



Addis Ababa University
College of Natural Sciences

**Automatic Soybean Quality Grading Using Image
Processing and Supervised Learning Algorithms**

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This is to certify that the thesis prepared by *Muhammed Hassen Ahmed*, titled: *Automatic Soybean Quality Grading Using Image Processing and Supervised Learning Algorithm* and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Computer Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

Soybean is one of the most important oilseed crops of the world which requires 25 to 30°C temperature for growth and proper modulation. Due to its high protein content and nutritional quality soybean usually used in food preparation, animal feed and industry sector. It is an input for food products like soy milk, for human consumption and as in put for industry for production like paper, plastic and cosmetics. The trading of soybean in Ethiopia is done through Ethiopian Commodity exchange internally as well as for export trading. Determining the quality grade of soybean is crucial in the trading process. It improves the production of quality soybeans and it helps to become competent in the market. This process is done manually in Ethiopian Commodity Exchange which is subjected to different problem: less efficient, inconsistent and vulnerable to subjectivity.

As a solution in this thesis we propose an automated quality grading of soybean using image processing techniques and supervised learning algorithms, which is the aim of this thesis. Image acquisition, image pre-processing, image segmentation, predict soybean type and determining the grading are the major steps that are followed. For image preprocessing, methods like median filter to remove noise, modified unsharp masking sharpening technique is used to enhance the quality of acquired soybean image. In image segmentation a modified Otsu's threshold segmentation method is used to apply to a color image. Nineteen typical characteristic parameters of samples are extracted as the characteristic soybean, which are 7 morphological, 6 colors and 6 texture features. Three different supervised learning algorithm classifiers are applied and compared: support vector machine algorithm, artificial neural network and convolutional neural network.

Experimental results show one dimensional convolutional neural network outperforms the others with accuracy rates of 93.71% on the test datasets collected from Ethiopian Commodity Exchange. We concluded that the CNN is superior to other supervised learning algorithm, and using aggregated features is better than using single type of features.

Keywords: *Soybean kernel, quality grading, image processing, support vector machine, artificial neural network, convolutional neural network and supervised leaning algorithms.*

Dedicated

***To ALLAH (S.W.T),
Then to my family***

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TABLE OF CONTENTS

TABLE OF FIGURES.....	iv
LIST OF TABLES.....	v
LIST OF ABBREVIATIONS.....	vi
CHAPTER ONE: INTRODUCTION.....	1
1.1 Background.....	1
1.2. Motivation.....	3
1.3. Statement of the Problem.....	4
1.4. Objective.....	6
1.5. Methods	7
1.6. Scope and Limitations	8
1.7. Application of Results	9
1.8 Organization of the Rest of the Thesis	9
CHAPTER TWO: LITERATURE REVIEW.....	10
2.1 Soybean sample constituent.....	10
2.2 Digital Image Representation	11
2.3 Digital Image Processing.....	12
2.3.1 Image Acquisition.....	13
2.3.2 Image 999588s00-Preprocessing	14
2.3.3 Image Segmentation	19
2.3.4 Feature Extraction.....	25
2.3.5 Classification.....	26
CHAPTER THREE: RELATED WORK.....	33
3.1 Introduction.....	33
3.2 Quality analysis on Soybean.....	33
3.3 Quality analysis on cereals	36

3.4 Quality analysis on other Agricultural crops	38
3.5 Summary	39
CHAPTER FOUR: THE PROPOSED SOLUTION	42
4.1 Introduction.....	42
4.2 The Proposed System Architecture	42
4.3 Training Phase	44
4.3.1 Image Preprocessing	44
4.3.2 Image Segmentation	45
4.3.3 Feature Extraction.....	48
4.3.4 Feature Selection	52
4.3.5 Model Training	54
4.4 Testing Phase	58
4.4.1 Image Preprocessing	58
4.4.2 Image Segmentation	59
4.4.3 Feature Extraction.....	60
4.4.4 Classification.....	60
4.4.5 Quality Grading	60
CHAPTER FIVE: EXPERIMENTATION	62
5.1 Introduction.....	62
5.2 Dataset	62
5.3 Implementation	63
5.4 Test Results.....	65
5.4.1 Support Vector Machine (SVM) Test Results	65
5.4.2 Artificial Neural Network (ANN) Test Results	66
5.4.3 Convolutional Neural Network (CNN) Test Results.....	66
5.5 Feature Comparison Test Result.....	68
5.5.1 Scenario One (Analyzing the effect of Morphological feature)	68
5.5.2 Scenario Two (Analyzing the effect of Color feature)	69

5.5.3 Scenario Three (Analyzing the effect of Texture feature).....	70
5.6 Discussion.....	71
5.7 Summary.....	73
CHAPTER SIX: CONCLUSION AND FUTURE WORK	74
6.1 Conclusion.....	74
6.2 Contribution of the Thesis	76
6.3 Future work.....	76
Reference	78
Annex A.....	83

TABLE OF FIGURES

Figure 1.1: <i>Soybean quality grading at ECX</i>	2
Figure 2.1: <i>Soybean samples (a). Immature kernels (b), insect bored kernels (c), mold-damaged kernel (d), Frost-damaged kernel</i>	10
Figure 2.2: <i>Image pixel notation</i>	11
Figure 2.3: <i>Fundamental Steps in Digital Image Processing</i>	13
Figure 2.4: <i>Commonly used convolution masks that are used as an alternative digital implementation of the Laplacian</i>	18
Figure 2.5: <i>The sobel convolutional masks for detecting horizontal edges (a) & vertical edges (b)</i>	23
Figure 2.6: <i>Values of θ between the center pixel and its eight neighboring pixels</i>	24
Figure 2.7: <i>Hyperplane and support vectors used by SVM in 2-D feature space</i>	29
Figure 2.8: <i>General artificial neural network architecture</i>	30
Figure 2.9: <i>CNN architecture with two convolutional layers only</i>	32
Figure 3.1: <i>System Architecture used in [12]</i>	34
Figure 4.1: <i>The Proposed System Architecture for Soybean Quality Grading</i>	43
Figure 4.2: <i>Sample image cropping and labeling during image segmentation</i>	46
Figure 4.3: <i>The designed Bank of Gabor filters</i>	52
Figure 4.4: <i>Architecture of the ANN in the proposed system</i>	55
Figure 4.5: <i>Architecture of the 1D-CNN in the proposed system</i>	56
Figure 4.6: <i>The Proposed 2D-CNN architecture</i>	57
Figure 4.7: <i>Example of detecting soybean seeds from a given image (a) input image, (b) binary segmented image, and (c) detected soybean seeds in the RGB image</i>	59
Figure 5.1: <i>Screenshot of the Web based User Interface of the Developed Prototype System</i>	64
Figure 5.2: <i>Comparison of Discriminative Power of Morphological, Color and Texture Features</i>	73

LIST OF TABLES

Table 1.1: <i>Soybean quality grading parameters used by ECX</i>	2
Table 3.1: <i>Summary of the related work</i>	41
Table 4.1: <i>Sample Image Segmentation Results</i>	47
Table 4.2: <i>Name and number of morphological features extracted</i>	49
Table 4.3: <i>Name and number of color features extracted</i>	50
Table 4.4: <i>Name and number of Texture features extracted</i>	51
Table 4.5: <i>The Selected Features after feature selection component</i>	53
Table 4.6: <i>ANN hyper-parameter values explored with their method</i>	55
Table 4.7: <i>1D-CNN hyper-parameter values explored with their method</i>	57
Table 4.8: <i>2D-CNN hyper-parameter values explored with their method</i>	58
Table 4.9: <i>The Grading Parameters used</i>	60
Table 5. 1: <i>Total dataset acquired for soybean graded images</i>	63
Table 5.2: <i>Main Python library packages used in implementation and prototype development</i>	64
Table 5.3: <i>Test Confusion Matrix of SVM Classifier</i>	65
Table 5.4: <i>Test Confusion Matrix of ANN Classifier</i>	66
Table 5.5: <i>Test Confusion Matrix of 1D-CNN Classifier</i>	67
Table 5.6: <i>Test Confusion Matrix of 2D-CNN Classifier</i>	68
Table 5.7: <i>Test Confusion Matrix without Morphological features in 1D-CNN</i>	69
Table 5.8: <i>Test Confusion Matrix without Color features in 1D-CNN</i>	70
Table 5. 9: <i>Test Confusion Matrix without Texture features in 1D-CNN</i>	71

LIST OF ABBREVIATIONS

1D-CNN	One Dimensional Convolutional Neural Network
2D	Two Dimensional
2D-CNN	Two Dimensional Convolutional Neural Network
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
ECX	Ethiopian Commodity Exchange
GLCM	Grey Level Co-occurrence Matrix
GPU	Graphical Processing Unit
LG	Lower Grade
QSAE	Quality and Standards Authority of Ethiopia
RGB	Red Green Blue
ROI	Region of Interest
SVM	Support Vector Machine
VGG	Visual Geometry Group

CHAPTER ONE

INTRODUCTION

1.1 Background

Agriculture is major pillars for developing countries, especially for Ethiopia that doesn't have rich natural sources like gas and minerals. The majority of Ethiopian population also relies on agriculture sector; due to this various research and technology have been done and developed in the agriculture sector to increase the yields and quality of agricultural products [1]. The agricultural sector is also playing significant role for export in Ethiopia as it is a source of economic growth which can be attributed to the foreign exchange [2]. Ethiopian oilseed crops play an important role in generating foreign exchange earnings next coffee. The three major oilseed crops (sesame, soybean, and niger seed) nearly contribute to 20% of Ethiopia's total agricultural export earnings, second only to coffee and generated nearly 430 million dollar in export earnings in the 2018/19 (Oct-Sep) according to Ethiopia Oilseeds annual report [2]. The oilseed consumption expected to be rise due to expansion of edible oil processing plants and integrated agro-industrial parks [2].

One of the major oilseed crops contributors is soybean which is mainly produces in Oromia, Benishagul gumuz and Amhara regions [1,2]. Soybean is additionally called as soya bean and mainly used in different food preparation and animal feed as well for industrial purpose. Soybean trading is conducted exclusively through Ethiopian Commodity Exchange (ECX) in the local trade as well as in the export trading [3]. The soybean trade expected to show rapid growth because of demands in exports market typically India as well as in domestic demands.

ECX is a commodity exchange company that is established 2008 works in Ethiopia. It offers an integrated warehouse, grading and trading system for major agricultural crops [3]. Soybean crops first deposited in warehouses operated by ECX in major surplus regions of the country. Soybean is then ranked for export as well as for domestic with the objective of producing the best quality and there by securing the best price possible.



Figure 1.1: Soybean quality grading at ECX

In ECX, the processes of quality grading of soybean have been done manually by experts using different techniques, such as visual inspection and weighting the soybean grains with scales based grading specification rules that are set by ECX as shown in Table 1.1. This manual grading approach is vulnerable to different problems: not consistence, time consuming, subjectivity by nature and so on. Thus it needs automatic grading approach which overcomes the problems in manual approach. This thesis work proposes automatic Ethiopian soybean quality grading system using computer vision techniques.

Table 1.1: Soybean quality grading parameters used by ECX

Parameter	Grade 1	Grade 2	Grade 3	Grade 4	LG
Test weight kg/hl(g/0.5 L)	66(33 7)				
Foreign Matter, max % by weight	1.0	3.0	4.5	6.0	8.0
Defects max % by weight	4.0	6.0	8.5	11.5	15.5
Insect bored beans, % max	1.0	1.5	2.0	2.5	3.0
Split / Broken beans max%	1.5	2.5	5	7	9
Contrasting Color, % by weight	≤ 5				

Computer vision is a science that aims to extract information out of digital images just like human vision does and use it for various application [4]. The primary purpose of computer vision is to build models or algorithms that can extract information from images. It uses various concepts, techniques, and ideas from digital image processing, pattern recognition, artificial intelligence and others disciplines to get insight about an image [4]. Digital Image Processing and Learning algorithm commonly used in different application of computer vision.

Digital Image Processing is about implementing computational transformations for images such as sharpening, contrast, noise removal among others so that model and algorithms easily and accurately extract information from the transformed digital image [5]. Whereas learning algorithms aims to learn from vast amount of data and build models /algorithm that used to classify or predict unseen new data.

Learning algorithms typically classified into two [6] supervised and unsupervised: (1) Supervised learning, first training of model took place to learn from labeled dataset by taking the labeled dataset as examples. Then the trained classifier model is used to classify new data. (2) Unsupervised learning uses the properties of the data to group them by similarity measures and these groups are known as cluster and the process is called clustering. In this case there is no already made labeled data used or required.

This thesis work aims to take a step towards the goal of developing an automated quality grading for Ethiopian soybean using image processing techniques and supervised learning algorithm technologies. This thesis works also study the effect (discriminative power) of morphological, color and texture features in the accuracy of quality grading of the soybean.

1.2. Motivation

In Ethiopia, a large segment of the population is involved in the agriculture sector as a result the agriculture sector become the main pillar for economy of country as well as in generating foreign exchange to the country. The agriculture 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 ECX proves this fact and one of its objectives is to support the production and trade of mainly on exported agriculture crops as well as research efforts.

Soybean is one of the major agriculture crops exported by Ethiopia. Soybean is well known by high quality content of protein and oil. Soybean local and export trading are done through only ECX. The production and trade of soybean in Ethiopia shown rapid growth in the last decades and also expect to grow in the future [2]. According to ECX [3] the production volume of soybean has increased by an annual average of 37% in the previous decade. The major reason is demand from local as well as in export for production cooking oil, soy-based foods and livestock feeds. It also expanded in new growing areas particular in Amhara region [2]. Despite this rapid growth of soybean in the market the quality grading process is performed by manual inspection on ECX by trained experts. The manual quality grading process is exposed to critical problems such as error prone, inconsistent, costly and less efficient. The problems will also have impact on the production of quality soybean and its market share on the international market.

The above mentioned issues attract the researcher to propose and conduct research on automatic soybean quality grading that have a significant advantage. Therefore, this research work will initiate a model for it with better performance by exploring image processing techniques and supervised learning algorithms.

1.3. Statement of the Problem

In ECX, the process of quality grading of soybean is done manually by experts. The general requirements for soybeans shall have a good natural color, free of objectionable odor, contains no weevil and other live insect and free from other materials free like glass and metal fragments [7]. The quality grading specification rules that are used by ECX are shown in Table 1.1. Accordingly, soybean is graded in to five grade level; the first grade level shows higher quality whereas the last (fifth) grade soybean indicate least quality. The fifth grade soybean is known with term Lower Grade (LG), which means any soybeans that registered highest rank of LG will be graded as LG soybean.

The manual approach for quality grading soybean is vulnerable to critical problems [6] [8] [9]:

- Inefficiency: The manual approach is time-consuming, costive and requires special trained experts. In general, it takes more resource during the quality grading process.
- Subjectivity: It is vulnerable to subjectivity. Which means the exactness of quality scrutiny via human assessment scheme is different from person to person according to the inspector's points of view.
- Inconsistency: it can't provide constant measurement accuracy, which is very difficult to achieve for human visual inspection because the human decision-making are usually affected by many factors.

Thus, we need automatic method to overcome the problems in the manual approach. The computer vision grading system reduces and overcomes the problems [6,9] in the manual quality grading approach. The applications of computer vision inspection technique have been applied in many and diverse areas like food industries and other agricultural sector to help the inspection and grading purpose by local and foreign scholars. Computer vision based inspection and grading for apple, oranges, strawberries, tomato, mushrooms, coffee bean and rice have been done widely [9,10]. Literature shows that inspection and grading technique proposed for one agricultural product will not be directly applied for others as well as for the same product produced in other geographic locations due to the difference in morphological, color and texture features as well as the determinant grading parameter [9,11].

Few researchers have conducted an automated quality grading system for soybean. To the best of our knowledge, only [12] and [13] applied image processing and Artificial Neural Network (ANN) to determine the quality grade of combed soybean according to their combing level. We cannot directly apply them to system that can determine the quality grade of for non-combed soybean according to them amount of impurities found in soybean samples due to the difference in the process and parameters used to determine the quality grade of the soybean samples.

To the best of our knowledge, there is no prior work attempting to develop a system for quality grading of soybean that are not combed (or filtered). As a result this research work aims at developing an automatic soybean grain quality grading system using image processing techniques and supervised learning algorithm according to ECX criteria. The

research work will also consider the morphological, texture and color characteristics into account.

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

- What are the optimal features of physical characteristics of soybean?
- What are the suitable classification algorithms to use for quality grading soybean?
- To what extent the prototype model determines the quality grading of soybean?
- Which type of feature has highest discriminative power?

1.4. Objective

General Objective

The general objective of this research is to design and develop an automatic soybean quality grading model by exploring image processing techniques and supervised learning algorithms based on the criteria set by the ECX.

Specific Objective

The Specific objectives that will help and focused the researcher to achieve the general objective are to:

- Review literature on image processing techniques and supervised learning algorithms in developing automatic quality grading for agricultural crops.
- Identify determinant parameter of morphological, color, texture characteristics of soybean in quality grading it.
- Design the model and specify the architecture for the proposed automatic soybean quality grading.
- Prepare soybean image corpus to train and to test the prototype that will be developed.
- Develop a prototype for the proposed models to grade and determining the raw quality value of soybean.
- Evaluate the performance and effectiveness of the proposed Prototype.

1.5. Methods

The following methods will be applied in the course of the research.

Literature review

Research works that have been done with the intention of quality grading for different agricultural crops specifically those which are used in export sector are reviewed to get a deeper understanding about models, approach, techniques and tools used in developing and testing automatic quality grading system. The researcher also reviewed research works that are done for soybean in Ethiopia to get a deeper understanding about determinant parameter of morphological, color and texture characteristics of soybean that are used to grade soybean in ECX.

Research Design

Research design defines a general framework that guides the researchers the way they follow to answer their raised questions. According to Hevner et al. and Vaishnavi et al. [14,15] design science research help researchers to develop and improve functional performance of (designed) artifacts. In this research design science research method was employed as the researchers want to design and select architecture, models and techniques based on their performance.

In order to answer the 4th raised research question we applied experimental research method to measure the effect of the features on the performance. According to Goodwin [16], experimental research design is a systematic research study that help manipulated and testing to understand causal process.

Data Collection

In order to train and test the model different and large volume of soybean graded images datasets are required. The data collection has been done on primary data source from ECX. A sample from all grade levels of soybean beans for this research will be obtained from ECX branch. The image corpus then built from sample soybean by taking picture of them for purpose to train and test the proposed model.

Prototype Development

To develop the prototype of the system Python version 3.0 programming language is used. In Python a very large and growing packages (libraries) of built in algorithms for image processing, for developing and evaluating machine learning and deep learning models is existed. Visio 2013 is used for designing the system architecture and model classifier architecture.

Testing and Evaluation

After developing the prototype for soybean quality grading, the prototypes developed will be tested to evaluate the performance. Following previous works, the model was evaluated on accuracy metrics. Accuracy is the most intuitive performance measures on classification problems and it is simply a ratio of correctly classified observation to the total observation [17]. High accuracy rate show better model performance. It is calculated as:

$$Accuracy = \frac{Total\ number\ of\ samples\ correctly\ classified * 100\%}{Total\ number\ of\ sample\ used} \quad (1)$$

1.6. Scope and Limitations

The main focus of this research is designing, modeling and prototype development of an automatic soybean (non-combed) quality grading model by using image processing techniques and supervised learning algorithms. The research considers only morphological, color and texture characteristics of the soybean, it doesn't consider other modalities of the soybean like odor due to its complexity and time it request.

The thesis will approach the classification as supervised way. Thus, the thesis only investigates there supervised learning algorithm for classification namely: Support Vector Machine (SVM), ANN and Convolutional Neural Network (CNN). Other supervised learning models are not covered.

Due to the lack of large annotated corpora, the available corpus were constructed manually from samples collected from ECX as discussed in the methodology section for training and testing the mode.

1.7. Application of Results

The main beneficiaries of this study will be ECX. Farmers, soybean exporters and researchers will be beneficiaries from this study either directly or indirectly. The advantages of the study will give is summarized as bellow:

- The automatic quality grading of soybean will require less resource like time, labor and cost. This makes ECX more efficient.
- Since the proposed system will be consistent, Farmers to be productive and encouraged to produce high quality soybean as well as for exporters helped to send high quality soybean to export.
- The proposed system will shift the nature of quality grading process from subjective to objective which reduce bias and increase reliability on quality grading process.
- It will benefit researchers who need to take part in achieving the goal of developing efficient computer vision techniques for different agricultural products tasks.

1.8 Organization of the Rest of the Thesis

The rest of this thesis is organized into five chapters. Chapter Two will assess literature in the field and provides all background information regarding image processing techniques, pipeline and classification algorithms.

In Chapter Three, image processing works that are related to cereal grain in general and soybean in particular will be reviewed and presented. Chapter Four will present the design of the proposed solution system architecture and discuss each component role in the architecture. In Chapter Five, the experiments used to evaluate the performance of the proposed solution and the analysis of the results obtained will be discussed. Finally, Chapter 6 concludes the thesis by providing summary conclusion, insightful recommendations and future works.

CHAPTER TWO

LITERATURE REVIEW

2.1 Soybean sample constituent

The following are the descriptions of soybean sample constituents.

- Foreign matter: All matters other than soybean like stems, coats, pods, sand and the likes.
- Defect: Include soybean kernel that are badly ground-damaged, badly weather-damage, mold- damage, insect bored, Immature, shriveled and the likes.
- Immature: Soybeans that are not fully developed and characterized by a green appearance in conjunction with wrinkled and misshaped appearance.
- Insect bored: Soybeans kernels which bear evidence of boring or tunneling shall be considered damaged.
- Split kernels: soybeans that are broken and cracked soybean kernels.
- Frost damage (Green): Soybeans kernels which are discolored green in cross section
- Mold Damage (pink): Soybeans kernels that are damaged by fungal activity. Soybeans that contain pink discoloration to the seed equal to or greater than the amount shown are considered damaged.

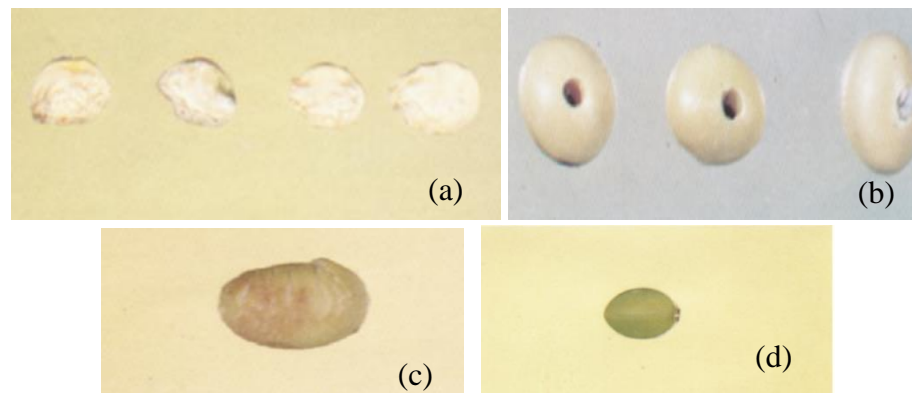


Figure 2.1: *Soybean samples (a). Immature kernels (b), insect bored kernels (c), mold-damaged kernel (d), Frost-damaged kernel*

2.2 Digital Image Representation

An image is a picture that contains visual representation of something or someone [18]. It may be a picture of an object, animals, a person, or scene. Image also the most commonly used static media in communication in which the contents and meaning doesn't depend on the presentation of time [19].

Digital image is an image that contains pictorial information in digital form [19,20]. Digital image is represented in two dimensions and composed of finite number of elements, each of which has a particular location and value. These elements are called *pixels or picture elements* [20]. The particular location of a pixel is specified in terms of indexes by the number of row and column they are found. The value of the pixels shows the intensity (brightness) of that pixel. Figure 2.1 shows that a pixel $F(3, 5)$ has an intensity of 65 and it is located in the third row, fifth column.

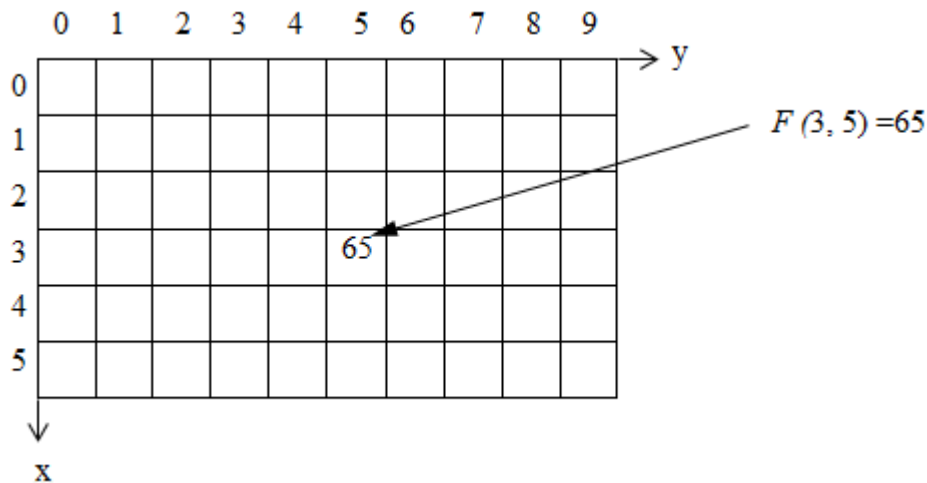


Figure 2.2: Image pixel notation

Preserving good quality of digital image is essential for visualization, processing and analyzing digital image for different application. There are two major factors affecting the quality of digital image [21]. The first factor is the number of pixels used to represent a digital image, known as *image resolution*. The image resolution has direct relationship with the quality of the digital image; the higher the resolution the more the quality has but it also requires more storage spaces. The second factor is the number of bits used to encode the value of the pixels. The major types are [20,21]:

- **1-Bit Binary Level Images:** a pixel is encoded with single bit, where 0=black and 1=white. They are sometimes referred to as binary/ logical images: pixel value is assigned a numerical value either 0 or 1 no other value is permissible [20,22].
- **8-Bit Gray Level Images :** The image of the pixel is represented with 8 bit with range 0 up to 255, where 0=black and 255=white, the numbers in between represent levels of gray forming a grayscale image [20,22].
- **24-bit Color Images:** are true color images that assigns 3 three numerical values to each pixel, each value corresponding to the red, green and blue (RGB) image channel component respectively. Each component value is encoded in 8 bits, resulting in 24 bits in total, they also called RGB image. With such an image, we can have $2^{24} = 16.777216 * 10^6$ different colors possibility [20,22].

2.3 Digital Image Processing

Digital image processing is a field that study about modifying and manipulating digital image by means digital computer using algorithms [18]. The changes that will be made on the images are rely on carefully designed algorithm and usually performed automatically [19].The purpose of modification of digital image might be: to enhance the image for better visualization, to transformed it to extract features for different application like object detection and pattern recognition and to compress it for transmission, storage and retrieval of the image [18,19].

Digital image processing also one of among rapidly growing field today, with its application in various aspects in business and human activity in medical, agriculture, industry ,military and others areas [18,19]. Digital image processing is a multidisciplinary field, with contributions from different branches of science particularly engineering and computer science disciplines [19].

There are no clear-cut boundaries in the scope of image processing; In this research work, we adopt the terminology used in [18] (among others) and employ the term *image processing* to refer to all the process and algorithms used in whether the output is a modified (i.e., processed) version of the input image, extract attributes from images, or a non-pictorial description of its contents or recognition of individual objects.

Moreover, we can distinguish among three levels of image processing operations [18]:

- *Low Level*: these are primitive operations that take an image as input and produce also image as output. Noise reduction, contrast enhancement, and image sharpening are some low level operation examples.
- *Middle Level*: are operations that extract attributes (e.g., edges, contours, regions, etc.) from a given images.
- *High Level*: are operations that analyze and interpret the contents of a scene like scene understanding and automatic navigation.

A computer-vision application using image processing techniques involves five basic steps such as image acquisition, preprocessing, segmentation, feature extraction and classification. This is illustrated in Figure 2.2:

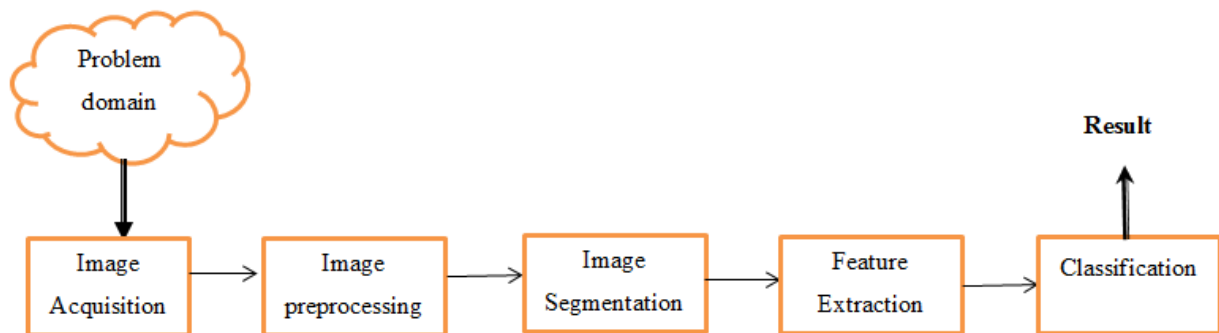


Figure 2.3: Fundamental Steps in Digital Image Processing

2.3.1 Image Acquisition

Image acquisition or imaging is the process of capturing an image using image sensor devices in real-time [18]. The main objective of image acquisition is to transform a real world/visual scene in to a two-dimensional array of numerical data that latter manipulated by digital computer [23]. It is the first step in the workflow sequence of image processing because without it, it not possible to proceed the other tasks. There are different types of devices are exist to capture an image but digital imaging device are used extensively in

various application ranging from computer vision .multimedia, sensor network up to astronomy [23].

During image capturing are shadow/shading, specularities and the occurrence of inconvenient color illumination under different environment results less quality image [23]. Thus, to get the high accuracy quantitative and qualitative data processing, choice of image capturing sources and sensors go to be thought-about very rigorously.

2.3.2 Image Preprocessing

The image that captured in the image acquisition step will be preprocessed first before fed into the next stages using different techniques and algorithms in order to remove noisy data on the image and to enhance the image quality so that it can be visualize and assess the visual information with greater clarity [19,22]. The method by which various initial image enhancing and noise removal techniques of the captured raw images are applied is considered as image pre-processing.

There are a lot of image preprocessing operation; image sharpening, noise removal, edge extraction, contrast enhancement, and brightness correction are among common operation used in different application [19]. The choice and usage of the operation is subjective because it depends strongly on the specific information the user is hoping to extract from the image [19]. Perhaps the most accurate and general statement we can make about the goal of image preprocessing is simply that the processed image should be more suitable than the original one for the required task or purpose.

The image filtering is a commonly used technique in image preprocessing that is use in noise removal and sharpening of a given image [22]. Filtering is the process by which filters act on an image to change the values of the pixels in some specified way. They are generally classified into two types: linear and nonlinear [22]. Linear filters are more common and discussed briefly in this section [22].

Filtering that take place on the actual pixel of the image itself is called *spatial domain filtering* [22]. In spatial domain filtering the value of the pixel under consideration at a given moment (i.e. target pixel) depends on the value of its neighbor pixels [22]. If the target pixel value is determined by some linear combination of the pixel values of its neighborhoods,

then it called *linear spatial filters* else they are known as *non-linear spatial filters* [19,22]. In linear spatial filtering, the specific linear combination of the neighbouring pixels that is taken is determined by the filter kernel also known as a *mask*. This is just an array/sub-image of containing the weights that are to be assigned to each of the corresponding pixels in the neighbourhood and exactly have the same size as the neighbourhood.

The mechanism of linear spatial filtering operation actually expressed in discrete formal process called *convolution* [22]. Filtering operations over a whole image pixel is done using convolution. The steps in linear (convolution) filtering can be summarized as follows [19,22]:

Algorithm 1: Steps in convolutional filtering

- (1) Define the filter kernel
 - (2) Slide the kernel over the image in such a way that its center pixel coincides with each (target) pixel in the image.
 - (3) Multiply the pixels lying beneath the kernel by the corresponding values (weights) in the kernel and sum the total.
 - (4) Copy the resulting value to the same locations in a new (filtered) image
-

2.3.2.1 Noise Removal

Noise on image can be defined as any undesired things that are found and contaminate the image [19]. The occurrence of noise in an image can be due to several sources starting from thermal noise in acquisition devices to periodic noise in the communication channel used to transmit an image from a remote sensing location to a base station, among several others [19].

Filtering have been used primarily in image preprocessing for noise removal (reduce the amount of noise on the image) [22]. There many types of filters have been proposed for noise removal from a given image but in the remaining part of this section, we present an overview for commonly used types of filters: mean, median and Gaussian filters.

Mean Filter

The mean filter , also known as *average filtering* , is perhaps the simplest linear filter and operates by giving equal weight W_K to all pixels in the neighbourhood as well as for the target pixel [22] . It operates on a $m \times n$ sliding kernel window by calculating the average of all pixel values within the window and replacing the center pixel value in the destination image with the result [19]. Its mathematical formulation is given as follows:

$$f(x, y) = \frac{1}{m \cdot n} \sum_{(r,c \in W)} g(r, c) \quad (2)$$

where g is the noisy image, f is the result image after the mean filter operation, and r and c are the row and column coordinates, respectively, within a window W of size $m \times n$ wherever the operation takes place on the noisy image.

The mean filtering is reasonably effective at suppressing the noises, but at the expense of a loss of high-frequency image detail (i.e. edges) [22]. It causes a certain amount of blurring, proportional to the window size, to the image, thereby reducing the effects of noise. Larger kernel sizes will further suppress the effect of noises but will result in further degradation of image quality [22].

Median Filter

Median filter is a commonly used and popular non-linear filter which overcomes the main limitations of the mean filter [22]. In median filter when each pixel is addressed, it is replaced by the statistical median of its $m \times n$ neighborhoods rather than the mean. The filter first sorts all values within a window in ascending order, then finds the middle number in which half of the numbers are less than middle number and half are greater than of it as the median value, and finally replaces the center (target) pixel value with the median value [19,22].

The median filter is superior to the mean filter in better preserving sharp high-frequency detail (i.e. edges) whilst conjointly eliminating noise, particularly isolated noise spikes [19]. The drawback of median filter is it requires greater computational cost since the median operator requires an ordering of the values in the pixel neighborhood at every pixel location [22].

Gaussian Filter

The Gaussian filter is a non-uniform averaging filter in that the weights in the kernel are not equivalent i.e. it doesn't give equal weight for the neighborhood pixels. The kernel coefficient values, however, are not a function of their distance from the center (target) pixel, but instead are modeled from the 2D Gaussian function [19]. Gaussian function shows the normal distribution in statistics for calculating the transformation to use to every pixel in the image. The 2D Gaussian function is defined as [18,22]:

$$f(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad (3)$$

Where x is the distance from the origin within the horizontal axis, y is that the distance from the origin within the vertical axis, and σ is the standard deviation of the Gaussian distribution. When once applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution from the center point [18].

Applying the Gaussian filter has the effect of smoothing the image, but it is used somewhat different to the mean filter and have most notable properties [22]. First, the degree of smoothing is controlled by the choice of the standard deviation parameter σ , not by the absolute value of the kernel size as in the mean filter. Second, the 2D kernel is separable, which can lead to fast computational implementations of filtering by two consecutive 1D convolutions. Third, the Gaussian function has a rather special property, namely that its Fourier transform is also a Gaussian function, which makes it very convenient for the frequency-domain analysis of filters [18,22].

2.3.2.2 Image sharpening

Image sharpening, also known with the term *edge enhancement* in the literature, is another method under image preprocessing that makes the input image to look more sharpen appearance [22]. It highlights the edges and fine detail of an image like points, lines and edges. It also uses filtering techniques to make image sharpened. The filters used in this method are called *high-pass filter* because the effect on the image preserve high level frequency/feature of an image (i.e points, edge, line) [19,22]. In the following section we will look at two common used spatial image sharpening filters: Laplacian filter and unsharp mask.

Laplacian

It is a popular filtering technique that uses Laplacian operation in order to sharpen an image [19]. Laplacian operation is a differential operator that helps to highlight the change in the gradient of grey or intensity level within the image and deemphasizes regions with slowly varying grey levels. Laplacian filter mainly used in image processing for edge detector and to calculate the second order derivative of an image [22]. In image sharpening it used to find second order derivative of an image. The Laplacian of an image $f(x, y)$ is defined as [19]:

$$\nabla^2 f(x, y) = \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2} \quad (4)$$

The second derivatives are usually approximated for digital signals as

$$\frac{\partial^2 f(x, y)}{\partial x^2} = f(x + 1, y) + f(x - 1, y) - 2f(x, y) \quad (5)$$

and

$$\frac{\partial^2 f(x, y)}{\partial y^2} = f(x, y + 1) + f(x, y - 1) - 2f(x, y) \quad (6)$$

When we combine expression 4 and 5 we go a convenient expression for the Laplacian:

$$\nabla^2 f(x, y) = f(x + 1, y) + f(x - 1, y) + f(x, y + 1) + f(x, y - 1) - 4f(x, y) \quad (7)$$

This expression can be implemented by the convolution kernel that can approximate the second derivative of an image [19]. The two commonly used small kernels are shown in the Figure 2.4 below.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

Figure 2.4: Commonly used convolution masks that are used as an alternative digital implementation of the Laplacian

After getting the second derivative of an image using Laplacian operator, we take the original image and add or subtract (commonly used) the Laplacian to get sharpened image artificially $f_{sharp}(x, y)$ as follow [19]:

$$f_{sharp}(x, y) = f(x, y) \pm \nabla^2 f(x, y) \quad (8)$$

Unsharp mask

Unsharp mask is another alternative image sharpening technique, as the name indicate it use unsharp or smoothing kernel filter to create a mask and sharpen an image [18,19,22]. In order to emphasize or enhance the high-frequency information in the image, the unsharp masking technique will subtract smoothed (or unsharp) version of an image from the original image. The rationale behind this technique is to “increase the amount of high-frequency (fine) detail by reducing the importance of its low-frequency contents. [22]” The procedure in unsharp mask can be summarized as below [19,22]:

- (i). First, it blurs the input image using smoothing filter like mean and Gaussian filter. Let's denote the smoothed image as: $f_s(x, y)$.
- (ii). Then, it produce unsharp mask by subtracting the smoothed image from the original image. Mathematically it expressed as: $g_{mask} = f(x, y) - f_s(x, y)$ where $f(x, y)$ is the original image and g_{mask} is the unsharp mask.
- (iii). Finally, the unsharp mask will be added to the original image with constant scaling factor k that ensures the resulting image is within the proper range and the edges are not ‘over sharp’ in the resulting image.

$$f_{sharp}(x, y) = f(x, y) + k * g_{mask}(x, y) \quad (9)$$

2.3.3 Image Segmentation

Image segmentation is one of the most important tasks in image processing and computer vision [18]. It is the operation that connects /marks the transition between low-level image processing to the high level (analysis and interpretation) one [19]. The task of image segmentation is to separate the given image, usually preprocessed image, into coherent regions/objects of interest [4]. After an image has been segmented, the resulting individual regions (or objects) can easily be represented, described, analyzed, and classified using different techniques.

Image Segmentation can be define as the process of partitioning a digital image into multiple non-overlapping regions. The regions are ideally corresponds to meaningful region which is known as *Region of Interest (ROI)*. Image segmentation is not a trivial task for machines instead it is very hard problem made even harder when it faces non uniform lighting, shadows, overlapping among objects, poor contrast between objects and background in the digital image [22]. The ROI is also varying in different application domain. As a result there is no universal single segmentation algorithm exists for segmenting the ROI in all images. Therefore we need to consider and apply many segmentation algorithms then select the one that performs best for a given requirement [19].

Most image segmentation algorithm uses either discontinuity or similarity properties that can be extracted from pixel values for segmentation [18,19]. In the discontinuity property, the approach is to partition an image based on the differences/changes in properties like intensity, color, texture etc. Whereas in similarity property, the principal approaches are based on partitioning an image into regions that have similar properties according to a set of predefined criteria.

Image segmentation algorithms can be classified in various ways and there is no universally accepted taxonomy for classification of image segmentation algorithms either [22]. One of the simplest of categorization different segmentation methods is based on pixel relationship into three: contextual, non-contextual and other type of image segmentation [19]. In the next subsection we will discuss one by one along taking at least one algorithm for each.

2.3.3.1 Contextual Methods

Contextual methods are image segmentation algorithms that consider how pixels are correlated in the neighborhoods and groups pixels with common properties in to the one region [19]. They also known as *region based methods*, rely on adjacency and connectivity criteria between a pixel and its neighbors. The best known examples of region-based segmentation techniques are *region growing* and *split and merge* [19].

Region growing is a bottom-up approach to segmentation in which it starts from individual pixels also called seeds then it grow a region around it by append pixels in the neighbourhood to the same region if/whenever they satisfy similarity criteria produces

segmented regions at the end of the process [19,22]. The basic idea of region growing methods is to start from a pixel and grow a region around it, as long as the resulting region continues to satisfy a homogeneity criterion [22]. It is, in that sense, a bottom-up approach to segmentation, which starts with individual pixels (also called *seeds*) and produces segmented regions at the end of the process. The similarity criterias are related to their intensity, color or related statistical properties of their own neighbourhood. Simple examples of similarity criteria might be [22]:

- The absolute intensity value difference between a candidate pixel and the seed pixel must lie within a specified range.
- The absolute intensity difference between a candidate pixel and the running average intensity of the growing region must lie within a specified range.
- The difference between the standard deviation in intensity over a specified local neighbourhood of the candidate pixel and that over a local neighbourhood of the candidate pixel must (or must not) exceed a certain threshold – this is a basic roughness/smoothness criterion

Many other criteria can be specified according to the nature of the problem. Choosing appropriate similarity criteria is the key factors in region growing segmentation. Selection of seed points and the definition of a stopping rule also among the key factors in region growing segmentation [22].

Split and merge employs a similar philosophy, but is the reverse approach to region growing i.e. top-down approach [19]. The segmentation procedure will begin by treating the whole image as a single region which is then successively broken down into smaller and smaller regions until each resulting region is considered homogeneous by some criteria [22]. When splitting process is finished/over two or more adjacent regions are combined into one if they are similar enough. This is the goal of the *merging* step: to merge two or more adjacent regions into one if they satisfy a homogeneity criterion

2.3.3.2 Non-contextual Method

Non-contextual methods are image segmentation algorithms that do not consider how pixels are correlated in the neighborhoods [19]. They also known by the term *intensity based*

methods, basically they work based on pixel distributions (i.e., histograms) of the image. The best-known example of non-contextual segmentation technique is *thresholding* [19,24].

Thresholding is most commonly used and popular image segmentation algorithm because of its simplicity and computational speed [22]. The basic idea of thresholding is the conversion of an image with many gray levels into another image with fewer gray levels, usually only two i.e foreground and background. This conversion is usually performed by choose *threshold value* such that pixel values possessing values falling below the threshold value are assigned to one region whilst those that are above the threshold are assigned to another (adjoint) region [19,22]. Mathematically, the process of thresholding an input image $f(x, y)$ will produce a binarized /binary version of it, $g(x, y)$, it can be described as [19,22]:

$$g(x, y) = \begin{cases} 0, & f(x, y) < T \\ 1, & f(x, y) \geq T \end{cases} \quad (10)$$

Where T is the threshold value. Thresholding usually used in preprocessing step in which there are relatively ROI and whose shape is more important than surface properties (such as texture). If we want to partition the image in to two regions (foreground and background), we define single threshold value. This threshold value is known as *global threshold*. Whereas, if we have multiple objects or ROI along with the background, we must define multiple thresholds. These thresholds are collectively known as *local threshold* [22].

One of the most popular and effective developed thresholding algorithms is called *Otsu's* thresholding algorithm [11,25]. It is invented by Nobuyuki Otsu in 1979 [26]. Nobuyuki Otsu [26] transforms the problem of finding an optimal threshold value k to an optimization problem, in which a threshold k value is selected which maximizes one of the objective functions (the criterion measures) that are already seated by exhaustively test every intensity value found in the input/given gray image [26].

The objective function proposed by *Otsu's* are [26]: within-class variance, the between-class variance and the total variance of levels. one can use either of them since all are directly correlated each other. If within-class variance objective function is chosen the goal is to find threshold value that minimizes within-class variance value.

2.3.3.3 Other Methods

These are segmentation methods that do not fall under the above two categories. These include segmentation based on texture, edges, and motion, among others [19].

The rational idea behind edge detection segmentation method is the fact that there is always an edge between two adjacent regions or objects with different intensity values in a given image [22]. The edges can be considered as the discontinuous local features of an image. We can make use of this discontinuity to detect edges and hence define a boundary of the object. This helps us in detecting the shapes of multiple objects present in a given image. We can detect these edges by using filters and convolutions [19].

Filters are helpful in extracting features from the given image [19]. Researchers have found that choosing some specific values for the filters weight/coefficient matrices help us to detect horizontal or vertical edges or a combination of horizontal and vertical edges. One of the well-known weight matrix for edge detecting is the *Sobel operator* [19]. The Sobel operator uses a pair of 3x3 convolution masks (Figure 2.4), one for detecting horizontal edges (i.e. in the x-direction) and the other for detecting vertical edges in the y-direction (rows). Then edge detection works by convolving these filters over the given image.

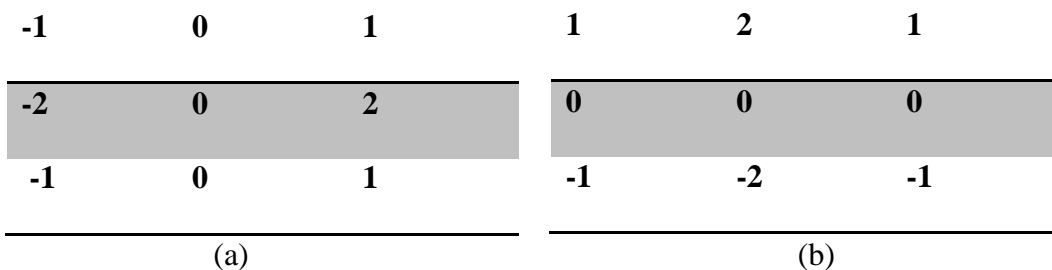


Figure 2.5: The sobel convolutional masks for detecting horizontal edges (a) & vertical edges (b)

Other way of edge detection is using algorithms. One of the best known edge detector algorithms is canny edge detector algorithm. The Canny edge detector [18] acknowledged as powerful and effective edge detection algorithm. Its algorithm can be described as follows [19,22]:

- (1) Noise reduction: edge detection results are highly sensitive to image noise. To get rid of the noise on the image it first smoothed using a Gaussian kernel/filter.

- (2) Gradient Calculation: The local gradient (intensity and direction) is computed for each point in the smoothed image to detect the edge intensity and identify the edge direction.
- (3) Digitize the edge direction: Once the edge direction is known, we approximate it to an edge direction that can be traced in a digital image. Considering an arbitrary pixel, the direction of an edge through this pixel can take one of only four possible values: 0° , 45° , 90° , and 135° . Accordingly to its neighboring pixels as shown in the Figure 2.5, we approximate the calculated by whichever of these four angles is closest in value to it.

135°	90°	45°
0°	PXL	0°
45°	90°	135°

Figure 2.6: Values of θ between the center pixel and its eight neighboring pixels

- (4) Non-maximum suppression: The edge points at the output of step 3 result in wide ridges. Thus, we must perform non-maximum suppression to make the edges thin.
- (5) The double threshold step uses two thresholds, T_{low} and T_{high} , to identifying 3 kinds of pixels: strong, weak, and non-relevant. The strong pixels are pixels have intensity so high that we are sure they contribute to the final edge. Weak pixels are pixels that have an intensity value that is not enough to be considered as strong ones, but yet not small enough to be considered as non-relevant for the edge detection. Other pixels are considered as non-relevant for the edge. Pixels with values greater than T_{high} are considered *strong edge pixels*; ridge pixels with values between T_{low} and T_{high} are said to be weak pixels. Whereas pixel with values below T_{low} are considered as *non-relevant*.
- (6) Hysteresis: Is the final step that transforms weak pixels in to either strong one or non-relevant. In hysteresis, weak pixel will be transformed into strong pixels if and only if at least one of the pixels around the one being processed is a strong one.

2.3.4 Feature Extraction

After segmentation is done, the next crucial step feature extraction will be performed. The task or goal of feature extraction is to convert segmented objects into a representation that better describe their main features and attribute of the segmented objects [19]. Feature extracted from the images should be representative of the objects and need to be in compact form amenable to subsequent recognition and classification processes [22].

There are mainly two reasons why extracting features is need to be done [27]. One reason is processing the digital image as its original from will be computational costive [27]. Digital images, even small size ones, have a very large number of pixels when each pixel is applied as an input to the classification process. Let take a grayscale image of size 100×100 pixels, there are $100 \times 100 = 10,000$ input variables to be applied to the model. For a small dataset of 100 samples, there will be a total of $100 \times 10,000 = 1,000,000$ inputs across the entire dataset. If the image is RGB, the total number is multiplied by 3. This requires a large amount of memory size in addition to being computationally intensive. Another reason is the input image has different types of objects with different properties, and we just want to target a single object [27]. For example if we want to detect the human beings only, and we do not care about other objects that might be on the image like dog or grass. If the complete image is feed as the input to the classification process, the dog and the grass will affect the results [27]. It is better to just use features exclusive to the human being only. It is clear that the human being physical appearance (like morphology and color) is different from others physical appearance in the image.

Due to the above stated reasons features extraction have a major importance in image classification performance. It is also a critical step in most computer vision and image processing solutions because it marks the transition from pictorial to non-pictorial (alphanumerical, usually quantitative) data representation [19]. 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. Morphological features are the geometric property of an image like shape and size [22,27]. They are physical dimensional measures that characterize the appearance of an object. For instance, area and perimeter are the two foremost commonly measured size features and similarly circularity measures the shape of image compactness.

Area: is defined as the number of pixels contained within an object (ROI). Area is computed by counting the total number of pixels belonging to the object in the binary image.

Perimeter: The perimeter of an object is the length of its boundary. It is computed by counting the number of pixels in the edge of the object.

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. one of mostly used color feature is histogram.

Histogram: histogram represents the distribution of the intensity values across the image. It is computed by calculating the frequency of each intensity (or grayscale) level in the image. It usually used with gray images, but there are modifications to use it with color images.

Texture is another powerful descriptor of an image, which loosely used to describe the 'roughness' of something. Accordingly, texture measures the attempt to capture characteristics of the intensity fluctuations between groups of neighbouring pixels, something to which the human eyes very sensitive. There are different approaches to extract the texture features from images. One of popular approach is *statistical approaches*. One of the simplest set of statistical features for texture description consists of the following histogram-based descriptors of the image (or region): mean, variance (or its square root, the standard deviation), skew, energy (used as a measure of *uniformity*),

Finally, after extracting all features they usually encoded in to a feature vector to fed to classification algorithm. A *feature vector* is an $n \times 1$ array that encodes the n features (or measurements) of an image or object.

2.3.5 Classification

The last step in image processing pipeline is classification process. The goal of classification process is to develop (design) a classification algorithm/model that can assigns a class to each image based on the feature extracted from the image to which they belong [18,27]. Classification techniques/approaches can be grouped into two main types: supervised and unsupervised.

Supervised classification, also called *supervised learning algorithm*, uses example of feature vectors which have already been assigned to a defined class [19]. It then use this sample of

example data as *training data* and construct a classification algorithm/model with the expectation (intention and hope) that examples of feature vectors which were not used in the design will subsequently be classified accurately. In supervised classification then, the aim is to use training data to construct a classifier which generalizes well to new unseen data also known as test *data* [22].

In contrast, unsupervised classification, also called *unsupervised learning algorithm*, does not require of existing examples from a known pattern class or training data [22]. The data are not labeled and seek to identify groups directly within the overall body of data by looking similarity features (properties) which enables to distinguish one group from another. These results a set of clusters where each cluster of data belongs to a specific class.

Depending on the application areas, various supervised classifiers have been proposed over the years. Among the commonly used supervised classifiers Support Vector machine (SVM), Artificial Neural Network (ANN) and CNN will be discussed.

2.3.5.1 Support Vector Machines

Support vector machines (SVMs), supervised learning method that is used for both classification and regression problems [28]. In a nutshell, the algorithm of an SVM can be summarized as follows. It first transforms the original training data into a higher dimension feature spaces using nonlinear mapping. Within this new dimension space, it searches for the linear optimal separating hyperplane also called a “*decision boundary*” that separates the tuples of one class from another class [29]. If SVM doesn't find a hyperplane in the new dimensional, it then transform the data to new more higher space feature spaces using nonlinear mapping again. This process is iteratively repeated until SVM finds hyperplane that separate data from different classes. Data from between classes can always be separated by a hyperplane using an appropriate nonlinear mapping to a sufficiently high dimension space. The SVM finds this hyperplane using *support vectors* (“essential” training tuples) and *margins* (defined by the support vectors).

There might be an infinite number of separating lines that could be used as hyperplane to separate the class. The SVM find the optimal separating hyperplane that can generalize also for unseen data by searching for the maximum marginal hyperplane [28,29]. The margin is

the shortest distance between two (or more) class of data. The hyperplane will be in the middle of margin so that the shortest distance from a hyperplane to one side of class of data is approximately equal to the shortest distance from the hyperplane to the other side class of data. This can be clearly depicted in the Figure 2.6 the data points that are closest to the hyperplane are called *support vectors* which influence the position and orientation of the hyperplane.

A separating hyperplane can be written as [29]:

$$0 = \mathbf{W} \cdot \mathbf{X} + b \quad (11)$$

Where \mathbf{W} is weight vector matrix, namely, $\mathbf{W} = \{w_1, w_2, w_3, \dots, w_n\}$ where n is the number of attributes; \mathbf{X} is one dimensional matrix that contains the values of features (or attributes) and b is a scalar often referred as a bias. In the Figure 2.5 there are two input features x_1 and x_2 as well as the number of classes are two. Then we can rewrite the Equation (11) as:

$$0 = w_1 x_1 + w_2 x_2 + b \quad (12)$$

SVMs have attracted a great deal of attention and popular from other decision boundary methods like decision trees and logistic regression because of SVMs are highly accurate despite they take longer training time, have a generalization capability. They are also much less prone to overfitting than other methods and works well in high dimensional feature vectors [28].

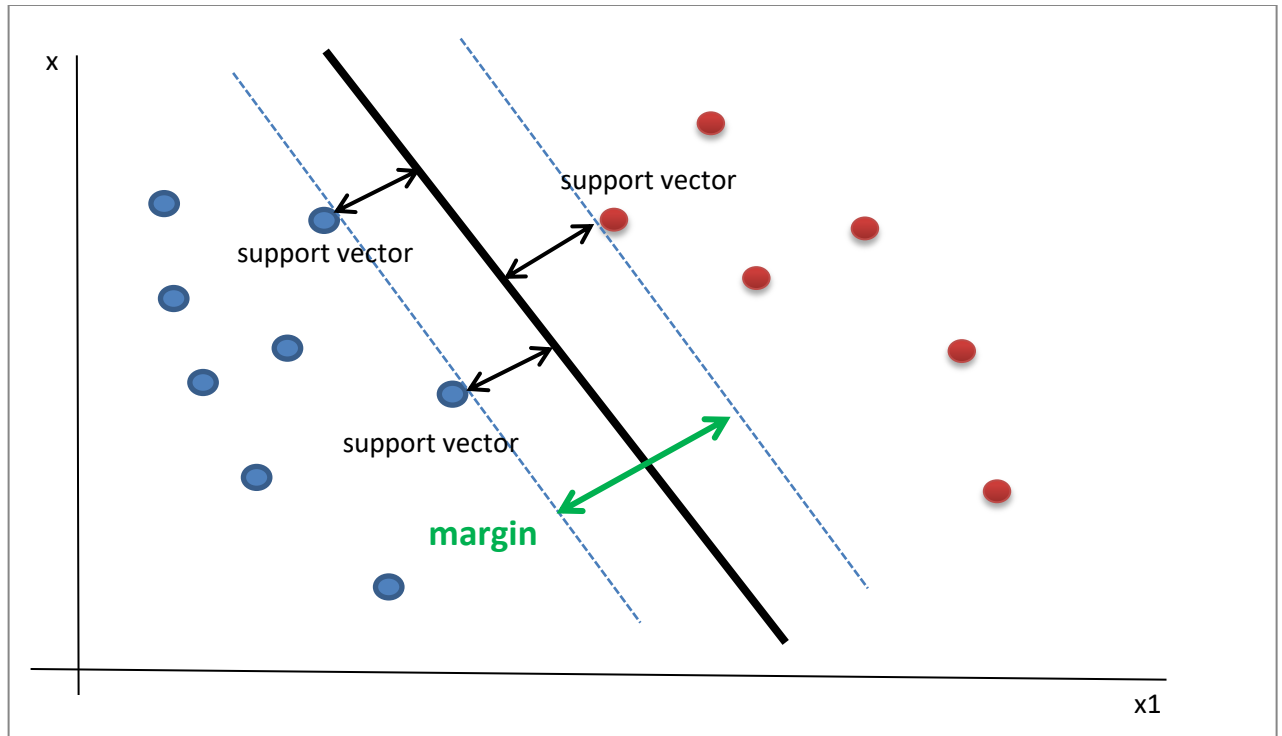


Figure 2.7: *Hyperplane and support vectors used by SVM in 2-D feature space*

2.3.5.2 Artificial Neural Network

An artificial neural network (ANN) is a kind of algorithm that works in different types of problems [30]. We only discuss supervised learning problem solving using ANN. ANN is a biologically inspired machine learning model that mimics the operation of the human brain. ANN is a large set of interconnected neurons, which execute in parallel to perform the task of learning [30]. ANN learning is also referred to as *connectionist learning* due to the connections between neurons. ANN resembles human brain in two perspectives [29]. The first property is that knowledge is acquired by the network through a learning process. The other is inter-neuron 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. Neurons in ANN are a way of mapping inputs to a general output [30]. The basic structure of an ANN can be modeled as shown in Figure 2.7.

In ANNs, neurons are arranged into three types of layers: input, hidden, and output [27,30]. First, the input data is feed in to neurons in the input layer. In input layer, there are as many

neurons as class attributes [29]. The output layer predicts the final output. There are as many neurons in the output layer as the number of classes. In between the hidden layers are existed which perform the most computation required by our network. The number of neurons in the hidden layer and the number of hidden layers depends on implementation. There are no clear rules as to the “best” number of hidden layers and number of neurons on them [29].

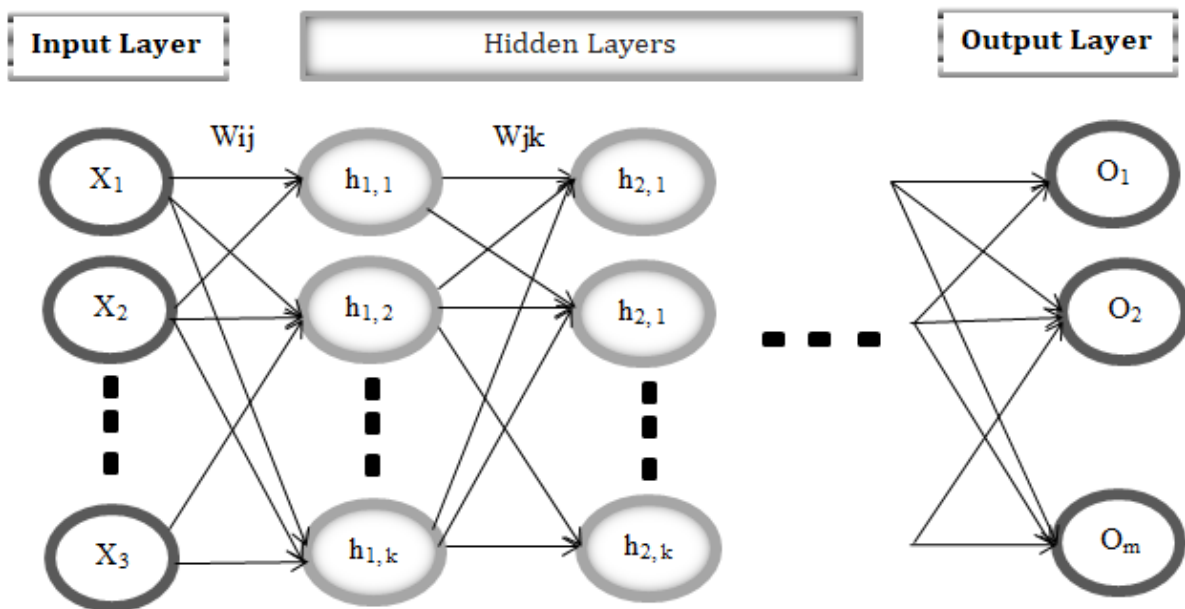


Figure 2.8: General artificial neural network architecture

ANN classification process can be summarized as follows [27]. First the input layer receives the input data. Neurons of one layer are connected to neurons of the next layer through channel. This is depicted in Figure 2.8 with the arrow. Each of these channels is assigned a numeric value known as *weight*. The input then multiplied by their corresponding weight and the sum sent as an input to neuron in the first hidden layer. Each of these neurons is associated with numerical value called *bias* which then added to the input sum. The result then pass through threshold function called activation function. The output of the activation function determines if a particular neuron will get activated or not. Activated neurons transmitted data to neurons of the next layer over the channels. In this manner the information is propagated through the network, this process known as *forward propagation*

[27]. Finally, when it reaches to the output layer, the neurons with the highest value fires and determines the output. The output value basically the probability of input data belongs to specific class [29].

During the training (or learning) phase, the predicted output compared against the actual output of the input data to realize the error in the prediction [27]. The magnitude of the error indicates how wrong we are and the sign suggest the predicted output value higher or lower than the expected output. This information then transferred backward through our network, the process known as *back propagation* [27]. Now, based on the information the weights are adjusted. These cycles of forward propagation and backward propagation is iteratively performed with all training data (multiple input) These process continues until the weight are assigned such that the network predict correctly for most of the data input.

2.3.5.3. Convolutional Neural Network

Convolutional Neural Network (CNN) is a state of the art deep learning model in image processing but it also works better in other problem domain like natural language processing [27,31]. Deep learning model are deep neural network with capabilities to extract features automatically and computational incompetence as compared to ANN [27]. When we consider a fully connected ANN, each neuron in a layer is connected to all neurons in next layers. Every connection between two neurons has two parameters: the weight and the bias. Adding more layers and neurons increases the number of parameters to be learned [27]. As a result, it is terrible long to train such networks even on devices on multiple graphics processing units (GPUs) and multiple central processing units (CPUs). It becomes not possible to train such networks on PCs with limited memory and processing capabilities [27].

In the previous approaches we perform feature extraction, which involve using a set of features that are representative for the problem being solved. This would possibly need the assistance of specialists with in the field being studied, because one feature might be robust for a given problem but weak for another [27]. Choosing the best features to a given problem is the challenge. Starting from a very large number of features might exist for the data, and reducing to the best minimum set will be another problem especially for image data. When there's a small variation in the data, we might able to find a set of features while

operating in small amount of data [27]. Whereas if there are a lot of variations exist in the data, the harder it becomes to find a set of features covering all of them. This well not be a problem in deep learning because features are extracted automatically [27].

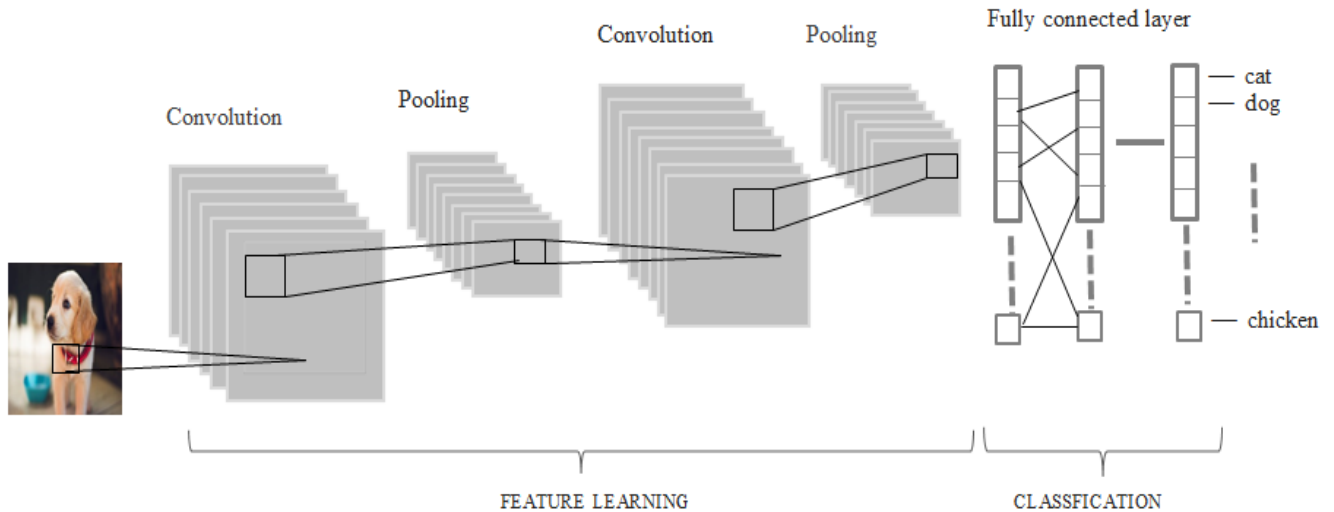


Figure 2.9: CNN architecture with two convolutional layers only

CNNs are usually composed by a set of layers that can be grouped by their functionalities [31] as follows:

- Convolutional Layer: the first layer in CNN that aims to extract features from the input image. They uses small size filters and perform convolutional operation .Its hyper parameters are *filter size* and the *stride*. The stride refers to the number of pixels by which the window or filter moves after each iteration.
- Pooling Layer: also known as sampling layer it is a down sampling operation that occurs /applied after each convolutional layers. The common methods are average pooling and max pooling. In average pooling the average value will be taken where as in max pooling the maximum value will be taken.
- Fully connected layers: are fully connected neural networks which are responsible for classification process and give class scores. It operates on flattened input and usually comes at the end of the CNN architecture.

CHAPTER THREE

RELATED WORK

3.1 Introduction

A preliminary literature review of the given title, on the area of Automatic grading system for agriculture crops specifically cereal grains has been carried out to guide our research and study of the existing approach and current status. The review has drawn on prominent peer reviewed journals and thesis paper of high reputation and published papers.

Various digital image processing works for agriculture crops quality inspection and grading objective are reported within the literature. These research works use image processing techniques to automatically analyze the quality of crops from the captured images samples of its grains. They use morphology, texture and color features of the grains to achieve their goals. Some use morphological features alone while others use a combination of texture, morphology and color features together.

The chapter is presented in three sections. In the first section automatic grading system for soybean is discussed. In the second section works on automatic grading system for main cereal types: rice, maize and wheat are discussed, and in third section related works on automatic grading system other agriculture crops that are mainly exported by Ethiopia are discussed. The chapter shows the position of this thesis research with respect to the literature.

3.2 Quality analysis on Soybean

Soedibyo [12] propose an automated system for grading of soybean based on their combing by extracting morphological and color features namely pod length, pod area, perimeter, defect area, index of red color, and index of green color as attributes for classification using image processing techniques and Artificial Neural Network (ANN). The aim of this research was to develop a computer program that can identify the quality of fresh soybean in Indonesia by using image processing and ANN according to their combing. According to

Soedibyo [12] the quality of soybean seed differs from each other based on the geographic locations of its sources Soedibyo [12] used four class of grade namely: standard quality, second grade, third grade, and reject seeds. Image acquisition, image pre-processing, image segmentation, feature extraction and seeds classification are the major steps followed by the researcher. The author [12] uses ANN single layer hidden layer with 20 nodes, input layer that contains 8 neurons corresponding to each 8 inputs and an output layer that consists of 4 neurons corresponding to each 4 output classes. The proposed architecture of ANN have been trained and tested on dataset and reported that 81.4 % accuracy on the test dataset collected from a national private company called *PT Mitratani Dua Tujuh in Indonesia*. The system architecture is used depicted on Figure 3.1. The author concluded that the automatic grading process is by far better than that of manual grading procedures. The limitation of this work is it considers limited number of morphological and color features, and representative features are missing that can lead to better performance and the color features are not extracted from ROI instead from the total image itself. During specification of the ANN architecture the hyper-parameters (i.e the number of hidden layers and number of neurons in the hidden layer): is tuned manually by trial and error. Tuning hyper-parameters using manually doesn't guarantee even far from getting the best parameter values combination since searching in large search space values is not possible manually.

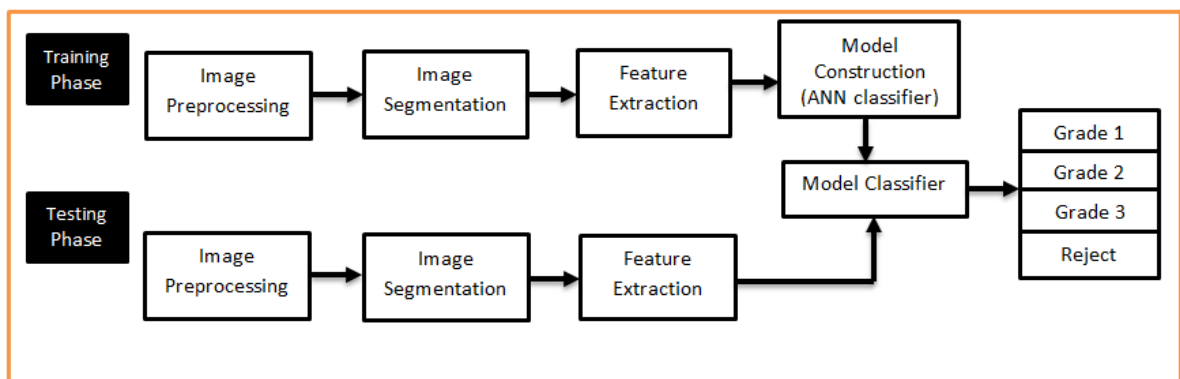


Figure 3.1: System Architecture used in [12]

Vaibhav and Pattalwar [13] also developed a similar system, using color and morphological features as attributes for classification of Indian soybean using image processing techniques and artificial neural network. They used three class of grade: Grade 1, Grade 2 and Grade 3 seeds. Image acquisition, image pre-processing, image segmentation, feature extraction and

seeds classification are the major steps followed by the researches. They concluded that the automatic grading process is by far better than that of manual grading procedures. However, the work does not mention the architecture they used and classification accuracy achieved. Basic morphological features that are going to be used for determining the class of soybean seeds like width of beans, length of beans and circularity were not extracted, and similarly the color features are not extracted from ROI instead from the total image itself. Manual hyper-parameters tuning approach also used during designing the architecture of the ANN.

Ifran et al. [32] also use image processing to characterize the symptoms associated with fungal damage, viral diseases, and immature soybean seeds. The objective of the study is to identify features using color analysis that best described symptomatic soybean seeds, and develop a color classifier for discriminating between asymptomatic and symptomatic seeds, and their types. The work showed that asymptomatic and symptomatic soybean seeds can be differentiated with their color. Six color features including averages, minimums, and variances for RGB pixel values was used for describing the seed symptoms. Overall classification accuracy of 88% is reported. The color analysis showed that color alone did not adequately describe some of the differences among symptoms on soybean seeds and the author recommended to use color with other type of features like morphology and texture. Since the color analysis is rule based one it will lack generalizability to new data and during color feature extraction the features are extracted from the color channel of the colored image instead of from the soybean seeds.

Jitanan and Chimlek [33] used image processing and machine learning for grading of Thailand soybean that can resist to illumination and shape variance. Their [33] aim is to determine soybean seed types from the images of soybean seeds using color and texture features. They [33] consider 5 types of seed: normal, purple, green, wrinkled and other seed type. The study used 1,320 soybean seeds from the seed research and development Center at Phisanuloke Province. The major steps they follow include image segmentation, seed cropping, feature extraction, model construction, selection of suitable classifier model, and accuracy assessment. They use color histogram algorithm and Grey Level Co-occurrence Matrix (GLCM) for the extraction of color and texture features. A support vector machine (SVM) is a supervised learning algorithm is used for model construction by the researchers.

They [33] report that an average accuracy of 99.2% achieved using their proposed approach. They [33] conclude that considering color and texture features improve classification accuracy rather than using color feature only. Morphological feature have not been addressed by the authors which is limitation of their work. Relevance of the features and duplication among the features is also not tested. During color feature extraction the features are extracted from the color channel of the colored image instead of from the soybean seeds.

Abdul et al. [34] develops an algorithm to detect materials other than grain in soybean sample image. The algorithm used image processing techniques which then applied to detect various forms of materials other than grain such as split beans, contaminated beans, defect beans, and stem/pods. Image processing techniques: smoothing, opening, closing, debridging, size and shape discrimination thresholding and segmentation have been used. The authors [34] reported that the algorithm successfully identified the target objects with accuracy rates of 96% for split beans, 75% for contaminated beans and 98% for defect beans and stem/pods. Since rule based classification is used, it will lack generalizability to new data. The other limitation is the color features are not extracted from ROI instead from the total image itself

3.3 Quality analysis on cereals

Neelamegam et al. [35] demonstrated the ability of ANN to accurately estimate the quality grade of basmati rice granules based on four morphological features only: Perimeter, Area, Minor-axis Length and Major-axis Length. First the captured color image is converted into gray color image then median filter applied to remove noise from it. Next, the image is segmented using Adaptive thresholding and edge was then extracted using canny edge detector algorithm. The features then extracted using Contour detection and fed to ANN classifier. The ANN they used has a single hidden layer with 9 neurons, 4 neurons in input layer as equal to number of features and 3 neurons in the output layer as equal to number of classes. They used 75 image dataset for training and testing the system 68% were used for training and 16% were used for validating and testing for each. Neelamegam et al. [35] reported that they got 98.7% accuracy, but the accuracy drops to 91.3% when there is overlap of grains, the ANN is not able to classify correctly in this case. In this work, few number of dataset and features have been used which is the limitation of the work.

A support vector machine (SVM) was used by S.Zemberal et al. [36] to demonstrate a method of quality grading of wheat grains with the help of image processing techniques. Using a total of 1300 datasets, 50% were used for training and the remaining 50% were used for testing. Median filter was first used to remove noise from the captured image. Then, a thresholding technique was used to separate the wheat kernel from the background. They used canny edge detector to detect edges with strong intensity. After edge detecting color features, morphological features and texture features were extracted, and then SVM and Naive Bayes classifiers were used for grading, with the SVM providing the highest accuracy at 94.45%. Limited number of morphological feature is used and the features are not tested whether they are relevant to the target class or not, and duplication among the features.

Ang Wu et al. [37] conducted study on classification of the quality of corn kernels using image processing techniques in Zhengzhou City, Henan Province. According to Ang Wu et al. [37] the quality of corn kernels differs from each other based on the geographic locations of its sources. The corn kernels 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 method for evaluating and classifying corn kernels quality three grades: Grade A, Grade B, and Grade C according to the national standard of china. Image processing techniques were employed to automatically classify the corn kernel samples according to their quality grade. Important corn kernel features based in morphology such as area of the kernel, target regional circumference, rectangularity, circularity, and shape complexity were extracted from 90 training images and 39 testing images. Artificial neural network (ANN), support vector machine (SVM) algorithm and SVM with parameter optimization were employed to automatically categorize the corn kernels. Experimental results show that the SVM and ANN without parameter optimization have the same classification accuracy rates of 92.31% with the best score. The classification accuracies also improved by using the support vector machine optimization algorithms and concluded that the SVM algorithm based on parameter optimization is superior to ANN algorithm with a relatively small number of samples. Ang Wu et al. [37] also concluded that the results of this study have revealed that image processing technique could be used as an effective method to classify quality of corn kernels. The dataset is small for machine learning algorithms and few numbers of morphological features is addressed.

Daniel Hailemichael [38] also uses digital image processing techniques and ANN to assess the quality of maize sample constituents based on the standard for maize set by the Quality and Standards Authority of Ethiopia (QSAE). The maize sample of an image is classified in to one of seven classes: health, foreign matter, shriveled, discolored, rotten and diseased, pest damage, and broken. Preprocessing technique was used to remove the false regions from the captured image based on their size. A hybrid of color structure tensor and thresholding segmentation method is then used to separate maize sample constituents the background and from one to another. In feature extraction, consider only color and morphological features and extract a total of 24 (14 color, 8 shape and 2 size) features. The ANN classifies maize data based on the features extracted by the feature extraction phase. The ANN architecture in this work is a three-layered: input layer that contains 24 neurons corresponding to each 24 inputs, hidden layer with 45 neurons and an output layer that consists of 7 neurons corresponding to each 7 output classes. Daniel Hailemichael [38] reported that the overall success rate for the classification of maize sample is 97.8% accuracy. The author [38] also compared the discriminative power of the features and find out color features have the highest discriminative power than that the other features. The limitations of this work are: during color feature extraction the features are extracted from the color channel of the colored image instead of from the soybean seeds, and the features are not tested whether they are relevant to the target class or not, and duplication among the features

3.4 Quality analysis on other Agricultural crops

Hiwot Desta [8] conducted study on the classification of Ethiopian sesame seed and determine the quality using image processing techniques. According to Hiwot Desta [8] the quality of sesame seed differs from each other based on the geographic locations of its sources. Image processing techniques employed to enhance and extract features from the given image. After extracting morphological and color features; rule based approach is used for classification and quality grading. A total of 750 images are used, 70 % are used for training and the rest 30% used for testing. Final Hiwot Desta [8] concluded that the results of this study have revealed that imaging technique could be used as an effective method to classify and grade sesame seed than that of the manual inspection method. Since rule based

classification is used, it will lack generalizability to new data. The other limitation is the color features are not extracted from ROI instead from the total image itself

Habtamu Minassie [39] also used digital image processing technique to classify different varieties of Ethiopian coffee based on their growing region. For the classification analysis, ten morphological and six color features were extracted from each coffee bean image. The type of coffee either washed or unwashed has been predefined initially. The researcher [39] used supervised learning methods namely Naïve Bayes and neural network. Accordingly, it was found that the classification performance of neural network classifier outperform 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 yields better classification accuracy. The limitations this works are: color features are not extracted from ROI instead from the channels of the colored image, and the hyper-parameters are tuned manually by trial and error when determining the number of hidden layers and neurons in the ANN architecture.

A Convolutional Neural Network (CNN) models has been used by Serawork Walleign et al. [10] to classify raw coffee beans into 12 quality grades. The researchers [10] used a total of 2109 image dataset collected from Jimma grading center in Ethiopia. The dataset were divided into three sets for training (70%), validation (10%) and testing (20%). They have use two types of CNN models. The first model is constructed by transfer learning on the pre-trained Visual Geometry Group (VGG) model. The second CNN model is designed from VGG model by replacing fully connected layer for the classifier with 1x1 conv layer followed by global average pooling and 7x7 filters with stride of 3 in first convolutional layer instead of 5x5 filters. They [10] used Keras deep learning framework for implementation of models. The authors [10] reported that they achieved 89.1% on the test dataset and the designed model is better that of pertained model. The limitation of this work is they consider only VGG architecture of CNN other architecture have not been addressed.

3.5 Summary

It can be concluded from the above researches that identifying and extracting determinant features from morphological structures, color and texture properties is crucial task in

computer vision systems for inspection and grading of agricultural products. As a classification technique, SVM and ANN are widely used and successful techniques for classification, inspection and grading of agricultural products.

In general, various techniques have been proposed over the years to automate the manual processes on agricultural products. The limitations of the works are summarized in Table 3.1. Literature reveals that the proposed techniques depend on the type of the agricultural product. Thus, a system developed for grading of agricultural product could not be directly applied for other products due difference in morphological, color, texture and determinant parameter of the product. Image processing and computer vision approaches give a better accuracy in grading system. Few works have been done to determine the quality grade of combed soybean according to their combing level. We cannot directly apply them to system that can determine the quality grade of for non-combed soybean according to them amount of impurities found in soybean samples due to the difference in the process and parameters used to determine the quality grade of the soybean samples. Thus, in this thesis, we propose an automatic grading system for soybean according to ECX criteria. As compared to related works done on soybean this thesis: we considers morphology, color and texture features, and design an appropriate and effective classification model that can determine the quality grade of soybean according to ECX criteria seeds with better performance by comparing SVM, ANN and CNN, which is deep learning models that achieves a state-of-the-art performance in various computer vision application. Furthermore it also overcomes the limitations of the related works particularly in feature extraction and model classifier development.

Table 3.1: Summary of the related work

Crop	Author	Objective	Method	Features	Limitations
Soybean	Soedibyo	Quality grading of soybean according to their combing level	Image Processing + ANN	Morphological & color feature	<ul style="list-style-type: none"> ▪ Few morphological & color features used ▪ Color features are not extracted from ROI ▪ In ANN, the hyper-parameters are tuned manually by trial and error
	Vaibhav and Pattalwar	Quality grading of soybean according to their combing level	Image Processing + ANN	Morphological & color feature	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ Few morphological features is used ▪ In ANN, the hyper-parameters are tuned manually by trial and error
	Ifran et al.	Detect disease on soybean seeds	Color analysis	Color feature	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ Generalizability
	Jitanan and Chimlek	Detect soybean seed types	Image Processing + SVM	color & texture features	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ Relevance of the features and duplication among feature is not tested
	Abdulhe et al	Detect foreign matters on soybean	Image processing + rule based classifier	morphological & color features	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ Generalizability
Cereals	Neelamegam et al.	Quality grading of basmati rice	Image Processing + ANN	Morphological feature	<ul style="list-style-type: none"> ▪ Few Number of features is used ▪ The data set is small
	S.Zemberal et al.	Quality grading of wheat grains	Image Processing + SVM, Naïve Bayes	Morphological ,color & texture feature	<ul style="list-style-type: none"> ▪ Few number of morphological features is used ▪ Relevance of the features & duplication among features also not tested
	Ang Wu et al.	Quality grading of corn kernels	Image Processing + SVM,ANN	Morphology feature	<ul style="list-style-type: none"> ▪ The dataset is small ▪ Limited number of morphological features is addressed
	Daniel Hailemic hael	Quality assessment on maize sample constituents	Image Processing + ANN	morphological & color feature	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ The relevant of the features to the target class is not tested ▪ Duplication among features also not tested ▪ In ANN, the hyper-parameters are tuned manually by trial and error
Others	Hiwot Desta	Classification & quality grading of Ethiopian sesame seed	Image Processing + Rule based classifier	morphological and color features	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ Generalizability
	Habtamu Minassie	Varieties Identification of Ethiopian coffee	Image Processing + Naïve Bayes, ANN	morphological and color features	<ul style="list-style-type: none"> ▪ Color features are not extracted from ROI ▪ In ANN, the hyper-parameters are tuned manually by trial and error
	Serawork Walleign et al	Quality grading of coffee	preprocessing techniques+ CNN		<ul style="list-style-type: none"> ▪ Only VGG CNN architecture is address

CHAPTER FOUR

THE PROPOSED SOLUTION

4.1 Introduction

The action of visualizing and quality grading of soybean is a complex and systematic task. Thus, it requires a great deal on design good soybean quality grading system in order to accurately classify (or predict) the quality grade of soybean as much as possible. This chapter presents, the details about the methods and algorithms employed in the proposed system architecture, image processing techniques and the models used for quality grading of soybean grain.

4.2 The Proposed System Architecture

The proposed system architecture for quality grading of soybean is shown in Figure 4.1. The architecture is adopted from the works [12] and [33]. The system first loads the image of soybean, preprocesses the acquired image, detect soybean sample constituents on the image which includes soybean seeds and other foreign matters using image segmentation technique, then the system perform quality inspection which determine the type of soybean sample constituents based on the model created in the training phase. The type's values of the soybean sample constituents can be among one of: normal, defect, split, insect bored and foreign matter soybean types. Finally, after knowing the types of each foreground things on soybean image; the system decides the quality of the soybean samples according to the rule followed by ECX.

The architecture also depicts two phases of classification process followed as a training phase and testing phase. During training phase the soybean quality inspection models will be created and they will be applied in the testing phase to determine the quality grade of soybean. The number of components differs in the two phases.

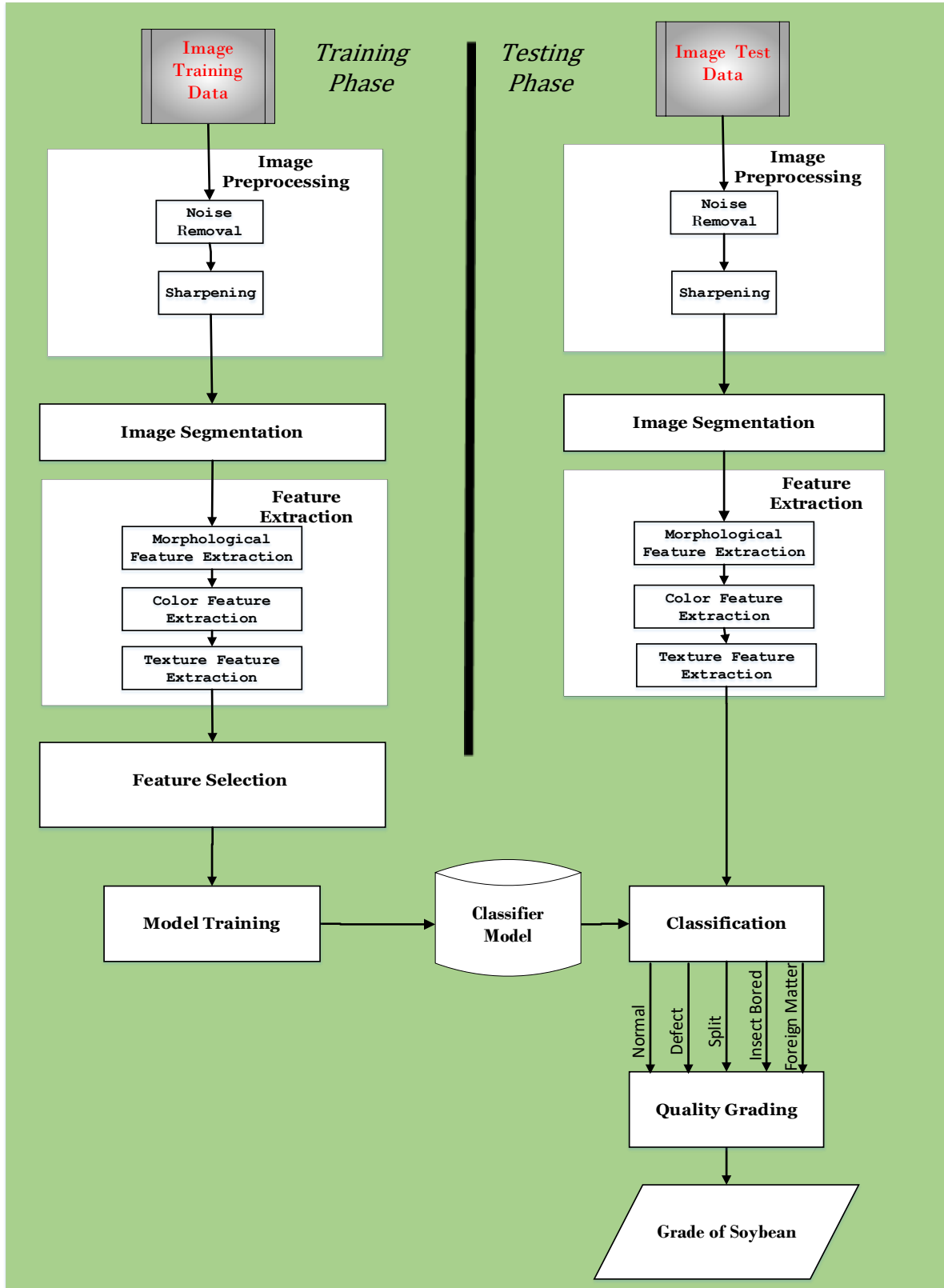


Figure 4.1: The Proposed System Architecture for Soybean Quality Grading

4.3 Training Phase

The quality inspection system is crucial stage in the quality grading process of soybean to determine the quality grade of soybean. The quality inspection should have to be done carefully otherwise any mistaken may alter the quality grade the sample soybean. The goal of the training phase is to develop a model that can accurately identify normal, defect, split, insect bored and foreign matter soybean seeds types.

The classifier model builds by the classification algorithm by analyzing or “learning” from the training dataset made up of data tuples and their associated class labels also called *labeled dataset*. In the training phase there are five components namely: image preprocessing, image segmentation, feature extraction, feature selection and model training (building) components.

4.3.1 Image Preprocessing

Image preprocessing is applied on the acquired images for improving the quality of image and to reduce the undesired portion from background of the images. Most image preprocessing techniques are applied to the intensity values of the region pixels for obtaining the correct brightness intensity value of the input images. The main reasons for the requirement of image preprocessing are image quality improvement, noise reduction, correction of missing or wrong pixel values, and 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 two discussed techniques were use in this study; noise removal and image sharpening.

4.3.1.1 Noise Removal

First, noise removal preprocessing image filtering was used on the acquired images. This process try to reduce the noise induced to image during image acquisition. One of the main goals of image preprocessing is removing the noise by reserving the edges. Thus, we use median filtering and Gaussian blurring flirting algorithms and compared each other. The reasons why we select these two filtering algorithms are that under certain conditions, they preserve edges while removing noise. As the experiment indicates median filter more perform than Gaussian filter. Since the acquired image is an RGB format we didn't directly

apply filtering to it instead we separate each RGB channels and apply filtering to each one independently then merge the result to get the final RGB filter image. The algorithm is described as below:

Algorithm 2: Steps in Noise removing

- (1) Split the image into separate 3 channels: Red, green, blue.
- (2) Filter each one independently using median filter.
- (3) Merge the result of each result image to get the output colored filtered image

4.3.1.2 Sharpening

In order to emphasize and preserve the high-frequency components of an image like fine details, lines and edges we apply sharpening technique to the noise reduced images. Sharpening is important task for subsequent processes especially for segmentation because sharpening highlights the transitions in intensity within the image so segmentation process can better performed/ successful. In this work we apply unsharp masking sharpening technique with scaling constant k value of 0.7 . Similar to noise removal step, here we separate each RGB channels and apply sharpening to each one independently then merge the result to get the final RGB sharpened image. The algorithm is described as below:

Algorithm 3: Steps in Sharpening

- (1) Split the image into separate 3 channels: Red, green, blue.
- (2) Sharpen each one independently using unsharp masking.
- (3) Merge the result of each result image to get the output colored sharpened image

4.3.2 Image Segmentation

The image segmentation component of our proposed architecture on training phase is responsible for carrying out the work of separating soybean sample constituents from each other, labels them with their type and determines the region of interest (ROI).

Separating soybean sample constituents and labeling is done manually here. By using cropping method we separately identified each soybean sample constituent and the type of each soybean sample constituent is determined by the experts from ECX. Figure 4.2 shows sample result of cropping and labeling.



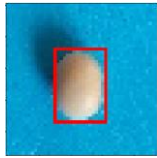


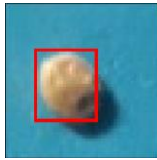





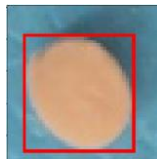


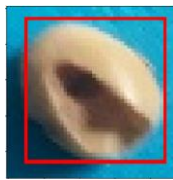





Figure 4.2: Sample image cropping and labeling during image segmentation

The final task of image segmentation is to determine ROI on the image. Various techniques have been discussed in Chapter Two that could play a role to identify ROI from a given image. Among these, here the used one is threshold segmentation based on the performance and quality in determining region of interest.

Threshold segmentation creates a binary image from gray level image. It operates by first selecting a threshold “T” intensity value that can separate foreground and background accurately. Then any pixel point that have higher intensity value from “T” value will be considered as object pixel and set their value to one(white) whereas the other pixels points will be considered as background and set their value to zero(black). We used modified version of Otsu’s threshold algorithm to make work for color image segmentation. After exhaustive experimentation we found that applying thresholding on saturation component of (Hue Saturation Value) HSV color image result the best performance. HSV is a cylindrical color model in which color image is created in the way of human color perceptions [18]. Just like in RGB, HSV have three components: hue, saturation and value. The hue defines the colors, saturation defines to the amount of gray in a color, and the value defines how much brightness or black is in a color.

Table 4.1: Sample Image Segmentation Results

Soybean Type	Original Image	Threshold Image	Detected soybean
Normal			
Defect			
Defect			
Split			
Insect Bored			
Foreign Matter			

We use the final binary image as a mask to extract features from colored image. Table 4.1 shows screen shot of the result after applying the segmented binary image as a mask to detect and count the soybean kernels in a given input image. The red rectangle shows the

bounding box of each soybean kernel in the given input image. The threshold segmentation algorithm that is used presented below.

Algorithm 4: Steps in Threshold segmentation

- (1) Convert the RGB input image to HSV image
 - (2) Extract the Saturation channel from the HSV image.
 - (3) Set our objective(criterion) function is between-class variance
 - (4) Find the threshold value T using Otsu's algorithm that maximizes our objective function.
 - (5) Convert Saturation channel to binary image by setting image pixels into white in those regions, where saturation values is greater than T and into the black in the opposite cases.
-

4.3.3 Feature Extraction

Feature extraction component is responsible for extracting the descriptive features of the soybean seed. Extraction of a meaningful set of empirical information and data of soybean parameters from the segmented images is the very essential task to model computer-assisted soybean quality value computation tasks. Thus, representative features from soybean need to be extracted. Feature extraction component extracts morphology, color and texture features from ROI from soybean images. To describe soybean sample constituents, we identified 67 total features: 25 morphological features, 18 color features, and 24 texture features. These features are identified with the direction of ECX guideline and experts information collected by asking questions at Annex-A.

4.3.3.1 Morphological Feature Extraction

In image processing, morphology indicates the geometric feature in an image. This includes information about the shape, size and structure of an object in an image. Area, perimeter, major and minor axes lengths, and aspect ratio are some of the foremost usually measured morphological features. Morphological features also widely used in automated grading, inspection, classification and detection of objects in industry. Morphological features in the

proposed system were obtained from the analysis of binarized images this is due to the extracting morphological feature from binary image is simple as compared to other type of image. The morphological features that are extracted in this sub-component are shown in Table 4.2.

Table 4.2: Name and number of morphological features extracted

Morphological Feature Property	No of features
Area:	1
Perimeter	1
Centroid:	2
Orientation:	1
Major axis length:	1
Minor axis length:	1
Diameter:	1
Extrema:	$(4*2)+2=10$
Eccentricity:	1
convex_area	1
Solidity	1
Circularity	1
Euler number	1
Extent	1
Bounding_box_area	1
Total:	25

4.3.3.2 Color Feature Extraction

Color is one of the visual attributes of soybean that is used for quality grading. It is a straight-forward feature that humans perceive when viewing an image.

Three color features have been selected to represent the color features of soybean sample constituents. The color features, extracted are based on the RGB and HSV color model from ROI. These features are the *mean*, *min* and *max* intensity values of ROI. The color features are extracted by logical indexing to binary segmented image and correspondent image we extract the mean, min and max intensity values. The color features that are extracted in this sub-component are shown below in Table 4.3.

Table 4.3: Name and number of color features extracted

Color Feature Property	No of features
Mean Intensity of RGB channels	1*3
Min Intensity of RGB channels	1*3
Max Intensity of RGB channels	1*3
Mean Intensity of HSV channels	1*3
Min Intensity of HSV channels	1*3
Max Intensity of HSV channels	1*3
Total	18

4.3.3.3 Texture Feature Extraction

Texture feature is another key element of human visual perception and is used in many image processing systems. Distinguishing different textures is an easy task for our naked eyes but for computer it not that much an easy as compared to other type of features. There are different approaches to the extraction of features characterizing the texture; among them we used a statistical approach called *GLCM* and convolutional filter called Gabor.

GLCM is one of the popular statistical texture feature extraction methods that rely on the second-order statistics extracted from the spatial relationship between pairs of pixels. As the name indicate, it accepts a gray scale image as input and returns a two-dimensional histogram that counts the number of co-occurrences between each pair of gray scale levels according to the distance between them. What makes GLCM different from the first-order histogram is that GLCM depends not just on the intensity but also on the spatial relationship of the pixels.

In this work GLCM is extracted from the gray image of the sharpen RGB image. After extracting GLCM four numbers of features have been extracted from the matrix to condense the GLCM matrix namely: *contrast*, *correlation*, *dissimilarity* and *energy*. All the work on texture feature extraction in this research has been done using built in function on scikit-image library.

Table 4.4: Name and number of Texture features extracted

Texture Feature Property Name	No. of Features
Contrast	1
Correlation:	1
Energy:	1
Dissimilarity	1
Mean	1*10=10
Variance	1*10=10
Total	24

The second method we have used to extract texture feature from the input image is Gabor filter. Gabor filters is well known convolution filters that are mainly used in generate features that represent texture and edge [40,41]. It is made up by combination Gaussian and sinusoidal terms. The Gaussian component provides the weight and the sinusoidal component provides the directionality. What make interesting of Gabor filter kernels is it actually mimics the visual cortex of how human recognize texture with our eyes is simulated with it [40].

The process of feature extraction using Gabor filter kernel is first by building bank of Gabor filter kernels by changing the orientation parameters and central frequency [41], in this work we build 10 Gabor filters which shown in in Figure 4.3. Then convolve each Gabor filter to the image. Finally mean and variance of feature is extracted from the image of filter response. The texture features that are extracted in this sub-component are shown in Table 4.4.

Algorithm 5: Steps in Texture Feature Extraction using Gabor filter

- (1) Convert the sharpen RGB image into gray level
 - (2) Construct bank of 10 Gabor filters with 2 frequency and 5 orientations
 - (3) Apply Gabor filters on the gray level of the image by convolution
 - (4) Compute the mean and the variance of from each of the filters responses image
-

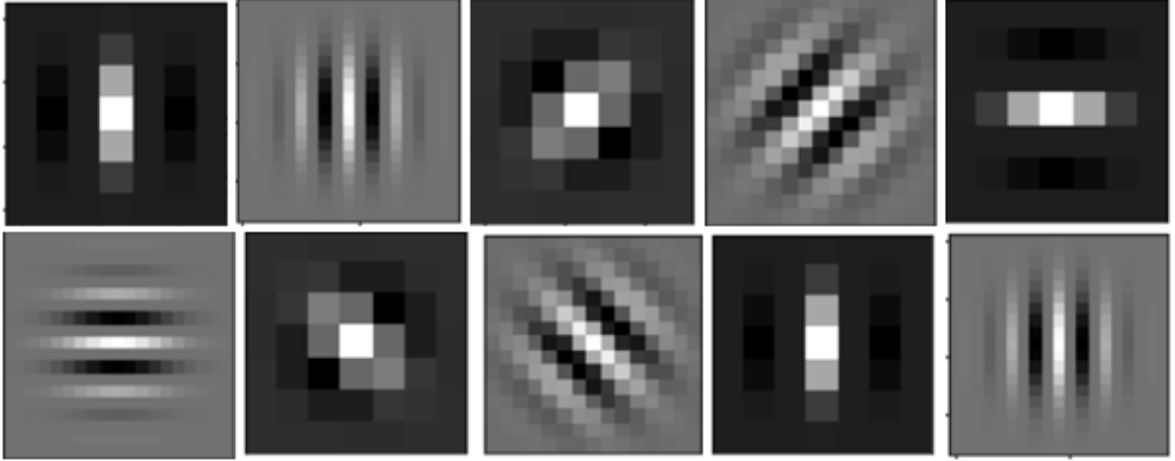


Figure 4.3: *The designed Bank of Gabor filters*

4.3.4 Feature Selection

The entire feature extracted initially might not all helpful and some may be redundant. Thus we need to eliminate non-important or bad features and kept only important features to the task we are solving. The process of removing certain features completely from the feature sets and keeping others is called *feature selection* [27]. The feature selection is very essential components that help to build a simple model that require less resource and even improve model accuracy result by removing unnecessary features from the entire feature sets.

Two types of features are going to be removed in this component from our entire feature sets that we built in the previous component. The first ones are redundant features. Redundant features are features that are highly correlated with each other, and thus only one feature is sufficient in describing the data and there is no need to use multiple features that work the same. Features that have higher than 0.85 correlation absolute values are consider as redundant feature in our work, and feature that have low correlation absolute value with the target class will be dropped.

The second types of features that are going to be removed are irrelevant features. These features have characterized by having no correlation with the predicted target class and they are regarded as noise. Such features will not enhance but rather degrade the results. So, it is preferred to detect such features and remove them so they do not affect the learning process. In our work, features that have below 0.2 correlation absolute value with the target class considered as irrelevant features.

Algorithm 6: Steps in Feature Selection

- (1) Built correlation matrix between all features and target class.
 - (2) Drop features that have less than 0.2 correlation absolute value with target class.
 - (3) Built correlation matrix among all features excluding target class
 - (4) Find features that have correlation absolute value 0.85
 - (4.1) If exist check their correlation absolute value with target class.
 - (4.2) then, drop feature that have less value
-

After applying the feature selection algorithm the number of feature is dropped from 67 to 19. Table 4.5 shows the selected features that going to be used in next components a well as in feature extraction component in the test phase.

Table 4.5: *The Selected Features after feature selection component*

Types of Feature	Name of the Feature	No. of Features	Total
Morphology	Extrema-Left-x:	1	7
	Extrema-Top-y:	1	
	Extrema-Bottom- y:	1	
	Extrema-Right-x:	1	
	Eccentricity:	1	
	Major-axis-length:	1	
	Circularity:	1	
Color	Min-intensity-R,B	2	6
	Mean-intensity-B,	1	
	Mean-intensity-V	1	
	Max-intensity-S	1	
	Max-intensity-r	1	
Texture	MeanGabor1, 2, 4, 6, 8	5	6
	Correlation:	1	
	Total		19

4.3.5 Model Training

The last component under training phase is model building also known with the term model construction in the literature. Supervised classification algorithms are used to build a classifier model through learning from the labeled training dataset meaning they are associated with predetermined class labels. As discussed earlier the class labels are: normal, defect, split, insect bored and foreign matter. In this component: supervised classification algorithms are applied to labeled training dataset to build their correspondent classifier model. The models weights and parameters will be adjusted during the leaning process to get high accuracy prediction results.

A random search optimization technique is used in the course of the study to determine each hyper-parameter optimal value search in model architecture development: The technique randomly combine hyper-parameters values to find the best solution to build a model.

The three supervised classification algorithms selected for the purpose of this study are Support Vector Machine (SVM), Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) classifiers.

4.3.5.1 Support Vector Machine (SVM)

Support vector machine (SVM) is a suitable supervised machine learning algorithm which can be used for classification and regression challenges. For this study SVM is utilized in classification problem is selected for better accuracy than the other classifiers based on scholar's recommendation. It works by seeking out optimum hyper plane to separate different categories of input data into higher dimension features space. And additionally 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 feature (attribute) being the value of a particular coordinate. SVM classifier is used from Scikit-learn python library for implementation.

4.3.5.2 Artificial Neural Network (ANN)

An artificial neural network (ANN) is a widely used classification algorithm which produces an effective computer-supported raw quality value classification model. There is essential

importance behind employing ANN classifier that makes it powerful analytical tools. These are flexible learning algorithm, diverse network topology, fast learning capability and high error tolerance.

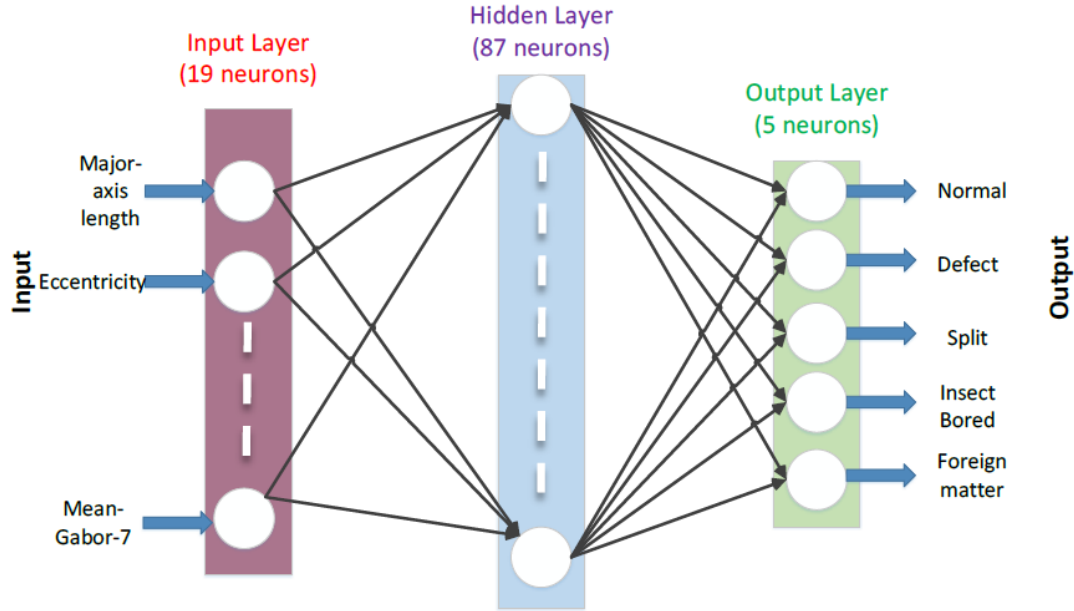


Figure 4.4: Architecture of the ANN in the proposed system

ANN has been the successfully used as classifier and regression model in numerous fields. The neural network architecture in this work is a three-layered network as shown in Figure 4.4. The input layer contains 19 neurons corresponding to each 19 inputs and the output layer consists of 5 neurons corresponding to each 5 output classes. The network is designed to have only one hidden layer consisting of 87 nodes. The number of hidden layers and number of neurons in the hidden layer is selected using random search *hyper-parameter tuning method*. The type of method used to determine each hyper-parameter found in ANN is shown the Table 4.6.

Table 4.6: ANN hyper-parameter values explored with their method

Methods	Hyper Parameter	Range
Random Search	Number of Hidden Layers	$z [1, 2]$
	Number of Neurons	$Z [14, 200]$

4.3.5.3 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is one of deep learning model that is currently a state of the art model in computer vision and image processing problems. In this thesis, we have used 1D-CNN and 2D-CNN models as classification model. The 1D-CNN model works on the hand crafted features that are extracted in the feature selection component, whereas the 2D-CNN works on the actual captured image of datasets and the feature extraction is fully by itself automatically as discussed in chapter two section 2.3.5.

1D-CNN:

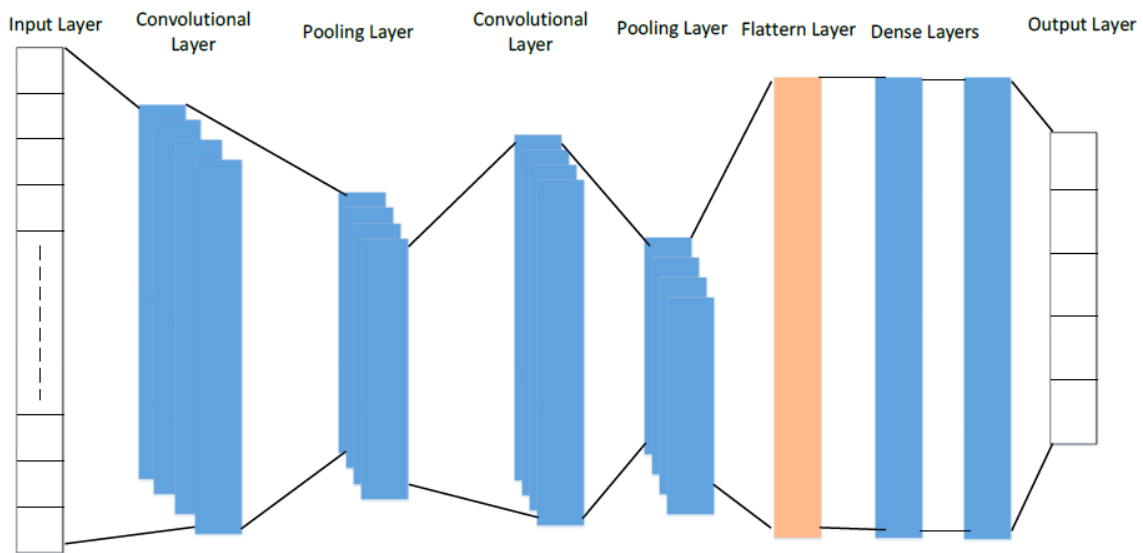


Figure 4.5: Architecture of the 1D-CNN in the proposed system

As shown in Figure 4.5 the proposed CNN model contains two layers feature extraction and three layers dense layers. This model consists of convolution, pooling and classification layers combined together. The feature extractor consists of two convolution layers them and max pooling with size of 2 between each convolution operations. The first convolutional layer consist 48 filters with size of 5 each. Whereas, the second convolutional layer contains 32 filters with size of 3 each. In the classifier part, 194 neurons have been used in the first dense layer and 476 in the second dense layer. The last dense layer consist 5 neuron as an output of this models. Flattening layer is also included before the fully connected layer to convert the output of feature extractor in to 1D feature vectors for the dense layer. Finding

optimal values for hyper-parameters is crucial in the model performance. The type of method used to determine each hyper-parameter found in 1D-CNN is shown the Table 4.7.

Table 4.7: 1D-CNN hyper-parameter values explored with their method

Methods	Layers	Hyper Parameter	Range
Random Search	Convolution	Convolutional Layers	$z [1, 4]$
		Filters	$Z [16, 100]$
		Kernel Size	(3) and (5)
	Dense Layer	Dense Layers	$Z [1, 2]$
		Neurons	$Z [20, 500]$
Trial and Error		Max Pooling	2 and 5

2D-CNN:

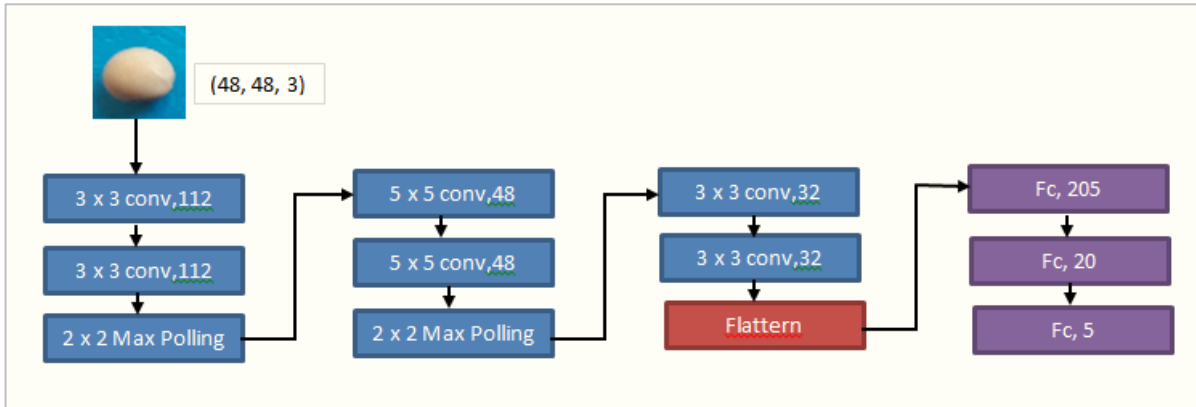


Figure 4.6: The Proposed 2D-CNN architecture

As discussed earlier the 2D-CNN models works on the actual image of the data. But, the input images should have the same size to feed them in the input (the first convolutional layer). To do so we first resize our image into size of 48 by 48. Since image type is RGB color the shape of our image becomes (48, 48, 3), where 3 correspondent to the number channels on the image. As depicted in Figure 4.6 the proposed 2D CNN model contains six layers feature extraction and thee layers of dense or fully connected layers. The first two convolutional layers contain 112 filters with size 3 by 3 each and followed by 2 by 2 max pooling layer. The next two convolutional layers contain 48 filters with size 5 by 5 each and followed by 2 by 2 max pooling layer. In the fully connected layers, the first layer consist

205 neurons and 20 neurons in the second layer. The third layer consist 5 neurons similar to then number of classes. Flattening layer is also included before the fully connected layer to convert the output of feature extractor in to 1D feature vectors for the classifiers. The type of method used to determine each hyper-parameter found in 2D-CNN is shown the Table 4.8.

Table 4.8: 2D-CNN hyper-parameter values explored with their method

Methods	Layers	Hyper Parameter	Range
Random Search	Convolution	Convolutional Layers	$z [1, 15]$
		Dense Layers	$Z [1, 4]$
		Filters	$Z [32, 128]$
		Kernel Size	(3) and (5)
		Dense Layer	Neurons
Trial and Error		Max Pooling	2 and 5

4.4 Testing Phase

Unlike the training phase the testing phase uses unlabeled dataset. The main goal of testing phase is to measure the performance or accuracy of the classifier model that we get from training phase. The test dataset is feed in to the quality inspection classifier model then the predicted class of the classifier is then the quality grade will be calculated from it and compared to the actual class of the dataset to measure its accuracy. The test datasets are separately prepared from the training dataset, and they are independent from the training dataset, meaning that they are not used to construct the classifier. In this phase there are five components namely: image preprocessing, image segmentation, feature extraction, classification and quality grading components.

4.4.1 Image Preprocessing

Image preprocessing is applied initially on the acquired images for improving the quality of image and to reduce the undesired portion from the background of the images. The image processing applied here are similar to the one we have done on image preprocessing component on the training phase of see section 4.3.1 for details.

4.4.2 Image Segmentation

Image segmentation is done on the preprocessed image to differentiate between foreground soybean sample constituents and background of the image. In this component we have used Otsu's thresholding algorithm for segmentation purpose. The algorithm we have used is similar to what we have done on image segmentation component on the training phase of see section 4.3.2 for details. Figure 4.7 shows screen shot of the result after applying the segmented binary image as a mask to detect and count the soybean kernels in a given input image. The red rectangle shows the bounding box of each soybean kernel in the given input image.

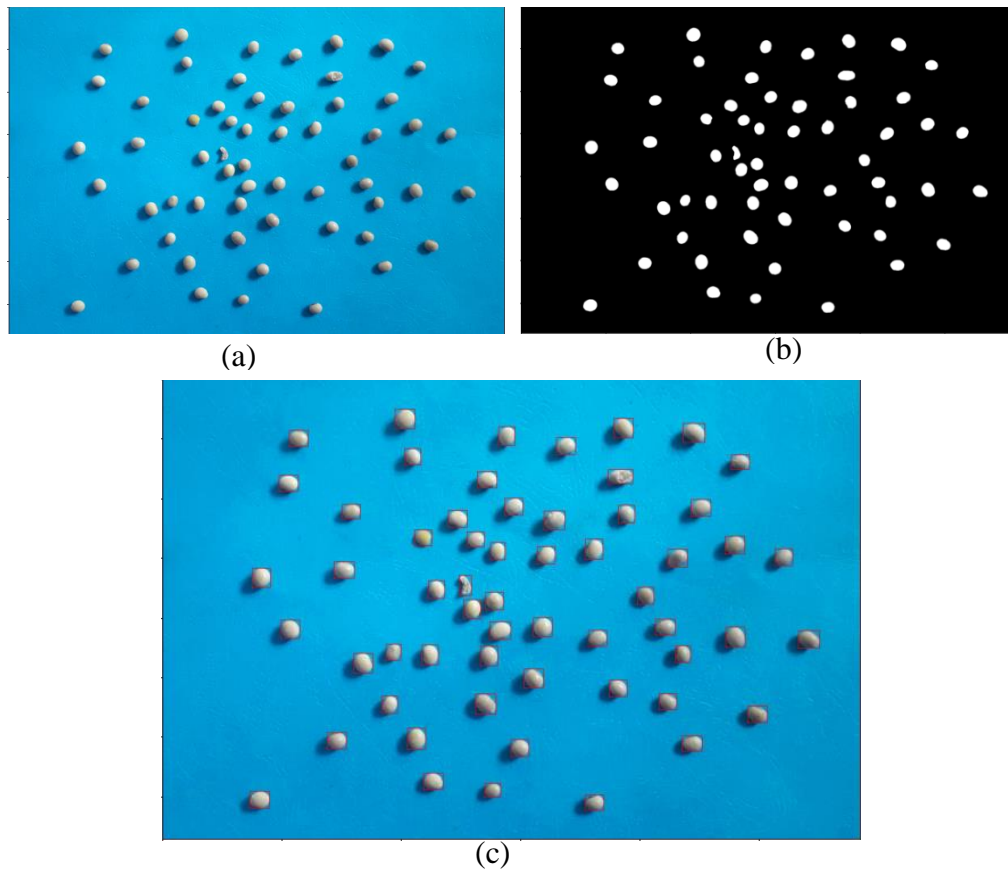


Figure 4.7: *Example of detecting soybean seeds from a given image (a) input image, (b) binary segmented image, and (c) detected soybean seeds in the RGB image*

4.4.3 Feature Extraction

The feature extraction component in our proposed architecture on testing phase is responsible to select representative features from segmented ROI. The selected 19 features during the training phase are extracted and will be feed into the next component.

4.4.4 Classification

The fourth component under testing phase is classification it can also be called *model usage* component. In this component: the models that are got from model building are used here to predict the type of soybean samples. The soybean samples that are used here are from test dataset which are unlabeled and new data to the model. The aim here is to understand/find out the accuracy /performances of the constructed models.

4.4.5 Quality Grading

The final component under the testing phase of proposed system architecture is the quality grading component. The main task/duty of the component is to determine the quality grade of the input soybean image.

Table 4.9: The Grading Parameters used

Soybean Type Grades	Defect %	Split %	Insect Bored %	Foreign Matter %
Grade 1	(0 , 4.0]	(0 , 1.5]	(0 , 1.0]	[0 , 1.0]
Grade 2	(4.0, 6.0]	(1.5 , 2.5]	(1.0 , 1.5]	(1.0 , 3.0]
Grade 3	(6.0 , 8.5]	(2.5 , 5.0]	(1.5 , 2.0]	(3.0 , 4.5]
Grade 4	(8.5 , 11.5]	(5.0 , 7.0]	(2.0 , 2.5]	(4.5 , 6.0]
Grade 5(LG)	(11.5 , 15.5]	(7.0 , 9.0]	(2.5 , 3.0]	(6.0 , 8.0]

Then, the quality grade sub-component determines the quality of the given soybean image based the number of each type of soybean sample constituents found in the input image based on the rule of ECX as shown in Table 4.9. First it calculates the total amount each soybean constituents types found on the given image. Then, the highest one will be selected to determine the quality grade of the soybean given image. During the highest one selection process normal soybean type will be excluded because the quality grading decision is made based on the impurities found on the soybean samples. The detail algorithm for quality grade component is show below.

Algorithm 7: Steps in Quality grade

- (1) Count the total amount of each soybean types.
 - (2) Find the highest one exclusively considering normal type seeds.
 - (3) Change highest amount of soybean seed type in to percentage
 - (4) Determine the quality grade based highest amount of soybean seed type according to the rule of ECX.
-

CHAPTER FIVE

EXPERIMENTATION

5.1 Introduction

In this chapter, we discuss the experiments we carried out to test the effectiveness of our proposed system and to answer the raised research questions. Accordingly, the type of classifier and the results achieved in the classification process will be discussed. The discriminative power of morphological, color and texture feature will be tested and compared. Alongside these; the dataset, programming languages, experimental setting and procedure followed in the experiment also presented.

5.2 Dataset

There is no readymade dataset in soybean for this type of research; as a result we have prepared our own dataset to evaluate the performance of the proposed system. To do so, soybean graded samples are collected from the ECX warehouses from Asossa branch. Three samples from each soybean quality grade classes with 100gm size each are collected. This dataset is used to build the soybean quality grading system. . The collected soybean grains samples are certified by the domain experts who work in the ECX laboratories. The total amount of soybean sample collected is depicted in Table 5.1.

After getting the quality graded soybean samples; well organized and managed image capturing was performed repeatedly to get clear and best images with less noise. There are various properties of image were tried to controlled: illumination, background, each soybean spacing, distance between the sensors and the scene, and camera adjustment.

All soybean grain sample images were taken from a fixed height (0.4m) oriented in a perpendicular manner directly above the sample soybean grains to retain uniformity between all the image pictures of the samples. The camera was mounted on a stand with the mentioned elevation of 0.4m above the beans for the sake of enabling simple movement vertically and to avoid blurred pictures.

During background color selection; we compared blue, white, and black colors. We observed that the blue color makes a good contrast with the foreground soybean grains, less vulnerable to shadow and achieved better segmentation result.

Table 5. 1: Total dataset acquired for soybean graded images

Grade	Number of images	Total number of Beans Processed
Grade 1	236	17,403
Grade 2	216	16,200
Grade 3	219	17,301
Grade 4	230	16,560
Grade 5	210	16,000
Average	222.2	16,692.8
Total	1,111	83,464

Nikon D72000 Digital camera and Samsung J6 mobile camera has been used in the image acquisition phase. The images were taken at a resolution of 6000 x 4000 pixels for the digital camera and 4128 x 2006 for mobile camera. 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 preprocessing was employed to carry out the necessary procedures and analysis.

5.3 Implementation

Python programming language used in developing the prototype. Python version 3.0 is used to develop the prototype of the system. The main Python library packages used during implementation and prototype development are listed in Table 5.2 with their version and description. Moreover, the specification of the computer on which the system is

implemented is Intel Core i3 laptop computer with 6GB RAM and 2.4 GHz processor. The graphical user interface of the developed prototype is shown in Figure 5.1.

Table 5.2: Main Python library packages used in implementation and prototype development

Library	Version	Description
Opencv	4.4.0.44	Open-source library for computer vision, machine learning, and image processing
Scikit-learn	0.20.3	Free software machine learning library
Scikit-image	0.18.1	Open source designed for image processing
Keras	2.2.4	Open source developing and evaluating deep learning models
Flask	1.1.2	Open source web application framework



Figure 5.1: Screenshot of the Web based User Interface of the Developed Prototype System

5.4 Test Results

Evaluation on the performance of the proposed soybean quality grading system are conducted on SVM, ANN and CNN classifiers to determine the best performing classifier based on the criterion of classification accuracy. On the next sub sections we will present their results.

5.4.1 Support Vector Machine (SVM) Test Results

After training the SVM model on training datasets, the performance of the SVM classifier was tested with **334** (30% of the total dataset) data items. The test confusion matrix of the trained SVM classifier is depicted in Table 5.3. The diagonal elements, which have shaded background color, indicate instances that were correctly classified where as the other cells show where the classier got wrong. For this classifier, the classification accuracy of Grade 1, Grade 2, Grade 3, Grade 4 and Grade 5 soybeans were **93.24%**, **79.03%**, **86.36%**, **87.5%** and **91.67%** respectively.

Table 5.3: Test Confusion Matrix of SVM Classifier

Predicted Class Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	69	3	2	0	0	93.24%
Grade 2	9	49	4	0	0	79.03%
Grade 3	1	3	57	6	0	86.36%
Grade 4	1	0	6	63	2	87.50%
Grade 5	0	0	2	3	55	91.67%
Average Accuracy	87.47 %					

5.4.2 Artificial Neural Network (ANN) Test Results

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. The ANN training process is halted at the 17th iteration (epoch).

Table 5.4: Test Confusion Matrix of ANN Classifier

Predicted Class \ Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	71	2	1	0	0	95.94%
Grade 2	3	53	5	1	0	85.48%
Grade 3	0	3	58	4	1	87.88%
Grade 4	1	1	3	65	2	90.28%
Grade 5	0	0	1	1	58	96.67%
Average Accuracy	91.32 %					

It is shown in the above Table 5.4 summary result of ANN classifier on the aggregated features that contains morphology, color and texture features showed an accuracy of Grade 1, Grade 2, Grade 3, Grade 4 and Grade 5 were **95.94%**, **85.48%**, **87.88%**, **90.28%** and **96.67%** respectively. The result showed that out of the total test set of 334 image soybeans, **91.32%** were correctly classified and **8.68%** were misclassified during ANN classifier experimentation.

5.4.3 Convolutional Neural Network (CNN) Test Results

Just like ANN, CNN also an adaptable classifier that can learn relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data. Furthermore, it also extracts important features by itself. During model creation in the training phase; the epoch and batch size value is set by trial and error in order to obtain

highest result in classification accuracy. These values become 128 and 19 for epoch and batch size value respectively.

Table 5.5: Test Confusion Matrix of 1D-CNN Classifier

Predicted Class \ Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	70	4	0	0	0	94.59%
Grade 2	5	55	2	0	0	88.71%
Grade 3	1	4	60	1	0	90.91%
Grade 4	0	0	2	70	0	97.22%
Grade 5	0	0	1	1	58	96.67%
Average Accuracy	93.71 %					

The result of 1D-CNN classification on the aggregated features that contains morphology, color and texture feature showed an accuracy of Grade 1, Grade 2, Grade 3, Grade 4 and Grade 5 were **94.59%**, **88.71%**, **90.91%**, **97.22%** and **96.67%** respectively as shown in Table 5.5. The result showed 1D-CNN perform **93.71%** average of accuracy on each soybean Grades. Grade 4 registered the highest accuracy while Grade 2 registers the lowest accuracy.

Table 5.6 shows the confusion matrix result of the 2D-CNN classification model. The result showed an accuracy Grade 1, Grade 2, Grade 3, Grade 4 and Grade 5 soybean images were **91.89%**, **90.32%**, **90.91%**, **91.67%** and **83.33%** respectively. The average accuracy becomes **89.82%**.

Table 5.6: Test Confusion Matrix of 2D-CNN Classifier

Predicted Class \ Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	68	4	2	0	0	91.89%
Grade 2	4	56	2	0	0	90.32%
Grade 3	1	3	60	2	0	90.91%
Grade 4	0	0	4	66	2	91.67%
Grade 5	0	0	3	7	50	83.33%
Average Accuracy	89.82 %					

5.5 Feature Comparison Test Result

We perform another experiment to identify the discriminative power each type of feature i.e. morphological, color and texture features. To do so, we experimented to see the effect of feature by training and testing 1D-CNN excluding the feature attribute from the aggregated feature data set. 1D-CNN classification model is selected because it achieves the highest accuracy score in the aggregated feature. On the next sub sections we will present their results.

5.5.1 Scenario One (Analyzing the effect of Morphological feature)

In this scenario, the discriminative power of the morphological feature is examined. We experimented to see the effect of morphological feature though training and testing 1D-CNN by excluding morphological feature from the aggregated feature dataset. The accuracy of the classifier was observed to less reduction from **93.71%** to **89.22%**. The confusion matrix is shown in Table 5.7.

Table 5.7: Test Confusion Matrix without Morphological features in 1D-CNN

Predicted Class Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	69	4	1	0	0	93.24%
Grade 2	4	55	3	0	0	88.71%
Grade 3	1	6	56	3	0	84.85%
Grade 4	0	0	4	66	2	91.67%
Grade 5	0	0	3	5	52	86.67%
Average Accuracy	89.22%					

5.5.2 Scenario Two (Analyzing the effect of Color feature)

In this scenario, we examined the discriminative power of color features. In light of this, we trained the 1D-CNN without the inclusion of these features in the dataset. We found out that the overall classification accuracy of the classifier on the test dataset was reduced highly from **93.71%** to **81.14 %**. The confusion matrix is shown in Table 5.8.

Table 5.8: Test Confusion Matrix without Color features in 1D-CNN

Predicted Class \ Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	59	10	4	1	0	79.73%
Grade 2	7	49	5	1	0	79.03%
Grade 3	2	7	50	6	1	75.76%
Grade 4	0	1	5	63	3	87.50%
Grade 5	0	0	4	6	50	83.33%
Average Accuracy	81.14%					

5.5.3 Scenario Three (Analyzing the effect of Texture feature)

In this scenario, the discriminative power of texture features is examined. This is done by training the 1D-CNN without the inclusion of texture features in the training set. In doing so, we found out that the 1D-CNN classification accuracy dropped from *93.71%* to *85.50%*. The reduction in each grade is shown in Table 5.9.

Table 5. 9: Test Confusion Matrix without Texture features in 1D-CNN

Predicted Class \ Actual Class	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Accuracy
Grade 1	67	6	1	0	0	90.54%
Grade 2	5	52	3	0	0	86.67%
Grade 3	0	7	54	5	1	80.60%
Grade 4	0	2	6	60	2	85.71%
Grade 5	0	0	3	7	50	83.33%
Average Accuracy	85.50 %					

5.6 Discussion

In this study, we propose quality grading system for soybean that works in similar manner to manual quality grading procedures by exploring image processing techniques and supervised learning algorithms. Different features and classification algorithms are tested to construct classification/ inspection model. The proposed model was tested on verified sample data collected from ECX Asossa branch. The researcher applied statistical measurement to test the performance of the developed model. The performance of soybean quality grading has been determined through accuracy rate.

The experiments were conducted using handcrafted aggregate feature of morphological, color features, texture features. Then, the performances of SVM, ANN and CNN classifiers were compared over the aggregated features. There were seven morphology features, six color features and six texture features, which are nineteen parameters totally. According to the experiments, 1D-CNN classifier registered the highest overall average accuracy of 93.71%. This result is found to be good enough by taking the worst scenario into consideration and the intra class similarity between the classes. Then we conduct an experiment to determine the discrimination power of features among morphological, color

and texture features alone using 1D-CNN as classifier, The experimental result on quality grading shows large discriminating power of the color features and morphology is not as good as the others because the varieties of soybean have similar morphology.

From experimental result, the discriminating power of morphology feature for Grade 5 soybean was better than others. This was because by its nature Grade 5 contains large amount of impurities like foreign matters as a result were mostly characterized by unique morphological features. The exclusion of texture feature result for soybean of Grade indicates relatively there is better discrimination power than other grade soybean. This is due to grade one contains almost 100% normal type soybeans, and the normal soybeans have smooth textures as compared to the other types.

However, the exclusion of color feature from the aggregated feature results the highest reduction and this confirms to the manual system to detect soybean types during inspection. The comparison of discriminative power of morphology, color and texture features is presented in Figure 5.2 as column chart. In this chart, the discriminative power of morphological, color and texture features is compared by using the observed drop in the classification accuracy during scenario 1, scenario 2 and scenario 3.

Automatically feature extraction from soybean images also performed and compared to the handcrafted performance using 2D-CNN. The accuracy performance of become dropped to 89.82% which is good when we consider intra class similarity high and the amount data we used. As a result it is expected to be a best performance if we leverage the amount of datasets into large volume and apply complex 2D-CNN architecture.

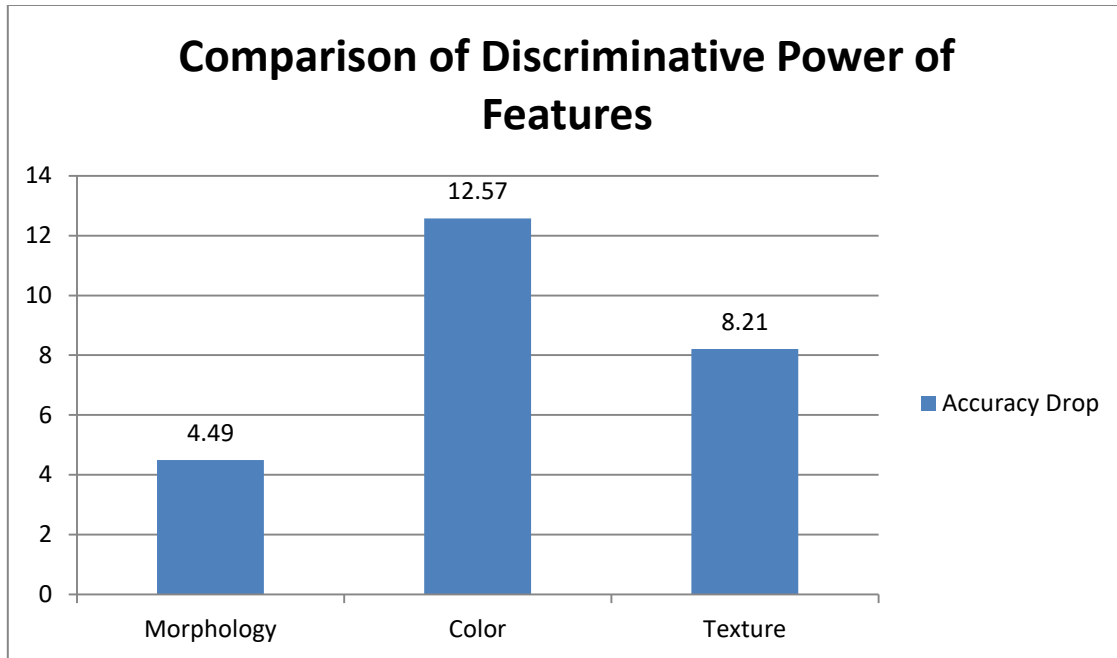


Figure 5.2: *Comparison of Discriminative Power of Morphological, Color and Texture Features*

5.7 Summary

We have shown that our proposed system and the models we used to for quality inspection of soybean sample constituent achieved their intended purposes. This is shown by a very high level of classification accuracy we achieved. Moreover, it has been shown that the discriminative power of color features is significantly greater than that of morphological and texture feature in quality grading of soybean.

CHAPTER SIX

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this thesis work we explored image processing methods and supervised learning algorithms for quality grading of soybean automatically using computer system. A thorough discussion on image processing in general, starting from the definition of image to the current state-of-the-art findings, methodologies and architectures were conducted. Fundamental steps in digital image processing are discussed and analyzed briefly along supervised learning algorithms.

The proposed system works in two stages; first, it will inspect the soybeans types and then it determines the quality of soybean based on the amount of detected soybean types. As is common in computer vision problem, an image dataset or corpus were prepared for use in preparing classification models for quality grading of soybean as well as for quality inspection models. Before feature extraction from the acquired images; image preprocessing and segmentation were done first to better and accurately locate each soybean kernels in the image. In the image preprocessing phase we applied noise removal and sharpening technique called median filter and unsharp masking respectively to enhance the quality of the acquired image. Then Otsu's threshold image segmentation help us to differentiate and locate only the soybean kernels in the images from background and other things in the image, these regions also called Region of Interest (ROI).

To this end, each detected soybean (or ROI) is feed in to the quality inspection model to determine the types of each soybean which is trained on labeled training dataset in training phase. The quality inspection model first extract morphological, color and texture features from ROI or extract features by itself, then it determines the type soybean. After getting the types of each soybean sample constituent detected in the given image the system determines the quality grade based on the percentage of the impurities following the ECX guideline rules.

In order to create the soybean quality inspection model we create a labeled training dataset that indicates the types of each soybean namely normal, defect, split, insect bored and foreign matters soybeans. The labeling task is done by the domain expert from ECX. After all, the quality inspection model trained on it in the training phase.

The image dataset are split into training and testing datasets. The training dataset contains 70% of the total dataset and to construct the quality inspection model by employing four supervised learning algorithms namely: support vector machine (SVM), artificial neural network (ANN), one-dimensional convolutional neural network (1D-CNN) and 2D-CNN.

In testing phase the quality inspection incorporated to determine the quality grade of the test image of soybean samples. Then the test dataset is used to evaluate the performance of the constructed quality grading model using evaluation techniques. Accuracy evaluation technique was utilized for the evaluation purpose, the question of how much correct soybean type label predicting is found.

The result of the experimentation showed that different quality grading of soybean has been classified more accurately by 1D-CNN than 2D-CNN, ANN and SVM. The overall accuracy rate for SVM, ANN, 2D-CNN and 1D-CNN are 87.47%, 91.32%, 89.82% and 93.71% respectively. These results show that, the proposed system architecture is effective in quality grading of soybean sample.

Furthermore, the morphological, color and texture features are tested individually and by combining them to discriminating power among them by feeding them to 1D-CNN. The experimental results show that color features have more discriminating power to classify soybean based on their quality grading than morphology and texture features. But the classification accuracy increases when the aggregated features were used together.

The major challenges during conducting this study were keeping the best quality control environment during image acquisition of soybean and getting large amount soybean samples from ECX.

6.2 Contribution of the Thesis

This research works has contribution new knowledge to the area of digital image processing in relation to automatic soybean quality grading and achievement of this research. The following are the major ones:

- We proposed system architecture for quality grading for soybean according the manual grading procedures.
- We identified a total of 19 features, which are all useful and non-duplicated, that are used to successfully quality grade soybean samples.
- We designed a classifier using SVM, ANN, 1D-CNN and 2D-CNN that can successfully quality grade soybean sample.
- We develop image corpus for soybean quality grading that can be utilized by other researcher as a base line.
- We develop a web based prototype for quality grading of soybean.

6.3 Future work

Though this study has achieved its goal, few works still remain on the table to get much better accuracy result and to implement in real world application. The following are the possible future works.

- In this study, during image acquisition various properties the image are controlled like lightening condition , background color, shadow and others as wells the images are taken using a single camera. Thus we need to have a system that can handle and tolerate these things.
- The other potential work for the future is solving the problem of touched soybean kernels even close ones. When soybeans touch each other or close each other the segmentation process consider the touched soybeans as one this result poor performance to the model. We propose conducting further experiment in applying advanced image segmentation techniques to handle it.

- In feature selection component, in order to detect the usefulness each features we rely on the relation between each features and the target class. As future work, we propose to include the relation between each features and model performance.
- By increasing the volume of the data items in each class applying complex 2D-CNN architectures.

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Annex A

A. Interview Questions for domain experts

1. What is quality grading of soybean and what it is benefit?
2. What are the procedures of quality grading of soybean in ECX?
3. What are the basic parameters for determining quality grade of soybean?
4. What should be performed in order to rank the quality of soybean by looking physical characteristics?

Signed Declaration Sheet

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

Declared by:

Name: _____

Signature: _____

Date: _____

Confirmed by Advisor:

Name: _____

Signature: _____

Date: _____