Digital Number) that show the average radiance of relatively small area within a scene, with DN values normally ranging of from 0 to 255 in 3 elements or 0 to 224-1 in single numbering. The size of this area effects the reproduction of details within the scene. As the pixel size is reduced more scene detail is preserved in digital representation. The field of digital image processing refers to processing digital images by means of a digital computer. Digital image processing involves efficient techniques of data acquisition and retrieval through sound image representation, display, pre-processing and segmentation approaches [21].

2.3 Image capturing

The main goal of acquiring images is to generate digital images from sensed data. The output of most sensors is a continuous voltage wave whose amplitude and spatial behavior are related to the physical phenomenon being sensed. There should be conversion and representation of the continuous sensed data into digital form to create a digital image. Sampling and quantization models are important tools by providing systematic procedures for such conversion and representation tasks [29]. An image may be continuous with respect to the x- and y-coordinates, and also in amplitude. To convert it to digital form, the function needs to be sampled in both coordinates and in amplitude. Digitizing the coordinate values is called sampling [29], providing the set of pixels. Digitizing the amplitude values, which is the gray level, is called quantization. Quantized images are commonly represented as sets of pixels encoding color/brightness information in matrix form [29].

Image resolution is also another focal point during image capturing. DPI is the measure of resolution for both on-screen and prints images. The resolution of a digital image is its pixels, generally expressed as Megapixels or MPwhich simple arithmetic, the horizontal pixel dimension of an image multiplied by its vertical pixel dimension. Image resolution can be restricted during capturing and saving on device. Image resolution depends on the quality of the original photo, whether higher DPI/PPI would display more detail or grainy dust, whether you scan a print or a negative. But there are some general guidelines for image processing resolution. 600 DPI is the minimum resolution value whereas up to 2400 DPI is fair for image analysis [14].

2.4 Image pre-processing

The method by which various initial image enhancing techniques of the captured raw images are applied is considered as Image pre-processing. After capturing images, the images captured should first be transferred onto a computer to convert it in to a digital image. Digital images, though displayed on the screen as pictures, are digits readable by the computer and are converted to tiny dots or picture elements representing the real objects [15].

A series of image pre-processing techniques precede image analysis and image understanding activities, so as to enhance image quality and avoid distortion, for a valuable image feature extraction. The effect of any noises that are corrupting the image during capturing, digitization and data transfer process can be reduced using different types of filtering techniques presently in use [9].

Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task [30].

2.4.1 Image filtering algorithms

Image filtering is the task of enhancing the quality of image by reducing noise and improves the visual quality of the image. There are various algorithms for image filtering such as linear and nonlinear algorithms [31]. With the aid of image filtering it is possible to perform several useful tasks in imaging technology. Linear filtering algorithms can be applied to reduce the amount of unnecessary information in image. Also filtering can be used to reverse the effects of blurring on an image. Nonlinear filters have quite different behavior compared to linear filters. For nonlinear filters, the filter output or response of the filter does not obey the principles outlined earlier, particularly scaling and shift invariance. Moreover, a nonlinear filter can produce results that vary in a non-intuitive manner [32].

2.4.1.1. Linear filtering algorithms

The most common, simplest and fastest kind of filtering is achieved by linear filters [32]. The linear filter replaces each pixel with a linear combination of its neighbors. Usually, convolution kernel is used in prescription for the linear combination. Linear filtering of a signal can be expressed as the convolution; $\mathrm{y\,(t)} = \int_{-\infty}^{\infty}(\mathrm{h(r)}\,.\,\mathrm{x(t-r)dr})$of the input signal x (n) with the impulse response h (n) of the given filter, i.e. the filter output arising from the input of an ideal Dirac impulse [32].

Mean filtering

The simplest and popular linear filtering algorithm is known as the mean filter [31]. The mean filter performs average smoothing on an image. The name perfectly describes the function of this filter. Each pixel in image I is replaced with the mean of the pixels that surround it. Especially, noise is blended into the rest of the picture. A filter that performs average smoothing must use a kernel with all entries being non-negative. Let I be an image of size NxN, and the kernel A of a linear filter, witha mask of size mxm, m should be an oddnumber smaller than image size N. A filter that performs average smoothing must use a kernel with all entries being non-negative. Below is equation of mean filtering [32]:

$$f(x,y) = \frac{mn}{\sum_{(s,t)\in S_{xy}} \frac{1}{g(s,t)}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2.1)$$

Where S_{xy}represents the set of coordinates in a rectangular sun image window of size m x n centered at (x, y). g (s, t) represent degraded images.

This filter is effective at attenuating noise because averaging removes small variations. The effect is identical to that of averaging a set of data to help reduce the effect of outliers. In a two-dimensional mean filter, the effect of averaging $m^{\wedge 2}$ noisy values around pixel divides the standard derivation of the noise by $\sqrt{m^2}$=m (size) [33].

Additionally, it is absolutely necessary for all the entries in the kernel to have a sum of one. If the sum is not equal to one, then the kernel must be divided by the sum of the entries. If the requirement is not met, then the filtered image will become brighter than the original image, along with undergoing the specified filtering effect. This limitation on the mean filter fulfills the second portion of the image filtering goal A. This filter is effective at removing noise because averaging removes small variations. The effect is identical to that of averaging a set of data to help reduce the effect of outliers [32]. Mean filtering which use smoothing technique specifically Gaussian blur filtering is recommendable and popularly filtering technique that was employed in this study.

2.4.1.2 Nonlinear filtering

Nonlinearfiltering is a filter whose output is not a linear function of its input [34]. That is, if the filter outputs signals$R$ and S for two input signals r and s separately, but does not always output $\alpha R + \beta S$ when the input is a linear combination $\alpha r + \beta s$.Non-linear filters have many applications, especially in the removal of certain types of noise that are not additive. For example, the median filter is widely used to remove spike noise that affects only a small percentage of the samples, possibly by very large amounts. Indeed, all radio receivers use non-linear filters to convert kilo- to gigahertz signals to the audio frequency range; and all digital signal processing depends on non-linear filters to transform analog signals to binary numbers [34].

However, nonlinear filters are considerably harder to use and design than linear ones, because the most powerful mathematical tools of signal analysis (such as the impulse response and the frequency response) cannot be used on them. Thus, for example, linear filters are often used to remove noise and distortion that was created by nonlinear processes, simply because the proper non-linear filter would be too hard to design and construct. Nonlinear filters have quite different behavior compared to linear filters. The most important characteristic is that, for nonlinear filters, the filter output or response of the filter does not obey the principles outlined earlier, particularly scaling and shift invariance. Furthermore, a nonlinear filter can produce results that vary in a non-intuitive manner [34].

Median filtering

Median filtering in signal processing is often desirable to be able to perform some kind of noise reduction in an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical preprocessing step to improve the results of later processing (for example, edge on an image)[32].

Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges of the images while removing noise. Median is a non-linear local filter whose output value is the middle element of a sorted array of pixel values from the filter window. Since median value is robust to outliers, the filter is used for reducing the impulse noise [31]. The below is equation for median filtering [35].

$$f\ (x, y) = \underset{(s,t)\in S_{xy}}{Median}\ \{g(s, t)\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (2.2)$$

Gaussian filtering

Gaussian blur is considered as a perfect blur for many applications which provide large enough kernel support that fit the essential part of the Gaussian. Gaussian filter on a square support is separable. In case of 2D filtering it can be decomposed into a series of 1D filtering for rows and columns. When the filter radius is relatively small (less than few dozen), the fastest way to calculate the filtering result is direct 1D convolution. First of all, it is considered that the result of convolution has a length N+M–1, where N is the signal size and M is a filter kernel size (equal to 2r+1), which means the output signal is longer than the input signal [36].

Secondly, calculating FFT of the complete image row is not optimal, since the complexity of FFT is O (N log N). The complexity of FFT (fast Fourier transform)can be reduced by breaking the kernel into sections with an approximate length M and performing overlap-add convolution section-wise. The FFT size should be selected so that circular convolution is not included. Usually optimal performance is achieved when FFT size F is selected as the smallest power of 2 larger than 2M, and signal section size is selected as F–M+1 for full utilization of FFT block. This reduces the overall complexity of 1D convolution to O (Norm).So, the per-pixel complexity of Gaussian blur becomes O (log r). However, the value of constant is quite large. So for many practical purposes Gaussian blur can be successfully implemented with simpler filters [36].

The Gaussian blur uses a Gaussian function which also expresses the normal distribution in statistics for calculating the transformation to apply to each pixel in the image. The formula of a Gaussian function in one dimension is [35]:

$$G(x, y) = \frac{1}{\sqrt{2\pi\delta 2}} e - \frac{x2}{2\delta 2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (2.3)$$

In two dimensions, it is the product of two such Gaussian functions, one in each dimension:

$$G(x, y) = \frac{1}{2\pi\delta 2} e - \frac{x2+y2}{2\delta 2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.4)$$

Where *x* is the distance from the origin in the horizontal axis, *y* is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution. When applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution from the center point. Values from this distribution are used to build a convolution matrix which is applied to the original image. This convolution process is illustrated visually in the figure on the right. Each pixel's new value is set to a weighted average of that pixel's neighborhood. The original pixel's value receives the heaviest weight having the highest Gaussian value and neighboring pixels receive smaller weights as their distance to the original pixel increases. This results in a blur that preserves boundaries and edges better than other, more uniform blurring filters; see also scale space implementation [35]. These are how Gaussian blur filtering works. Specifically Gaussian blur filtering was applied and selected for coffee beans image filtering purpose under this study.

2.4.2. Edge detection

Edge detection is a fundamental tool used in most image processing applications to obtain information from the frames as a predecessor step to feature extraction and object segmentation [37]. This process detects outlines of an object and boundaries between objects and the background in the image. An edge-detection filter can also be used to improve the appearance of blurred image. Edge detection is more common for detecting discontinuities in gray level than detecting isolated points and thin lines, as isolated points and thin lines do not occur frequently in most practical images. There are different methods of edge detection techniques including Sobel Operators, Roberts Cross Edge Detector and Canny Edge Detector Technique. For this research work Sobel Operators methods was used for detecting edges of region of interest from the original coffee bean image [37].

The Sobel edge detector uses a pair of 3 X 3 convolution masks, one estimating gradient in the x direction and the other estimating gradient in y-direction [33]. It is easy to implement than the other operators. Transferring a 2-D pixel array into statistically uncorrelated dataset enhances the removal of redundant data, as a result, reduction of the amount of data required to represent a digital image. It helps to extract useful features for pattern recognition. Although the Sobel operator is slower to compute, it's larger convolution kernel smoothes the input image to a greater extent and so makes the operator less sensitive to noise. The larger the width of the mask, the lower its sensitivity to noise and the operator also produces considerably higher output values for similar edges. Sobel operator effectively highlights noise found in real world pictures as edges though; the detected edges could be thick. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image [33].

Sobel edge detection algorithm [33]

Input: A Sample Image.

Output: Detected Edges.

Step 1: Accept the input image.

Step 2: Apply mask Gx, Gy to the input image.

Step 3: Apply Sobel edge detection algorithm and the gradient.

Step 4: Masks manipulation of Gx, Gy separately on the input image.

Step 5: Results combined to find the absolute magnitude of the gradient.

Step 6: The absolute magnitude is the output edges.

2.4.3. Image Normalization

In image processing, normalization is a process that changes the range of pixel intensity values. Applications include images with poor contrast due to glare. Normalization is sometimes called contrast stretching or histogram stretching. In more general fields of image processing, such as digital image processing, it is referred to as range expansion [32]. The purpose of dynamic range expansion in the various applications is usually to bring the image, or other type of signal, into a range that is more familiar or normal to the senses, as the term normalization. Often, the motivation is to achieve consistency in dynamic range for a set of data, signals, or images to avoid mental distraction or fatigue.

Normalization transforms an n-dimensional grayscale image I in to normalized output image. For example, if the intensity range of the image is 50 to 180 and the desired range is 0 to 255 the process entails subtracting 50 from each of pixel intensity, making the range 0 to 130. Then each pixel intensity is multiplied by 255/130, making the range 0 to 255[23].

Normalization of Image I = (Pi-MIN)*(NEWMAX/ (MAX-MIN))……………………….. (2.5)

Where Pi is pixel intensity at a given point.

2.5Image analysis

2.5.1. Image Segmentation

Image segmentation is useful component of image analysis method that determines the quality of the final outputs. Image segmentation enables to segment or discriminate images from its background. Under this stage of image analysis image is separated in to foreground / region of interest and background. Segmentation also subdivides an image into its constituent parts and the level to which this subdivision is carried out depends on the problem being viewed. Segmentation involves partitioning of 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. Three popular image segmentation techniques are: thresholding, edge-based, and region-based techniques [38].

2.5.1.1 Histogram based Thresholding segmentation

Thresholding is effective tool for image segmentation which separate objects and background into non-overlapping. Thresholding is used in characterizing image regions based on constant reflectivity or light absorption of their surface. This shows the fact that regions with similar features are characterized and extracted together [22].

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, histogram-based image thresholding was used as it is simple and computationally inexpensive [36].

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 [39].

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 2.1shows a typical histogram of a single coffee bean image.

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 [39]:

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

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

Here bij = 1, for the object pixels and bij = 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 such that background and foreground (object)
iii. Compute mean gray value μ1 and μ2 of background and object regions respectively.
iv. Compute the new threshold $T \longleftarrow \frac{\mu 1 + \mu 2}{2}$
v. Repeat steps 2 to 4 until there is no change of T.

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 0area 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.

2.5.1.2. Edge-based segmentation

Edge detection is also used in most image processing applications to obtain information by object segmentation [40]. This process detects outlines of an object and boundaries between objects and the background in the image. Edge detection is more common for detecting discontinuities in gray level than detecting isolated points and thin lines, as isolated points and thin lines do not occur frequently in most practical images [37]. Detection algorithms for segmentation are the same with filtering by detecting edges of the object. There are Sobel Operators, Roberts Cross Edge Detector and Canny Edge Detector Technique. Let us see each one by one with their algorithms.

The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks (figure 2.2), one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows)

-1	**0**	**1**
-2	0	2
-1	0	1

1	**2**	**1**
0	0	0
-1	-2	1

Figure 2.2: The Sobel convolution masks [40]

The Roberts Cross operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. It thus highlights regions of high spatial frequency which often correspond to edges. In its most common usage, the input to the operator is a grayscale image, as is the output. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. Figure 2.3 shows Roberts cross convolution mask.

1	**0**
0	-1

0	**+1**
-1	0

Figure 2.3: Roberts cross convolution mask [40]

Canny technique is very important method to find edges of an image and the critical value for threshold, after isolating noises from the image, with this noise detection having no adverse effect on the features of the edges in the image [37].

2.5.1.3. Region Based segmentation

Region based segmentation involves the grouping together and extraction of similar pixels to form regions representing single objects within the image. In this process the other regions are deleted leaving only the feature of interest. The image is partitioned into connected regions by grouping neighboring pixels of similar intensity levels, in the beginning. Adjacent regions are then merged under some criterion involving homogeneity within resulting segments, in homogeneity across neighboring segments or sharpness of region boundaries [37].

A region denoted by R of an image is explained as a connected homogenous subset of the image regarding some criterion such as gray level or texture [15]. Regions in an image are a group of connected pixels with similar properties. In the region approach, each pixel is assigned to a particular object or region. Compared to edge detection method, segmentation algorithms based on region are comparatively manageable and more immune to noise [41]. Edge based methods break up an image based on brisk reforms in intensity near edges whereas region based methods, partition an image into regions that are close according to a set of predefined criteria [40].

In the region-based segmentation, pixels corresponding to an object are grouped together and marked. Region-based segmentation also requires the use of appropriate thresholding techniques. The important principles are usefulness similarity which have gray value differences and gray value variance and spatial proximity which consists of Euclidean distance and compactness of a region. Segmentation algorithms based on region mainly include following methods [42]:

A) Region Growing

Region growing [42] is ability for removing a region of the image that is connected based on some predefined criteria. This criterion is based on intensity information. Region growing is an approach to image segmentation in which neighboring pixels are examined and joined to a region class of no edges are detected. This process is iterated for severally boundary pixel in the region. If adjacent regions are found, then a region-merging algorithm is used in which weak edges are disappeared and strong edges are left intact. A new region growing algorithm is proposed in this paper based on the vector angle color similarity measure. The region growing algorithm works as follows [42].

1) Firstly select seed pixels within the image
2) Then from each seed pixel grow a region:
   a) After that Set the region prototype to be seed pixel;
   b) Calculate the similarity between the region prototype and the candidate pixel;
   c) And Calculate the similarity between the candidate and its nearest neighbor in the region;
   d) Include the candidate pixel if both similarity measures are higher than experiment all set thresholds;
   e) After that Update the region prototype by calculating the new principal component; f. At last go to the next pixel to be examined.

This algorithm presents several advantages over other image segmentation algorithms. Region growing approach is simple. The border of regions found by region growing are perfectly thin and connected. The algorithm is also very stable with respect to noise. Limitation is that, it requires a seed point, which generally means manual interaction. Thus, each region to be segmented, a seed point is needed [40].

B) Region Splitting and Merging

Split and merge method is the opposite of the region growing. This technique works on the complete image. Region splitting is a top-down approach. It appears with a complete image and splits it up such that the segregated sliced are more homogenous than the total. Splitting single is insufficient for sensible segmentation as it severely limits the shapes of segments. Hence, a merging phase after the splitting is always desirable, which is termed as the split- and-merge algorithm. Any region can be split into sub regions, and the appropriate regions can be merged into a region. Rather than choosing kernel points, user can divide an image into a set of arbitrary unconnected regions and then integrate the regions [42]in an attempt to serve the shapes of rational image segmentation. Region splitting and merging is usually executed with theory based on quad tree data [40].

Region splitting and merging is an image-segmentation technique that takes spatial information into consideration. The region-splitting and merging method is as follows [40]:

1) Region splitting Method

i. Suppose R represent the entire image. Select a predicate P.
ii. Split or subdivide the image successively into smaller and smaller quadrant regions.

The splitting method has a convenient representation in the form of composition called a quad tree. In a quad tree, the root of the tree corresponds to the entire image and each node corresponds to subdivision [42].

2) Region Merging Method

This method Merge any adjacent regions that are similar enough. The procedure for split and merge is given [42].

i. Firstly start with the whole image.
ii. If the variance is too large then break it into quadrants.
iii. Merge any adjacent regions that are similar enough.
iv. Repeat step (2) and (3) again and again until no more splitting or merging occurs.

This technique requires the input data to be organized into a pyramidal grid structure of regions, with each region organized in groups of four in case of 2D, and of eight in case of 3D [40].

2.6Feature extraction

Feature extraction focuses on a set of specifically known features characterizing the application domain, probably with some consideration for non-overlapping or uncorrelated features. As a formative procedure of various attributes and properties associated with regions or objects, it operates mainly on abstracted image information obtained through segmentation. The image objects could be measured and described based on their features and characteristics after proper completion of the image segmentation of the external grading system process of the samples [43].

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 could be 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 in different studies. Morphology, color and texture are some of the basic image features [13]. Morphological features are the geometric property of an image like shape and size [24]. 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 [22].

Image geometrical measurements are computed from binary images. 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 [22]. 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, first the boundary object pixels covering an area should be identified. Then, perimeter is defined by the sum of these boundary object pixels [44].

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[45],

$$A=\sum i \ \sum_j \ \mathrm{O}\,(\mathrm{i},\mathrm{j}) \quad \ldots\ldots\ldots\ldots (2.6)$$

WhereO (i, j) represents the object pixels (binary 1).

In line with this, circularity or roundness is a typical measure of image shape compactness. It is defined as [16];

$$C= {}^{4\pi A}/_{P2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.7)}$$

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[19].

The below figure 2.4shows 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 2.4: Pixel square of a binary image [22]

Morphological features are widely used in automated grading, sorting and detection of objects in industry [18]. 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.

Besides morphological features, Color and textural features can be extracted from the properties of pixels inside the object boundary [19]. 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. The reason is, it is easier to manipulate such arrays and convert them to displays. In line with this, the statistical values of color features like mean, mode, standard deviation, are widely used for image classification [19].

Texture feature is an intrinsic characteristic of image that is related to its roughness, granulation and regularity of pixel structure [21]. The texture of an image like segmentation, classification and image interpretation are used to get useful information such as energy, entropy, contrast and homogeneity. Textural features can be calculated using equations 2.5 TO 2.8[21].

Energy: it is a feature to measure the concentration of intensity pair in co-occurrence matrix and is calculated as [21],

Energy = $\sum_{i1} \sum_{i2} P2(I1, I2)$………………………………………………………… (2.8)

Entropy: it is a feature used to calculate the degree of randomness of intensity distribution and it is given as [21],

Entropy = $\sum_{i1} \sum_{i2} p2\ (i1, i2) \log_{p}(i1, i2)$……………………………….………… (2.9)

Contrast: it is a feature to measure the difference in the strength between intensity in image [21].

Contrast = $\sum_{i1} \sum_{i2} p2\ (i1, i2)(i1 - i2)^2$…………………………………………… (2.10)

Homogeneity: it is an inverse of contrast, which measures the homogeny feature of the intensity variation within the image [21].

Homogeneity = $\sum_{i1} \sum_{i2} \frac{p(i1,i2)}{1+|i1-i2|}$…………………………………………………… (2.11)

In the equations above, p denotes the number of occurrences of gray levels within a given image, which shows the value of the element within co-occurrence matrix, while $i_1$and i_2 show the intensity couple from the neighboring intensity. This neighboring couples in co-occurrence matrix act as row and column matrix. Standing on this reality, image features such as morphology, color and texture were used as inputs to a pattern classifier that discriminates objects coffee in this study, into different categories.

2.7 Classification algorithms

Recognition of the characteristics of objects in an image from a specific set of measured values of features of the object facilitates the stratification of an image into various classes with similar features. This is the core business of design of classifiers, which utilizes specified features of an object as its inputs, thereby generating a classification label or value depicting the correct class allotment of the object [23].

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 [23].

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; that is, 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 [46].

A number of 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. 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 [46]. 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. Below both a statistical classifier and neural network classifier are described.

2.7.1 Artificial Neural Network

Artificial neural networks (ANN) are highly distributed interconnections of adaptive nonlinear processing elements [47]. In other words, they are large set of interconnected neurons, which execute in parallel to perform the task of learning. ANN resembles human brain in two respects [47]. 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. 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 [43].

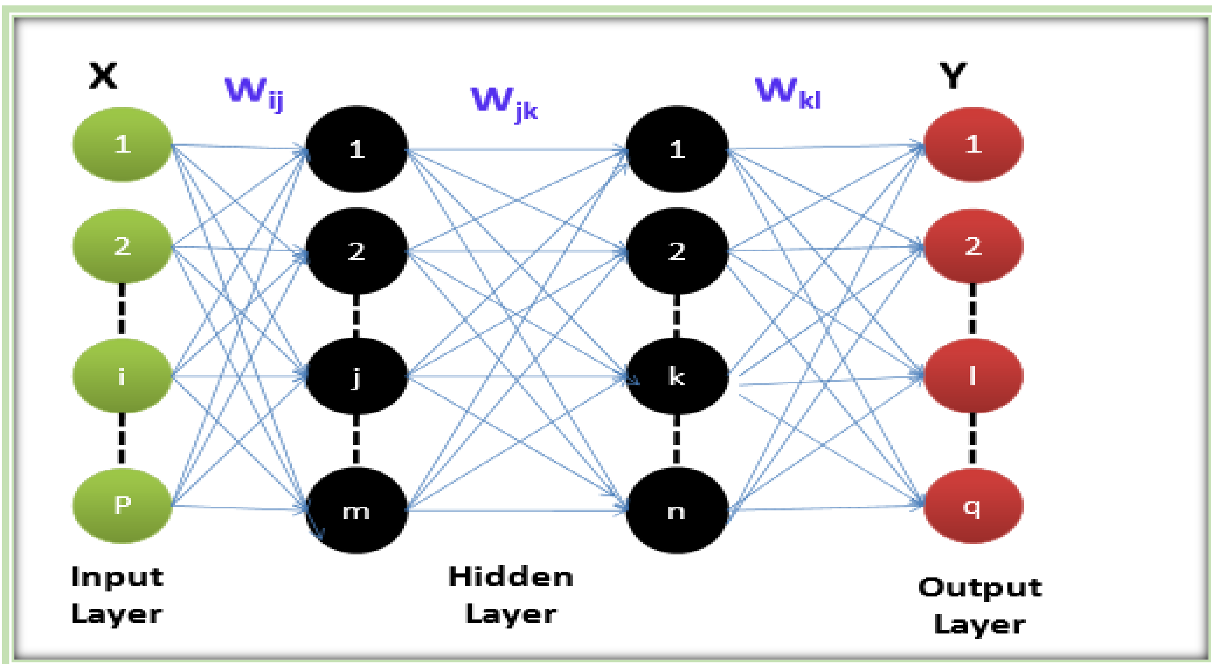

Figure 2.5: Architecture of two hidden layer neural network [48]

In a p-class problem where the patterns are m-n dimensional, the input layer consists of m-nneurons and the output layer consists of q neurons. There can be one or more middle or hidden layer(s). The above figure 2.8 shows a two hidden layer case, which is extendable to two numbers 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 [48].

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 [48].

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 share the concepts of biological brains. 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 [43].

Unlike more analytic-based information processing methods, neural computation effectively explores the information contained within input data, without further assumptions [49]. Statistical methods are based on assumptions about input data ensembles such as priori probabilities and probability density functions. 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 [49]. They are training or learning phase and testing which is also called 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.

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

$$I^h_j = \sum_{n=1}^{N} x_n W_{ij} + \theta_{jh} \quad \ldots\ldots (2.12)$$

The output of the jth hidden layer neuron is

$$O_j = f^h J(Ihj) = {}^{1}\!/_{1 + e^{1Ihj}} \quad \ldots\ldots (2.13)$$

Where x1, x2, . . . , xn is the input pattern vector, weights wij represents the weight between the hidden layer and the input layer, and 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 Ok. The error (Tk - Ok) 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 back propagation. The average error E is a function of weight as shown below [49]:

$$E\left(W_{jk}\right) = 1/2 \sum_{k=1}^{M} (T_k - O_k)^2 \quad \ldots\ldots (2.14)$$

To minimize the error E, find the root of the partial derivatives

$$\sum_{k=1}^{M} \frac{\partial E}{\partial W_{jk}} = 0 \quad \ldots\ldots (2.15)$$

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

$$W_{jk}^{(new)} = W_{jk}^{(old)} + \eta \delta_j O_J \quad \ldots\ldots (2.16)$$

Where, η is the learning rate of the hidden layer neurons.

In summary, artificial neural networks can be regarded as a mother 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 [43]. These conditions are commonly found in tasks involving grading and classification of agricultural products. This study also test and applied this classifier along with other classifiers such as support vector machine.

2.7.2 Support machine vector

Support vector machines (SVMs) are a set of related supervised learning techniques used for classification and regression [44]. They belong to a family of generalized linear classification. A special property of SVM is, SVM simultaneously minimize the empirical classification error and maximize the geometric margin. So SVM is called Maximum Margin Classifiers [50]. SVM is based on the Structural risk Minimization (SRM). Viewing input data as two sets of vectors in an n-dimensional space, an SVM will construct a separating hyper-plane in that space, one which maximizes the margin between the two data sets [44]. To calculate the margin, two parallel hyper-planes are constructed, one on each side of the separating hyper-plane, which are "pushed up against the two datasets. A good separation is achieved by the hyper-plane that has the largest distance to the neighboring data points of both classes, since in general the larger the margin the lower the generalization error of the classifier [44]. This hyper plane is found by using the support-vectors and margins.

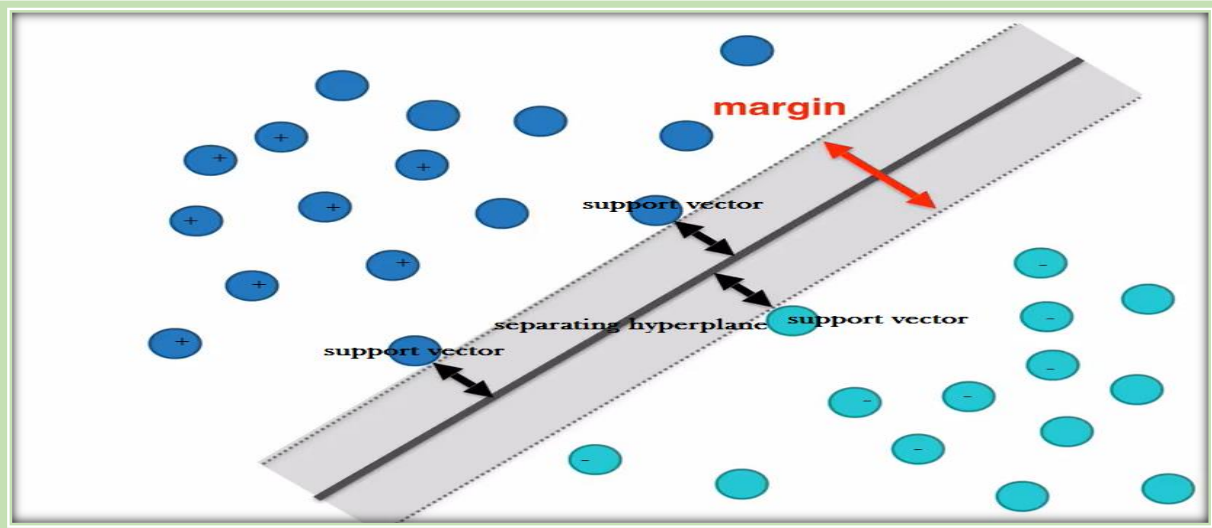

Figure 2.6: Hyper plane and support vectors used by SVM [44].

SVM map input vector to a higher dimensional space where a maximal separating hyper plane is constructed. The separating hyper plane is the hyper plane that maximizes the distance between the two parallel hyper planes. An assumption is made that the larger the margin or distance between these parallel hyper planes the better the generalization error of the classifier will be. We consider data points of the form {(x1, y1), (x2, y2), (x3, y3)… (Xn, yn)}, where yn=1 /-1, a constant denoting the class to which that point x_n belongs. n = number of sample. Each x_n is p-dimensional real vector. The scaling is important to guard against variable (attributes) with larger variance.

To view this training data, by means of the dividing (or separating) hyper plane, which takes w. x + b = o [44], Where b is scalar and w is p-dimensional Vector. The vector w points perpendicular to the separating hyper plane. Adding the offset parameter b allows us to increase the margin. Absent of b, the hyper plane is forced to pass through the origin, restricting the solution. As with the interest in the maximum margin, we are interested in SVM and the parallel hyper planes. Parallel hyper planes can be described by equation 2.14 and 2.15 [50],

$w.x + b = 1$ ……………………………………………………………………..… (2.17)

$w.x + b = -1$ ……………………………………………………………………… (2.18)

If the training data are linearly separable, we can select these hyper planes so that there are no points between them and then try to maximize their distance. By geometry, we find the distance between the hyper planes is $2 / \lVert w \rVert$. So we want to minimize $\lVert w \rVert$. To excite data points, we need to ensure that for all I either $w. x_i - b \geq 1$ or $w. x_i - b \leq -1$ this can be written as [44],

$$y_i (w. x_i - b) \geq 1, 1 \leq i \leq n \quad \text{(2.19)}$$

SVM has been applied to feature selection, time series analysis, reconstruction of a chaotic system, and non-linear principal components. Further advances in these areas are to be expected in the near future. SVMs and related methods are also being increasingly applied to real world data mining. In SVM, an attribute, and a transformed attribute that is used to define the hyper plane is called a feature. The task of choosing the most suitable representation is known as feature selection. A set of features that describes one case (i.e., a row of predictor values) is called a vector [50].

So the goal of SVM modeling is to find the optimal hyper plane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other size of the plane. The vectors near the hyper plane are the support vectors. An SVM classifies data by finding the best hyper-plane that separates all data points of one class from those of the other class. The best hyper-plane for an SVM means the one with the largest margin between the two classes. The support vectors are the data points that are closest to the separating hyper-plane; these points are on the boundary of the slab. The following figure illustrates these definitions, with + indicating data points of type 1 and – indicating data points of type –1. Support vector machine (SVM) is an algorithm and is popularly used in many pattern recognition problems, including texture classification. In SVM, the input data is non-linearly mapped to linearly separated data in some high dimensional space providing good classification performance. SVM maximizes the marginal distance between different classes [50].This study uses SVM classifier algorithm.

2.7.3 K-nearest neighbor

The k-nearest neighbor (KNN) algorithm is a method for classifying objects based on closest training examples in the feature space. KNN is a type of instance-based learning, or lazy learning [51]. It can also be used for regression. The k-nearest neighbor algorithm is amongst the simplest of all machine-learning algorithms. The space is partitioned into regions by locations and labels of the training samples. A point in the space is assigned to the class c if it is the most frequent class label among the k nearest training samples. Usually Euclidean distance is used as the distance metric; however this will only work with numerical values. In cases such as text classification another metric, such as the overlap metric (or Hamming distance) can be used. Nearest neighbor is one of the most popular classification technique introduced by Hodges and Fix [51].

Without any additional data, classification rules are generated by the training samples themselves. K nearest neighbor (KNN) is a simple algorithm, which stores all cases and classifies new cases based on similarity measure.KNN algorithm also known as case based reasoning, k nearest neighbor, example based reasoning, instance based learning, and memory based reasoning, lazy learning. KNN algorithms have been used since 1970 in many applications like statistical estimation and pattern recognition etc. [51].KNN is a non-parametric classification method which is broadly classified into two types; structure less NN techniques and structure based NN techniques. In structure less NN techniques whole data is classified into training and test sample data. From training point to sample point distance is evaluated, and the point with lowest distance is called nearest neighbor. Structure based NN techniques are based on structures of data like orthogonal structure tree, ball tree, k-d tree, axis tree, nearest future line and central line [45].

In 1968, Cover and Hart [52]proposed an algorithm of the K-Nearest Neighbor, which was finalized after some time. K-Nearest Neighbor can be calculated by calculating Euclidian distance, although other measures are also available but through Euclidian distance we have splendid intermingle of ease, efficiency and productivity [45].

The example is classified by determining the majority of samples of the labels for K-Nearest neighbor. In other words, this method is very easy to enforce; for instance, if an example “x” has k nearest examples where feature space and majority of them are having the same label “y”, then instance “x” belongs to class “y”. The K-NN method is mostly depends upon furthermost theorem while considering theory. When the decision course is considered consider small number of nearest neighbor. Hence when this method is used, example disproportion problem can be solved. While limited number of nearest neighbor are considered by K-NN, not a decision boundary. Hence exceptional to say that K-NN is suitable to classify the case of example set of boundary intercross and in that case example overlapped. The Euclidian distance can be calculated as follows [4]. If two vectors xi and xj are given, where xi = (xi1, xi2, xi3, xi4, xi5……. xin) andxj = (xj1, xj2, xj3, xj4, xj5……. xjn). The distance between xi and xj is,

$$D\ (xi, xj) = \sqrt{\sum_{k}^{n=1}((xik - xjk))}\,2 \ldots\ldots \quad (2.20)$$

In this experiment, this formula is used to estimate the nearest neighbor of an example. The KNN algorithm is very powerful and lucid to implement. But one of the main drawbacks of KNN is its inefficiency for large scale and high dimensional data sets. The main reason of its drawback is its lazy learning algorithm natures and it is because it does not have a true learning phase and that results a high computational cost at the classification time. Yang and Liu [30] set k as 30-45 since they found stable effectiveness in those range. In the same way, Joachim [31] tried over different k€ {15, 30, 45, 60}. When the above two attempts are considered, k values are explored, where k€ {15, 30, 45} for the K-NN classifier and have the best performance for the value of ’k’ that results on the test samples as shown in figure. The KNN classifier also known as instance based classifier perform on the premises in such a way that classification of unknown instances can be done by relating the unknown to the known based on some distance/similarity function. The main objective is that two instances far apart in the instance space those are defined by the appropriate distance function are less similar than two nearly situated instances to belong to the same class [45]. KNN is also used in this study.

2.8. Related works

Over the last 30 years, technological advancement for imaging technology has initiated several studies on the development of systems, mainly to evaluate the quality of different agricultural products [18]. The majority of these studies were focused on the application of computer vision system to agricultural products quality inspection and grading. Computer vision based inspection and grading of apple, oranges, strawberries, nuts, tomato, mushrooms, wheat, corn and rice have been done widely [5].

Edwin, Arnel and Ruji [53] conducted a study on classification of coffee bean species using image processing techniques in Cavite, Philippines. According to Edwin, Arnel and Ruji [53], the quality of coffee beans differs from each other based on the geographic locations of its sources. The coffee bean quality is conventionally determined by visual inspection, which is subjective, requiring considerable effort and time and prone to error. This paper was conducted with the objective of developing an appropriate computer routine that can characterize coffee beans from the different towns of Cavite, Philippines. Imaging techniques were employed to automatically classify the coffee bean samples according to their specie. Important coffee bean features based in morphology such as area of the bean, perimeter, equivalent diameter, and percentage of roundness were extracted from 195 training images and 60 testing images. Artificial neural network (ANN) and K nearest neighbor (KNN) were employed to automatically categorize the coffee beans. Using ANN, classification scores of 96.66% were achieved while using KNN. Edwin, Arnel and Ruji [53] concluded that the results of this study have revealed that imaging technique could be used as an effective method to classify coffee bean species and recommended to conduct study on coffee bean classification based on green analysis. ANN is the more preferred method over KNN in classifying coffee beans.

According to Habtamu [18], digital image analysis technique based on morphological and color features was developed to classify different varieties of Ethiopian coffee based on their growing region to determine the regional origin of coffee. For the classification analysis, ten morphological and six color features were extracted from each coffee bean image. The processing type of coffee (washed or unwashed) has been also predefined during the analysis. The researcher also compared classification approaches of Naïve Bayes and Neural Network classifiers on each classification parameter, such as morphology, color and combination of the two. To evaluate the classification accuracy, from the total of 4844 datasets, the researcher used 80% for training and the remaining 20% for testing. The classification system was supervised at the corresponding predefined classes of growing regions. Accordingly, it was found that the classification performance of neural networks classifier was better than Naïve Bayes classifier. It was also described that the discrimination power of morphology features was better than color features; however combined use of both morphology and color features resulted increased classification accuracy. The best classification accuracies of 80.7%, 72.6%, 56.8%, 96.77%, 95.42% and 69.9% were obtained for Bale, Harar, Jimma, Limu, Sidamo and Welega, respectively using neural networks when both morphology and color features were used together. The overall classification accuracy yielded by the model was 77.4% [19]. Habtamu [18] concludes that computer inspection can be applied on agricultural products for grading, defect detection and counting particles and strongly recommend conducting on coffee bean grading as future work.

Asma [17] investigates classification of Ethiopian coffee using image processing techniques was developed to determine the grade of coffee beans from Wollega region. For the classification purpose eight morphological and six color features were extracted from each coffee bean image. The automated raw quality value classification experimentation comprised the analysis of images of washed coffee beans of varying grades from Wollega region, using major attributes of morphological structures (shape and size), and color features. The Naïve Bayes, C4.5 and Artificial neural networks (ANN) were implemented for classification purposes. A combined morphological and color features aggregate function dataset was used to develop the base model, though model attempts with separate features were conducted. Feed-forward multilayer perceptron's with two hidden layer and back propagation algorithms were used in the ANN classifiers.

Model robustness and sensitivity was analyzed by using perturbation analysis involving manipulations of model evaluation techniques and dataset characters. Alteration of number of beans in discretization and the use of different number of hidden layers constitute the trial modeling in this regard. Classification model was also run with various combinations of features of the coffee beans as listed with the attribute selection feature of Weka tool, where the final selection of the 21 features was done at a maximal model performance level for the Naïve Bayes and ANN classification approaches. The system`s performance was 54.6. Total of 4585 image datasets were used. The researcher highly recommended that the performance of the model should be modified by using larger datasets and focusing on representative coffee bean feature extraction. This is the gap the researcher have identified to do it by using larger datasets of around 10,000 image datasets and focusing more on representative coffee bean raw quality feature extraction.

It can be concluded from the above researches that morphological structures and color are the most viable features used in computer vision systems for inspection and grading of agricultural products. As a classification technique, Artificial Neural Network is the most appropriate technique for classification, inspection and grading of agricultural products, especially coffee [5].

In general, all the above studies showed that morphological features, color and texture features of crops 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 brightness of light intensity. For this reason, morphological feature registers better classification performance than color. It was also shown that the texture feature has less discriminating power than the two. But when different features were combined the classification accuracy was increased. Hence in this study an attempt is made to conduct experiments using different morphological and color features individually and by combining them for scaling Ethiopian coffee raw quality using artificial neural network (ANN), Support machine vector (SVM) and K-Nearest Neighbor (KNN) classifiers.

CHAPTER THREE

METHODS AND ALGORITHMS

3.1 Overview

The action of visualizing and scaling of coffee beans is complex and systematic procedures in which there are various phases starting from coffee beans region identification to the final process of scaling coffee beans. The study attempts to design an automatic scaling of coffee beans and classifying into its appropriate classes. The very initial stage of scaling and ranking process starts from preparing the raw coffee bean samples which come from different coffee producing centers. After having coffee beans samples, it is followed by classifying the coffee beans based on the region of product like coffee beans from Jimma, Wollega, Harar, Bale, Sidamo and limmu. After determining the region of sample coffee beans the activity of prediction of raw and liquor quality values of coffee bean samples were performed. According to the rules and principles of ECX, a team of three experts participate on cup-tests of roasted sample coffee beans. Parallel to cup test, raw quality measurement should be performed by those similar experts.

The combination of these values to the prediction of the coffee bean rank comprises 40% for raw quality and 60% for liquor quality. The final rank of sample coffee beans is decided by summing their respective values for the liquor and raw qualities.

The raw quality value of coffee beans can be obtained objectively and scientifically for a meaningful sorting, classification and ranking purposes of coffee beans. This requires the development of an automated system with minimum human error and bias in the grading process. For this purpose, this study aims to construct classification model that assist experts to determine the raw quality value of sample coffee beans by using imaging technology. Accordingly, this chapter presents the methods and algorithms employed as per architecture of the proposed prototype.

3.2. The architecture

The below Figure 3.1 shows the architecture proposed in this study for automatic scaling and ranking of coffee beans and classifying into its appropriate classes. The architecture depicts the two phases of classification process followed as a training phase and testing phase. The training phase mainly performs labeling each coffee bean based on their parametrical values. Coffee bean images should be prepared for each grade to train in to their respective cluster. Acquired images should be preprocessed so that unnecessary data/pixels on the images would be removed and easily manipulated images are prepared.

Image filtering is the first task after loading image on computer. Two filtering algorithms were tested and one was selected based on its best performance. Median filtering and Gaussian blur filtering were tested to improve coffee bean images quality. Normalization is the next step to normalize the images to the normal human eye sense. Then Binarization is applied on images and quality enhanced coffee bean images were produced. After preprocessing image the next step is analyzing images for further understanding of it. Segmentation is performed in order to separate region of interest from background. K-means clustering and histogram based thresholding were tested. After determining region of interest from the image, features of each identified region of interest were computed. Based on the generated dataset of coffee beans, classification model is created using the features extracted for each grade of coffee bean. The classification model is used for scaling raw coffee beans.

Under testing phase the steps followed are, acquiring images, preprocessing and analyzing images for image segmentation and feature extraction. After generating features of new coffee beans, the extracted coffee bean features are compared with trained model for scaling coffee beans.

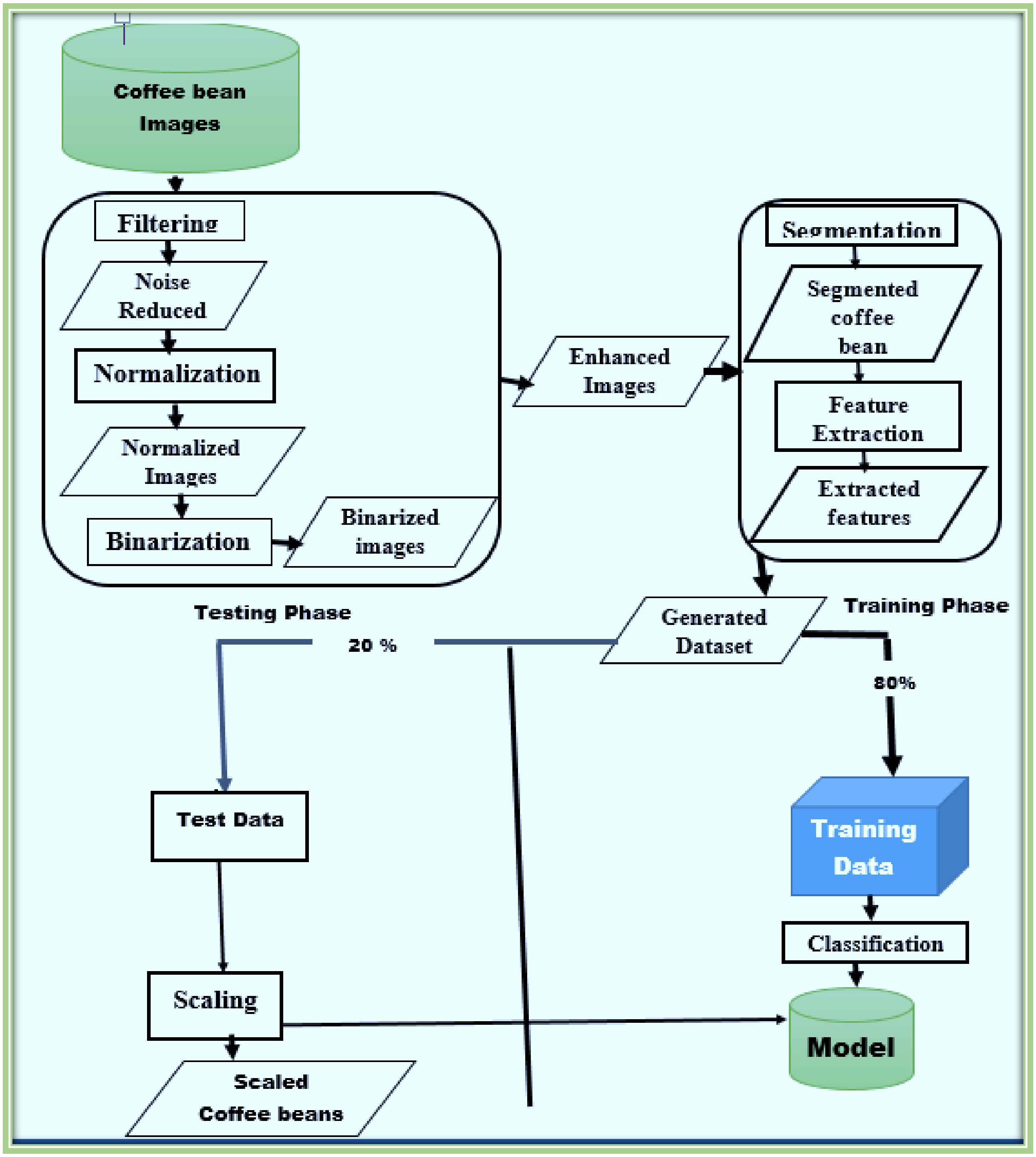

Figure 3.1: The proposed architecture for scaling raw coffee beans

3.2. Coffee beans image acquisition

A well organized and managed computational processes and mechanisms were performed repeatedly in the image capturing stage, till the most appropriate and suitable images were captured finally. There are various properties of image that should be controlled such as illumination, background, each coffee bean spacing, distance between the sensors and the scene, camera adjustment and manageable coffee beans sample size selection. All these properties of acquired images were the most important issues for acquiring clear and best images with less noise, especially for training purpose.

All coffee bean sample images were taken from a fixed height (0.5m) oriented in a perpendicular manner directly above the sample coffee beans to retain uniformity between all the image pictures of the samples. The camera was mounted on a stand with the mentioned elevation of 0.5m above the beans for the sake of enabling simple movement vertically and to avoid blurred pictures. Coffee beans were prepared on white background table and captured properly which help the researcher to segment background from foreground of coffee bean image. The images were taken at a resolution of 1240 x 800 pixels.

All the captured images are with PNG image format. This image file format was selected because PNG file format is lossless file format in which data is not lost over time. After capturing images in PNG format, it was then transferred into computer and image pre-processing was employed to carry out the necessary procedures and analysis. The below figure 3.2 shows a sample coffee bean image captured and ready for further automated image processing.

Figure 3.2: Coffee beans Image capturing

Summary of the total dataset collected and digitized for training and testing is presented in table 3.1 below.

Table 3.1: Total dataset acquired coffee bean images

Grade	Number of images	Total number of Beans	Processing type
Grade – I	29	2150	Washed
Grade – II	40	2655	
Grade – III	45	3043	
Grade – IV	31	2152	
Average	36	2,500	
Total	145	10,000	

As shown in the above table 3.1 a dataset of 10,000 coffee beans were collected from various grade levels. The researcher collected three samples from each grade. The coffee that scores the highest mark, medium mark, and the lowest mark of the grade were collected. For example, according to ECX grading guidelines [2]for the first grade, the coffee should score more than 85 marks. Coffee beans which scored 75-84 are registered under grade II, those which scored 63-74 are registered under grade III and coffee beans which score 47-62 are registered under grade IV [2]. The researcher took sample which scored 85, 92 and 100 marks. From the second grade the researcher took coffee beans which scored 76, 78 and 84 marks. From the third grade the coffee beans which scored 63, 71 and 74 marks were collected. From the fourth grade the researcher collected coffee beans that scored only 62 marks because any other sample which scored less than the maximum value of that grade was not preserved in their warehouse. The mark is given by experts working on coffee grading laboratory of ECX Jimma center.

Grade I coffee beans were sampled in to 29 images in which each images contain between 65 to 70 coffee beans. The total samples of Grade I coffee beans were 2150. Grade II sample of coffee beans were sampled to 40 images and contain total of 2655 coffee beans dataset. Grade III were sampled in to 45 images with a total of 3043 coffee bean datasets were collected. Grade IV were sampled to 31 images and a total of 2152 coffee bean datasets were recorded. Therefore, a total of 145 images and 10,000 datasets were collected and used for this study. The main reason for the imbalance of the sample of coffee is the limited amount of samples found in the centers warehouse.

3.3. Coffee beans image preprocessing

Image preprocessing is a common name for operation with images at the lowest level of abstraction in which both input and outputs are intensity images usually represented by a matrix of image function values (brightness). The color image segmentation step starts with conversion of the RGB of original image to HSB color space model. HSB color space is generated from RGB color space and was used for color image segmentation. It was used to enhance image when the background of enhanced image was off-white. In addition, Gaussian filter, a nonlinear digital filtering technique was used to remove noise information from images. Gaussian filtering was widely used in digital image preprocessing because, under certain condition, it preserves edges while removing noise. Therefore, Gaussian filter in color image has been applied on separate channel and recombined to a single channel.

After that, the images were further pre-processed by ImageJ tool and Matlab R2018a programming language to enhance the retrieval of accurate information. ImageJ was used for image processing, image segmentation and feature extraction. The first tasks of ImageJ were subtracting background from the images to avoid blurs, light distortions and other noises that could be formed due to light effects during image capture and some external objects on the background. After background subtraction, conversion of the RGB images to 8-bit gray scale image and histogram thresholding for the purpose of extracting morphological and color features from the thresholded original images were done by ImageJ. Conversion to gray scale images of the RGB images supports the production of binary images which help extraction of morphological features.

Image preprocessing is applied on the acquired images for improving the quality of image and to reduce the undesired portion from the background of the images. Most of preprocessing techniques applied the intensity value of the region pixel for obtaining the brightness intensity value of the input images. The dominant reason for the requirement of preprocessing are image quality improvement, noise reduction, contrast enhancement, and correction of missing or wrong pixel values, optimal preparation of data for segmentation and elimination of acquisition specific artifacts. Additionally, image preprocessing depends mainly on the quality of image acquired from the image acquisition. During image preprocessing the below four discussed techniques were use in this study; filtering, resolution enhancement, normalization and Binarization.

A) Image filtering

Background subtraction was the first process conducted to avoid blurs, light distortions and other noises that could be formed due to illumination effects and some external objects on the background. On ImageJ platform there is component for image preprocessing. By using Process submenu of ImageJ, the researcher has preprocessed all images acquired in order to have better image. Filtering was performed by using Gaussian blur filtering algorithm and noises were detected from the images. Gaussian blur filtering algorithm reduces noises from image in a linear manner.

ImageJ also used for noise removal and hole filling in the image. Unclear backgrounds of the coffee bean images resulting from inconsistent image acquisition environment could be the causes for these.

B) Resolution enhancement

Resolution of images is enhanced by using smoothing technique on ImageJ. After filtering and reducing noises from acquired image, the researcher conducts enhancing of the quality of images to produce image with enough information. The enhancement of original image subtracts the background of an image. Regardless of the enhancement measures taken in background subtraction, there appeared to exist some outliers on some coffee bean images. The outlier removal feature of the tool, ImageJ was used to perform image preprocessing.

C) Normalization

In image processing, normalization is a process that changes the range of pixel intensity values. Images were normalized and converted in black-white space for further processing and analysis of images. Dynamic range expansion in the image is usually applied to bring the image into a range that is more familiar or normal to the senses which achieve consistency in dynamic range for a set of images to avoid mental distraction or fatigue. The range of image matrices value before applying the normalization was [0 255] and it was normalized to the range of [0 1].

D) Binarization

Conversion to gray scale images of the RGB images supports the production of binary images for the sake of extraction of morphological features. The result of the thresholded image is a binarized image, which is an image whose pixel values are changed into zero (black) and one (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. Histogram thresholding technique was applied for the sake of segmenting the images with the constituents partitioned into homogenous attributes by using ImageJ. The upper and lower limits of thresholding used were 0 and 215, respectively. After Binarization, binary images which is also the products of tresholded gray scale image was used for the purpose of extracting morphological features of respective coffee beans images.

Some coffee beans on many of the produced binary images were seen to contain holes which is the result of defects on the surface of the coffee and due to over drying of the coffee beans in the coffee processing phase by using ImageJ. These holes affect the computation of some features like coffee bean area, which might affect the performance of the next process, feature extraction.

After the enhancement of the image and Binarization, images were segmented by using histogram based thresholding technique

3.4. Coffee beans image analysis

After images were preprocessed, quality enhanced coffee bean images were produced, which were ready for further analysis and interpretation. Since the aim of capturing images was interpreting those images and recognizing the cluster under which it can be categorized, analysis of the images was take place. Image analysis includes two main tasks [18]: Segmentation and feature extraction. They were performed for the purpose of generating statistical data from image data. Below they are discussed with their respective result.

3.4.1Coffee beans Image Segmentation

After image preprocessing employed, image segmentation is the very crucial part that should be dealt to extract good quality features for classifying images based on values of parameters. The main goal of image segmentation is clustering pixel of the image having same intensity value from the whole image regions, separate region or object of desired part of the original image, hiding the undesired region or objects.

Coffee bean images segmentation process has been done accurately for the analysis task. Various techniques have been discussed in literature that could play a role to segment coffee bean image. Among these, here used is histogram-based thresholding based on the performance and quality in determining region of interest.

3.4.1.1. Histogram-based thresholding segmentation algorithm

Thresholding is the simplest method of image segmentation. From a grayscale image (8-bit), thresholding was used to create binary images [36]. Histograms are constructed by splitting the range of the data into equal-sized bins which is called classes. Then for each bin, the numbers of points from the data set that fall into each bin are counted. Thresholdingsupposes that the gray-level histogram corresponds to an image, f(x, y), composed of dark objects in a light background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way used to extract the objects from the background is selecting a threshold 'T' that separates these modes. Then any point (x, y) for which f(x, y) > T is considered as an object point and the other point is considered as a background point [22]. The below set of steps were applied on coffee bean images to segment by using histogram based thresholding [36].

1) Select an initial estimate for T.
2) Segment the image using T. This produce two groups of pixels. G_1 consisting of all pixels with gray level values >T and G_2 consisting of pixels with values <=T.

3) Compute the average gray level values mean1 and mean2 for the pixels in regions G1 and G2.
4) Compute a new threshold value T=(1/2)(mean1 +mean2)

3.4.1.2. Edge detection segmentation algorithm

Edge detection is an image processing technique for finding the boundaries of objects within images [37]. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. Common edge detection algorithms include Sobel, Canny, Prewitt, Roberts, and fuzzy logic methods. Sobel was tested and discussed in this study.

Sobel Operator

The Sobel operator is used for edge detection in this study, and it is technically a discrete differential operator used to calculate the approximation of the gradient of the image luminance function. The Sobel operator is a typical edge detection operator based on the first derivative. As a result of the operator a similar local average operation, so the noise has a smooth effect, and effectively eliminates the impact of noise of coffee bean images. The influence of the Sobel operator on the position of the pixel is weighted, which is better than the Prewitt operator and the Roberts operator. The Sobel operator consists of two sets of 3x3 matrices, which are transverse and longitudinal templates, and are plotted with the image plane, respectively, to obtain the difference between the horizontal and the longitudinal difference in image segmentation [40].

- **Algorithm and its description**

It works by calculating the gradient of image intensity at each pixel within the coffee bean image. It finds the direction of the largest increase from light to dark and the rate of change in that direction. The result shows how abruptly or smoothly the image changes at each pixel, and therefore how likely it is that that pixel represents an edge of coffee bean. It also shows how that edge is likely to be oriented. The result of applying the filter to a pixel in a region of constant intensity is a zero vector. The result of applying it to a pixel on an edge is a vector that points across the edge from darker to brighter values [37].

It was concluded that, thresholding is an important part of image segmentation to create binary images. Binary image analysis is useful for image feature extraction. It simplifies the computation of geometrical features of an image. In this study, histogram-based image thresholding and edge detection are used as they are simple and computationally inexpensive. But since it is easy histogram based thresholding is selected in this study by researcher. The segmented image is ready for extracting features. This task of segmenting background from foreground was done by ImageJ.

3.4.2 Coffee beans image feature extraction

Extraction of a meaningful set of empirical information and data of coffee beans parameters from the pre-processed images is the very essential task to model computer-assisted coffee bean raw quality value computation tasks. The collections of extracted attributes represent a particular feature, and a vector of such a feature is called a pattern [18]. Features are used as inputs to the algorithms for classifying and ranking the objects into different classes or categories. Pattern recognition can be done by analyzing the morphology, color, texture (spatial distribution of color), or a combination of these features of the images.

Particle analyzer method of ImageJ was used to extract morphological and color features of the sample coffee beans from the previously processed and analyzed binary and thresholded images. ImageJ conducts the calculation of the features for each coffee bean from the region of interest within the concern image by giving a unique label for each bean. A total of 145 images of coffee beans were used for the extraction of features.

3.4.2.1Morphological Feature

Morphology is the geometric of images [19]. Shape features are physical dimensional measures that characterize the appearance of an object. Area, perimeter, major and minor axes lengths, and aspect ratio are some of the most commonly measured morphological features. Morphological features are widely used in automated scaling/ranking, sorting and detection of objects in industry. Morphological dataset were obtained from the analysis of binarized images.

Here is provided a description of the morphological features extracted from each coffee bean images [19].

Area: It is the number of pixels inside the region covered coffee beans image, including the boundary region. Area A is measured in square pixels (see equation 3.1), where r is the radius [15].

$$\boldsymbol{A = \pi r^2} \ldots\ldots\ldots\ldots \textbf{(3.1)}$$

Perimeter (P): The perimeter P is the mathematical sum of the Euclidean distances between all the successive pairs of pixels around the circumference of the kernel [27].

$$\mathrm{P} = 2\mathrm{L} + 2\mathrm{W} \ldots\ldots\ldots\ldots \textbf{(3.2)}$$

Length/height: It is the length of the smallest rectangle enclosing a coffee bean [19].

Width: It is the width of the smallest rectangle enclosing a coffee bean [19].

Major Axis Length (Major): It is the distance between the end points of the longest line that could be drawn through the coffee bean region. The major axis end points are found by computing the pixel distance between every combination of border pixels in coffee bean boundary and finding the pair with the maximum length [27].

$$Major\ axis = (a + b) \ldots\ldots\ldots\ldots \textbf{(3.3)}$$

Where a,b are the distance from each focus to any point on the coffee bean

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 [27].

$$Minor\ axis = \sqrt{(a + b)^2 - f^2} \ldots\ldots\ldots\ldots \textbf{(3.4)}$$

Where f is the distance between foci, and a, b are the distance from each focus to any point on the coffee bean

Feret Diameter (FD) – This is the diameter of a circle having the same area as the object and is computed as [27]:

$$FD= [(4A)/\pi]^{1/2} \quad \textbf{(3.5)}$$

Aspect Ratio (AR) (Elongation) – The elongation ratio of the length of the minor axis to the length of the major axis. This is given as [27]:

$$AR = MA/MI \quad \textbf{(3.6)}$$

Circularity (Cr) –circularity is a measure of shape compactness. This morphological attribute of the coffee beans is given by [27]:

$$Cr = (4\pi A)/P^2 \quad \textbf{(3.7)}$$

Roundness (R) –is the measure of how closely the shape of an object approaches. **It** is dominated by the shape's gross features rather than the definition of its edges and corners, or the surface roughness of an image object. This attribute is described as [27]:

$$R = \frac{4A}{\pi MA2} \quad \textbf{(3.8)}$$

3.4.2.2. Color features

Color is an important and the most straight-forward feature that humans perceive when viewing an image. Since human vision system is more sensitive to RGB color information, color is the main parameter used for feature extraction. The most commonly used color feature model in image processing is based on the primary spectral components of red (R), green (G) and blue (B). Color features of an object are extracted by examining the R, G and B levels of each pixel within the object's boundary. The histogram of these pixels shows the brightness distribution found in the object.

The three common perceptual descriptors of a light sensation in relation with RGB color are Brightness (B), Saturation (S) and Hue (H). The color features are extracted by computing the mean values of RGBs and HSBs of coffee bean images. Computation of the mean values for each component of these color spaces needs to split each component to separate image stacks. The

RGB and HSB stack splitting assignments were done with the respective RGB and HSB stack splitting features of ImageJ.

$$R = \frac{R}{R+G+B}\ , G = R = \frac{G}{R+G+B}\ , B = \frac{B}{R+G+B}\ldots\ldots\ldots\ldots\ldots \quad (3.9)$$

$$H = arccos\{\frac{[(R-G)+(R-B)/2]}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\}\ldots\ldots\ldots\ldots\ldots \quad (3.10)$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R, G, B)]\ldots\ldots\ldots\ldots\ldots \quad (3.11)$$

$$B = \frac{1}{3}(R + G + B)\ldots\ldots\ldots\ldots\ldots \quad (3.12)$$

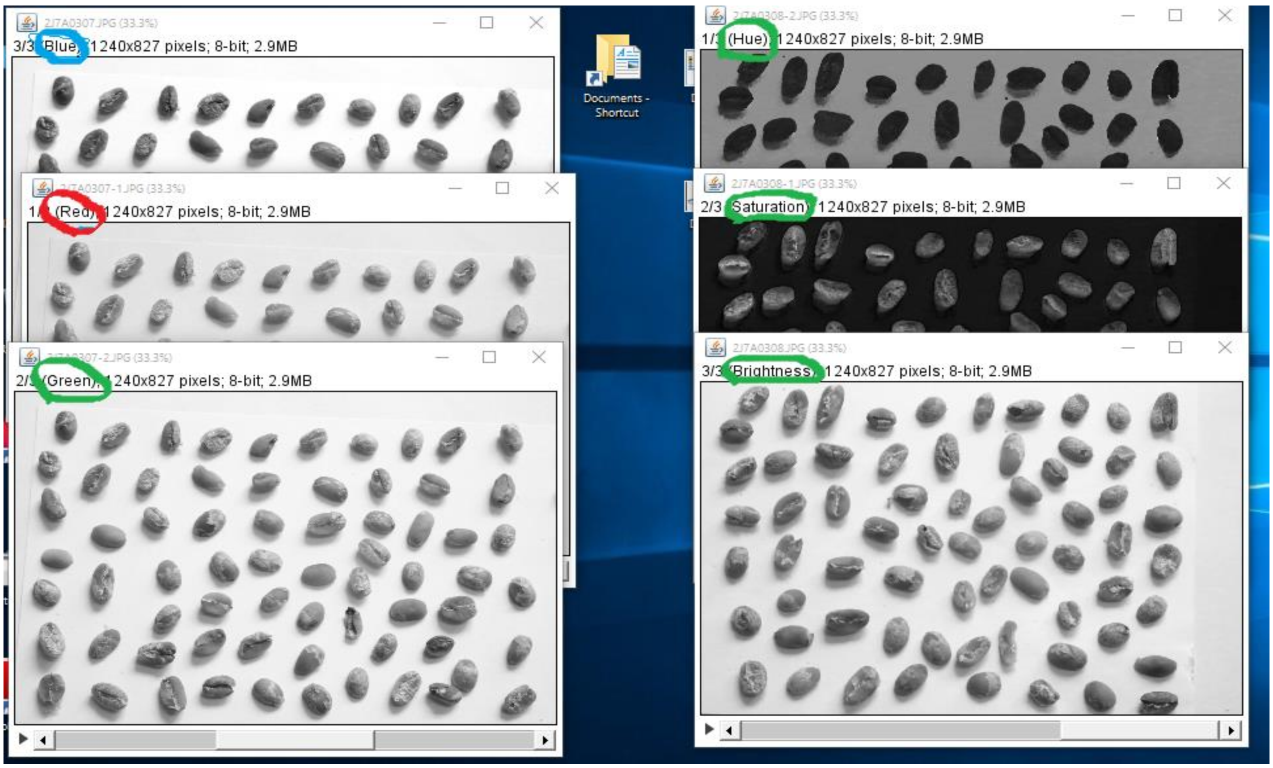

Figure 3.3: RGB stacks and HSB stacks

3.4.2.3 Aggregated features

Aggregated features are combined attributes of morphological and color features: Morphological and color features of coffee bean were merged together after generating them separately. Features were combined by taking first morphology followed by color and taking first color followed by morphological features. The way the features were combined didn't matter on the performance of the scaling under this study. So, first taking morphology followed by color is selected in feature selection under this study.

3.5. Coffee beans image raw quality classification model.

Image classification is a final stage in computer vision system where each unknown new patterns is assigned to a category. Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest, make sound and reasonable decision about the categories of the patterns [18].

The final task of classification model is the selection of pattern classifier or recognizer. A pattern recognizer is a technique that is used to train, test and analyze a problem based on the training and testing model of the classification algorithm. The classification problem that needed to address provides complete information about the number of grades and their labels. Hence it is supervised. The three classifiers selected for the purpose of this study are K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Artificial Neural Network (ANN) classifiers.

The main reasons for using these algorithms were their natural compatibility with homogenous data and many scholars recommended the use of these algorithms for agricultural product classification. Combined attributes of morphological and color features were used as input patterns to build the models. Selection of a set of appropriate input feature variables is an important issue while trying to develop classification models by employing the most appropriate respective classifiers. The purpose of feature variable selection is to find the smallest set of features that can result in satisfactory model performance.

About 80% of the dataset was assigned to the training set and 20% to the test set. Training data is the portion of the data employed to actually train the network. This is normally the largest portion of the data. Test data was used to validate the results of a trained network by using new unknown data coffee bean images. The analytical computations of coffee bean feature attributes are conducted using classification algorithms from the training set which is iteratively evaluated to build the model. This will finally generate the classifier model after being evaluated for its performance with the predefined test set.

Artificial Neural Network (ANN) classifier

An artificial neural network (ANN) is a widely used classification algorithm which produces an effective computer-supported raw quality value classification model. There are essential importance behind employing ANN classifier that makes it powerful analytical tools. Those importance are flexible learning algorithm, diverse network topology, fast learning capability and high error tolerance. Matlab R2018a which is latest version software tool assists this artificial neural network classification task, with the dataset modified to Matlab format.

Statistical raw quality values extracted from coffee beans is converted to nominal scale which made possible raw quality values as first rank (Grade I), second rank (Grade II), third rank (Grade III) and fourth rank (Grade IV), representing the data preparation approach for the model. These nominal values were used as an output column label name in the excel spreadsheet together with the associated input attribute values. The values for these nominal raw quality value output columns was then filled with the use of binary numbers, reflecting the presence or absence of the specific nominal value that represents the specific set of record in the actual dataset.

A supervised feed forward multiple layer preceptors (MLP), a universal pattern classifier allowing the discriminant functions to take any shape, assisted to model the classifier with 2 hidden layers. Back propagation learning rule was incorporated to calculate the shares of the errors in model building and to modify connection weight. MLP is also suitable as the desired response of the outputs is known beforehand. It is one of the most commonly implemented neural network topologies.

The trained results are automatically tested for the neural networks, providing a summary of the network performances in the model as an output. The training and testing simulations in this classifier focus on confusion matrices, percent correct and performance matrices.

Support Vector Machine (SVM) Classifier

Support vector machine (SVM) is a supervised machine learning suitable algorithm which can be used for classification challenges. For this study SVM which was mostly used in classification problems is selected for better accuracy than the other classifiers based on scholar's recommendation. It can used be to find optimal hyper plane to separate different categories of input data into higher dimension features space. And also SVM has advantage of fast training techniques, even with large number of input data. In these algorithms, the plot each data item as a point in n-dimensional space (where n is number of features used) with the value of each features (attributes) being the value of a particular coordinate. SVM classifier is used on Matlab R2018a to categorize coffee bean based on the quality required from it.

K-Nearest Neighbor (KNN) classifier

K-nearest neighbors is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure. KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970's as a non-parametric technique.

A promising approach toward image content recognition is the use of classification techniques to associate images with classes according to their features value. KNN classification algorithms decide about the class of an image by searching for the K images of the training set most similar to the image to be classified, and by performing a class weighted frequency analysis. The k closest images are identified relying upon a similarity measure between images. As an alternative approach, in this study a new KNN based classification method relying on images represented by means of local features generated over interest points were proposed. With the use of local features and interest points, KNN classification algorithms were revised to consider similarity between local features of the images in the training set rather than similarity between images, opening up new opportunities to investigate more efficient and effective strategies. In fact, direct use of similarity between local features is generally easier to be handled than sets of local features.

In addition, it has been seen that classifying at the level of local features can exploit global information contained in the training set, which cannot be used when classifying only at the level of entire images. In this study, it was studied the effect of local feature cleaning strategies and perform several experiments by testing the proposed approach with different types of image features. In pattern recognition, the K-Nearest Neighbor algorithm (KNN) is a non-parametric method used for classification of coffee beans.

To combat the limitations of traditional K-NN, a novel method to improve the classification performance of K-NN using Genetic Algorithm (GA) is proposed in this study. The proposed G-KNN classifier is applied for classification and similar k-neighbors are chosen at each iterations for classification by using GA, the test samples are classified with these neighbors and the accuracy is calculated for different number of K values to obtain high accuracy; hence the computation time of K-NN is reduced from the obtained results in this method. The MATLAB image processing toolbox based implementation is done on the coffee bean images and the classifications of these images are carried out. The k value, execution time and accuracy is calculated and tabulated.

The image classification model has three main components. They are representation of image features, learning and testing process for classifying using these representations and the classifier/ recognizer. A classifier or recognizer is a program that takes input feature vectors and assigns it to one of a set of designated classes.

3.6. Evaluation methods

Evaluation of the model was performed by using test set, which is taken20% of the total dataset in the corpus. The evaluation metrics was accuracy rate. Accuracy is the most intuitive performance measures and it is simply a ratio of correctly classified observation to the total observation. High accuracy rate show better model performance. Experts were also selected from the center in order to evaluate user acceptance performance of the model. Five experts were selected purposively and their acceptance rate was analyzed.

$$\text{Accuracy} = \frac{no\ of\ coffee\ beans\ correctly\ classified}{total\ number\ of\ dataset\ for\ testing} * 100 \ldots\ldots \textbf{(3.13)}$$

CHAPTER FOUR

EXPERIMENTATION AND DISCUSSION OF RESULT

4.1. Overview

Scaling is the process of classifying coffee beans based on the given parameters value scored by each coffee beans sample. So, classification is concerned with constructing a model that can be used for identifying the whereaboutness each new item on the basis of the observed attributes or features.

In this study, image processing technology is employed to recognize the raw quality value of Ethiopian coffee by characterizing and formulating distinct pre-defined classes that served as the basis for assigning the new sample beans into their respective classes. The pre-defined classes depend on the values of the morphological, color and textural features computed from coffee bean images. The captured and acquired images for the purpose of this research were pre-processed for noise reduction and image enhancement in order to improve the quality of coffee bean images for accurate use in extracting the necessary features using image analysis and processing techniques.

Coffee bean images that passed through image preprocessing techniques were used in the training phase. In addition to image preprocessing coffee bean images were segmented using histogram based thresholding methods of image segmentation to identify the region of interest (ROI). After identifying the region of interest in the coffee bean images, useful features were extracted in order to reduce the complexity of the computational cost of the model. Sixteen different features, ten morphological and six color features were extracted for training the classification model.

Necessary statistical computations of each coffee beans parameters and features were done to generate simplified and representative data, which support researcher for further development of the final quality determination model. Appropriate classification techniques were applied to differentiate a given coffee bean sample to the appropriate category using the generated data from image as input. The below Figure 4.1shows the various procedures passed to develop a simulation model that support the determination of raw quality value.

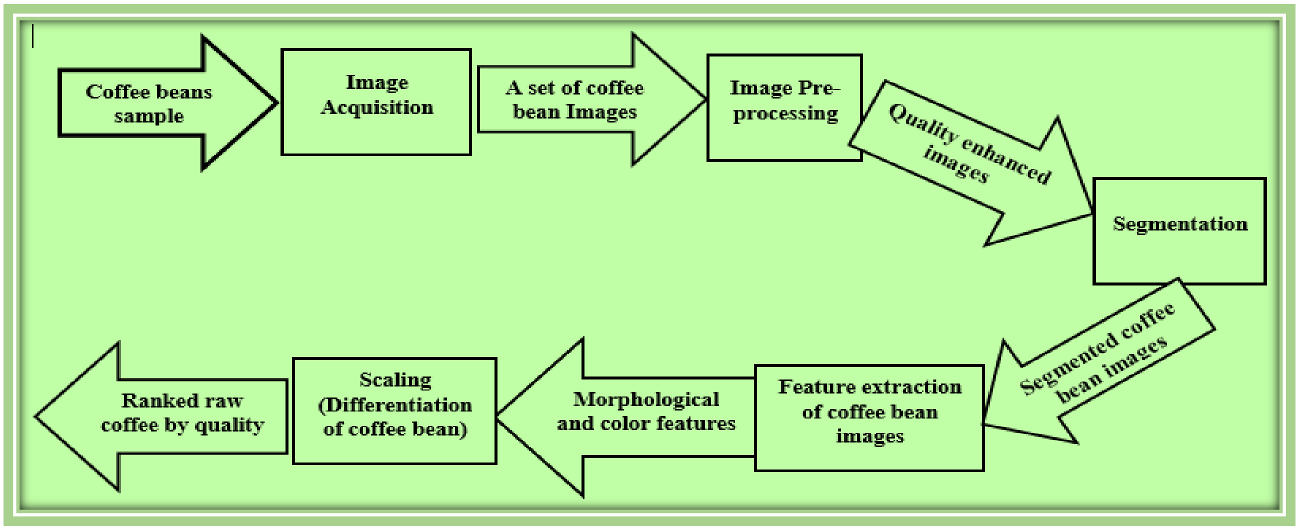

Figure 4.1: Coffee bean raw quality value scaling process

4.2Coffee beans feature representation

Features or attributes are values measured from coffee bean images. The features of coffee bean images generated are morphological features and color features. It has been identified ten morphological features and six color features for the classification of Ethiopian coffee beans based on their parametric value. There are four categories or classes of coffee, which are Grade I, Grade II, Grade III, Grade IV. The tabular representation of features or attributes was shown in Table 4.1below.

Table 4.1: Parametric feature representation

no	Perimeter	length	Area	Major	Minor	..	E(R)	E(G)	E(B)	E(H)	E(S)		class
1							Training……80% of X						Rank 1
2													Rank 2
3													
…							Testing……20% of X						?????
x													

As indicated in Table 4.1, the feature values of each coffee bean image in the sample data sets are computed. In the training process the class values was provided because supervised learning was used. In order to test the classification accuracy of the system, feature datasets that are not in the training data set was used. In the classification process, the total dataset is partitioned to 80% for training and 20 % for testing.

The class labels corresponding to names of the grade of a coffee are categorical data. Hence, we represent these values by using binary numbers to simplify the representation that is appropriate to the pattern classifier program.

Input matrix **Output matrix**

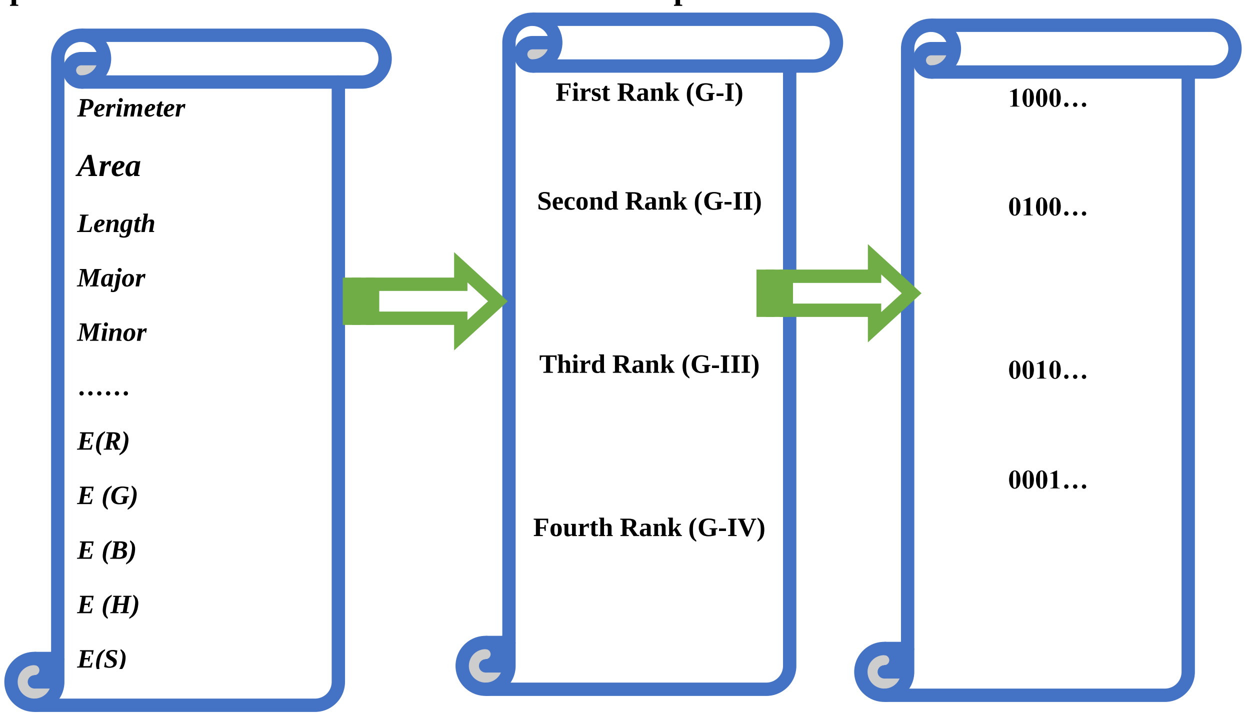

Figure 4.2: Vector representation of input and output features

As indicated in Figure 4.2, the output vectors which are classes has been represented by using the binary numbers 0 and 1. Since there are four classes that correspond to the predefined rank of coffee beans, there should be 4 bit binary numbers. Each bit refers whether that feature belongs to a rank represented at that bit position. As shown in Figure 4.2, first, second, third and fourth bit represent First Rank (G-I), Second Rank (G-II), Third Rank (G-III) and Fourth Rank (G-IV) 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 dataset 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.

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. Training and testing process has been described separately. Training process trains the model by feeding the data for each cluster. The training process is shown in Figure 4.3.

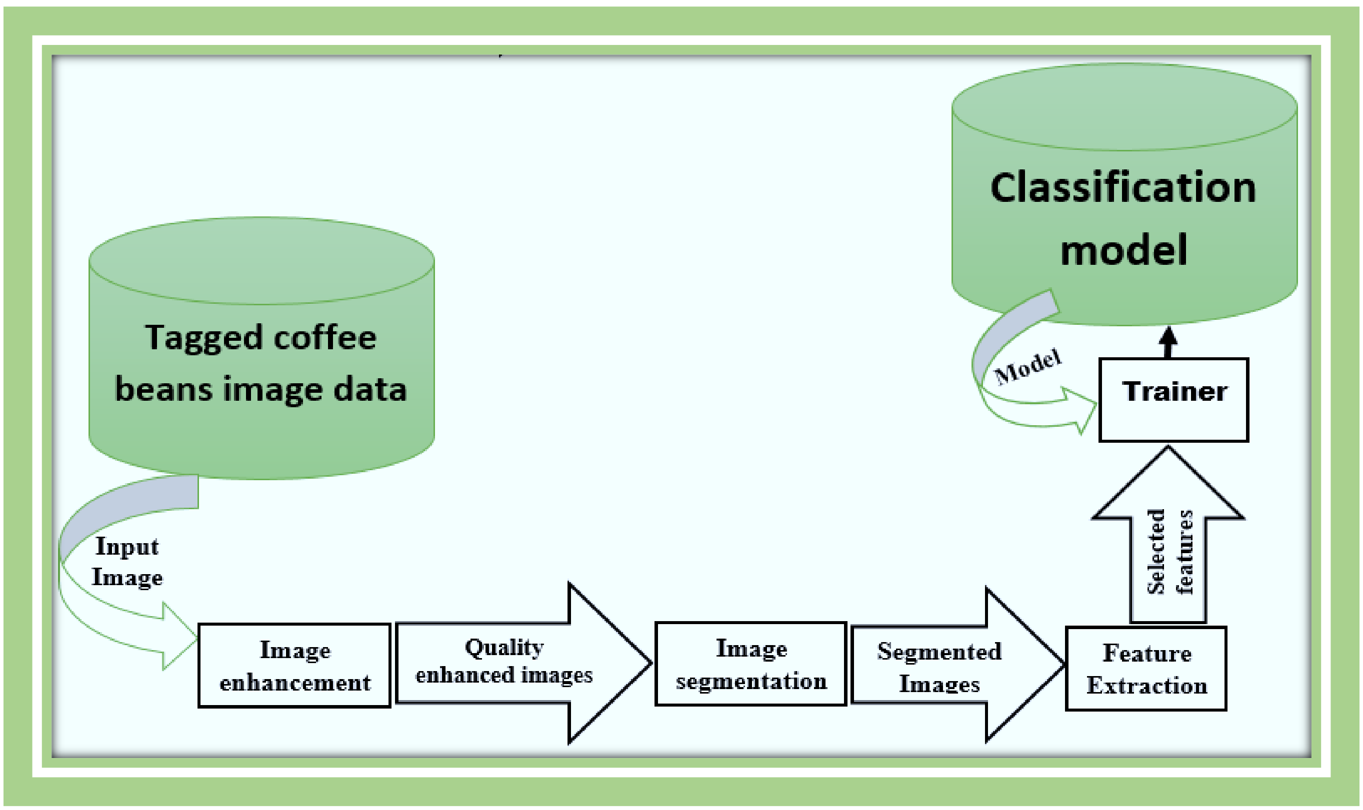

Figure 4.3. The training process

As indicated in Figure 4.3 to classify a coffee bean image, first each coffee bean image is taken from a particular rank and labeled with the name of its grade. For example, coffee considered as first grade is tagged as first grade category or class. Therefore, imaged data to be analyzed have been tagged. Then, features are extracted from tagged images by using image analysis as described in the previous section. In relation with the extracted features, then select features that are used as input to the pattern recognizer and then the model is trained by the classifier from the developed model.

The process finally generate a model which is the primary input for any decision making process at testing phase. The model should be used to test the accuracy of the classifier. The testing process of grading coffee is shown below in figure 4.4.

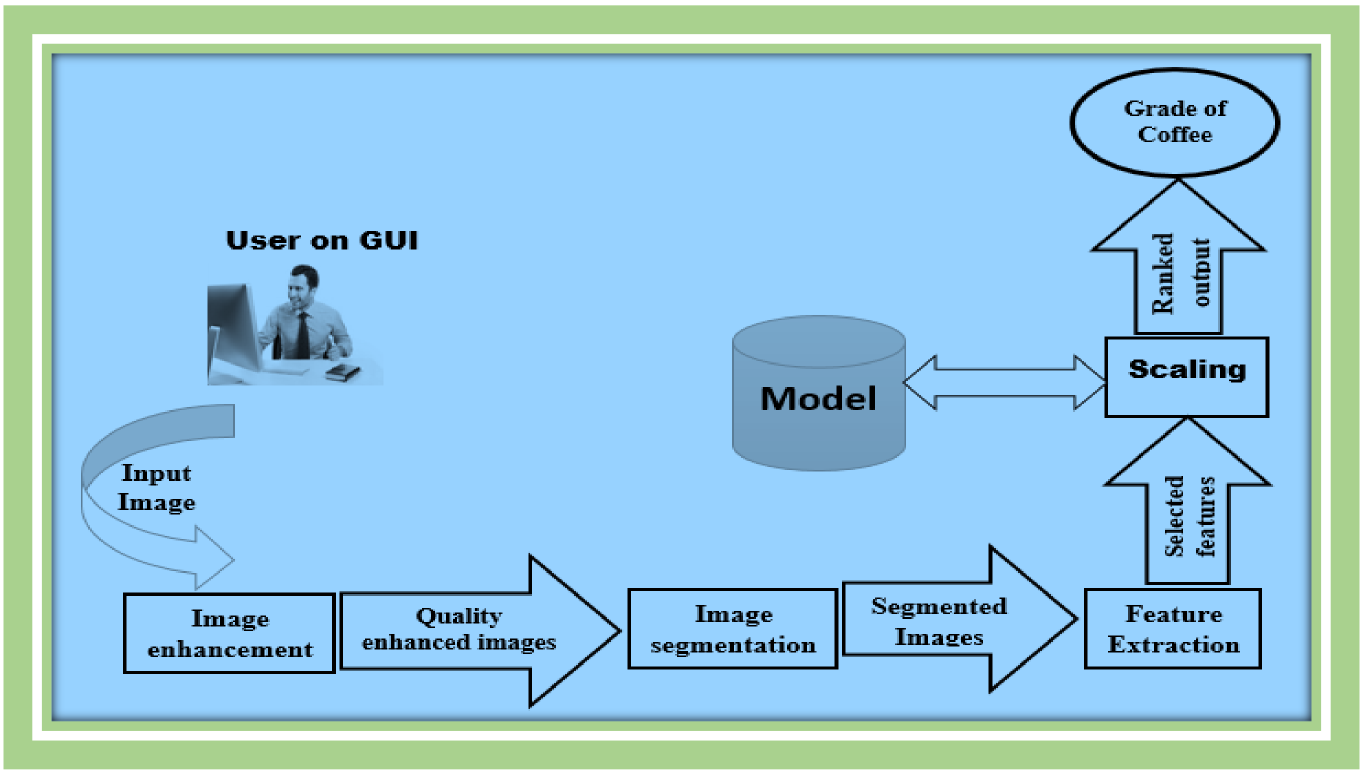

Figure 4.4: The testing process

As described in Figure 4.4, an image of coffee bean that is not in the training dataset is used in the testing process. The feature extraction and selection of the testing process was done in the same way as the feature selection and extraction of the training process. The selected features from the test image were used as input to grade coffee. It is the task of the classifier to compare and identify the class or category of the coffee bean image by consulting the model developed in the training process.

4.3. Model development environment

The development of coffee bean raw quality classification by using image analysis techniques needs a lot of effort to invest. Starting from image acquisition, it needs high quality digital camera, and well established and controlled environment to acquire images. In addition to this, image preprocessing techniques were resource intensive. They need powerful computers with high resolution processing speed, larger memory and disk capacity. The model was developed and tested on a PC of processor is Intel® core™i5-4200U CPU with 2.30GHz speed, memory (RAM) is 4.00GB of hard Disk capacity, with 64 bit Microsoft Windows 8.1 operating system.

Beneficiaries of the model especially experts working on scaling of coffee raw quality value expect models which must have precise structural and behavioral abstractions in order to be correctly rank the product. The developed prototype as per requirement proposed in objective of this research, scaling and determination of the raw quality values of unknown new coffee bean samples on the basis of an automated learning model, was tried to be achieved by utilizing the approaches, procedures and tools that have been mentioned in the design part of this study. The results of the model developed were somehow different depending on the types of the classifier employed. On this basis, performance of each classifier was analyzed on numerous methods to make decisions on the best practicable and applicable algorithms.

4.4 Image preprocessing results

Image preprocessing is the operation with images at the lowest level of abstraction in which both input and outputs are intensity images usually represented by a matrix of image function values (brightness). Gaussian filter, a nonlinear digital filtering technique was used to remove noise information from images. Gaussian filtering was widely used in digital image preprocessing because, under certain condition, it preserves edges while removing noise.

The images were further pre-processed by ImageJ tool and Matlab R2018a programming language to enhance the retrieval of accurate information. ImageJ is used for image processing, image segmentation and feature extraction.

The first tasks were subtracting background from the images to avoid blurs, light distortions and other noises that could be formed due to light effects during image capture and some external objects on the background. After background subtraction, conversion of the RGB images to 8-bit gray scale image and histogram thresholding for the purpose of extracting morphological and color features from the thresholded original images were done by ImageJ. Conversion to gray scale images of the RGB images supports the production of binary images which help extraction of morphological features. During image preprocessing the results of the below four discussed techniques were used in this study; filtering, resolution enhancement, normalization and Binarization.

A) <u>Image filtering algorithms and its results</u>

Filtering was performed by using Gaussian blur filtering algorithm and median filtering so as to detect noises from the images. Gaussian blur filtering algorithm reduces noises from image in a linear manner. ImageJ also used for noise removal and hole filling in the image. Unclear backgrounds of the coffee bean images resulting from inconsistent image acquisition environment could be the causes for these.

Gaussian filtering algorithm produces better quality coffee bean images compared to median filtering. Their results were evaluated by using peak signal –to-noise ratio (PSNR) and mean square error (MSE). PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image. The mean-square error (MSE) and the peak signal-to-noise ratio (PSNR) are used to compare image compression quality. The comparison result of PSNR and MSE of two filtering algorithms are show in below table 4.2. The below figure 4.5 and figure 4.6 show the result produced by two filtering algorithms. Gaussian blur filtering which is used to reverse the effects of blurring on a particular picture yields better performance over median. In the below Table, PSNR and MSE results are displayed.

Table 4.2: Comparison of PSNR AND MSE values for noises

	Average value of PSNR	Average value of MSE
Gaussian Filtering	35.0435	6.5780
Median Filtering	32.4874	4.0923

The advantage of Gaussian filtering over median filtering in this study is that it's faster and accurate because multiplying and adding is probably faster than sorting

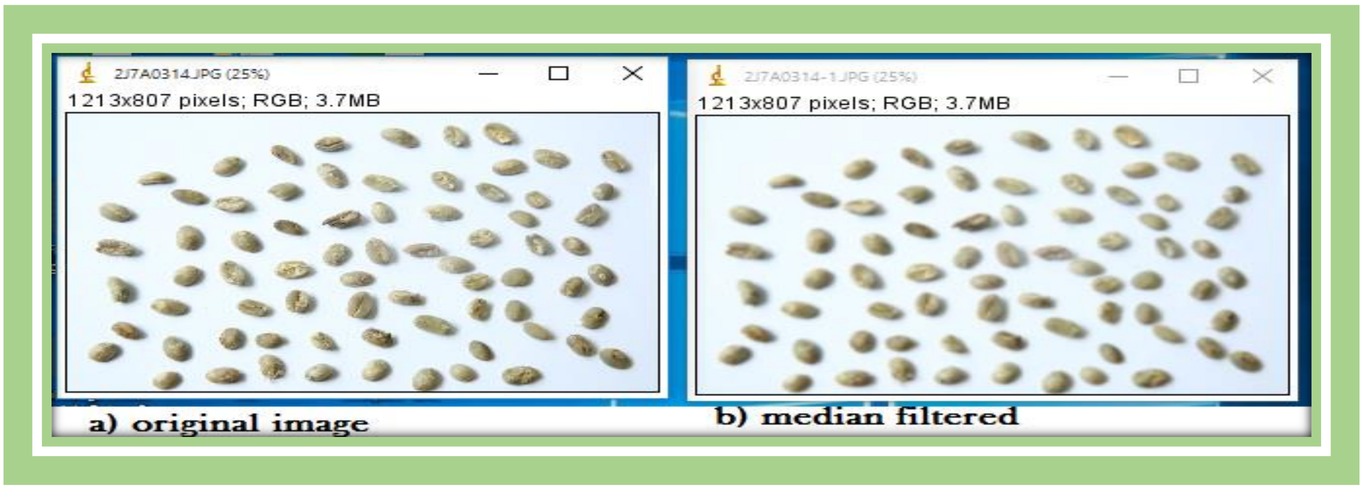

Figure 4.5: Coffee bean image, (a) Original image and (b) after applying median filtering algorithm

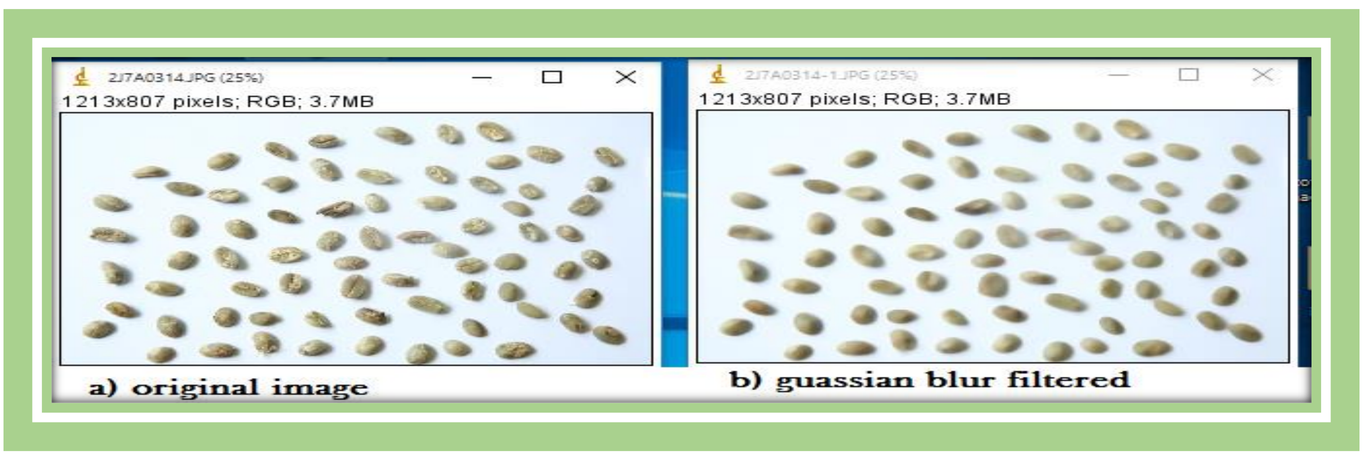

Figure 4.6: Coffee bean image, (a) Original image and (b) after applying Gaussian blur filtering algorithm

4.5. Image analysis results

Image analysis involves investigation of the image data specific to classify coffee beans in to its appropriate class. Normally, the raw data of a set of images is analyzed how they can be used to extract desired information from coffee bean images. In image processing and pattern recognition, feature extraction analysis is an important step, which is a special form of dimensionality reduction. ImageJ program performed a great task of image processing, analysis and feature extraction activities of all the captured coffee bean images. Enhanced and segmented coffee bean images were outputs of the research, whereby same were used as inputs for the succeeding phase of feature extraction in the program.

4.5.1 Segmenting coffee bean images

After applying image preprocessing and segmentation, various image processing algorithms and tools were employed for extraction of coffee bean features from a given sample of coffee bean image. Image segmentation was done to separate each coffee bean images from the background by using thresholdingtechniques. It was concluded that, thresholding is an important part of image segmentation to create binary images. Binary image analysis is useful for image feature extraction. It simplifies the computation of geometrical features of an image. In this study, histogram-based image thresholding and edge detection are used as they are simple and computationally inexpensive.

But since it is easy and yields better binarized images, histogram based thresholding is selected in this study by researcher. The selection was made based on visual inspection from the two generated images by segmentation. The segmented image is ready for extracting features. This task of segmenting background from foreground was done by ImageJ.

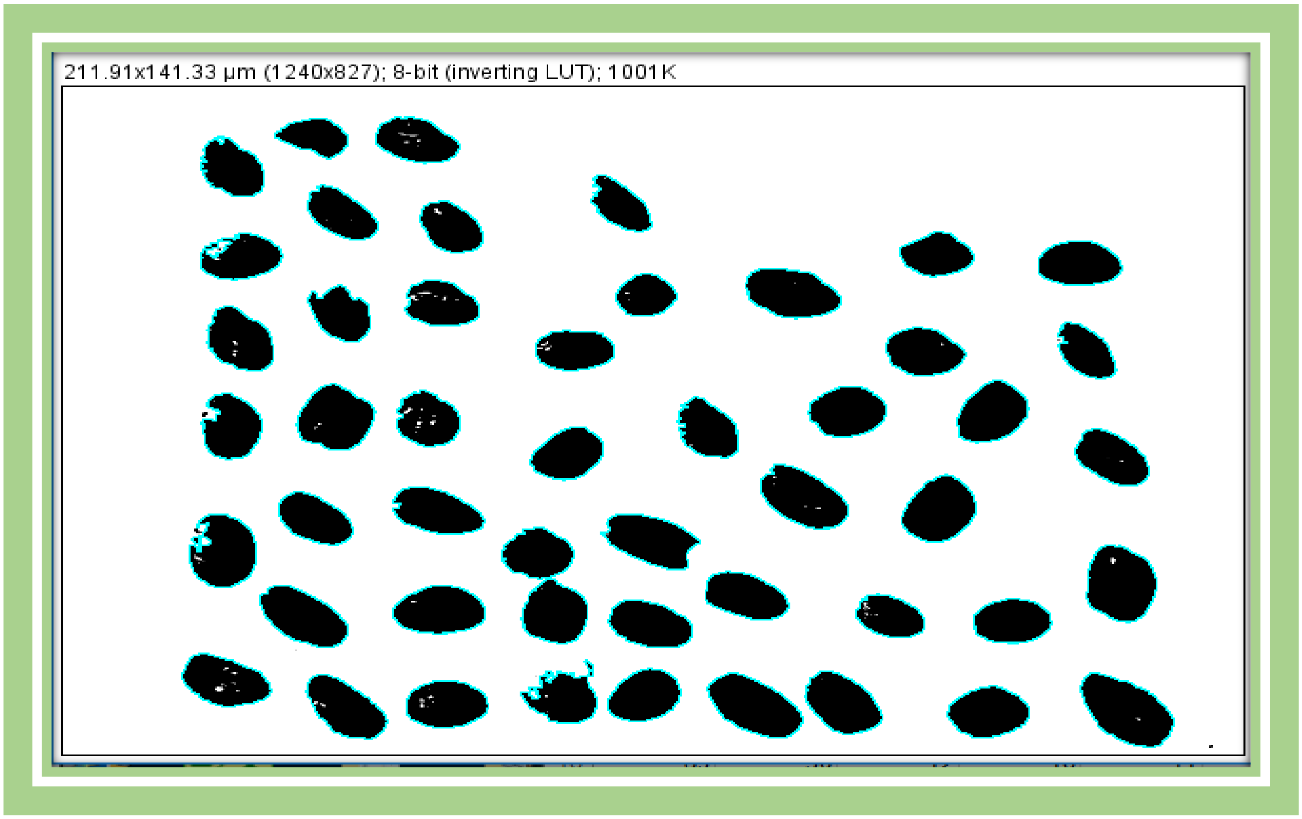

Figure 4.7: Segmentation using Histogram based thresholding

The developed output from such image enhancement, segmentation and advanced enhancement of all the coffee bean sample images is represented below in figure4.8.

Computations of morphological features requires image enhancement and segmentation procedures as the extraction of color features was performed by conducting background subtraction and image thresholding. Application and manipulation of the images by minimizing noises from the background and by improving the clarity of the images made easy the acquisition of necessary features of the captured images for further modeling and evaluation using imaging technologies. Improvement of the clarity and spacing of the beans with respect to the background, meaningfully subdivided individuals with similar attributes and geometrically well represented coffee beans are seen as series of image development procedures as shown below in Figure 4.8.

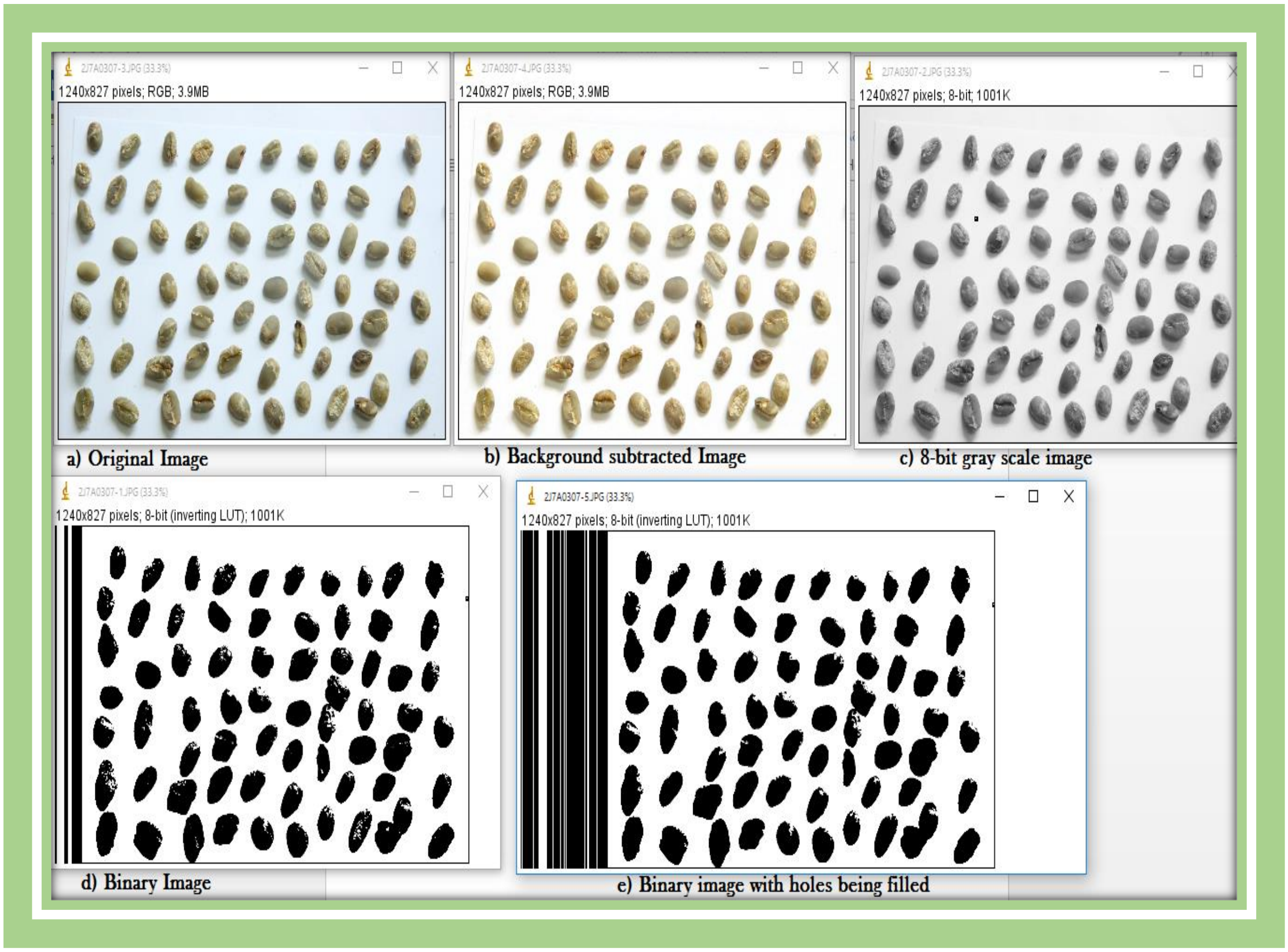

Figure4.8: Sampled preprocessed image; (a) A representation of an original coffee bean image;(b) background subtracted image; (c) converted to gray scale; (d) a binary/segmented image; (e) holes filled image

The HSB color space is widely used to generate high quality of images in computer graphics. It was used to select various different colors needed for identifying particularly coffee bean images. HSBcolor is important for identifying coffee bean objects as it gives the color according to human perception about the object region. Then it was computed and plotted the histogram of each HSB color.

Figure4.9: Converted RGB to HSB color space with Histogram Value

4.6. Extracted coffee bean features for scaling

The output of enhanced images plays a great role in the generation and computation of the important and actual parameter's features of these agricultural products. Morphological and color features of the coffee beans were the focal concern in this research and were extracted accordingly to generate statistical values for raw quality value rank modeling. A sample extracted morphological feature of a coffee bean sample is shown below in figure 4.10.

A statistical variability has been observed between the various values of the coffee bean morphological features, as a result of variability of coffee beans. On the other hand, almost the entire sample beans possess higher similarity for their certain features. Different coffee grades have similar and relatively related morphological values.

Area	Perim.	Width	Height	Major	Minor	Circ.	Feret	AR	Round
90	59	13	10	12	9	0	13	1	1
90	43	12	10	12	10	1	13	1	1
93	40	15	9	15	8	1	15	2	1
75	60	13	9	12	8	0	13	2	1
80	45	14	10	13	8	0	14	2	1
54	43	9	9	9	8	0	10	1	1
86	51	12	11	12	9	0	13	1	1
62	50	11	10	10	8	0	12	1	1
78	51	13	9	12	8	0	13	1	1
101	38	12	12	13	10	1	13	1	1
88	43	11	11	11	10	1	12	1	1
71	51	11	11	10	9	0	11	1	1
68	40	13	10	12	7	1	14	2	1
60	43	10	9	10	8	0	11	1	1
83	36	12	10	11	9	1	12	1	1
59	52	12	10	12	6	0	13	2	1
84	43	12	10	13	8	1	13	1	1
99	39	14	10	14	9	1	14	2	1
13	20	6	5	5	3	0	6	2	1
85	59	15	8	15	7	0	15	2	1
71	41	13	9	12	7	1	13	2	1

Figure 4.10: Sample morphological features of coffee beans

The color attributes of all the sampled items were extracted in a similar manner and made available for further applications. A sample extracted color feature of a coffee bean sample is shown below in figure 4.11.

	RMean	Gmean	Bmean	HMean	Bmean	Smean
2	113	113	119	38	138	76
3	108	105	90	41	141	93
4	112	105	86	41	125	100
5	112	106	94	41	122	83
6	126	124	88	37	133	82
7	109	104	100	39	147	79
8	114	132	95	37	138	72
9	135	113	110	38	136	91
10	114	111	99	39	137	83
11	134	130	88	39	121	84
12	117	115	103	36	141	88
13	127	122	96	42	144	78
14	114	110	96	38	126	65
15	112	110	84	39	123	92
16	132	132	89	42	120	98
17	114	113	112	40	136	66
18	134	131	93	35	156	69
19	125	123	103	40	124	100
20	126	123	102	41	139	89
21	125	123	107	41	127	69
22	117	115	97	39	131	92

Figure 4.11: Sample color features of coffee beans

Aggregated features analysis for scaling model

The combination of morphological and color feature was used for the purpose of training and testing model. Combination of morphological and color features were done by merging their result after generating separately. The below figure 4.12 shows sample aggregated features of Morphological and color features.

	Area	Perim.	Width	Height	Major	Minor	Circ.	Feret	AR	Round	RMean	Gmean
2	90	59	13	10	12	9	0	13	1	1	148	147
3	90	43	12	10	12	10	1	13	1	1	138	138
4	93	40	15	9	15	8	1	15	2	1	137	135
5	75	60	13	9	12	8	0	13	2	1	149	146
6	80	45	14	10	13	8	0	14	2	1	154	153
7	54	43	9	9	9	8	0	10	1	1	148	147
8	86	51	12	11	12	9	0	13	1	1	150	150
9	62	50	11	10	10	8	0	12	1	1	148	146
10	78	51	13	9	12	8	0	13	1	1	143	142
11	101	38	12	12	13	10	1	13	1	1	153	151
12	88	43	11	11	11	10	1	12	1	1	161	158
13	71	51	11	11	10	9	0	11	1	1	149	147
14	68	40	13	10	12	7	1	14	2	1	148	146
15	60	43	10	9	10	8	0	11	1	1	148	146
16	83	36	12	10	11	9	1	12	1	1	144	143
17	59	52	12	10	12	6	0	13	2	1	145	143
18	84	43	12	10	13	8	1	13	1	1	152	151
19	99	39	14	10	14	9	1	14	2	1	127	122
20	13	20	6	5	5	3	0	6	2	1	144	141
21	85	59	15	8	15	7	0	15	2	1	149	148
22	71	41	13	9	12	7	1	13	2	1	152	150

Figure 4.12: Sample of aggregated features

4.7Graphical user interface of the model

A graphical user interface (GUI) is a platform through which users of the model interact with the system which can create interactive communication between a model and a user. GUI has been designed for the user action to display the coffee bean grade determined from statistical data generated and computed by using imaging technology. It helps user of the model to easily deal with the prototype by using graphical options supported by the interface. GUI of coffee bean scaling enhances the usability of the prototype by providing users with a consistent appearance and with intuitive controls like button, boxes, axis, menu and textual information. In this study the researcher created GUI based on user guide who enables to simplify and easily browse image and conduct analysis of the uploaded images which can finally display the scale and quality rank of browsed coffee bean images. The graphical user interface developed is shown below in figure 4.13.

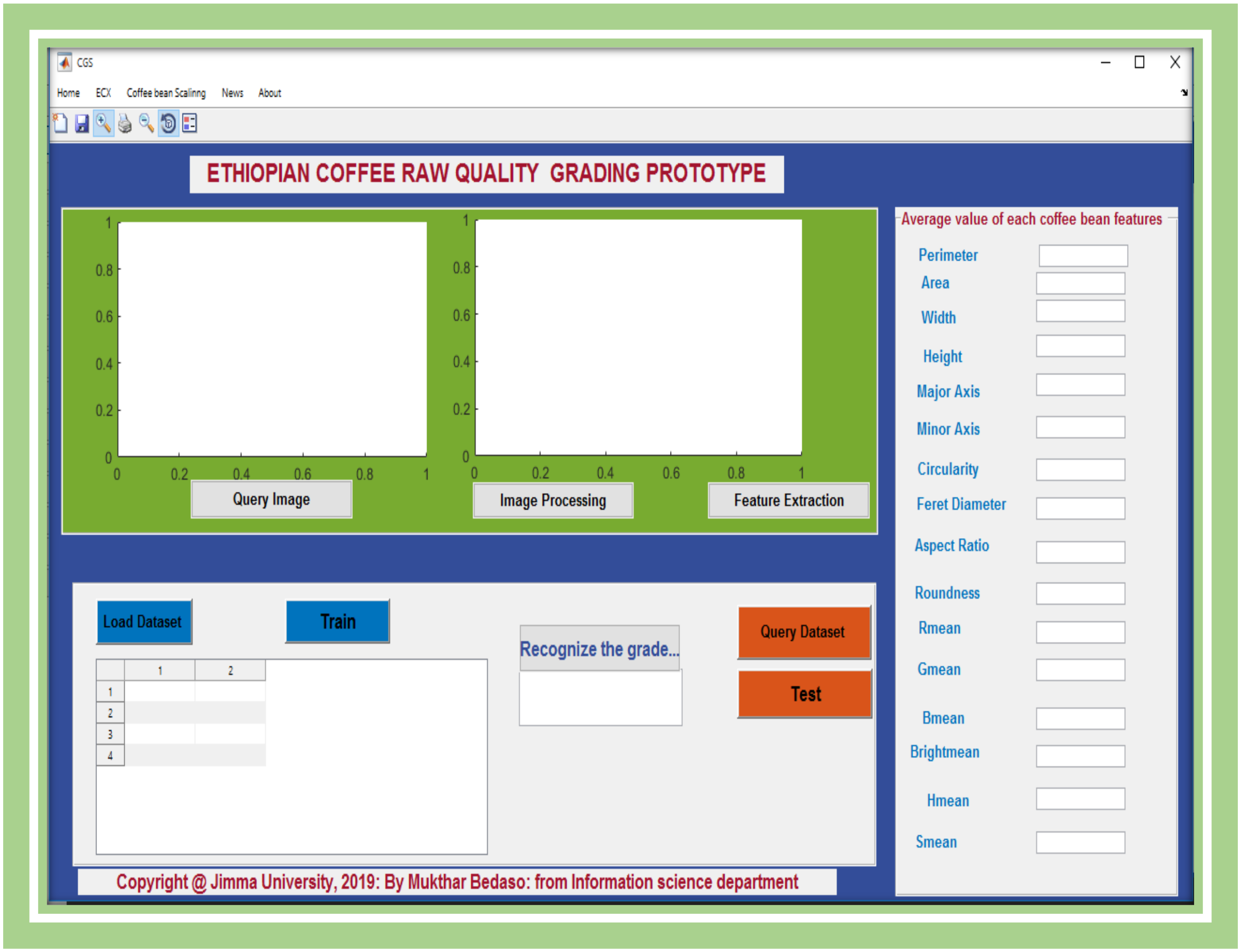

Figure4.13: The graphical user interface

As shown in figure 4.13, there are various tasks that can be performed by the prototype. There are clickable buttons at the right side of the user interface which provide us different options that can be done by the system. In this study there are two main processes which we can call them offline process and online process. Offline processes are option of the system's activities which is done at the back of the system like training the model. The model was trained based on the parametric value of each coffee bean samples provided from the center and extracted by ImageJ. The data images were captured and statistical data of each coffee bean samples were also recorded in to Matlab tool. Model was trained in two ways. The first one is by uploading excel data generated by ImageJ. And the second option is by applying all processing and analyzing of images Matlab could train model. After offline process is accomplished, the online process tests the model by using new unknown coffee bean images provided by users.

The first task that should take place is uploading new unknown images by using button represented by **Query image** or **Query dataset**. After uploading new coffee bean image, all processes could be applied on the image or if it is dataset, extracted features were compared with the trained one. All image processing and analysis is applied on the newly uploaded image by clicking image processing and feature extraction respectively. The displayed result can provide the user a better view about each processed coffee bean images and statistical value of testing image. The other GUI of the system display the grade of coffee bean image being tested by altering the callbacks functions with enough statistical data. The Interface allows to decide the parameters that should be used without rewriting the script and allows fast and efficient scaling and grading of coffee bean sample.

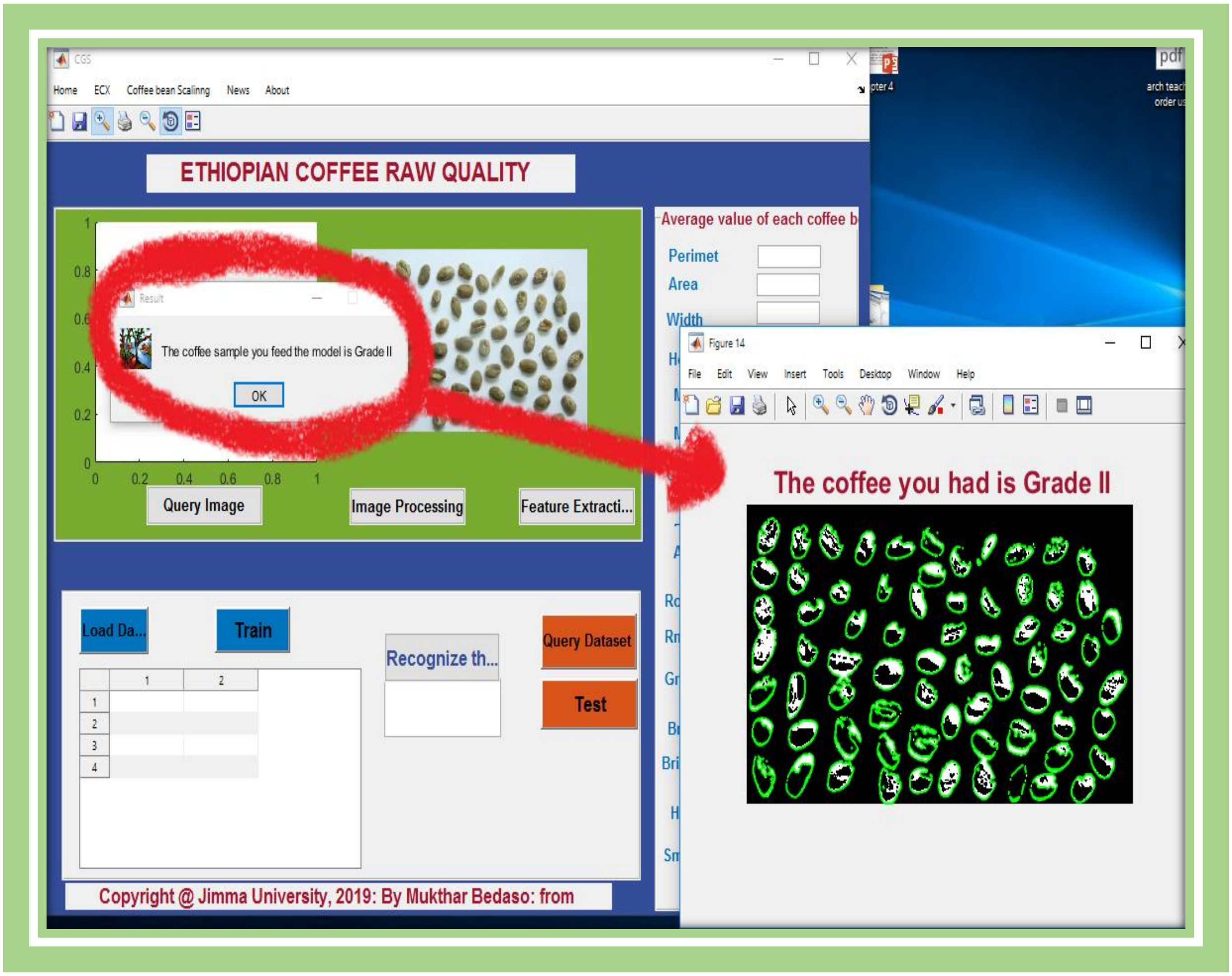

Figure 4.14: The page that show us the final result of tested data image

As indicated on the above figure 4.14, the final result or recognition of coffee bean is displayed and user is informed about the class of coffee sample provided by the model. After all processes are completed final decision by the model would be showed through result informing or message box with the sample of coffee uploaded. Therefore this model can help experts in recognizing the cluster under which coffee bean sample should be categorized.

4.8 Experimentation

For experimentation and constructing classification model Artificial Neural Network classifier, Support Vector Machine and K-Nearest Neighbor classifiers were used. After separately testing morphological features and color features of coffee bean images, a combination of these two features is used in this experimentation. The accuracy and efficiency of models relies on the procedures of setting up the model initialization and parameter value. The overall automated system modeling activity is conducted by using attributes that were either selected by the model itself or by the researcher based on their suitability to the particular model. Experimental result ensures the realization of the developed system architecture. It is an integral part of the development of coffee bean raw quality grading system. Classification was tested by using morphological features, color features and combination of both morphological and color features.

There are two basic phases of classification used in this study. Those are training and testing phases. Data was repeatedly presented to the classifier in the training phase. The trained system is applied to new data to check the performance of the classification in testing phase. Classifier was designed by partitioning the total dataset into training and testing dataset. From the total dataset of each grade, 80% was used for training and 20% was used for testing data. This means that, out of the total10, 000 datasets, 116 images (with 8000 piece of coffee beans) were used for training and 29 images (with 2000 piece of coffee beans) were used for testing.

4.8.1Artificial neural network (ANN) classifier and its output

An artificial neural network is an adaptable classifier that can learn relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data. They are a large set of interconnected neurons, which execute in parallel to perform the task of learning. Artificial neural network (ANN) classifier model was used in this study. Feed forward multilayer perceptron was used in the study. It was used for classification tasks due to its importance in classifying data effectively.

The network was trained to yield output 1000, 0100, 0010, 0001 in the correct class of the output vector for Grade I, Grade II, Grade III and Grade IV respectively. When the network was trained, the neuron number of the input layer depends on the selected features. The neuron numbers of hidden layers were sixteen for the first hidden layer and ten for the second hidden layer neurons. The neuron number of the output layer was four based on the number of coffee bean grade that were proposed for the study. When the network training was finished, the network was tested with 20% of the total dataset. As proposed, Matlab version R2018a software was used as artificial neural network simulation program.

The training and testing of the classification/scaling model using ANN is simulated together by specifying the portion of the training and testing in the coffee bean image dataset. There were four layers in ANN classifier which are an input layer consisting of nodes/parameters for morphological and color features, the two hidden layers, and an output layer nodes representing the nominal values of raw quality value of coffee bean images which are Grade I, Grade II, Grade III, Grade IV.The simulation was conducted on the combined color and morphological features of sample coffee beans. Classifier outputs for the modeling dataset partitions yielded meaningfully lower values of mean square errors and higher values for correlation coefficients. 88.2% of the samples are classified correctly with regard to their real raw quality value group.

4.8.1.1. Using morphological features

In this experimentation, ten morphological features of coffee were used as input to the network and the neuron numbers of the input layer were ten. The output neurons were four that corresponds to four predefined coffee grade considered in this study. The network was trained by 80% of the total dataset and for measuring performance of the trained network, 20% of the total dataset was used.

The confusion matrix of table 4.2 shows that the correctly classified and misclassified instances of each class. The elements of the table show the number sample dataset to test in which the actual class was the row list and predicted class was the column list. The diagonal elements show instances that were correctly classified and the other elements showed misclassified instances in relation to the corresponding row and column labels.

Table 4.3: Confusion matrix of morphological features in ANN

Actual Class / Predicted Class	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**391**	24	0	0
Grade-II	29	**460**	82	18
Grade-III	10	93	**518**	53
Grade-IV	0	14	8	**360**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**90.93%**	**86.62%**	**85.19%**	**83.52**
Correctly classified (Precision)	**94.2%**	**78.2%**	**76.9%**	**94.2%**

As shown in the above table 4.3, the summary result of artificial neural network classifier using morphology feature showed that from the total test of**2000** coffee beans images, **86.45%** were correctly classified and **13.55%** were misclassified. The percentage of recall for each grade was shown in the last row of table 4.3. The recall accuracy performance of Grade I coffee was better than the three other grades (Grade II, Grade III and Grade IV).The result of Artificial Neural Network (ANN) classification using morphology feature showed that the classification recall of Grade I, Grade II, Grade III and Grade IVcoffees were **90.93**%, **86.62**%, **85.19%**% and **83.52**% respectively. The precision of Grade I, Grade II, Grade III and Grade IV coffees were **94.2**%, **78.2**%, **76.9%**% and **94.2**% respectively. Grade I and Grade IV coffees register equal precision, highest performance than other Grades (Grade II and III) which is 94.2%.

Grade I coffee was misclassified to Grade II coffee (6.7%) and Grade II coffee was more misclassified to Grade IIIcoffee (17.5%). This shows that there is strong morphology relationship between Grade II and Grade IIIcoffee beans.Asimilarlook at the morphological feature of these coffee been shows that their relative bigger size from other beans. There is also a misclassification of Grade IIand Grade III coffee bean images to Grade IV (2.6% and 1.4% respectively) coffees since the structure and bean shapes of these coffees were correlated. Grade I coffees were not misclassified to Grade IV.Grade III and Grade IV coffees were not misclassified to Grade I because they is morphological feature differences between them. Grade IV coffees were also misclassified to Grade II and Grade III.In general, the morphological classification pattern in Artificial Neural Network classifiers was the best in performance accuracy. From the overall performance results, the overall grading accuracy was 86.45% under this experimentation. The ANNclassifier yield best accuracy performance and also has advantage of compatibility with pool illumination in coffee bean images.

4.8.1.2. Using Color Features

In this experimentation six color features were used as input to the neural network and the neuron numbers of the input layer were also six. The output neurons were four corresponds to the four labeled coffee grades for this study. The below Table 4.4 shows the summary result of artificial neural network classifier using color features. Out of the total test set of 2000 coffee beans**59.1%** were correctly classified and **40.9%** were incorrectly classified.

Table 4.4: Confusion matrix of color features in ANN

Actual Class / **Predicted Class**	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**296**	33	51	25
Grade-II	68	**280**	199	33
Grade-III	48	192	**318**	85

Grade-IV	18	26	40	**288**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**68.8%**	**52.74%**	**52.3%**	**66.8%**
Correctly classified (Precision)	**73.1%**	**50%**	**50.1%**	**77.4%**

The result of ANN classification using color feature showed that recall ofGrade I, Grade II, Grade III and Grade IV coffees were **68.8%, 52.74%, 52.3** and **66.8%** respectively. The result of ANN classification using color feature showed that precision of Grade I, Grade II, Grade III and Grade IV coffees were **73.1%, 50%, 50.1** and **77.4%** respectively. Here the result shows Grade I and Grade IV score better precision and recall.

Grade I coffee was misclassified to all Grade II, III and IVcoffee, but it was classified more toGradeII coffees (16%).GradeII coffee was more misclassified to GradeIII coffee (36%) and Grade coffee III is also more misclassified to Grade II coffee (33%). Grade IV coffee was classified to all other grades and more misclassified to Grade III coffee (18%). In addition, there is a significant misclassification among each Grade using color features. There is a better classification pattern than SVM and KNN color feature classification and also a better classification performance was obtained in most Grades than the others though there is slight color difference in each coffee grades. This shows that there is slight difference in color between each grade coffee.

4.8.1.3. Using aggregated Features

The aggregations were made first taking morphological features followed by color features after testing it in both ways. Since there were no difference in results yielded, combination is done by taking morphology features first followed by color features. Sixteen features corresponding to ten morphological features and six color features were used as input to the neural network in this case. There are sixteen neuron numbers for the input layer. The same to others, this experimentation has four output classes corresponding to the predefined coffee grades. After the network was trained using the training data set, the result of the test dataset and its respective confusion matrix was shown in the below Table 4.5

As shown in the above Table 4.5the summary result of artificial neural classifier using both morphology and color feature showed that from the total test of 2000 coffee bean images, **89.45%** were correctly classified and **10.55%** were misclassified. The percentage of correctly classified instances for each class was shown in the last row of the above Table 4.5.

Table 4.5: Confusion matrix of aggregated features in ANN

Actual Class / Predicted Class	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**403**	9	6	0
Grade-II	12	**480**	61	13
Grade-III	14	40	**529**	41
Grade-IV	1	2	12	**377**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**93.7%**	**90.39**	**87.00%**	**87.47%**
Correctly classified (Precision)	**96.4%**	**85%**	**84.7%**	**96.1**

The result of ANN classification using morphology and color feature showed that recall of Grade I, Grade II, Grade III and Grade IV coffees were **93.7%, 90.39%, 87.00%** and **87.47%** respectively. The result showed that precision of Grade I, Grade II, Grade III and Grade IV coffees were **96.4%, 85%, 84.7%** and **96.1%** respectively. Grade I coffee registered the highest recall and precision.

In this experimentation all of the three algorithms produce increased classification accuracy in terms of recall and it reflects the property of both features. The analysis result of this experiment yields good performance accuracy. But here also it can be concluded there is a great feature relation between Grade II and Grade III coffee. Color contributes its part on misclassifying Grade I to Grade IV coffee and vice versa, which wasn't happened in morphological feature experimentation. It was found that aggregated features of morphological and color features are good to use for developing model.

4.8.2 Support Vector Machine (SVM) classifier

Support vector machine (SVM) classifier model is a two-class classification algorithm [50]. It is widely used for classification tasks due to its generalization properties and computational efficiency. SVM classifier works by constructing decision plane that defines decision boundaries. A decision plane is one that separates between a set of coffee bean objects having different class memberships [50]. SVM classifier was used and experimented for this study on the classification of coffee bean raw quality value. The result of training and testing SVM classifier using morphological, color and aggregated features is presented below.

4.8.2.1. Using Morphological Features

In SVM also ten morphological features of coffee were experimented. The classifier was trained by 80% of the total dataset and the performance of the classifier was tested using 20% of the total dataset. The classification result and confusion matrix that indicates the correct classification and misclassification of testing data was shown in the below Table 4.6.

Table 4.6: Confusion matrix of morphological features in SVM

Actual Class / Predicted Class	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**367**	4	3	0
Grade-II	29	**430**	94	32
Grade-III	27	83	**488**	46
Grade-IV	7	14	23	**353**

Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**85.34%**	**80.97%**	**80.26%**	**81.90%**
Correctly classified (Precision)	**98.12%**	**74.5%**	**76.7%**	**88.9%**

It is shown in the above Table 4.6summary result of support vector machine classifier using morphology feature. The result showed that out of the total test set of **2000**coffee bean images, **81.9%** were correctly classified and **18.1%** were misclassified during SVM classifier experimentation.

The result of support vector machine (SVM) classifier using morphological features showed that, the classification recall of Grade I, Grade II, Grade III and Grade IV coffees were **85.34**%, **80.97%, 80.26%**and **81.90%**respectively. The result showed that, the classification precision of Grade I, Grade II, Grade III and Grade IV coffees were **98.12**%, **74.5%, 76.7%**and **88.9%**respectively. Under this experimentation, Grade I coffee registered the highest precision and recall whereas Grade IV registered the lowest recall and better precision.

The same to the artificial neural network of morphology feature experimentation, GradeII coffee was misclassified more to Grade III coffee (20%) and Grade III coffee was more misclassified to Grade IIcoffee (22%). Here also SVM is telling us there is strong morphology relationship between Grade II and Grade IIIcoffee beans. There is also misclassification of Grade I and Grade IV coffee bean images to Grade II (7% and 7.5% respectively). Grade IV coffees were not misclassified to Grade Icoffees as in ANN, But Grade I was misclassified to Grade IV. In general, the morphological classification pattern of SVM classifiers was less inperformance accuracy than ANN. From the performance results, the overall grading accuracy of SVM using morphological features was 81.9%.

4.8.2.2. Using Color Features

In this experimentation the six color features are used in SVM classifier. The classifier was trained by 80% of the data set and tested by 20% of the dataset. The below table 4.7shows the confusion matrix that indicates the correct classification and misclassification testing data. The result of SVM classifier using color feature showed that from the total test examples of **2000** coffee bean images, **57.35%s** were correctly classified and **42.65%** were incorrectly classified.

Table 4.7: Confusion matrix of color features in SVM

Actual Class / **Predicted Class**	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**287**	40	41	36
Grade-II	66	**269**	170	45
Grade-III	34	160	**314**	73
Grade-IV	43	54	83	**277**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**66.74%**	**50.65%**	**51.64%**	**64.26%**
Correctly classified (Precision)	**71.03%**	**49.9%**	**54.04%**	**60.61%**

The result of SVM classification using color feature showed that the classification recall ofGrade I, Grade II, Grade III and Grade IV coffees were **66.74%, 50.65%, 51.64%**and **64.26%**respectively. The result of SVM classification using color feature showed that the classification precision of Grade I, Grade II, Grade III and Grade IV coffees were **71.03%, 49.9%, 54.04%**and **60.61%** respectively. Here Grade I registered the highest recall and precision.

All grade coffees were misclassified to each other. Here also Grade I coffee yields better accuracy performance than other grades and Grade II coffee attain the least accuracy performance. Grade I coffee was misclassified to Grade II coffee in 15.3%, Grade III in 8% and Grade IV in 10%. Grade II coffees were more misclassified to Grade III coffee in 30.13%. Grade III coffee was also misclassified to all others Grade coffee. Grade III coffee was more misclassified to Grade II coffee by 27.96% and also misclassified to Grade I and Grade IV coffee by 6.74% and 13.65%

respectively. Grade IV coffee is also misclassified to Grade I, II, III and more classified to grade III by 16.93%. In addition there is a significant misclassification among each grade as shown in ANN color feature experimentation. There is a better classification performance was obtained in most regions but less accuracy performance than ANN using color features.

4.8.2.3. Using aggregated Features

The sixteen features of morphological and color features are combined and used in SVM classifier. After the classifier was trained using the training data set, the result of the test set was shown in the below Table 4.8. The summarized result of SVM classifier using aggregated feature shows that from the total dataset test of **2000** coffee bean images, **83.75%** were correctly classified and **16.25%** were misclassified. The percentage of correctly classified instances by class was shown in the below Table 4.8.

Table 4.8: Confusion matrix of aggregated features in SVM

Actual Class / **Predicted Class**	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**372**	7	5	1
Grade-II	35	**444**	91	29
Grade-III	22	60	**493**	35
Grade-IV	1	20	19	**366**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**86.5%**	**83.6%**	**81.1%**	**84.9%**
Correctly classified (Precision)	**96.6%**	**74.12%**	**80.81%**	**90.14%**

The result of SVM classification using aggregated feature shows that the classification recall of Grade I, Grade II, Grade III and Grade IV coffees were **86.5%, 83.6%, 81.1%** and **84.9%**

respectively. The result shows that the classification precision of Grade I, Grade II, Grade III and Grade IV coffees were **96.6%, 74.12%, 80.81%** and **90.14%** respectively. Grade I registered the highest recall and precision and Grade IV registered better precision and recall.

Grade I coffee accuracy performance was greater than others` and Grade III coffee yields the least accuracy performance under this experimentation. As compared to morphological and color features individually, their combination features of coffee bean yields better performance under this experimentation. The result shows that, there was no misclassification between Grade I and Grade IV coffee in morphological feature experimentation of ANN but here color value had contributed to change that value.

4.8.3. K-Nearest Neighbor (KNN) classifier and its output

K-nearest neighbor (KNN) classifier model was used in this study. For classifying coffee bean based on its raw quality value computed KNN was experimented and its respective accuracy in yielding result was evaluated based on the proposed performance measurement tools. In classifying coffee beans into four categories, KNN classifier was used on the selected coffee bean images. As in other classifiers, KNN also used the same dataset for training and testing purpose so as to classify the coffee bean image to Rank I, Rank II, Rank III and Rank IV. The total number of coffee bean data was 145 images (10,000 coffee beans), out of which 80% of these dataset was used for training and 20% was used for testing purpose. The result of training and testing KNN classifier using morphological, color and aggregated features is presented below.

4.8.3.1. Using Morphological features

In KNN also ten morphological features of coffee were experimented. The classifier was trained by 80% of the total dataset and the performance of the classifier was tested using 20% of the total dataset. The classification result and confusion matrix that indicates the correct classification and misclassification of testing data was shown in the below Table 4.9.

The overall classification of KNN classifier on the selected morphological feature showed that from the total test dataset of **2000** coffee bean images, **74.2%** were correctly classified and **25.8%** were misclassified.

Table 4.9: Confusion matrix of morphological features in KNN

Actual Class / Predicted Class	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**321**	0	0	0
Grade-II	63	**384**	110	24
Grade-III	46	112	**456**	84
Grade-IV	0	35	42	**323**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**74.65%**	**72.31%**	**75%**	**74.94%**
Correctly classified (Precision)	**100%**	**66.1%**	**65.32%**	**80.75%**

The result of KNNclassifier using morphological features shows that the recall of Grade I, Grade II, Grade IIIand Grade IV coffees were **74.65%, 72.31%, 75%**and **74.94%** respectively. The result shows that the classification precision of Grade I, Grade II, Grade III and Grade IV coffees were **100%, 66.1%, 65.32%** and **80.75%** respectively. Under this experimentation Grade I coffee registered 100% precision which wasn't achieved under other experimentation.

Grade I coffee was misclassified more to Grade II coffee by **15%** and Grade III by 11%. Grade I coffee wasn't misclassified to Grade IV coffee. Grade II coffee was misclassified to Grade II. 21% of Grade II was misclassified as Grade III coffee. There is morphological relationship between Grade II and Grade III coffee beans as shown in the above experimented classifiers. There is also a misclassification of Grade III coffee bean images to Grade II 18%. Grade III coffee is also misclassified to Grade IV coffee (7%) coffees since the structure and bean shapes of these coffees were correlated. Grade IV coffee was misclassified to Grade III by 20%. These coffees were relatively less misclassified to Grade II because the size of these coffee beans is small.

Grade I coffee wasn't misclassified to Grade IV coffee and Grade II coffee wasn't misclassified to Grade I coffee. Grade III and Grade IV coffee also weren't misclassified to Grade I. This shows that nonexistence of strong morphology relationship between Grade I and the left three grades (Grade II, Grade III and Grade IV) coffee according to the result obtained from this experimentation. So KNN was perfect on classifying Grade I coffee and also didn't misclassified other coffee Grade to Grade I.KNN was better in classifying Grade I coffee than SVM even if the overall accuracy of this classifier was less than that of SVM using morphological features. From the performance results, the overall grading accuracy of KNN using morphological features was 74.2%. The KNNalgorithm yields the least accuracy performance as compared to ANN and SVM classifier.

4.8.3.2. Using Color Features

The result of KNN classifier on the selected color features is depicted in Table 4.10. Accordingly, from the total test dataset of **2000**coffee bean images, **70.6%** were correctly classified and **29.4%** were misclassified instances.

Table 4.10: Confusion matrix of color features in KNN

Actual Class / Predicted Class	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**302**	31	16	32
Grade-II	55	**376**	87	56
Grade-III	46	63	**436**	45
Grade-IV	27	61	69	**298**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**70.23%**	**70.80%**	**71.71%**	**69.14%**
Correctly classified (Precision)	**79.26%**	**65.5%**	**73.9%**	**65.5%**

The result of KNN classification using color feature showed that the grading recall of Grade I, Grade II, Grade III and Grade IV coffees were **70.23%, 70.80%, 71.71%** and **69.14%** respectively. The result showed that the grading precision of Grade I, Grade II, Grade III and Grade IV coffees were **79.26%, 65.5%, 73.9%** and **65.5%** respectively. Grade I coffee scored the highest recall and precision (70.23%, 79.26) respectively.

Grade Icoffee was misclassified more to Grade II coffee (13%) and Grade II coffees were more misclassified to Grade III coffee (12%). Grade III coffee was more misclassified to Grade II coffee (14.3%) and Grade IV coffee is also more misclassified to Grade II coffee (13%). All grades were misclassified to each other because there is slight difference in color feature between each coffee grade and there is no regular pattern regarding color feature classification. Grade III coffee were better in accuracy than the others and Grade IV were the least under this experimentation.

4.8.3.3. Using aggregated Features

In this experimentation, the classification input features weresixteen,by combining ten morphological features and six color features. There are also four output classes. As indicated in Table 4.11, the summary result of KNN classifier using both morphology and color feature showed that, from the total test of **2000** images, **77.85%** were correctly classified and **443 (22.15 %)** were incorrectly classified.

Table 4.11: Confusion matrix of aggregated features in KNN

Actual Class / Predicted Class	Grade-I	Grade-II	Grade-III	Grade-IV
Grade-I	**340**	4	9	16
Grade-II	53	**413**	77	27
Grade-III	34	86	**473**	57
Grade-IV	3	28	49	**331**
Total	**430**	**531**	**608**	**431**
Correctly classified (Recall)	**79.1%**	**77.77%**	**77.79%**	**76.79%**
Correctly classified (Precision)	**92.1%**	**72.4%**	**72.7%**	**80.53%**

The result of KNN classification using aggregated features showed that the classification recall ofGrade I, Grade II, Grade III and Grade IV coffees were **79.1%, 77.77%, 77.79%** and **76.79%** respectively. The result of KNN classification using aggregated features showed that the classification precision of Grade I, Grade II, Grade III and Grade IV coffees were **92.1%, 72.4%, 72.7%** and **80.53%** respectively. Grade I coffee registered the highest accuracy performance in recall and precision.

Under this experimentation most of the images are classified under their respective classes. Under all classifiers, aggregated features produce better accuracy performance over the separate features. But, under this experimentation one thing that can be concluded is color contribute its part on misclassifying other grade to grade I which wasn't happened in ANN. Here also aggregated features were selected as per its accuracy performance over other features.

4.8.4. Summary of Model grading performance

The overall model performance was evaluated and tabulated below in table 4.12. The higher model performance value in ANN is attributed to homogeneous data images like coffee when having very similar data content of datasets. This result of higher model statistical values and lower error rates for performance evaluation tell us, we can implement automated computer inspection system in agricultural sector which can classify products in to various categories using similar dataset and tools.

Table 4.12: Summary of model grading performance

Classifiers	Aggregated Feature Performance (correctly classified)				Overall Average performance (%)
	Grade I	Grade II	Grade III	Grade IV	
1. Artificial neural network (ANN)	**93.7%**	**90.39%,**	**87.00%**	**87.47%**	**89.64**
2. Support vector machine (SVM)	**86.5%**	**83.6%**	**81.1%**	**84.9%**	**84.02**
3. K-nearest neighbor (KNN)	**79.1%**	**77.77%**	**77.79%**	**76.79%**	**77.85%**

The result obtained from all experimentations is promising. Based on different feature content, experiment has been done. In every experimentation ANN yields better performance accuracy and aggregated features produces best accuracy over morphology and color features lonely. Generally based on the accuracy performance, **ANN**was selected for developing the model.

4.9. User Acceptance

Domain experts were purposively selected to get necessary information and comment at different stage of experimentation and evaluation as well as discussion and unstructured interview is conducted. For knowledge acquisition and user acceptance testing purpose domain experts were selected from office of Ethiopian commodity Exchange Jimma Branch. User acceptance test was also conducted to test the model developed. The user acceptance test was conducted as per checklist proposed for this study and annexed as annex 1.

Out of five experts four experts rate the functionality of the model in terms of performance as excellent and one experts rated it as good. All of the experts (5) rated the model excellent in terms of its effectiveness. Error tolerance capacity of the model is rated good by four experts and excellent by one expert. Model`s ability to self-learn is also rated as good by all of the experts selected (five).Graphical user interface design of the model is rated as excellent by two of five experts, as good by two of five experts and as average by one expert. Five experts had rated model`s user friendless in to good division whereas operational performance of the model was rated as excellent by all of the experts (five). The overall analysis of user acceptance checklist shows the model developed is good in helping experts working in coffee scaling activity.

4.10 Discussion of result

In this study, different features and classification algorithms are tested to construct classification model. The proposed model was tested using sample data selected from the ground truth and sources of data mentioned previously. The researcher applied statistical measurement to test the performance of the developed model. The performance of coffee bean raw quality value scaling has been determined through accuracy rate.

The experiments were conducted using morphological features, color features and aggregating the two features. Then, the performance of ANN, SVM and KNNclassifiers were compared over the three experimentation cases. There were ten morphology features and six color features which is sixteen parameters totally. According to the experiments, ANN classifier registered the highest overall average accuracy of 89.64**%.**This result is found to be good enough by taking worst scenario into consideration. The experimental result shows the large discriminating power of the morphological features and color is not as good as morphology because many varieties of coffee have more similar color.

From experimental result, the discriminating power of morphology feature for Grade I and Grade IV coffee was better than others. This was because by its nature, Grade Iand Grade IV coffees were mostly characterized by a unique morphological features shape, roundness and perimeter. Color feature classification result for coffees of Grade I and Grade IV indicates relatively there is better discrimination power than other grade coffees and this confirms to the manual system in which color is used as a parameter of classifying and grading of coffees.

The classification accuracy of Grade I and Grade IV coffee were less discriminated than others. From the labeled Grades, the size and area of Grade II and Grade III are relatively similar and also they inherit color properties. The area and size of Grade Iis medium in respective to others. The length, width and area of Grade II coffee and Grade III coffee were relatively similar and this resulted in that some of the coffee beans of Grade II were misclassified as Grade III coffee. Similarly, most coffees of Grade III were misclassified as Grade II. In other words, there is an ambiguity of grading between Grade II and Grade III Coffee beans and also between Grade I andGrade II Coffee beans.

In general, the overall result showed that morphology features have more discriminating power in grading coffee beans than color features and the aggregated feature increases the discrimination power. Asma`s [18] work also indicated that aggregated features increases the discrimination power than morphological and color features. The grading accuracy performance of artificial neural network (ANN) is better than Support vector machine and K-nearest neighbor classifiers.

The grading of coffee bean based on green analysis had some limits on color feature of each grades. The image acquisition environment and other imaging factors may affect the result during acquiring images of coffee beans besides homogeneity of color features between each grade. In addition to this, the time coffee bean samples were collected has also contributed its part as production period of Ethiopian coffees are from August to January. These samples were taken in May 2019 which was a slack time. There was shortage of different samples of each grade coffees this period. For example different samples of Grade I and Grade IV coffee were not in their warehouse during data collection period. We had collected one sample which scores single marks for Grade I and Grade IV and that is why the number of coffee beans of Grade I and Grade IV were reduced. This property was what observed on the experimentation results. These were the challenges for misclassifying coffee images. The result of this study was modified as per what was proposed to fill the gap different scholars [18] stated. The result difference is due to the increment in morphological features that fully express and represent the real working environment and the current work values difference in coffee.

As per the researcher knowledge, there is one local research attempts made to classify coffee bean images by using image processing techniques, but it used other different algorithms and tools which yield somewhat less accuracy status than this study. By considering the above performance results of system using image processing techniques, it is important to compare with previous studies done by Asma Redi [18] in 2011.

Table 4.13: Comparison of the developed model with the existing one

Author	Dataset	Preprocessing techniques	Segmentation techniques	Feature extraction techniques	Classifier	Performance measurements and results in (%)
Newly developed model (Muktar Bedaso)	10,000 coffee beans (145 images)	✓ Filtering. ✓ Quality enhancement. ✓ Normalization. ✓ Binarization.	✓ Thresholding ✓ Edge detection	✓ Binarized thresholding extraction technique	✓ ANN ✓ SVM ✓ KNN	89.64%
Model developed by Asma Redi	4848 coffee beans	✓ Filtering. ✓ Quality enhancement. ✓ Normalization. ✓ Binarization.	✓ Thresholding ✓ Edge detection	✓ Binarized thresholding extraction technique	✓ Naïve Bayes ✓ C4.5 ✓ ANN	80.25

It is shown in the above table 4.13 that newly developed model achieved better performance in accuracy measure in comparing with previously done.

In Asma Redi [18] work the model misses morphological features like width, height and circularity for which makes its own contribution for a minimum accuracy than the current work. The current researches filled gab by analyzing the existing situation which applied ten morphological and six color features combined together.

ANN classification algorithm is one of the advanced statistical classifier and the proposed suitable algorithm to determine the scale of coffee product. Under this study, ANN was the best algorithms, which classified the computed morphological and color features successfully. Moreover, the previous works used limited number of sample images/datasets, whereas this dealt with various sample. However, challenges are still reflected while computing to determine coffee bean quality based grading.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Coffee is commodities for Ethiopia and Ethiopians. There is a great cultural connection between Ethiopians and their coffee. Besides, for Ethiopia coffee is a backbone of foreign currency and plays lion`s share for the country`s GDP. Coffee production is getting governmental and nongovernmental attention due to its significance in commercial activities. But, nowadays the foreign currency that should Ethiopia earn from coffee is reducing because of various factors. The first factor is quality in production and export. ECX is Ethiopian sector governing the grading and qualification of coffee used domestically and exported internationally. However, there are challenges in successfully sorting and classifying coffee that can feet world`s market competition. Automated sorting and classification systems for agricultural products are proven to be less costly, efficient and non-destructive. Application of proper technology makes effective quality control and inspection aspects for such economically important commodities.

In this study an attempt is made to apply image processing for scaling raw quality of Ethiopian coffee beans. To this end, morphological and color features were extracted from a coffee bean images taken from Jimma ECX center by using image analysis techniques. These features are tested individually and by combining them to construct the classification model by employing artificial neural network (ANN), support vector machine (SVM) and K-Nearest Neighbor (KNN) classifiers.

The experimental results show that morphological features have more discriminating power to classify coffee based on their quality than color features in all of the classification algorithms used. But the classification accuracy of coffee increases when the morphological and color features were used together. The result of the experimentation also showed that different grade of coffees has been classified more accurately by artificial neural network (ANN) than support vector machine (SVM) and K-Nearest neighbor (KNN) classifiers. The overall performance of the model in classifying sample coffee bean was 83%.It is concluded that there is a possibility of applying classification of raw quality images of coffee beans using computer inspection system. The major challenges during conducting this study were keeping the best quality control environment when acquiring images, extracting best features of HSB color feature and the homogeneity of coffee bean color features. There is a great similarity in color between each of four coffee grade samples.

5.2. Recommendation

Though 85% of Ethiopian people's are farmer and Ethiopian economy is based on agriculture, few researches have been conducted in this direction to support the sector. The current study investigates the application of image processing for scaling Ethiopian coffee. Based on the findings of this study, the following recommendations are forwarded.

- The performance of the classification model is highly affected by coffee image quality. To reduce the effect of noises in image, we propose conducting further experiment in applying advanced image filtering techniques.
- In this study the most widely used classification algorithms are applied to constructed classification model. Further study needs to compare the performance with other classification algorithms, such as deep learning which can have the advantage of improving both feature extraction and classification.
- In this study an attempt is made to develop raw coffee grading. Further research is required to develop a model for grading roasted coffee beans.
- Identification of coffee varieties from mixed components of coffee beans and computer vision for coffee defect identification and counting are also the other research direction recommended by the researcher.
- The researcher strongly recommend to convert paper based research and creative idea of automating agricultural product (coffee and others) in to problem solving project. This automated technique might also be a potential approach in Ethiopia assisting quality control and grading/sorting activities of other important agricultural products like fruits and cereals.

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Appendix

Annex 1

A. Interview Questions for domain experts

1. What is raw quality coffee scaling and how it is performed?
2. What are the differences between raw quality coffee scaling techniques and cup test scaling techniques?
3. What are the detail procedures when scaling raw quality coffee beans that should be followed?
4. What are the pre-requisite for taking coffee bean in to evaluation center for scaling?
5. What are the basic parameters for determining raw quality scale of coffee beans?
6. What should be performed in order to rank the quality of coffee by looking physical characteristics?

B. User Acceptance testing questions checklist

Note that: The users of this model are experts working on raw quality scaling of coffee.

Checklists	Very Poor	Poor	Average	Good	Excellent
1. How do you rate the functionality of the model in terms of performance?					
2. How do you rate the effectiveness of the model?					
3. How do rate the model based on its error tolerance?					
4. How do you rate the model based on its nature towards easy to learn?					
5. How do you rate the graphical user interface design of the prototype?					

6. How do you rate the prototype in terms of user-friendliness?					
7. How do you rate the operational performance of the prototype?					

8. Do you think this computer vision system is better than human based inspection approach?
9. Did you encounter any difficulty while using the prototype?
10. Does the system flexible when providing decision and giving recommendations?
11. Kindly recommend any improvement(s) for this model (if applicable).