ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

COLLEGE OF NATURAL SCIENCES

DEPARTMENT OF COMPUTER SCIENCE

AUTOMATIC RECOGNITION OF ETHIOPIAN PAPER CURRENCY

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DEDICATION

To Jesus Christ, the person whom I love the most.

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ACRONYMS

ANN	Artificial Neural Network
ATM	Automatic Teller Machine
BPN	Back Propagation Network
BRISK	Binary Robust Invariant Scalable Key-point
DSP	Digital Signal Processing
ENN	Ensemble Neural Network
ERM	Empirical Risk Minimization
ETB	Ethiopian Birr
FAREK	Fast Retina Key-point
GA	Genetic Algorithm
HMM	Hidden Markov Model
HOG	Histogram of Oriented Gradients
HSB	Hue Saturation Brightness
HSV	Hue Saturation Value
IR	Infra Red
JPEG	Joint Photographic Experts Group
KNN	K Nearest Neighbor
LBP	Local Binary Pattern
LED	Light Emitting Diode
LVQ	Linear Vector Quantization
MATLAB	MATrix LABoratory
NBC	Naive Bayes Classifier
NN	Neural Network
PCA	Principal Component Analysis
RBF	Radial Basis Function
RGB	Red Green Blue
RMB	Renminbi
ROI	Region Of Interest
RP.	Ribu

SIFT Scale Invariant Feature Transform

SURF Speeded Up Robust Feature

ABSTRACT

Currency recognition is an image processing technology that is used to identify currency of various countries. Due to the use of currency in day to day life, the importance for automatic methods for currency recognition has been increasing. An efficient currency recognition system is vital for automation in many sectors such as vending machine, railway ticket counter, banking system, shopping mall, currency exchange service, etc. Due to this, automatic currency recognition has been the interest of many researchers and currency recognition was done for different countries' currencies such as United States (US) dollar, Euro, Chinese Renminbi (RMN), Indian rupee and Mexican peso. However, to the best knowledge of the researcher, there is no any research done towards designing and implementing recognition of Ethiopian currency. The absence of such currency recognition is a big gap in Ethiopia.

This thesis describes the design of automatic recognition of Ethiopian currency. In this research, a software solution which takes the image of an Ethiopian currency from a scanner and camera as an input is proposed. The researcher combined the approaches of currency characteristic comparison and local feature descriptors to design a four level classifier. The design has a categorization component, which is responsible to denominate the currency notes into their respective denomination and verification component which is responsible to validate whether the currency is genuine or not.

Both components of the design are implemented using MATLAB. The design is tested using genuine Ethiopian currencies at different condition, counterfeit Ethiopian currencies and other countries' currencies. The denomination accuracy for genuine Ethiopian currency, counterfeit currencies and other countries' currencies is found to be 90.42%, 83.3% and 100% respectively. The verification accuracy is 96.13%. The overall processing time of the model is 1. 986 second. Therefore our model has a good performance with a denomination and verification accuracy more than 90%.

KEY WORDS: Image Processing, Currency Recognition, Speeded Up Robust Feature (SURF) Feature, MATLAB, Hue Saturation Value (HSV), Counterfeit Detection, Classifier, Feature Extraction.

CHAPTER ONE: INTRODUCTION

1.1 Background

Currency is used almost everywhere. It is the indispensable part of everyone's daily routine. In Ethiopia there are both paper and coin currencies. The current legal currency of Ethiopia includes six coin currencies and five paper currencies. The coin currencies are one cent, five cent, ten cent, twenty-five cent, fifty cent and one Birr cent. The paper currencies are one Birr, five Birr, ten Birr, fifty Birr and hundred Birr. A paper note in one denomination has specific feature which distinguishes it from a note in other denomination. In addition to this, there are other additional features on the note in each denomination to differentiate it from counterfeit notes [*See Appendix A*].

Since currency has great importance in day to day life, currency recognition becomes a great area of interest for researchers. Apart from that, due to development of automated systems the importance for automatic methods for currency recognition has been increasing. An efficient currency recognition system is vital for the automation in many sectors such as vending machine, railway ticket counter, banking system, shopping mall, currency exchange service, etc. Automatic machines capable of recognizing banknotes are massively used in automatic dispensers of a number of different products, ranging from cigarettes to bus tickets, as well as in many automatic banking operations [1].

Until now, there are many methods proposed for currency recognition for different countries' banknotes. Among the different techniques used artificial neural network, currency characteristic comparison, principal component analysis (PCA), local feature descriptors comparison, genetic algorithm (GA), Hidden Markov Model (HMM), and Naïve Bayes classifier are the major ones. For example, Neural Network (NN) is applied in Sri Lankan currency note recognition [2], Bangladeshi currency recognition [3], Indian currency recognition [4] and US dollar recognition [5]. The currency characteristic comparison approach is applied in Indian currency recognition [6, 7, 8], Sir Lankan banknote recognition [9], Chinese RMB word number recognition [10], Mexican banknote recognition [11] and Pakistani paper currency. Other approaches are also applied on other countries' currencies as described in chapter two.

1.2 Motivation

The motivations of this research work are:

- The absence of automatic teller machine (ATM) which enable a person to deposit cash into his/her account or other customer's account. Such kind of ATMs does not exist in Ethiopia. Obviously such ATMs should have a mechanism to identify counterfeit paper currencies from genuine ones.
- To contribute towards the achievement of automatic vending machine, bus/railway ticket counter, note counter in banking system, shopping mall, currency exchange service, etc. All these are not currently available in Ethiopia.
- The number of research works being carried out in the area of currency recognition in different part of the world but being an untouched area in Ethiopia.

1.3 Statement of the Problem

Paper currency recognition is widely applied in many fields such as bank system and automatic selling-goods system. The method of extracting highly qualified monetary characteristic vectors from currency image is an important problem area that requires solution today [12]. Different researches have been carried out at different part of the world to suggest a solution in identifying paper currency of their own country and others too. To mention some of the researchers who contribute in this regard, *Takeda and Omatu* [13] on Japanese and US paper currency identification, *Jahangir and Chowdhury* [14] on Bangladeshi banknotes, *Pathrabe and Bawane* [15] and *Sharma et al* [1] on Indian banknotes. These researches become software solution in designing automatic vending machine, railway ticket counter, banking system, shopping mall, currency exchange service, etc. In addition to these, it has been one big step forward in achieving ATM which do not only dispose cash but also receive paper currency and deposit in other customer's account. To the best knowledge of the researcher, there is no work done on recognition of Ethiopian paper currency. Therefore the purpose of this research is to design and develop a prototype that can identify the paper currency of Ethiopia that are currently functional (1 Birr, 5 Birr, 10 Birr, 50 Birr and 100 Birr) and categorize them in their denominations. In addition to this, the proposed solution will identify counterfeit currency from genuine Ethiopian currencies.

1.4 Objectives

General Objective

The general objective of this research is to design a model which recognises the currently existing Ethiopian paper currencies.

Specific Objective

The specific objectives of this project are to:

- Review literatures on currency recognition systems, major processes of currency recognition systems and different countries' currency recognition approaches.
- Collect sample counterfeit and genuine currencies at different status.
- Extract the major features of each denomination by doing pre-process activities on each currency denominations.
- Design automatic Ethiopian currency recognition
- Develop a prototype for the system
- Evaluate the prototype using sample currencies.
- Recommend further research works in the area.

1.5 Scope and Limitation

1.5.1 Scope

The proposed solution will be able to classify and recognize the currently available or functional Ethiopian currency. Therefore the design has two components, the denomination component and verification component. The first is to classify the currencies into their respective denomination and the second is to verify whether the classified currency is genuine or counterfeit. The research is a software solution to detect the paper currencies of Ethiopian from one side and one direction only. Therefore Ethiopia coin currency recognition is out of scope of this research.

1.5.2 Limitations

This thesis work has the following limitation:

- Unable to find a good number of counterfeit notes for testing the prototype.
- Unable to find a good number of other countries' currencies for testing the prototype.

1.6 Methodology

1.6.1 Literature Review

Conducting literature review on currency recognition concept and on the major processes in currency recognition, reviewing previously implemented currency recognition approaches and related works previously done on other countries' currencies.

1.6.2 Data collection

Different sample currencies were collected. Among these sample currencies, two hundred forty were genuine Ethiopian currencies, twenty-four were counterfeit Ethiopian currencies and five were other countries' currencies. This sample contains new and worn out Ethiopian currencies as well as currencies of some other countries.

1.6.3 Developing a prototype

In developing the prototype, image of each denomination was first captured using a scanner and high resolution camera. Then a pre-processing activity was done on each currency denominations by extracting the colour and major feature information of each currency denominations. Based on this information, a prototype was developed to classify and verify each currency.

1.6.4 Experiment

Experiment was done with two hundred forty genuine Ethiopian currencies, twenty-four counterfeit Ethiopian currencies and five other countries' currencies. These sample currencies contain both old and new notes. After the prototype was tested with these sample currencies, the accuracy of classification and verification was calculated.

1.7 Significance of the Research

This thesis work aims to develop a prototype that will be a software solution in classify Ethiopian currency in their respective denomination and verify each currency whether it is genuine or counterfeit. This work can be an input in ATM which can count, receive and deposit cash in customer's account rather than just help the user to withdraw cash. In addition to this, it can be a software component for implementing automatic vending machine, bus/railway ticket counter, banking system, shopping mall, currency exchange service etc. Since the proposed solution identifies counterfeit currencies from genuine ones, it can be a great input and solution to the banking industry and the society in fighting counterfeiting.

CHAPTER TWO: LITERATURE REVIEW

In this Chapter, the researcher presents works that are related to currency recognition systems. First, currency recognition system in general is discussed. Then, the major processes in currency recognition system are discussed in detail. Finally, seven different approaches used in currency recognition systems with sample researches in each approaches are presented.

2.1 Currency Recognition Systems

Currency recognition is an image processing technology that is used to identify currency of various countries. There are approximately fifty currencies all over the world, and each of them looks totally different. This difference can be either of size of the paper currency, or colour or pattern drawn on the paper. And the aim of currency recognition system is to help people to recognize different currencies and to help them work with convenience and efficiency [16].

Currency recognition systems have a wide range of application in the real world environment. Because of these, there are a number of researches done for recognition of different countries' currencies. And in recent years, such kind of research has been ever increasing everywhere. Some of major applications of currency recognition systems are: assisting visually impaired people, distinguishing original note from counterfeit currency, enabling automatic selling-good and enhancing banking applications.

2.2 Processes in Currency Recognition

In general, any paper currency recognition includes five major processes: Image acquisition, pre-processing, segmentation, feature extraction and classification.

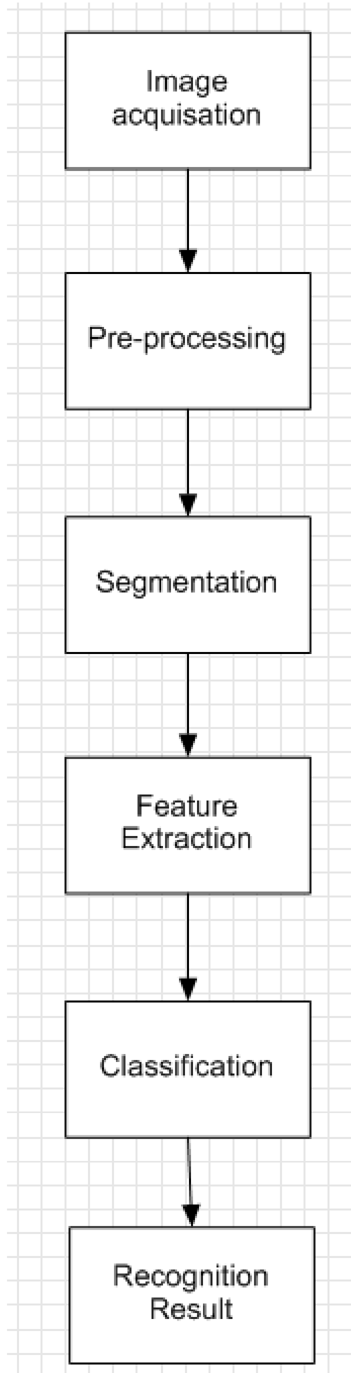

Figure 2. 1: Processes in Currency Recognition System

2.2.1 Image Acquisition

Image acquisition is an activity of acquiring the currency image in a digital form using a specific hardware designed for this purpose, usually scanner or camera. As the first step in currency recognition, it is a very basic process because without the currency image the other processes will not follow. The image is gained so that it may pass through the remaining currency recognition processing steps. This image is completely raw and unprocessed and it is purely the result of the camera or scanner used to generate it. One of the ultimate goals of image acquisition process is to have a source input image that operates within a controlled and measured guideline, that this same image can be perfectly reproduced under certain conditions with inconsistent factors that are easier to locate and eliminate [17].

2.2.2 Pre-processing

Pre-processing is a general name for operations done on images at the initial level where both input and output are intensity images. The aim of pre-processing is an improvement of the currency image by suppressing unnecessary distortions or enhancing major image features important for further recognition processes. Among the pre-processing activities in currency recognition systems, image enhancement and image restoration are the major ones.

- **Image enhancement**

Image enhancement is among one of most simplest and interesting areas of digital image processing. Enhancement techniques are to enhance or magnify details in the currency image that are hidden or lost because the currency image quality is degraded. It can be said as well, highlighting some interesting features in a currency image. One of the common examples of enhancement is to increase the contrast of the currency image to make it look better. To look better is very subjective as it depends on the person who perceives it and hence enhancement as well is a very subjective area of image processing [18].

Image enhancement processes consist of a collection of techniques that has an aim to improve the visual appearance of the currency image or to convert the image to a form better fitting for analysis by a machine. Unlike in image restoration, in an image enhancement system the effort is not to improve the image to conform to some predefined image form. As image enhancement is a very subjective processing task, a much distorted image can fit the user preference for a particular application. Therefore in general, an enhanced image may not be a restored image. The opposite may happen in some instances.

There is no general unifying theory or model of image enhancement till now because there is no general common defined standard of image quality that can be used as a design criterion for an image enhancement processor. Only different variety of techniques that have proved to be useful for human observation improvement and image analysis are considered [19].

- **Image restoration**

Image restoration like image enhancement is an area that concerned about improving the appearance of an image. But, unlike image enhancement, which is very subjective, image restoration is objective. Image restoration techniques rely on mathematical or probabilistic models to restore degraded images. But as it was discussed in the above section, enhancement, on the other hand, is based on human subjective preferences regarding what constitutes a "good" enhancement result [18].

In order to design effectively a digital image restoration system, it is necessary to characterize the image degradation effects of the physical imaging system, the image digitizer, and the image display quantitatively. Basically, the procedure is first to model the image degradation effects and then perform operations to undo the model to obtain a restored image. Therefore it can be said that accurate image modelling is often the key to effective image restoration. There are two basic approaches to the modelling of image degradation effects: apriori modelling and aposteriori modelling. In the apriori modelling, to determine their response for an arbitrary image field measurements are made on the physical imaging system, digitizer, and display. In some instances it will be possible to model the system response deterministically, while in, other situations it will only be possible to determine the system response in a stochastic sense. The aposteriori modelling approach is to develop the model for the image degradations based on measurements of the particular image to be restored. Basically, these two approaches differ only in the manner in which information is gathered to describe the character of the image degradation model [19].

2.2.3 Segmentation

Generally speaking, image segmentation is the process of dividing an input image into regions according to predefined criteria set beforehand. The name of the operation comes from the result of the operation, which are segments. Segmentation is a process found between image pre-processing and image analysis. It is considered as an operation found at the early stage of image analysis, which is a high-level image processing task consisting of object detection and recognition. As an operation found in early stage, error or inaccuracy in segmentation causes a major error for the rest of the image analysis operations. Therefore it is advisable to have accurate image segmentation operation as per the requirement of the specific application. In addition, ideally, it is desired that each resulting region or segment represents an object in the original image. This means that each segment is a component useful to make image content analysis and interpretation. Therefore the set of segmented objects can be matched to a predefined model for interoperating a test image [20].

2.2.4 Feature Extraction

Feature extraction is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval [21]. Before the feature extraction task is done, the features of the object need to be first detected. And the feature extraction is for feature matching. Therefore feature extraction is a task between feature detection and feature matching. In addition to currency recognition systems, feature extraction is a major part of object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification problems.

There are mainly two types of features: structural feature, which describes geometrical and topological characteristics of pattern by representing its global and local properties and statistical features, which describes characteristic measurements of the pattern [16]. The common feature techniques which help to extract both types of features are Histogram of Oriented Gradients (HOG), SURF, Local Binary Patterns (LBP), Haar wavelets, and colour histograms.

2.2.5 Classification

Classification includes a broad range of decision-theoretic approaches to the identification of images. All classification algorithms are based on the assumption that the image in question depicts one or more features and that each of these features belongs to one of several distinct and exclusive classes. The classes may be specified priori by an analyst (as in supervised classification) or automatically clustered (i.e. as in unsupervised classification) into sets of prototype classes, where the analyst merely specifies the number of desired categories. Classification algorithms consist two phases of processing: training and testing. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, i.e. training class, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features [22].

The class in a currency recognition system which is designed to classify the currencies of different countries is the currency names. And in the case of a currency recognition system of a specific country, the class is the denomination of the currency. In both cases, the input to the classifier is a test currency image and the output is the currency name, for the first case, and the denomination of the currency, in the second case.

2.3 Approaches of Currency Recognition

Researches on currency recognition have been conducted for number of currencies of other countries. These researches on currency recognition follow different approaches which are discussed in this section.

2.3.1 Artificial Neural Network

Artificial neural network (ANN) is an information processing theory that is inspired by the way biological nervous systems, such as the brain, process information. It is composed of a large number of highly interconnected processing elements (neurones) working in harmony to solve specific problems. ANNs, like people, learn by example. An ANN is designed for a specific application, such as pattern recognition or data classification, through a learning process. As learning in biological systems involves adjustments to the synaptic connections that exist between the neurones, such facts exist in ANNs as well [23]. ANN have been applied in various application domains for solving real world problems such as, feature extraction from complex data sets, direct and parallel implementation of matching and search algorithm, forecasting and prediction in a rapidly changing environment, recognition and image processing applications etc. The currency recognition is one of the significant application domains of artificial neural networks [24].

The researches done on currency recognition which employs the approach of NN approach are many. But few of them are mentioned here. *Gunaratna et al.* [2] used a three layered feed forward neural network with back propagation (BP) learning with a hidden layer having number of output nodes representing classes of Sri Lankan currency note. *Debnath et al.* [3] designed a Bangladeshi currency recognition system using ensemble neural network (ENN) where the individual neural networks are trained via negative correlation learning. The negative correlation learning helps to expertise the individuals on different parts or portion of input patterns in an ensemble. *Ghosh and Khare* [4] proposed a currency recognition system using neural network that uses histogram based feature extraction and multilayer perception model for classification of Indian paper currency. *Sargano et al.* [25] proposed a three layers feed-forward back-propagation neural network (BPNN) for classification of currency note. They proposed a technique which was simple and comparatively less time consuming that made it suitable for real-time applications. *Takeda and Omatu* [5] proposed a recognition system of US dollars using a NN with random masks which solved the problem of same slab values (sum of input pixels) which may be obtained for different inputs.

2.3.2 Currency Characteristics Comparison

Characteristic or feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. Feature extraction is the process of transforming rich content of image into various content features that can be used in the selection and classification operations. The features that will be extracted are those features that have relatively higher discriminating or classifying capacity. Other features which have low classifying ability are not selected in the extracting process; rather they will be discarded [26].

The most common features in paper currency are colour, texture, size and pattern. There are a number of researches done on currency recognition based on these features. *Aggarwal and Kumar* [6] have developed an interactive system of Indian currency recognition using localization and colour recognition with the help of MATLAB. They suggested that each currency note has at least one predominant colour which can be used for recognition. *Kavinda and Dhammika* [9] made a money detector system which was used to detect Sri Lankan banknote by visually impaired community using a system of Light Dependent Resistor (LDR) sensors and

Light Emitting Diode (LED) which are programmed to sense the colour patterns of the banknotes. *Arora et al.* [7] proposed a system which can detect the theft of Indian currency notes by matching the serial number of the note. This proposed system used number colour plane extraction and brightness control methods for extracting the serial from each currency. *Zhu and Ren* [10] proposed a currency recognition method of RMB word numbers based on character features. *Mirza and Nanda* [8] proposed a recognition method of Indian paper currency which used edge based segmentation to extract identification mark, security thread and watermark from the image of the currency to compare them with a genuine image. *Garcia-Lamont et al.* [11] proposed a recognition method by using artificial vision which classifies Mexican banknotes based on extracted colour features in RGB space and texture features in LBP. *Ahmed and Manzoor* [27] proposed a recognition system which classify and recognize Pakistani paper currency based on Euler distance, area, aspect ratio, height and width.

2.3.3 Principal Component Analysis

PCA is a multivariate technique that analyzes a data set in which observations are described by several inter-correlated quantitative dependent variables. Its goal is to extract the important information from the data set, to represent it as a set of new orthogonal variables called principal components, and to display the pattern of similarity of the observations and of the variables as points in maps [28].

Some researchers apply PCA technique for currency recognition systems. *Ahmadi et al.* [29] proposed a reliable Neuro–classifier paper currency by using PCA algorithm. *Ahmadi et al.* [30] an improved neuro-classifiers for US dollar currency recognition in which they use local PCA method to remove non-linear dependencies among variables and extract the main principal features of data.

2.3.4 Local Feature Descriptors

In some application it is not enough to extract a single type of feature from an image point to represent the image. Rather, two or more features need to be extracted from each image point and represented accordingly. The extraction of these features is carried out by feature detectors and these extracted features are represented by a single vector called feature vector or descriptor. Finally the feature vectors together form the feature space.

Local features and their descriptors are the building components of many computer vision algorithms such as image registration, object detection and classification, tracking, and motion estimation. The descriptors which can be used in these algorithms are scale, translation and rotation invariant. The most common descriptors are HOG, Scale-Invariant Feature Transform (SIFT), Fast Retina Key point (FREAK), Binary Robust Invariant Scalable Key points (BRISK) and SURF.

There are some researches which used local feature descriptor for currency recognition system. *Paisios et al.* [31] proposed a SIFT key-point classification by using a k-means clustering approach to recognize partial and even distorted images of US paper bills. *Hasanuzzaman et al.* [32] proposed a component-based framework for banknote recognition by using SURF which is effective in handling background noise, image rotation, scale, and illumination changes.

SURF is a novel scale- and rotation-invariant detector and descriptor. It approximates or even outperforms previously proposed schemes with respect to repeatability, distinctiveness, and robustness, yet can be computed and compared much faster. This is achieved by relying on integral images for image convolutions; by building on the strengths of the leading existing detectors and descriptors (specifically, using a Hessian matrix-based measure for the detector, and a distribution-based descriptor); and by simplifying these methods to the essential. This leads to a combination of novel detection, description, and matching steps [33].

The SURF approximates the second order Gaussian derivate with box filters (mean or average filter), which is able to be calculated fast through integral images. The localization of interest point is determined by the determinant of Hessian matrix. So, interest points are finally localized in scale space and image space by using non-maximum suppression in their 3×3×3 neighbourhood. In the construction of descriptor of an interest point, a circular region around a detected interest point is first constructed. Then, a dominant orientation based on this circular region is calculated and assigned to this region, which enable the descriptor invariance to image rotations. The dominant orientation is calculated by the response of Haar wavelet in x and y directions. This process is also very fast by integral images. After the estimation of the dominant orientation, a square patch around an interest point is extracted to construct the SURF descriptor. The square patch is divided into a 4×4 sub-blocks. The gradients of each sub-block are used to construct the final descriptor vector [32].

An integral image, despite its pretty name, is just an image which its each pixel value is the sum of all the original pixel values left and above it. The advantage of integral image is that after an image is computed into an integral image, it can compute block subtraction between any 2 blocks with just 6 calculations [34].

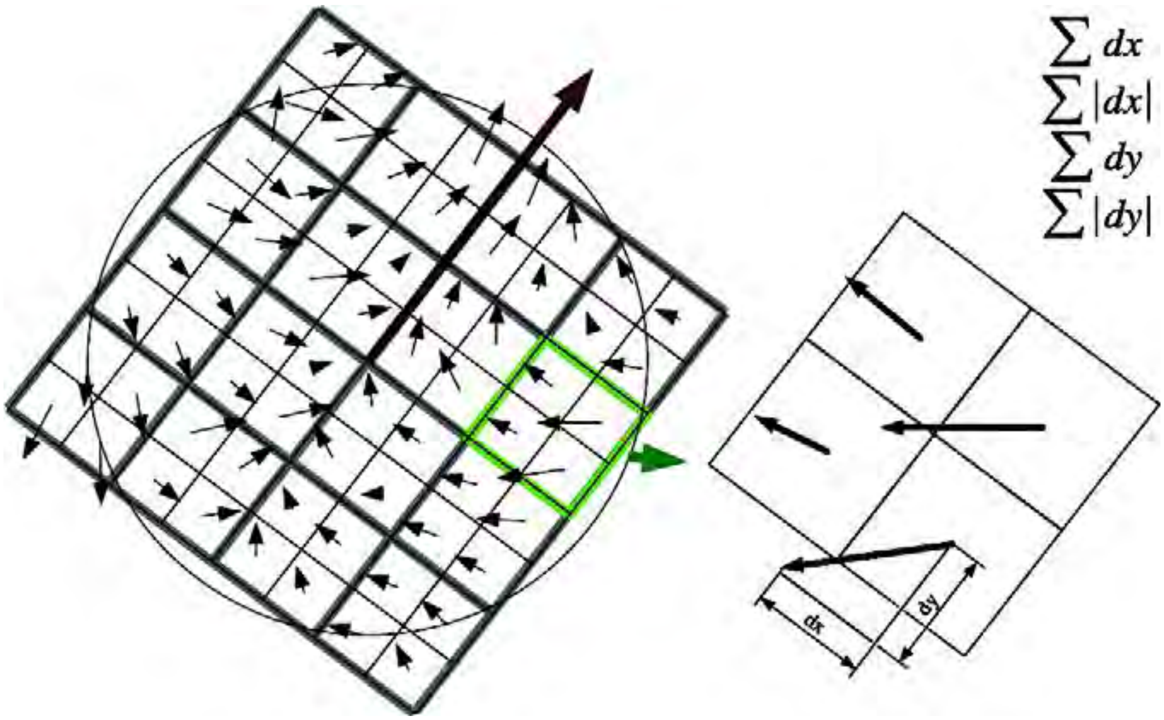

Figure 2. 2: Formation of SURF Descriptor [33]

To build the descriptor, an oriented quadratic grid with 4 x 4 square sub-regions is laid over the interest point (left). For each square, the wavelet responses are computed from 5 x 5 samples. For each field, the sums dx, |dx|, dy, and |dy| is collected and computed relatively to the orientation of the grid (right) [33].

2.3.5 Genetic Algorithm (GA)

GA is an unbiased optimization technique of machine learning which derives its behaviour from a metaphor of the processes of evolution in nature which is useful in image enhancement and segmentation. The aim is to enhance the quality of the image and to convert the image into segments to get more meaningful image and it will be easy to analyze the image using the algorithm [35].

GA is used in currency recognition system with masking technique and NN. *Takeda and Omatu* [36] proposed a Neuro-paper currency recognition method using optimized masks by genetic algorithm. *Takeda et al.* [37] proposed a paper currency recognition using a unique mask called, symmetrical masks, optimized by GA is proposed for Japanese, Italian, Spanish, and French currency.

2.3.6 Hidden Markov Model

HMM is a powerful statistical tool for modelling generative sequences that can be characterised by an underlying process that generates an observable sequence [38]. *Hassanpour and Hallajian* [39] proposed a new technique for recognizing paper currency from each side and any direction using HMM. The technique uses texture characteristics of paper currencies. In another research, *Shan et al.* [40] proposed a RMB banknote recognition system based on HMM which used the empirical risk minimization (ERM) principle.

2.3.7 Naïve Bayes Classifier

A Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong but naive independence assumptions. In simple terms, a naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature [41]. *Liliana and Neforawati* [42] proposed a Rupiah currency recognition using the RGB colour feature with Naïve Bayes Classifier.

2.4 Summary

In this chapter, currency recognition system in general is discussed. In addition to that, acquisition, pre-processing, segmentation, feature extraction, classification, and recognition are discussed as the major processes in any currency recognition system. Finally NN, currency characteristic comparison, PCA, local feature descriptors, GA, HMM and naive Bayes classifier are discussed in detail as the different approaches which have been used in currency recognition systems.

Among the different approaches of currency recognition, NN and currency characteristic comparison are the most common ones. NN needs large volume of data for training. In addition to this, if a new currency denomination is introduced in the banking system, the whole model need to be designed again. Therefore currency characteristic comparison is a candidate to apply for Ethiopian currency recognition. But this approach alone cannot give a good result because the sizes of each denomination of Ethiopian currencies are not consistent and the texture as well, is not as good as other countries' currencies. The other feature of a currency is its colour. Since the colour feature alone could not give a good result, local feature comparison approach in addition to currency characteristic comparison need to be chosen for Ethiopian currency recognition.

CHAPTER THREE: RELATED WORKS

In this Chapter, research works done in the area of paper currency denomination and verification is presented. There are a number of researches done on paper currency denomination and recognition of different countries' currencies. But to the best knowledge of the researcher, no research was done till now for automatic recognition of Ethiopian currency. Because of this reason, the review is focused only on researches done for other countries' currency recognitions.

3.1 Euro Paper Currency Recognition

Aoba et al. [43] proposed a Euro banknote recognition system using two types of neural networks: a three-layered perception and a Radial Basis Function (RBF) network. The three-layered perception is the classification part of the proposed system and the RBF is the validation part of the system. While the three-layered perception is a well known method for pattern recognition and also very effective for classifying banknotes, the RBF network has a data approximation property, which seems a proper tool for rejecting unknown data.

The input image to the system was acquired by a sensor that lights a green and an IR LED alternatively to capture a visible and an IR image. After pre-processing, the images were supplied to the first part of the recognition component which was the classifier. If the image passed the classification, it goes to the second part of the recognition which is the validation component. If the image passed the validation part, the banknote was recognized to be an accepted Euro. If the input images failed to pass the classification, it was considered to be a non-Euro banknote and did not need to pass through the validation component.

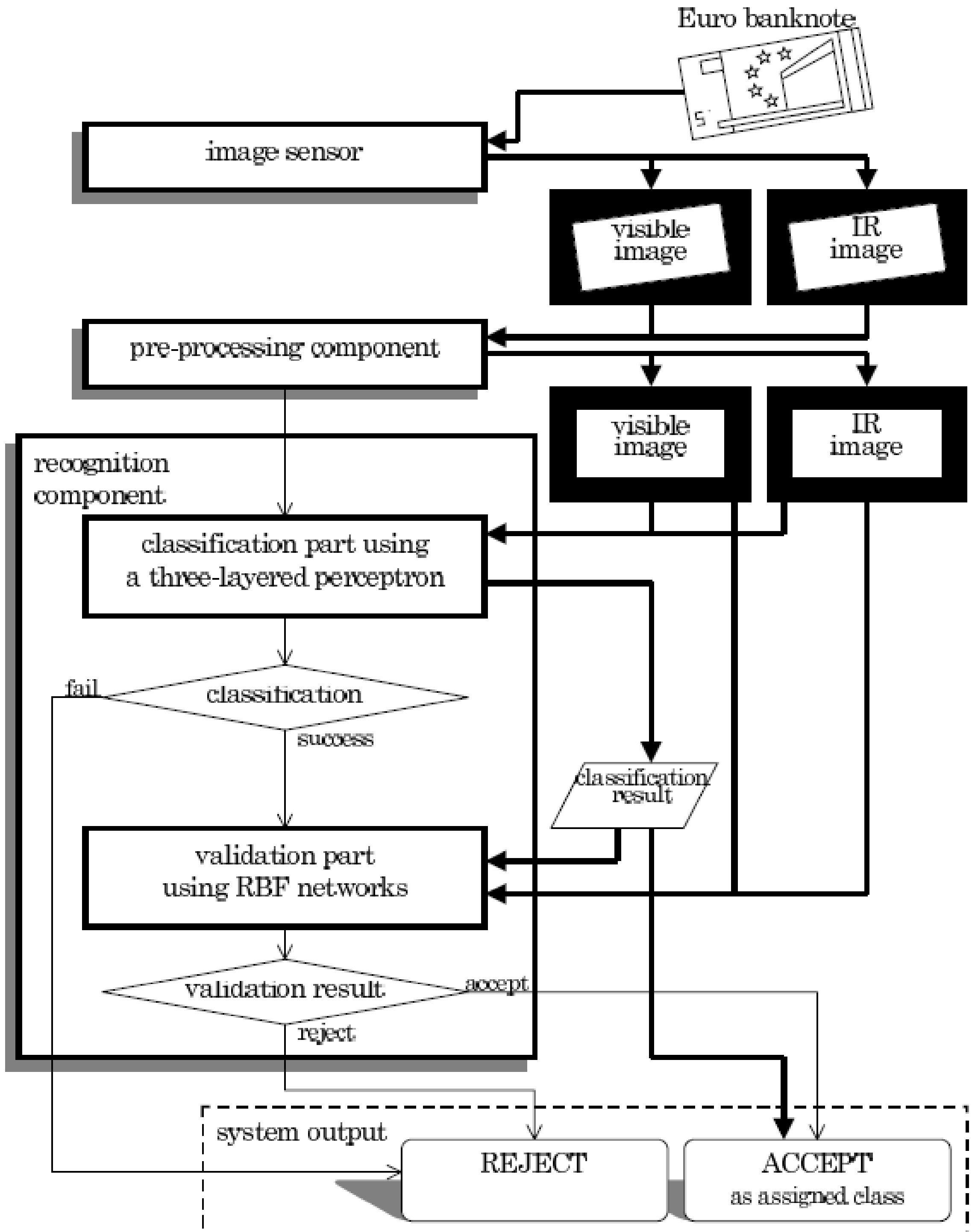

Figure 3. 1: Overview of Euro Banknote Recognition System [43]

The proposed system was trained with 200 pieces of new banknotes for each kind of Euro banknotes, namely 5, 10, 20, 50, 100, 200 and 500 Euro. These 200 new banknotes and an additional 200 pieces of dirty banknotes from each kind of Euro banknotes are used to verify the acceptance performance of the system for valid banknotes. The acceptance rate of valid new and dirty banknotes of the proposed system was claimed to be 100% and the acceptance rate of invalid banknote was claimed to be 0%.

3.2 US Dollar Currency Recognition System

In their research work *Ahmadi et al.* [44] proposed a reliable method for classifying banknotes, specifically US Dollars, using ANN. The proposed system uses PCA for feature extraction and linear vector quantization (LVQ) as the main classifier. In order to have a comparative study on the results of classification, HMMs, which is proper for sequential input data instead of the LVQ, is used as an alternative classifier.

Two kinds of sensors were used for reading data: point sensors and line sensors. The data generated by point sensors were used in LVQ classifier and the line sensor data are used in HMMs because of its sequential shape which comes as a sort of frames. The main features extracted in each frame were intensity (the percentage of black pixels within each frame), number of white pixels, mean value of pixels, variance of pixels, and number of transition between black and white pixels. After thresholding was done on the pixels in grey-scale level and the original pixel size is compressed data vectors of the frames were generated as the observation data of the bill. Using PCA and these data vectors as an input, components of these vectors were extracted. Finally the LVQ classifier was applied to classify the six kinds of US bills, namely $1, $5, $10, $20, $50, and $100. For comparative result HMM is also used as an alternative classifier.

To check the classification method and the reliability of the algorithm of the proposed system, 3570 samples from the six kinds of US dollar bills were used (taking four directions of rotation for each bill). The combined use of the LVQ and HMM classifier claimed to give 95% reliability rate. The reliability of the system claimed to increase if there was a clustering stage before LVQ classifier was applied and continuous densities instead of quantized date was supplied in the HMM.

3.3 Indian Paper Currency Recognition

Jain and Vijay [45] tried to recognize the different Indian currencies in their research. The primary focus of the research was to solve the difficulty of counting the different Indian currencies in bunch. The research work claims to denominate the current Indian currencies, which are, Rs. 1, 2, 5, 10, 20, 50, 100, 500 and 1000.

In the research work a digital image processing approach was employed to do the recognition. As the steps are described in *Figure 3.2*, first the image of each currency was acquired using a simple scanner, then the denomination part which the researcher called the region of interest (ROI) were extracted from each currency note. And after, the ROI was converted into greyscale image, different filtering was done on the ROI for smoothing and removing some noises from the denomination value of the ROI. Finally, NN and pattern recognition techniques were applied for pattern matching.

As the researcher claimed, the methodology was simple and easy to implement but many things were not addressed. To mention few of them, firstly the work did not mention how effective the system was for old currency notes, which is one of the major challenges in currency recognition systems. Secondly, comparison of the system with currently available recognition systems for Indian currency was not done. Thirdly, even though the work was claimed to be effective for denominating the Indian currency, a non-Indian currency with one of the denomination values of the Indian currency written on it can be identified by the system as Indian currency. Lastly, the proposed system could not able to identify a genuine currency from counterfeit.

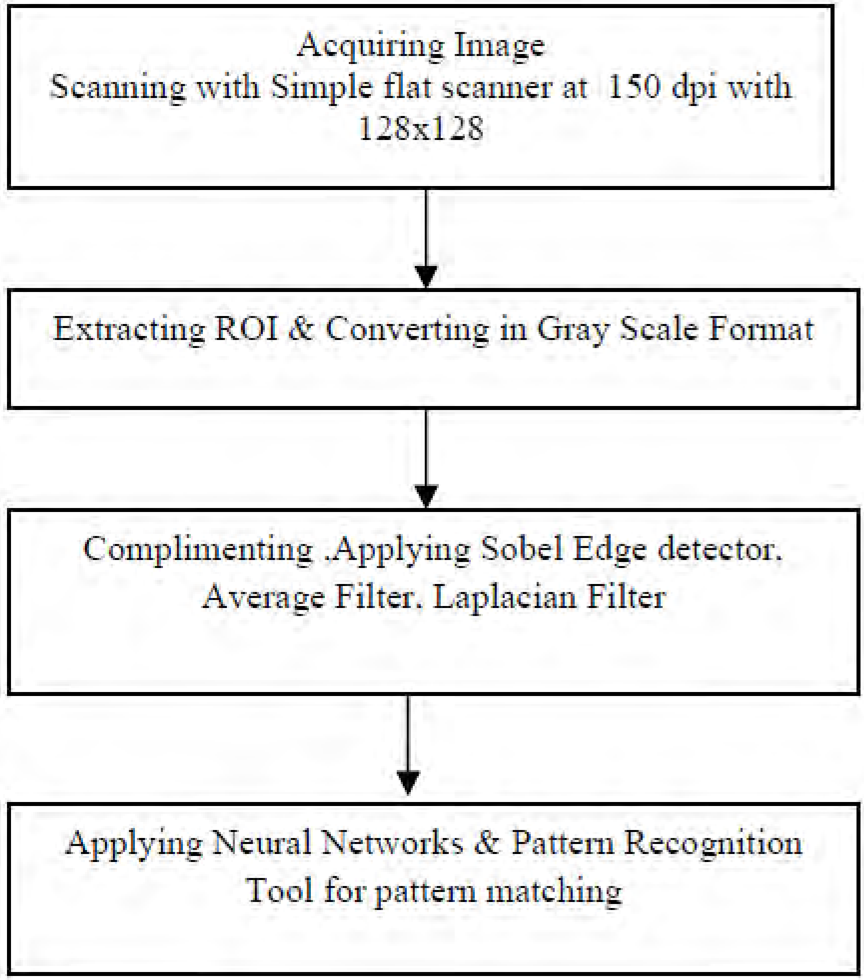

Figure 3. 2: Architecture of Indian Currency Recognition [45]

Mirza and Nanda [8] did a research for authenticating 100, 500 and 1000 Indian paper currency using image processing techniques. The method in the research work was inspired by the analysis of hidden marks on the image of the paper currency. Even though extracting the hidden attributes on the paper currency was a challenging task, in the work it was possible to capture the hidden marks of the currency by taking a picture of the currency using a camera by applying a white backlighting on the paper currency. After the image was captured through camera, further processing was done on the image by applying the image processing techniques like image pre-processing, edge detection, image segmentation, characteristics extraction.

In pattern recognition and in image processing, feature extraction is the special form of dimensionality reduction. It is the method of capturing the visual content of images for indexing and retrieval. When the input data to an algorithm is too large to be processed and it is suspected to be extremely redundant (much data but not much information) then the input data will be transformed into a reduced representation set of features (also named feature vector). If the attributes extracted are cautiously chosen, it is expected that the attributes set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Thus feature extraction involves simplifying the amount of resources required to describe the large set of data [8].

In the work after the image was captured through camera and some pre-processing activities, like image resizing, greyscale conversion and edge detection were done. Mainly three features were extracted from the currency image, namely identification mark, security thread and watermark. Then, the features were extracted using edge based segmentation by Sobel operator. Lastly, the extracted features were compared with the extracted features of the original currency by calculating the number of black pixels of segmented image.

In the research, even though there was advancement from previous researches in achieving a mechanism for authenticating Indian currency, the system was not complete. Firstly, it didn't include all Indian paper currencies which are seven in number. Secondly, it didn't denominate the paper currencies in their relative group. Thirdly, because the mechanism used to compare the features of the paper currency was counting the number of black pixels, which can be easily affected as the currency becomes old, the system may not be efficient for a relatively old paper currency.

3.4 Indonesian Paper Currency Recognition

Liliana and Neforawati [42] proposed one of the simple machine learning method called Naïve Bayes classification method for recognition of Indonesian paper currency. Naïve Bayes Classifier (NBC) works by finding the posterior probability of a pattern and classify them into a class that has the largest posterior value [46].

Bayesian decision theory is a fundamental statistical approach used in pattern recognition. The approach is based on quantification trade-offs between various classification decisions which applies probability and the costs incurred in the decisions making [47]. Advantages of using NBC is that the method only requires a small amount of training data to estimate parameters needed in the classification process. If the class label is known, NBC estimates the probability of class condition by assuming that attributes are conditionally independent [42].

The dataset for the training of the system contains the seven Indonesian currencies: Rp.1000, Rp.2000, Rp.5000, Rp.10, 000, Rp. 20,000, Rp.50, 000, and Rp.100, 000. And the feature vectors used were the mean intensities of each RGB on a specific area of the image of the currency.

The weakness observed in the research work was that the classification depends totally on the RGB components of each currency. There are a number of factors affect the colour intensity of the paper currency. Light illumination and condition (oldness) of the paper currency are some among the different factors that affect the colour intensity. As the RGB component intensity is not a reliable factor in different conditions for recognizing paper currencies, it is possible to say that the proposed system in the research work might not be robust.

3.5 Pakistan Paper Currency Recognition

The main objective of the research work of *Ahmadi and Manzoor* [27] was to identify and recognize the Pakistan paper currencies which are different in size, colour and pattern. The system was claimed to reduce the human effort in recognizing the different denominations and avoid purchasing expensive hardware.

In the research work, after the currency images were captured using simple scanner, common pre-processing techniques like conversion from RGB to greyscale, noise removal and conversion from grey-scale to binary was done. Instead of comparing the whole image, features of each sample images of the currencies were extracted and stored in a small database so that it may be compared with the features of the currency image to be recognized. Apart from the features, other characteristics of the currency images were captured and stored in the database for later comparison. Euler number, area, height, width, aspect ratio were among these characteristics. Based on these features the test currency, which needs to be grouped under one of the seven denominations, was classified using an instance based classifier algorithm called nearest neighbour classifier (KNN) classifier. Instance-based classifiers such as the KNN classifier operate on the premises that classification of unknown instances can be done by relating the unknown to the known according to some distance/similarity function. Classification (generalization) using an instance-based classifier can be a simple matter of locating the nearest neighbour in instance space and labelling the unknown instance with the same class label as that of the located (known) neighbour. This approach is often referred to as a nearest neighbour classifier [27].

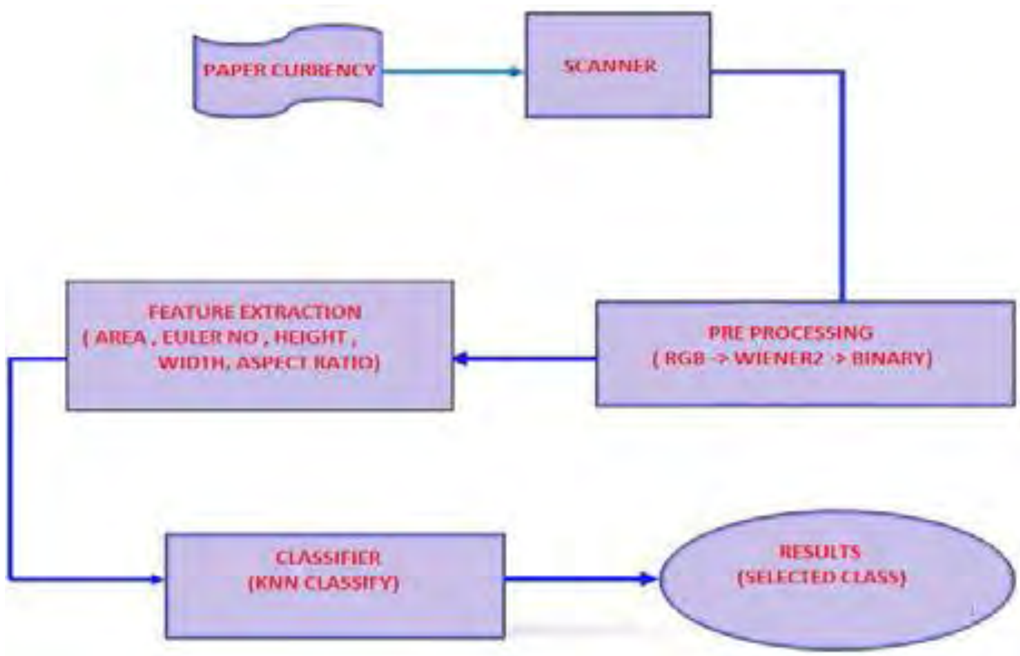

Figure 3. 3: Pakistan Paper Currency Recognition Model [27]

Even though the system was able to classify each of the seven currencies in their respective denomination with 100% accuracy, the system interface was designed to identify currency notes one at a time. And as such it is difficult to implement the system in real life currency recognition problems, like for ATM machines, auto-seller machines and bank money-counters.

In another research work by *Sargano et al.* [25] a new intelligent system for Pakistani paper currency recognition system was done. Extracting the robust features of the banknotes and apply three layers feed-forward BPNN for classification, makes the system to be simple and comparatively less time consuming to be suitable for real-time applications.

The proposed methodology in the research work consists of the following major parts; image acquiring of the banknotes using a scanner and developing a database to store the images, pre-processing to remove the noises in the images, selecting and extracting important currency features which has good discrimination power, passing the extracted feature through NN to train the system for classification, and finally classify the test image of banknotes with the trained model. The extracted features were aspect ratio of the banknote, set of effective colour features, binary pattern of lettering block of the banknote, binary pattern of see through block of the banknote and binary pattern of identification marks block of the banknote.

Figure 3. 4: Features of Pakistan Paper Currency [25]

The proposed system was tested for 175 banknotes, that is, for 25 banknotes from each class (10, 20, 50, 100, 500, 1000, and 5000) of rupees and claimed to have successful result.

3.6 Thai Paper Currency Recognition

In the research work of *Takeda et al.* [48] a Thai paper currency recognition system was proposed. The recognition process consists, slab values extraction, the NN system and DSP application. The banknotes were first collected and image pre-processing task was applied to detect the edges and centre of the banknote images to locate a mask set for the slab value extraction. An axis-symmetry mask set was used and characteristics of banknotes were represented in the slab values. And the slab values were given as an input for the NN system for learning and recognition. After the recognition capability was tested on a PC, everything was transferred to the DSP unit to test the recognition capability for real banking system. The whole process was summarized in the following *Figure 3.5*.

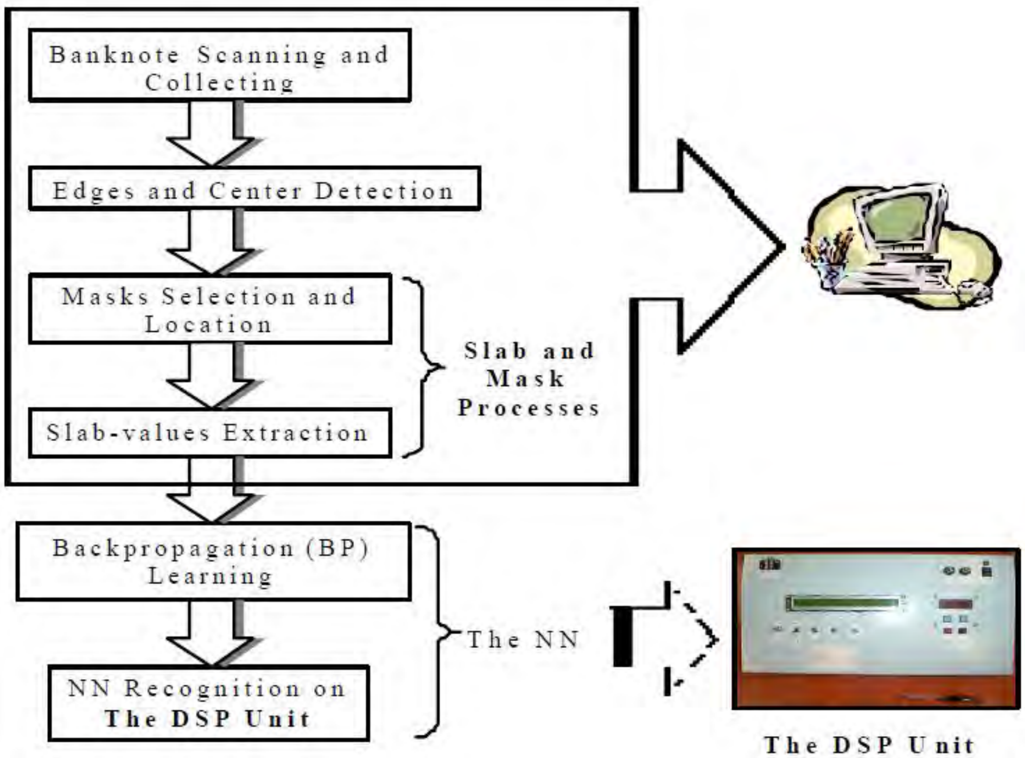

Figure 3. 5: Thai Banknote Recognition Using NN [48]

The proposed system was tested both on PC and DSP unit with 80 banknotes per 20 learning data/pattern and claimed to give 100% accuracy except two head patterns of 50 Baht and 100 Baht. For the two cases, the recognition capability was 95.56% and 98.89% respectively. Therefore the recognition system reliability has such fluctuation which was caused by mask set and threshold value. As such an improved threshold value selection method and a new algorithm for mask selection need to be proposed to improve the reliability of the system's recognition.

3.7 Mexican Paper Currency Recognition

The main objective of the research work of *Garcia-Lamont et al.* [11] was to propose a method for classifying Mexican banknotes by using artificial vision. The features used for classifications were the colour and texture features. The colour feature was modelled using the RGB colour space and the texture feature was modelled using Local Binary Patterns (LBP) method after the image was converted to grey-scale. For each banknote the dominant colour was extracted and represented using a unit vector. LBP which was used to model the texture feature was a grey-scale invariant texture primitive statistic, which was very robust in terms of greyscale variations and computational simplicity.

After a pre-processing was done on degraded banknotes using Wiener filter, the dominant colour was extracted and represented in a vector. For the texture extraction, thresholding was applied on the central pixel and its neighbours, followed by histogram representation of the different local binary patterns. The histogram was normalized and represented in a vector. A combination of the colour feature and texture feature was given as an input to the classifiers. The first classifier was a LVQ network classifier, which is a supervised version of vector quantization. The second classifier was a classification model via G statistics. G statistics is a non-parametric pseudo metric that measures likelihoods that a given sample is from alternative texture classes based on exact probabilities of feature values of previously pre-classified texture models.

The proposed model was claimed to have low processing time and work well for much degraded banknotes with very high accuracy. In addition to this, the recognition was invariant of image rotation, that is, at any image's orientation, the banknote can be classified accurately.

3.8 Chinese Paper Currency Recognition

The main objective of the research work of *Zhu and Ren* [10] was to propose a recognition method of RMB word numbers based on character features. RMB is the legal currency of China, and every RMB banknote has a unique crown word number, which identifies each not uniquely. The proposed identification system consists of image pre-processing, number region location, character segmentation, feature extraction and character recognition. To reduce the processing time in the recognition process grey-scale scaling, image de-noising with a 5x5 median filter and image binarization or thresholding was done as a pre-process task. By applying horizontal and vertical projection, the number location was obtained and by finding the tilt angle, the image tilt was corrected. Then the characters were segmented and normalized. For feature extracting and character recognition, 8-direction gradient feature extraction method and nearest neighbour algorithm were applied respectively.

The identification system failed to identify if the banknote had wrinkle. In addition to this, it didn't differentiate between similar characters like 1 and I or 0 and O. As such, the system needs a lot of improvement and cannot be applied in real world ATM.

3.9 Summary

In this Chapter, the researcher has mainly discussed research works related to currency recognition systems. Eight countries' currency recognition systems, namely United Kingdom, US, India, Indonesia, Pakistan, Thailand, Mexico and China are reviewed. At least one research work was presented for each country's currency recognition. To the best of the knowledge of the researcher, no research work was done towards the recognition of Ethiopian currency.

Each of the recognition systems which are reviewed in this chapter has their own limitations so that it may not be applied for Ethiopian currency recognition. Euro, US dollar and Thai currencies' recognition systems used a hardware component. Since these recognition systems involve a hardware component as a major component, it could not apply in this research for Ethiopian currency recognition. Mexican currency recognition used the texture of the currencies. But the textures of Ethiopian currencies are poor. Chinese recognition system used a unique number, which cannot be found in Ethiopian currencies. Indonesian currency recognition used the intensity values of the RGB of the currencies. These cannot be applied for Ethiopian currency recognition because the intensity values of the RGB of Ethiopian currencies are easily affected by light illumination. Pakistan currency recognition used the geometry of the currencies. Since each denomination of Ethiopian currencies has a non-consistent size, it cannot apply for Ethiopian currency recognition. The first Indian currency recognition used the denomination value on the currency for denominating the currencies. But this is not robust because it can recognize other currencies as Indian currency if it has the same denomination value on it as Indian and cannot be applied for Ethiopian currency recognition. The second Indian currency recognition was not a complete system because it assumed that the currencies were already denominated. It can be used only to verify whether a given denominated Indian currency is genuine or counterfeit.

Since none of the above currency recognition systems can not apply for Ethiopian currency recognition, a new classification algorithm based on colour and local features of the currencies was designed. The verification component of Ethiopian currency recognition was motivated by the Indian currency recognition. But instead of counting the number of black pixels, the number of solid line is counted in Ethiopian currency recognition.

CHAPTER FOUR: ETHIOPIAN CURRENCY RECOGNITION

In this Chapter, the design of the proposed automatic recognition of Ethiopian paper currency is presented. The system architecture with the components contained in it is presented first. The major components of the design namely, the denomination component and verification component are discussed in detail with its flowcharts. When the components are presented, the currency recognition activities at each stage are also presented in detail.

4.1 System Architecture

Figure 4.1 shows the proposed system architecture. The system consists of two major components, the currency denomination and currency verification component. Both components are composed of a number of sub-components. The currency denomination component contains pre-processing, feature extraction and currency categorization sub-components. The currency denomination sub-component, which is responsible for classifying the paper currency into their respective denomination, is a four level classification. In this four level classification, dominating colour, Hue value, correlation coefficient of the dominating colour and feature comparison is done consecutively. After the paper currency are categorized into their respective denomination, the second major component is applied for verifying the specific paper currency whether it is genuine of counterfeit. In the verification component, ROI is extracted and the final verification step is done by comparing the extracted ROI with the original.

This architecture is unique because it takes two different inputs for the denomination component and the verification component. It takes a scanned image for the denomination component and camera image for the verification component. The other thing that makes the architecture unique is the methods applied in the categorization. The categorization considers four features of the currency, namely dominating colour, the hue value, correlation coefficient and local features. After each feature is extracted, categorization is applied. If the first categorization is successful, it will continue to the second feature extraction and apply the second categorization. Otherwise, the currency is recognized as non-Ethiopian currency. If it passes the second categorization, it will go to the third and the fourth in a similar fashion. A currency image which passes the four iterative extraction and categorization will go through the verification component for validation.

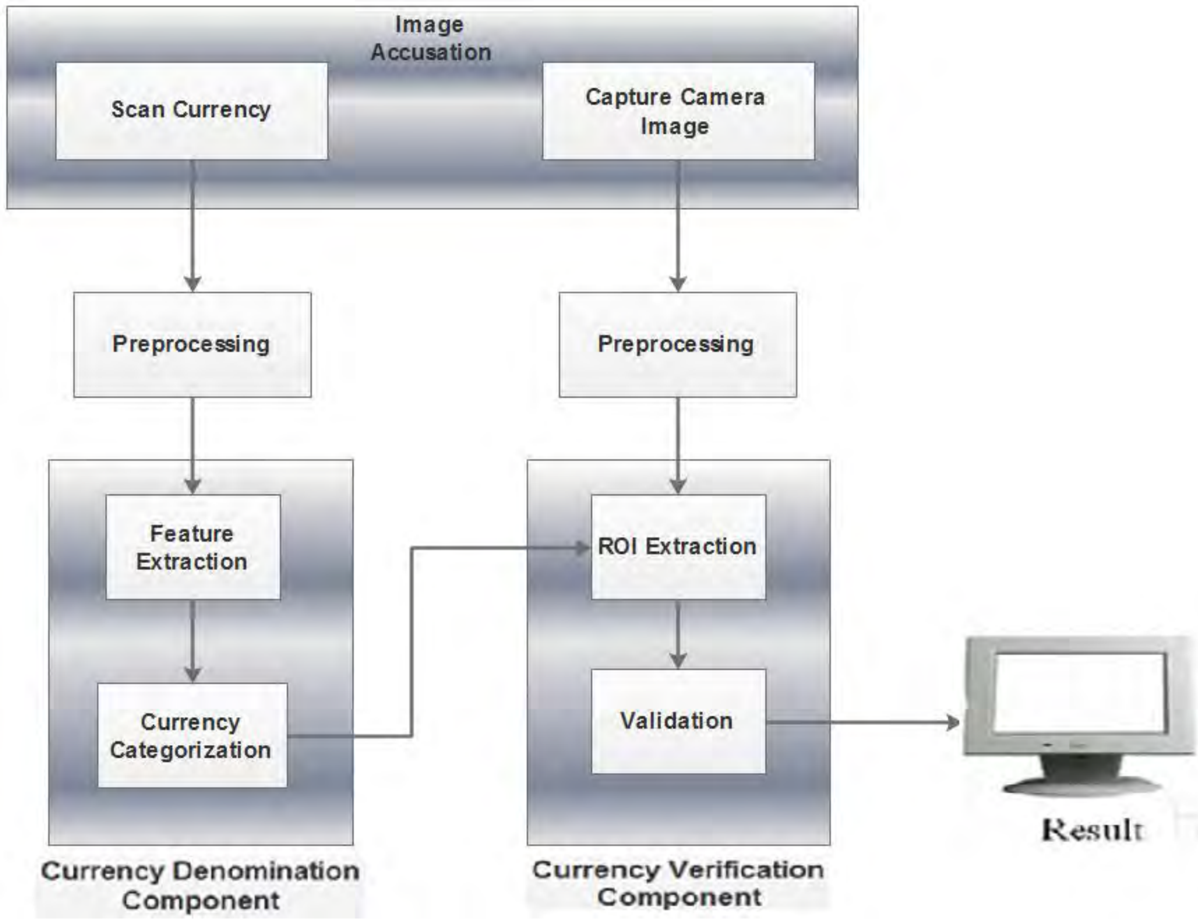

Figure 4.1: Architecture of Automatic Ethiopian Currency Recognition

4.2 Image Acquisition Device

The image acquisition device is responsible for acquiring the image of the paper currency. This component contains both scanner and photo camera. Each paper currency is scanned as well as its image is captured using a photo camera and both images pass to the image pre-processing component.

4.3 Pre-processing

The pre-processing component is responsible for preparing the paper currency image to the main image processing activities. Mainly two tasks are done in pre-processing: Image resizing and image enhancement.

Image Resizing

All the five Ethiopian currencies have different sizes. Since size is not used as a feature for categorization in the proposed design and the size of the image need to be similar for comparing the correlation coefficients of the RGB components among the different currencies, the image sizes of the currencies is brought to a common value.

Image enhancement

Old Ethiopian currencies have a degraded image quality. To improve the quality of such input images, the images are filtered using a Gaussian filter of window 3x3 and 3x2.

4.4 Feature Extraction and Classification

Feature extraction and classification are the main parts of the first major component of the paper currency recognition system, which is the currency denomination component. For the classification or categorization of the currencies, four different features are selected. These features are dominating colour of the image, the distribution of the dominating colour, the hue value of the currency image and SURF features of the currency. Based on these features, the classification into their respective denomination is carried out. The classification is applied after each feature is extracted. Because of this, the classifier is called a four level classifier. At each stage, a currency image can be a candidate to be categorized to one of the five Ethiopian denomination but needs to pass through the four levels to be fully. For the recognition algorithm to be more robust, a four level classifier is chosen.

The flowchart in *Figure 4.2 and Figure 4.3* describe the four level classifications of the proposed solution.

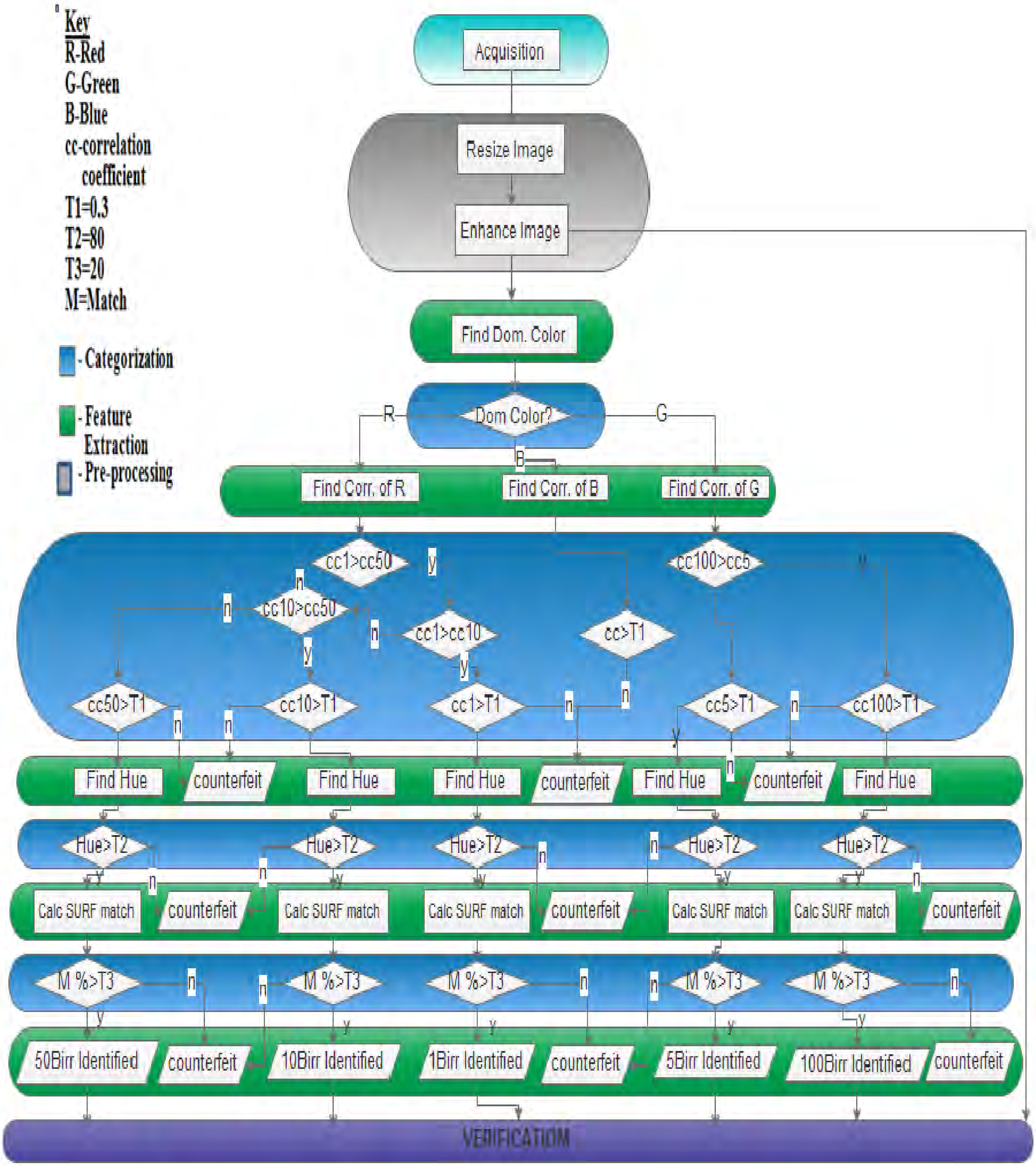

Figure 4.2: Denomination Flowchart

4.4.1 Dominating Colour

The image is acquired in RGB format and it has three major components; red, green and blue. The composition of these three components gives the specific colour of the currency image. In each image either red or green or blue is the dominating colour. In other words, either red, or green or blue has the maximum pixel occupancy in the image.

The five Ethiopian paper currency notes have different colours for human eyes. 100 Birr is green, 50 Birr is yellow, 10 Birr is red, 5 Birr is blue and 1 Birr is grey. Each colour of the currencies is different because the combination of the primary colours (Red, Green and Blue) is different in each currency. In addition to this, one of the three primary colours has greater pixel occupancy in the image. To find the maximum pixel occupancy, the pixels occupied of each of the primary colour are added and compare the three results. Among the three the one with maximum pixel sum is declared to be the dominating colour. Through such computation, the following result is obtained.

Table 4. 1: Dominating colour of Ethiopian Paper Currency

Dominating Colour	**Currency Name**
RED	1Birr or 10Birr or 50Birr
GREEN	5Birr or 100Birr
BLUE	5Birr

At this point, a test image with a dominating colour of Blue is a candidate of 5 Birr denomination. Yet further classification has applied to assure the candidate is in 5 Birr denomination.

4.4.2 Correlation Coefficient

Correlation is a method for establishing the degree of probability that a linear relationship exists between two measured quantities. When there is no correlation between the two quantities, then there is no tendency for the values of one quantity to increase or decrease with the values of the second quantity. The correlation coefficient matrix represents the normalized measure of the strength of linear relationship between variables. The MATLAB function corrcoef produces a matrix of correlation coefficients for a data matrix (where each column represents a separate quantity). The correlation coefficients range from -1 to 1, where values close to 1 suggest that there is a positive linear relationship between the data columns, values close to -1 suggest that one column of data has a negative linear relationship to another column of data (anti-correlation) and values close to or equal to 0 suggest there is no linear relationship between the data columns [49]. To calculate a scalar double (which ranges from 0 to 1) instead of a matrix as the correlation coefficient, a different MATLAB function called corr2 is used. Corr2 computes the correlation coefficient using between two matrixes using:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \bar{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \bar{B}\right)^2\right)}}$$

Where $\bar{A}$ = mean2 (A), and $\bar{B}$ = mean2 (B). [17]

In the proposed system, the dominating colour of the image to be classified (test image) is already identified. Therefore, instead of comparing the correlation coefficient of the image as a whole with the sample images in each class (target images), the dominating colour component of the image to be classified (test image) and the sample images in each class (denomination) are compared. This means in the proposed system, A and B denotes the dominating colour component of the test image and the target images.

Therefore, based on the dominating colour of the test image, the following correlation is done.

i. If the dominating colour of the image is Blue, the blue component of the test image is correlated with the blue component of the standard five Birr.

ii. If the dominating colour of the image is Green, the green component of the test image is correlated with the green component of the standard hundred Birr and five Birr.

iii. If the dominating colour of the image is Red, the Red component of the test image is correlated with the Red component of the standard one Birr, ten Birr and fifty Birr.

By empirical analysis, it is found that new Ethiopian currencies have a threshold value close to 1 and old Ethiopian currency close to 0.3. To include old Ethiopian currencies, a threshold value of 0.3 was taken. In each case the correlation coefficient need to be greater than this threshold value for the test image to be classified as a candidate into that specific class or denomination. And by now any test image is classified as a candidate into each denomination or rejected as non-Ethiopian currency. The *Table 4.2* summarize the correlation matrix.

Table 4. 2: Summary of Correlation Matrix Pairs

Correlation		Each Denomination Standard Image														
		1Birr			5Birr			10Birr			50Birr			100Birr		
		R	G	B	R	G	B	R	G	B	R	G	B	R	G	B
Dominating Colour of Test Image	R	x						x			x					
	G					x									x	
	B						x									

4.4.3 Hue value

The HSV colour model, also called HSB (Hue, Saturation, Brightness), defines a colour space in terms of three constituent components: Hue, Saturation and Value. Hue is the colour type (such as red, magenta, blue, cyan, green or yellow), Saturation refers to the intensity of specific hue and Value refers to the brightness of the colour [50]. As hue varies from 0 to 1.0, the corresponding colours vary from red through yellow, green, cyan, blue, magenta, and back to red, so that there are actually red values both at 0 and 1.0. As saturation varies from 0 to 1.0, the corresponding colours (hues) vary from unsaturated (shades of grey) to fully saturated (no white component). As value, or brightness, varies from 0 to 1.0, the corresponding colours become increasingly brighter [51].

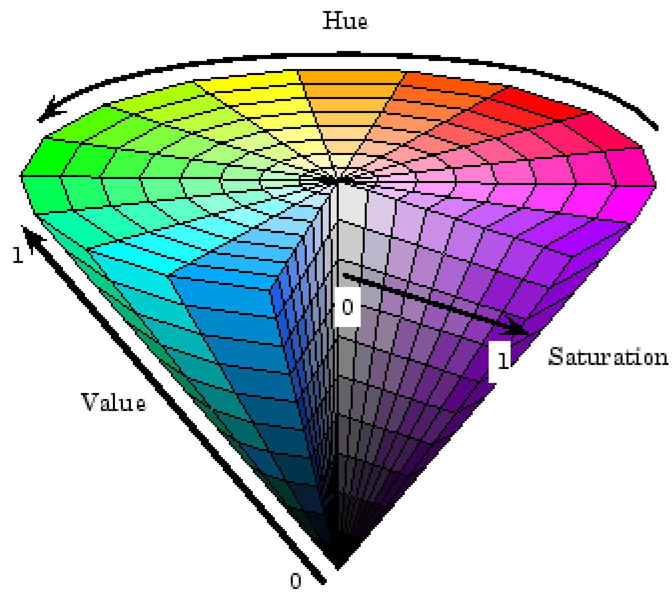

Figure 4.3: Illustration of HSV colour space [51]

Among the three components, hue component is selected to compare the different currency images because the other two components easily affected by the currency degradation and light effect while the image is scanned or captured. In addition to that, each image has a specific Hue value.

In the proposed system, the hue value of the test image is compared with each class of currency image's hue value. Since the test image is classified in the second classification step, the denomination of the test image is known at this stage. Therefore, the Hue value of the test image is compared against the Hue value of a standard image of its class. By Empirical analysis, it is found that the Hue difference of a genuine Ethiopian paper currency and the standard Ethiopian currencies is not more than 75. Therefore, if the Hue value difference between the test image and the standard image is less than 75, that test image is assured again as a candidate of an Ethiopian currency in that specific denomination. Otherwise it is considered as a non-Ethiopian paper currency.

4.4.4 SURF Features

This is the final classification step to re-assure that the denominated paper currency images are really true Ethiopian currencies. This component compares the features of the paper currency by building its own SURF descriptor. The steps for doing this are discussed one by one below.

Step 1: Find the interest Points or SURFpoints

The SURF approximates the second order Gaussian derivate with box filters (mean or average filter), which is able to be calculated fast through integral images. The localization of interest point is determined by the determinant of Hessian matrix. So, interest points are finally localized in scale space and image space by using non-maximum suppression in their $3 \times 3 \times 3$ neighbourhood [32].

SURFpoints is a scalar object which contains many points. It has five properties, namely Count, Scale, Metric, SignOfLaplacian and Orientation. Count gives the number of points held by the object, Scale specifies scale at which the interest points were detected, Metric is the value describing strength of detected feature, SignOfLaplacian is an integer parameter -1,0 or 1 that accelerate the feature matching process and Orientation is an angle in radians which is useful for visualization purposes. The MATLAB function is: **points = detectSURFFeatures(Image);**

```
points =                                              100 BIRR

  3471x1 SURFPoints array with properties:

                Scale: [3471x1 single]
      SignOfLaplacian: [3471x1 int8]
          Orientation: [3471x1 single]
             Location: [3471x2 single]
               Metric: [3471x1 single]
                Count: 3471
```

```
points =                                              50 BIRR

  1095x1 SURFPoints array with properties:

                Scale: [1095x1 single]
      SignOfLaplacian: [1095x1 int8]
          Orientation: [1095x1 single]
             Location: [1095x2 single]
               Metric: [1095x1 single]
                Count: 1095
```

```
points =                                              10 BIRR

  2585x1 SURFPoints array with properties:

                Scale: [2585x1 single]
      SignOfLaplacian: [2585x1 int8]
          Orientation: [2585x1 single]
             Location: [2585x2 single]
               Metric: [2585x1 single]
                Count: 2585
```

```
points =                                              5 BIRR

  2791x1 SURFPoints array with properties:

                Scale: [2791x1 single]
      SignOfLaplacian: [2791x1 int8]
          Orientation: [2791x1 single]
             Location: [2791x2 single]
               Metric: [2791x1 single]
                Count: 2791
```

```
points =                                              1 BIRR

  2920x1 SURFPoints array with properties:

                Scale: [2920x1 single]
      SignOfLaplacian: [2920x1 int8]
          Orientation: [2920x1 single]
             Location: [2920x2 single]
               Metric: [2920x1 single]
                Count: 2920
```

Figure 4.4: SURFpoints object of Sample Ethiopian currencies

Step 2: Select Strongest Points

As it is shown in *Figure 4.5*, the SURFpoints are in thousands. Constructing feature vectors for all the interest points and matching the feature vectors is expensive computationally. Therefore the features points those have strong metric or more relevant features need to be selected. By empirical analysis, it is found that taking the first 100 strongest points includes some important features which can differentiate the five Ethiopian currencies. Among these features are the denomination values in English and in Amharic (both in number and in letter), the alphanumeric note number and the currency identification sign for visual impaired people. Increasing the number of strongest points might include some other important features, but it also increase the processing time as well. Since we found some important features which can help to categorize the five Ethiopian currencies by taking the first 100 strongest points, the first 100 strongest points are selected to construct the feature vectors. The following MATLAB function selects the first strongest points which have strongest metric: **points = points.selectStrongest(100);**

Step 3: Construct Feature Vectors or Descriptors

In this step, the feature vectors or descriptors from the selected strongest points are constructed. The MATLAB function extractFeatures takes the image and points as its argument. It returns extracted feature vectors, also known as descriptors, and their corresponding locations, also known as valid points. The valid points have the same format as the input. The function extracts descriptors from a region around each interest point. If the region lies outside of the image, the function cannot compute a feature descriptor for that point. When the point of interest lies too close to the edge of the image, the function cannot compute the feature descriptor. In this case, the function ignores the point and the point is not included in the valid points output. Therefore valid points, not the input points, are associated to each feature vector. This can be summarized by the MATLAB function: **[features,validPoints] = extractFeatures(I,points);**

In figure 4.5, the feature vectors around the first 100 strongest points are shown in green colour.

Figure 4.5: Feature Vectors of Sample Genuine Ethiopian Currencies

Step 4: Match Features

In the previous step, the feature vectors are constructed. Here relatedness of the feature vector of a test currency image and a standard currency image of that specific denomination is checked. This is done using a MATLAB function called matchFeatures which takes the two feature vectors (that of the test currency image and corresponding standard currency in its denomination) and other optional arguments as its input and returns a P-by-2 matrix, indexPairs, containing P pairs of indices. These indices contain features most likely to correspond between the two input feature sets. The MATLAB function is: **indexPairs = matchFeatures(features1,features2)**;

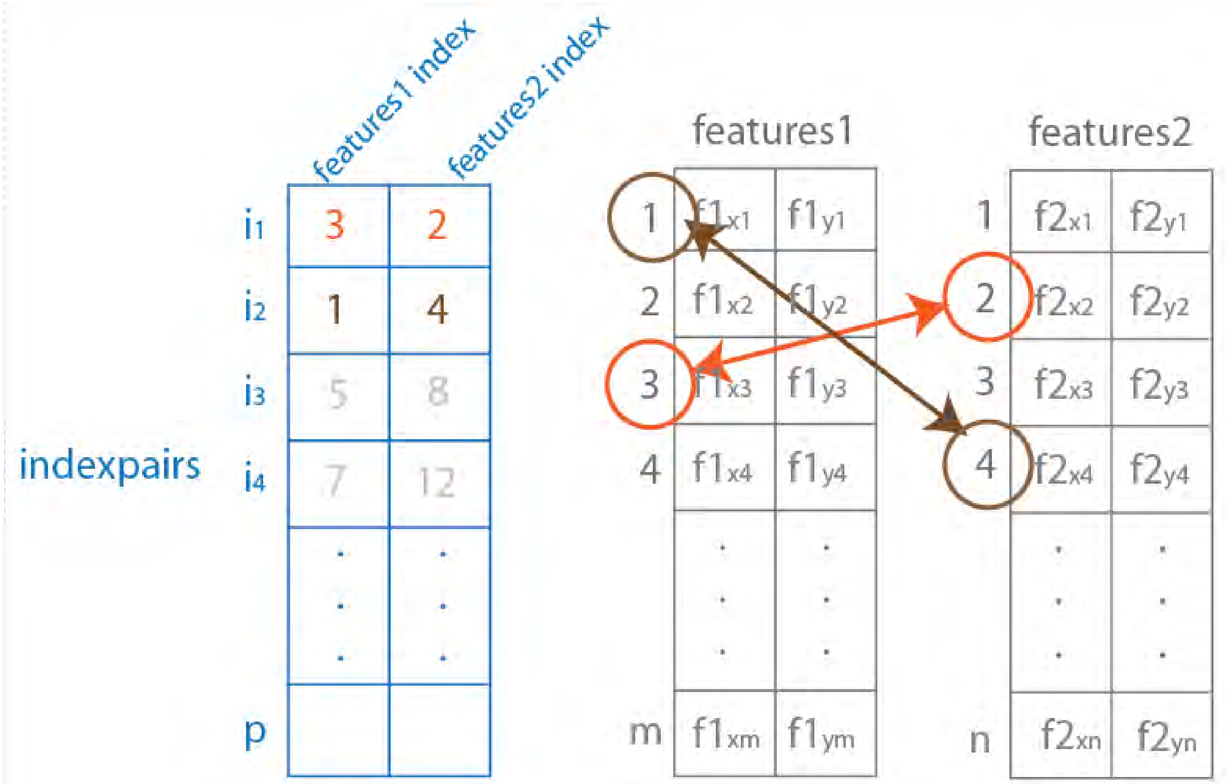

Figure 4.6: Index-Pairs of Two Feature Vectors [49]

Step 5: Calculate Match Percentage

In the previous step, the indexPairs, which in a way contains the matched corresponding features of the test currency image and standard currency image, are obtained. Taking this indexPairs as an input, the valid points which have a match are obtained using the MATLAB function:

matchedPoints = vpts1(index_pairs(: , 1)); or

matchedPoints = vpts2(index_pairs(: , 1));

To calculate the match percentage, the matchedPoints and the validPoints in either of the features are counted and take the ratio of the two. This can be summarized in the following equation:

$$\text{matchpercent}\,(\%) = \frac{\text{length}(\text{matchedPoints1})}{\text{length}(\text{vpts1})} \text{x}100$$

After the matchpercent is calculated, by experiment the matchpercent for genuine Ethiopian currencies is found to be more than 30. Therefore, if the matchpercent between a test image and a target image is greater than 30, it is identified as an Ethiopian currency and otherwise it is non-Ethiopian currency.

The classification of the test image into its respective denomination is fully achieved here and the next major component of the system, which is the verification of the denominated currency whether it is genuine or counterfeit, will continue from here.

4.5 Verification

This component of the system is for checking whether the paper currency is genuine or not. In Ethiopia paper currencies there are few features that distinguish the genuine currency from the counterfeit (*See Appendix A*). Most of these features can be seen in the scanned image of each currency. The most outstanding feature in all denominations, except 1 Birr note, is the broken thin golden strip, which become solid line when it is seen from the direction of background light. In addition to this thin golden strip, in 50 Birr and 100 Birr, there is a wider golden strip which bears the name and sign of National Bank of Ethiopia in Amharic and in English. Almost all the rest features are captured through the scanned image and used in the currency denomination. In addition to this, it is possible to find these features in counterfeit notes. Because of these two reasons, only the golden strip as a verification mechanism is used in this research.

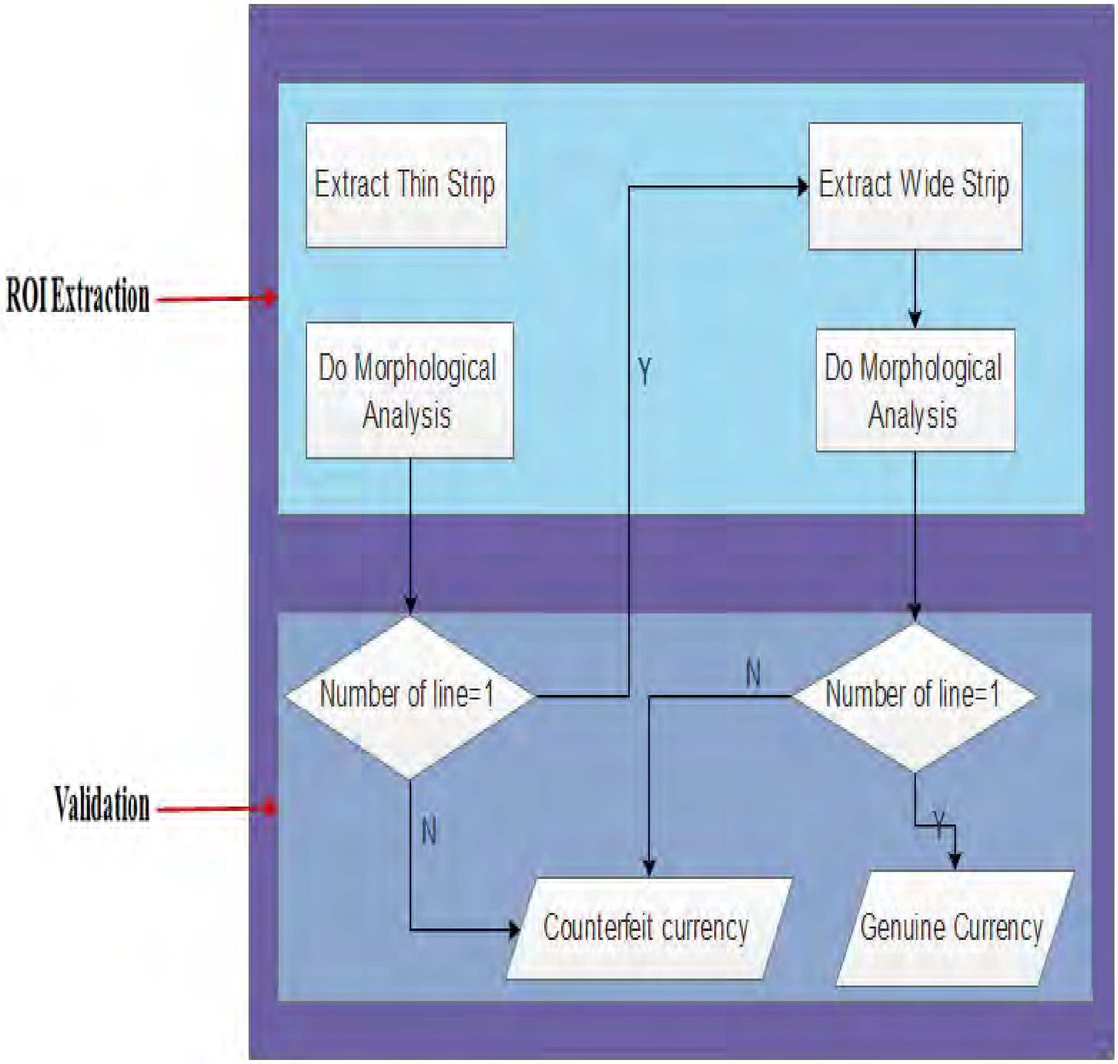

Figure 4.7: Verification Flowchart of 100Birr and 50Birr

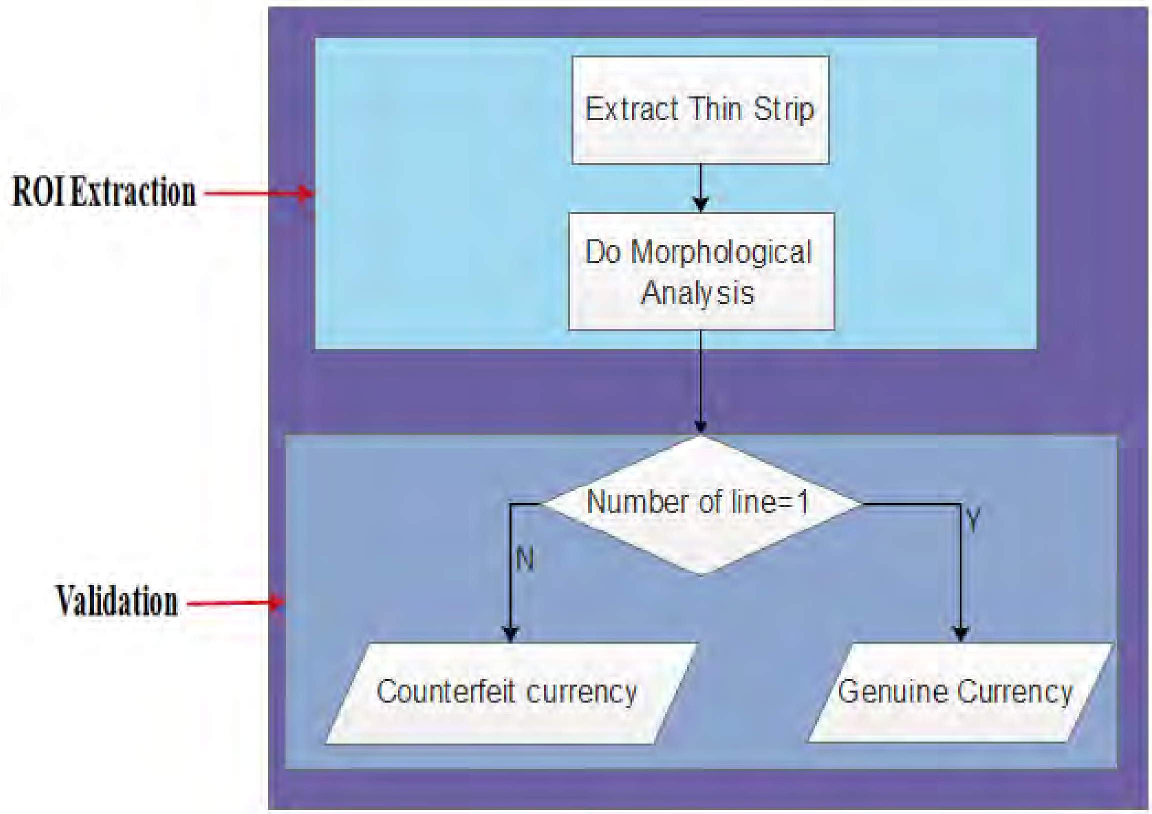

Figure 4.8: Verification Flowchart of 5Birr and 10Birr

For the golden strip to appear on the image, a camera image of the paper currency is taken by applying a background light against the currency.

Figure 4.9: Camera Image of Genuine 100Birr and 50Birr

After the image is captured, the verification process for 50 Birr and 100 Birr is twofold, that is, verifying using the wide strip as ROI and the thin strip as ROI. But for 5 Birr and 10 Birr, the verification is done using the thin strip as ROI. Since 1Birr of Ethiopia does not have a strip in it, correctly denominated 1 Birr currency is assumed to be genuine currency note. And there is no further verification done on 1 Birr currency note.

4.5.1 Verification 50Birr and 100Birr by the wide strip ROI

Step 1: Image Resizing

To speed up the currency recognition, the image size is adjusted to a smaller size of 800 x 400 pixels.

Step 2: ROI Localization

Crop the wide strip automatically by giving the specific locations which is between 450 to 500 pixels. The MATLAB function used for this operation, given the pixel positions of the strip x and y as an input, is:

croppedImage = Image(:,x:y,:);

Figure 4.10: Wide Strip of 100Birr and 50Birr

Step 3: Change to greyscale Format

For better processing, the RGB is converted to greyscale colour format.

Step 4: Binarization

Binarization is a process of converting a greyscale input image to a binary image by using an optimal threshold. The purpose of binarization is to extract those pixels from some image which represent an object. Though the information is binary, the pixels represent a range of intensities. Thus the objective of binarization is to mark pixels that belong to true foreground regions with a single intensity and background regions with different intensities.

By empirical analysis, it is found that for genuine Ethiopian currency a region with pixel value less than 30 is noise. Therefore, binarization is applied with a pixel intensity threshold of 30. This operation considers pixels intensity less than 30 as noise and therefore removes those pixels.

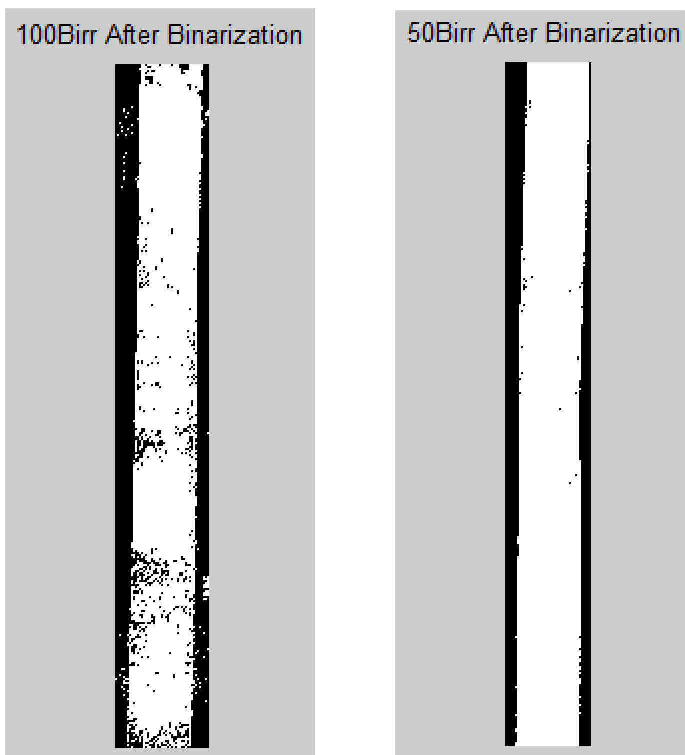

Figure 4.11: Wide Strip of 100Birr and 50Birr after Binarization

Step 5: Area Opening

A morphological area opening is an operation which removes from a binary image all connected components (objects) that have fewer than a given threshold pixels, producing another binary image. It is assumed that those objects which has fewer area than the given threshold pixels are noises that need to be removed from the ROI. In the proposed system, an area opening by 100pixel object is done.

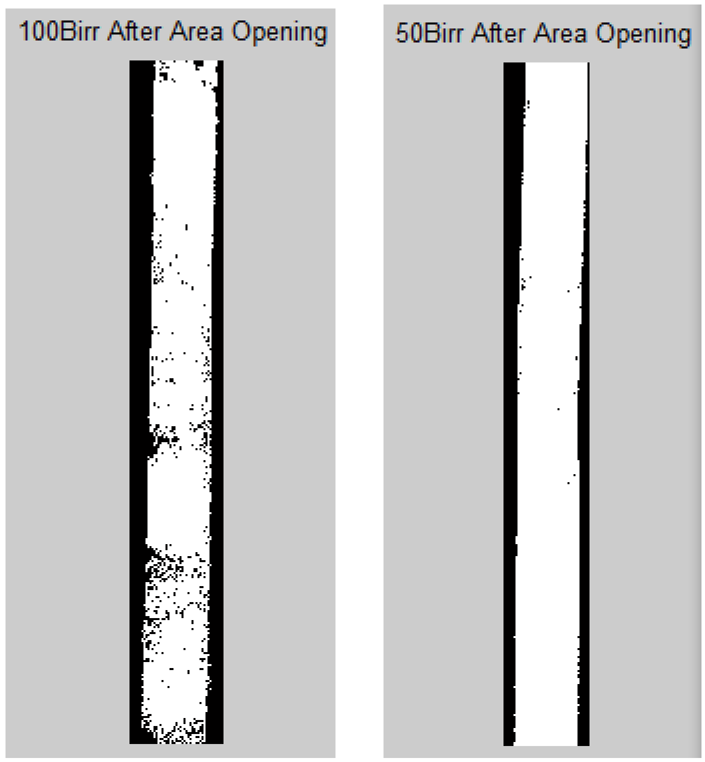

Figure 4.12: Wide Strip of 100Birr and 50Birr after Area Opening

Step 6: Morphological Closing

Morphological operations apply a structuring element to an input image, creating an output image of the same size. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. Morphological closing of an image is dilation followed by erosion, using the same structuring element for both operations. In the proposed system, a morphological closing with square structural element of size 5 symmetric with respect to the neighbourhood centre is applied. This size of the structural element is found through experiment.

Figure 4.13: Wide Strip of 100Birr and 50Birr after Closing

Step 7: Counting the Number of Objects

Here the numbers of objects in the cropped image are counted. If the number of object is one, the next recognition process will continue. Otherwise the test currency image is recognized as a counterfeit.

```
% This function checks the existence of the wide strip and
% returns the number of object in the wide strip.
function countWide=WideStrip(TestPicture,x,y)
    for i=x:20:y
        %Segement the wide strip
        CroppedWideStrip = TestPicture(:,x:y,:);
        %Convert into grayscale
        GreyWideStrip = rgb2gray(CroppedWideStrip);
        %Binarization
        WideStripBW = ~im2bw(GreyWideStrip, 30/255);
        %Area opening
        AreaOpenWide = bwareaopen(WideStripBW, 100);
        %Morphological Analysis
        se = strel('square', 5);
        BWImageCloseWide = imclose(AreaOpenWide, se);
        %Count the number of objects in this strip
        [~,countWide] = bwlabel(BWImageCloseWide);
            if countWide==1
               break;
            end
    end
end
```

Listings 4.1: Wide Strip Check Code Fragment

4.5.2 Verification by the thin strip ROI

Step 1: Image Resizing

To speed up the currency recognition, the image size is adjusted to a smaller size of 800 x 400 pixels.

Step 2: ROI Localization

The position of the thin strip is not in a specific location for currencies in a specific denomination. Therefore, the existence of the thin strip is checked by taking a 5 pixels wide strip iteratively in the range of 180 to 270 pixels for 100 and 50 Birr and in the range of 200 to 300 pixels for 10 and 5 Birr. The MATLAB function used for this operation, given the pixel positions of the strip x and y as an input, is:

croppedImage = Image(:,x:y,:);

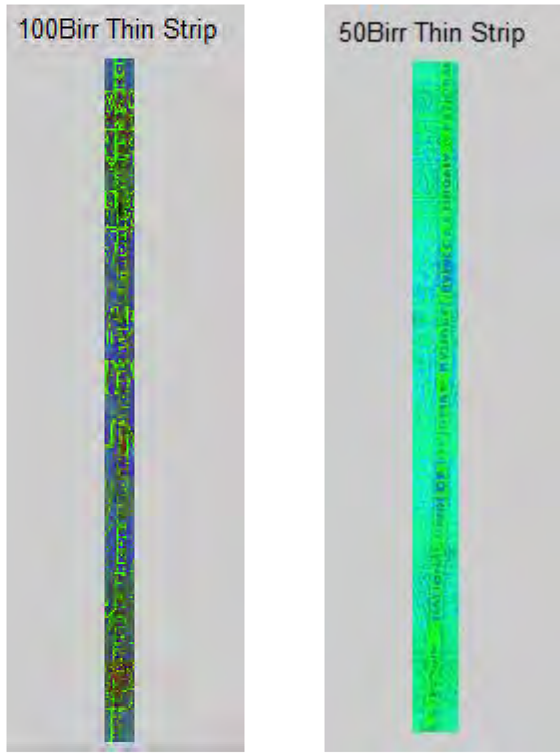

Figure 4.14: Thin Strip of 100Birr and 50Birr

Step 3: Change to HSV Format

For better processing, the RGB is converted to HSV colour format.

Step 4: Binarization

From the three HSV components, only saturation and value components are usually exposed to noise. And therefore binarization is applied on these two components of the image with 0.3 value and 0.4 saturation thresholds. This threshold value is found through experiment.

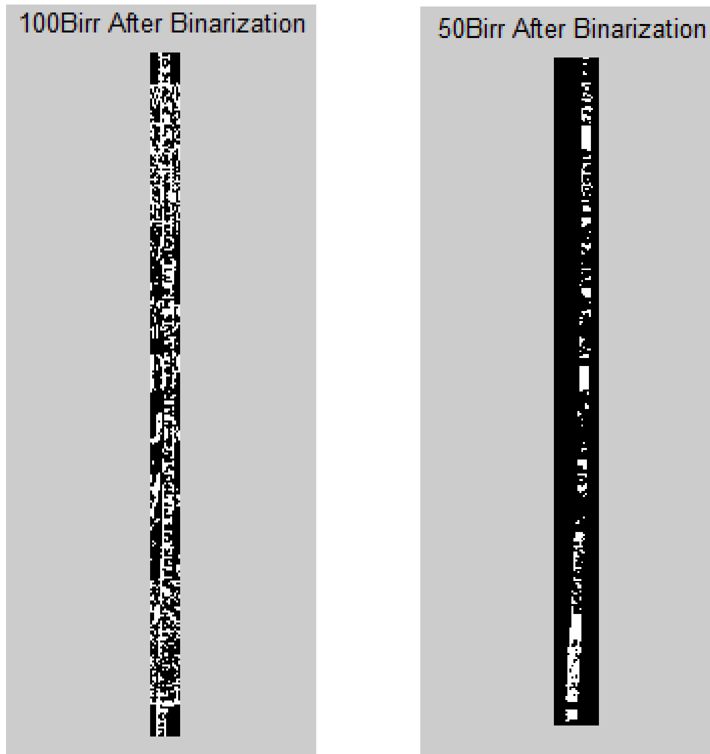

Figure 4.15: Thin Strip of 100Birr and 50Birr after Binarization

Step 5: Morphological Closing

A morphological closing with a line structural element symmetric with respect to the neighbourhood centre is applied.

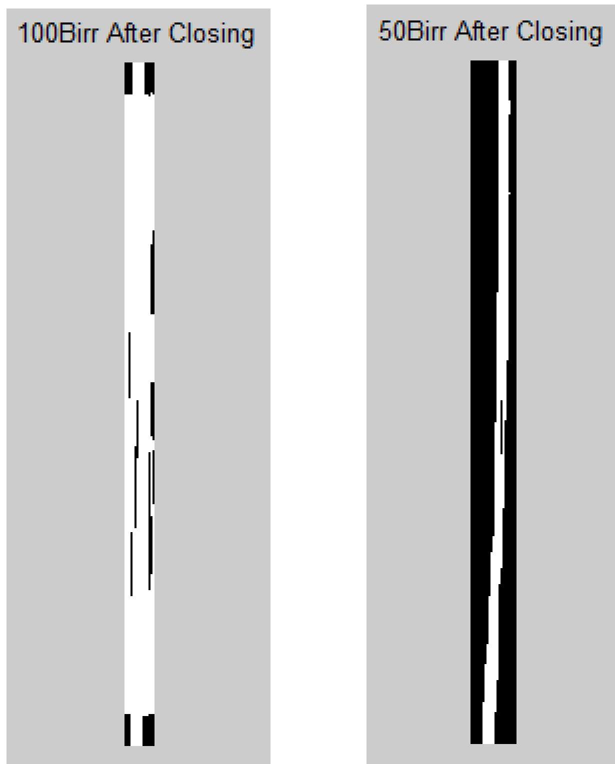

Figure 4.16: Thin Strip of 100Birr and 50Birr after Closing

Step 6: Area Opening

A morphological area opening is applied with 30 pixel area to remove objects less than 30 pixel area. The value 30 is found by experiment.

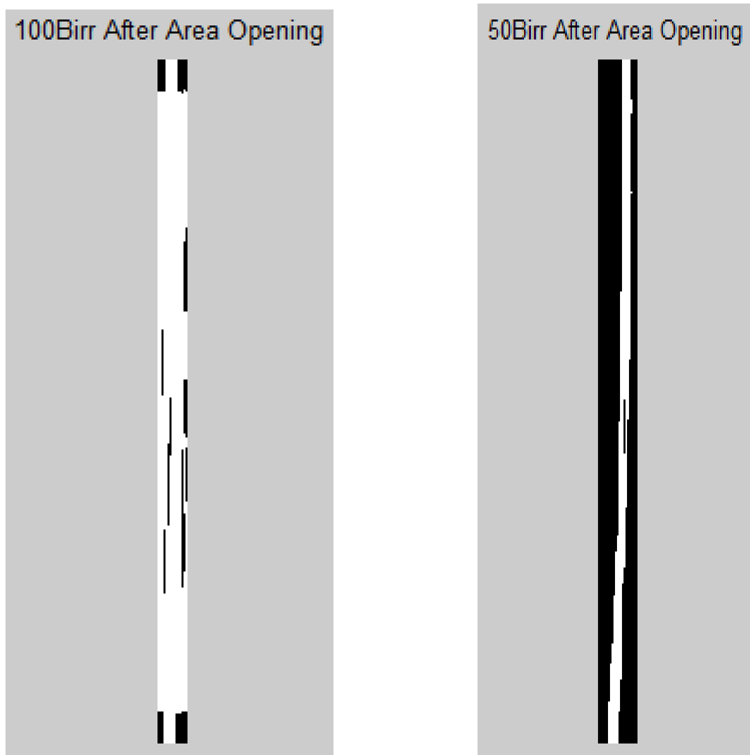

Figure 4.17: Thin Strip of 100Birr and 50Birr after Area Opening

Step 7: Counting the Number of Objects

The final recognition step is to count the number of objects in the cropped image. If the number of object is one, it is a genuine currency and otherwise it a counterfeit.

```matlab
%This function checks the existence of the thin strip in an image.
function flag=OneStripCheck(x,y)
    %Read in image
    prompt = 'Enter the file name of the scanned image: ';
    inputPicture = input(prompt,'s');
    TestPicture=imread(inputPicture,'jpg');
    %Convert into grayscale
    hsvImage = rgb2hsv(TestPicture);
    for i=x:5:y
        %Segement the thin strip
        croppedImage = hsvImage(:,i:i+5,:);
        satThresh = 0.4;
        valThresh = 0.3;
        BWImage = (croppedImage(:,:,2) > satThresh & croppedImage(:,:,3) < valThresh);
        %Morphological Analysis
        se = strel('line', 6, 90);
        BWImageClose = imclose(BWImage, se);
        %Area opening
        areaopen = bwareaopen(BWImageClose, 15);
        %Count the number of objects in this strip
        [~,count] = bwlabel(areaopen);
           if count==1
               flag=1;
               break;
           end
    end
    if count~=1
        flag=0;
    end
end
```

Listing 4.2: Thin Strip Check Code Fragment

4.6 Summary

In this chapter, the design of the Ethiopian paper currency recognition system is discussed in detail. The components that constitute the system, the relationship among these components, and the responsibility of each component are discussed. The design is composed of two major components; denomination and verification. The first component is responsible for classifying the paper currency into the five denomination of Ethiopian currency, that is, 1 Birr, 5 Birr, 10 Birr, 50 Birr and 100 Birr. In first component, there are sub-components like pre-processing and different level of classifications. The second component is responsible for verifying the denominating paper currency whether it is a genuine currency or a counterfeit. The second component has sub-components in it which enabled the system to recognize the paper currency and display the result in the display unit.

CHAPTER FIVE: EXPERIMENT

In this chapter, the evaluation and testing of the proposed prototype for its accuracy and performance is presented. The proposed system capability in denominating the Ethiopian currencies into their respective denomination is evaluated and tested. In addition to this, the verification capability of the prototype to identify genuine from counterfeit Ethiopian currency is also evaluated and tested. First, currency collection is discussed. Second, the implementation environment is discussed. Third, the evaluation criteria for denomination and verification with the test result are discussed. Finally, the overall experimenting process is discussed.

5.1 Currency Collection

For evaluating and testing the proposed prototype, different denomination of Ethiopian and non-Ethiopian currencies are collected. Genuine sixty 100 Birr notes, sixty 50 Birr notes, forty 10 Birr notes, forty 5 Birr notes, forty 1 Birr notes are collected. In these notes new, a little old, very old and worn out currency notes are included. To test the verification capability of the system, counterfeit currency notes are collected. Among these counterfeit notes, previous Ethiopian genuine notes are also included. In addition to these currencies, other countries' currencies are also collected, namely US dollar, Rand, Dirham, and Shilling. Both scanner and camera images of these currencies are acquired and stored for evaluating and testing the system.

The scanner used is HP Scan jet G2710. Each currency is scanned with a resolution of 200dpi, size 1122 x 570 pixel and saved in a jpg image. From the scanned image a standard image is selected from each denomination and stored in an array of size five to be a later reference for comparing the test currency image.

Figure 5.1: Scanned Image of Ethiopian Currency

The camera used to capture the images is Canon PowerShot SD1400 IS Digital ELPH with 14.1 Mega pixels. The images of the currency are taken with a background white light, so that the broken thin golden strip to be straight line. As it is seen in *Figure 5.2*, the golden strip is straight line.

Figure 5.2: Camera image of Ethiopian Currency

5.2 Implementation Environment

For this research work, MATLAB tool is used as a development environment. MATLAB® is a high-level language and interactive environment for numerical computation, visualization, and programming. The version of MATLAB tool used in this research work is MATLAB 2014a. Its language and built-in math functions are used for the implementation.

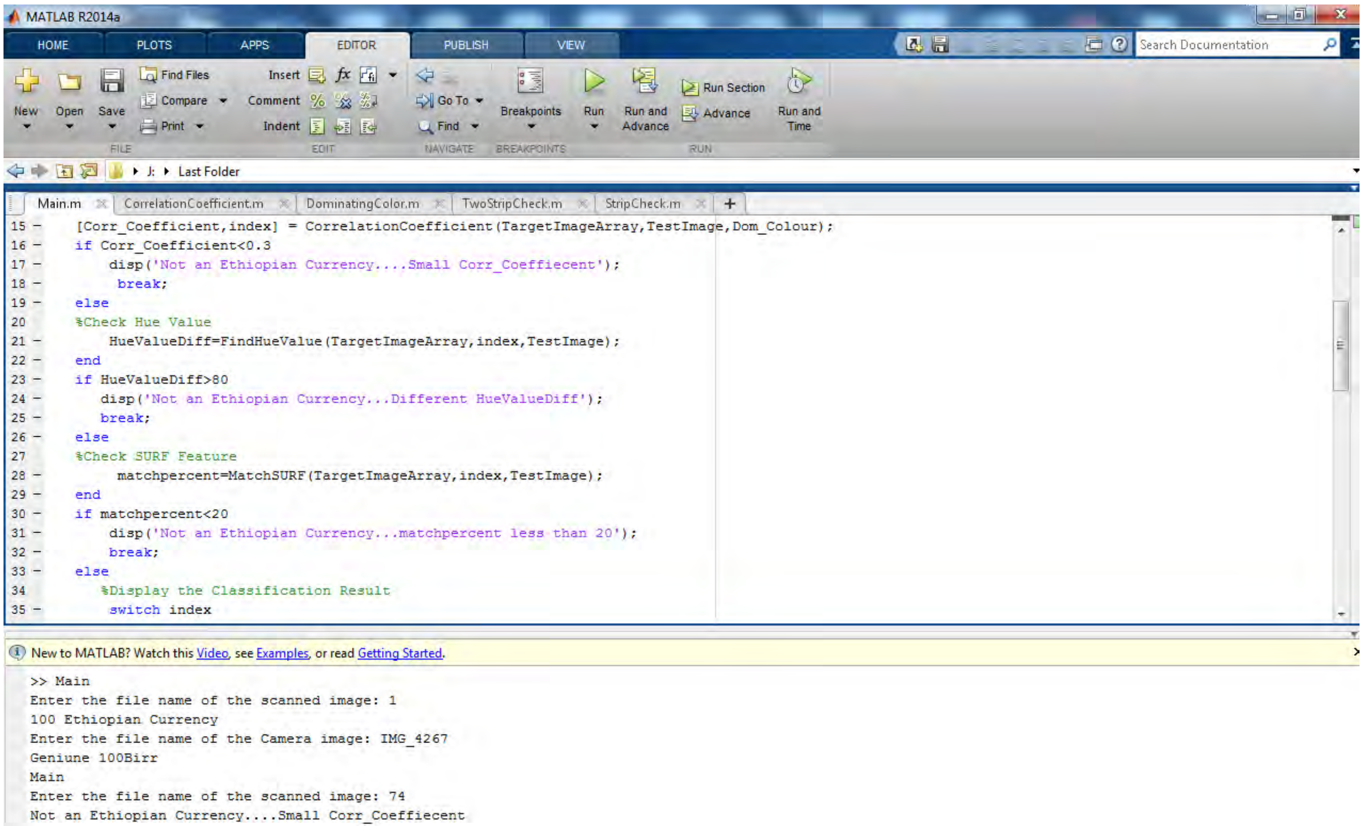

Figure 5.3: MATLAB Environment

Toshiba laptop of the following specification is used for the research: Windows 7 32-bit operating system. The hardware component comprises of Intel(R) Core(TM) 2 Duo CPU of 2.1 GHz, 3GB memory, and 500GB hard disk.

5.3 Test Result

5.3.1 Evaluation Criteria

The prototype's denominating and verification capability is evaluated. The denominating capability is concerned about measuring the effectiveness of the system in classifying a test currency image into one of the five Ethiopian currency denominations, which are 1Birr, 5Birr, 10Birr, 50Birr and 100Birr. The verification capability concerned with identifying a genuine Ethiopian currency from a counterfeit currency. Therefore the prototype for its accuracy in denomination and verification is evaluated.

The accuracy of the denomination or denomination rate is measured by the ratio of number of accurately denominated currencies and the total number of currencies tested. And the accuracy of the verification or the verification rate is measured as the ratio of number of accurately verified currencies and the total number of accurately denominated currencies. Both the denomination rate and verification rate is calculated for each denomination of Ethiopian currency.

$$\text{Denomination rate (\%)} = \frac{\text{Correctly Denominated Currency Images}}{\text{Total Test Currency Image}} \text{x100}$$

$$\text{Verification rate (\%)} = \frac{\text{Correctly verified Currency Images}}{\text{Correctly Denominated Currency Images}} \text{x100}$$

The total time taken to denominate as well as to verify is calculated.

5.3.2 Testing Denomination Component

The denomination accuracy of the system is tested with a total of 269 sample currency notes. In the sample both new and worn out genuine paper currency are included. In addition to this, the system is tested with non-Ethiopian currencies. The accuracy of the classifier is evaluated for genuine Ethiopian currencies of each denomination, counterfeit Ethiopian paper currencies of each denomination and non-Ethiopian paper currencies.

Table 5.1: Test Summary of Genuine Ethiopian Currencies Denomination

Currency Denomination	Total Test Images	Correctly Denominated	Denomination Rate (%)	Processing Time (in Second)
100 Birr	60	58	96.67	1.61
50 Birr	60	51	85.00	1.73
10 Birr	40	37	92.50	1.72
5 Birr	40	35	87.50	1.66
1 Birr	40	36	90.00	1.71
Average	240	217	**90.42**	**1.68**

As shown in detail in *Table 5.1*, the average denomination rate is 90.42% with an average processing time of 1.68 second. In the experiment, it is shown that the denomination rate for relatively new currencies of all denominations is 100%. But for older and very old notes, the denomination rate is between 80 and 90%. The denomination rate of 50Birr is affected due to its texture which degrades very much as compared to other currency notes.

Table 5.2: Test Summary of Counterfeit Ethiopian Currencies Denomination

Currency Denomination	Total Test counterfeit Images	Denominated as Counterfeit Test Images	Denomination Rate (%)
100Birr	10	2	80
50Birr	7	2	71.4
10Birr	4	0	100
5Birr	3	0	100
Average	24	4	**83.3**

As the test result is summarized in *Table 5.2*, the denomination accuracy for the 100Birr and 50Birr counterfeit notes is not 100%. This shows that some of 100Birr and 50Birr counterfeit notes pass the denomination step and denominated as one of the Ethiopian currency. And these notes need to pass through the next verification step.

Table 5.3: Test Summary of Non-Ethiopian Currencies Denomination

Currency Denomination	Total Test Images	Denominated as Non-Ethiopian Currency	Denomination Rate (%)
USD	2	2	100
RAND	1	1	100
SHILLINGS	1	1	100
DIRHAM	1	1	100
Average	5	5	100

All of non-Ethiopian currencies which are used for testing are denominated as non-Ethiopian currencies. Therefore, the denomination rate for these sample notes is found to be 100%.

5.3.3 Testing Verification Component

The verification rate or verification accuracy of the system is tested with a total of 185 sample currency notes. The sample consists new and worn out genuine Ethiopian paper currencies and counterfeit Ethiopian currencies. The test result is shown in the *Table 5.4* and *Table 5.5*.

Table 5.4: Test Summary of Genuine Ethiopian Currencies Verification

Currency Denomination	Correctly Denominated Test Images	Correctly Verified	Verification Rate (%)	Processing Time (In milliseconds)
100Birr	58	56	96.55	343
50Birr	51	50	98.04	324
10 Birr	37	35	94.60	296
5Birr	35	33	94.29	261
Average	181	174	**96.13**	**306**

As shown in *Table 5.4*, the average verification rate of the prototype is **96.13%** with an average processing time of **306 milliseconds.** As in the case of the denomination, the verification rate for relatively new currencies is 100%.

Table 5.5: Test Summary of Counterfeit Ethiopian Currencies Verification

Currency Denomination	Counterfeit Denominated as Ethiopian Currency	Verified as Counterfeit	Verification Rate (%)	Processing Time (In millisecond)
100Birr	2	2	100	332
50Birr	1	1	100	313
Average	3	3	**100**	**322**

As summarized in the *Table 5.5*, all the counterfeit notes are recognized as counterfeits by the prototype. Therefore it is possible to achieve 100% verification rate to identify counterfeit notes using the prototype.

5.4 Discussion

The prototype's denomination rate and verification rate is tested. Genuine paper currencies at different condition from brand new to very old notes and counterfeit notes other country banknotes are used to test the prototype. The prototype can denominate the genuine Ethiopian notes with an average denomination rate of 90.42%. For new notes the prototype works with 100% denomination accuracy. When the prototype is tested with counterfeit notes of Ethiopia, its denomination accuracy is found to be 83.3%. Because the prototype denominate previously used Ethiopian currencies, which are considered counterfeit notes currently, as genuine one, the denomination rate for counterfeit notes below that of the genuine currency denomination rate. The denomination accuracy for other countries notes is found to be 100%. This means that, the prototype fully identifies other country notes as non-Ethiopian currencies at the denomination stage.

The system's verification rate is also tested with those test currency images that pass the denomination stage. Among correctly denominated genuine Ethiopian currencies, 96.13% are correctly recognized. Some of the counterfeit paper currencies pass the denomination level but all these counterfeit notes are recognized as counterfeit notes at the verification level. Therefore, the verification rate for counterfeit notes is found to be 100%.

The average processing time for denomination is 1.68 second and that of verification is 306milliseconds. Therefore, the overall average processing time of the proposed prototype is 1.986 second.

CHAPTER SIX: CONCLUSION AND RECOMMENDATION

6.1 Conclusion

In this thesis the researcher has designed, developed a prototype and tested automatic Ethiopian currency recognition system. The prototype is able to classify Ethiopian currencies into their respective denomination and recognizes counterfeit currencies. The different currency recognition systems of other countries are reviewed and currency characteristic comparison and local feature descriptors are adapted for Ethiopian currency recognition. The design has two major components: the denomination component, which is responsible for denominating the currencies into their respective class and a verification component, which is responsible for verifying whether the classified currency is genuine or counterfeit. The denomination component takes a scanned currency image as an input and classifies the image as 1Birr, 5Birr, 10Birr, 50Birr or 100Birr. The verification component takes the denominated currency camera image as an input and identifies the currency as genuine or counterfeit.

As being the first Ethiopian currency recognition system, the evaluation result of the prototype can be considered as one that has a good performance. The prototype is tested and evaluated with new, old, very old genuine Ethiopian paper currencies, counterfeit Ethiopian currencies and other countries currencies. Both the denomination rate and verification rate of the prototype is evaluated. The average denomination is found to be 90.42% and the average verification rate is found to be 96.13%. 100% of verification rate is achieved for counterfeit notes. The overall processing time of the prototype is 1.986 second.

The main contributions of this thesis work are listed as follows:

- The study has adopted some of the approaches of currency recognition system of other countries for Ethiopian currency context.
- The study has paved the way to build full-fledged automatic Ethiopian currency recognition by building a prototype.
- The study showed the strategy, algorithms, and techniques in developing automatic

Ethiopian paper currency recognition prototype.

- The study has designed automatic Ethiopian paper currency recognition prototype that denominate the currencies in their respective domain.
- The study has designed automatic Ethiopian paper currency recognition prototype that recognize whether a currency is genuine Ethiopian currency or counterfeit.
- The study identified and showed the major components to construct automatic currency recognition prototype and how they can be easily integrated and function as one unit.
- The study identified basic challenges in developing and implementing automatic Ethiopian paper currency recognition system and the possible approaches to solve those challenges.

6.2 Recommendation

Designing and implementing a currency recognition system is not a simple task. Because of the vastness of the work and the limited resources and expertise, there are still tasks that can be done in the future to improve or upgrade the system. The following are some of the recommendation that the researcher proposes for future work:

- Improving the classification algorithm so that it may give a better denomination rate for very old paper currency notes.
- Improving the pre-processing techniques for better denomination of old and very old paper currency notes.
- Improve the design to have better processing time.
- Improving the design for better recognition by including other features that distinguish a genuine Ethiopian paper currency form counterfeit.
- Improving the system to recognize a genuine Ethiopian currency only from a scanned image.
- Extending the design to denominate and recognize paper currency from each side and any

direction.

- Extending the design and developing Ethiopian coin recognition in addition to paper currency recognition.
- Extending the design and developing Ethiopian currency recognition system for visually impaired people.
- Extending the design and implementing to work on android platform by receive image from mobile camera.

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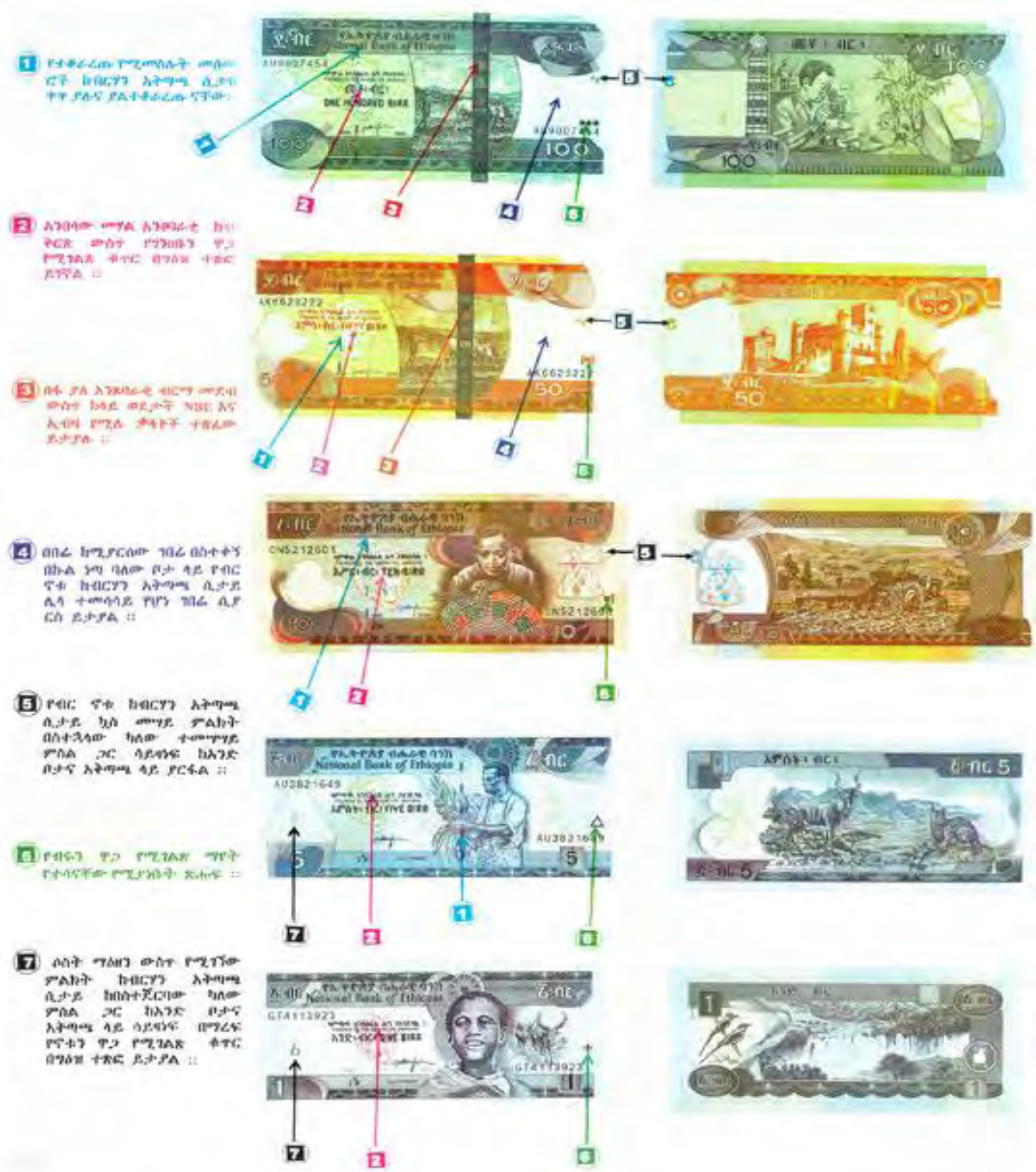
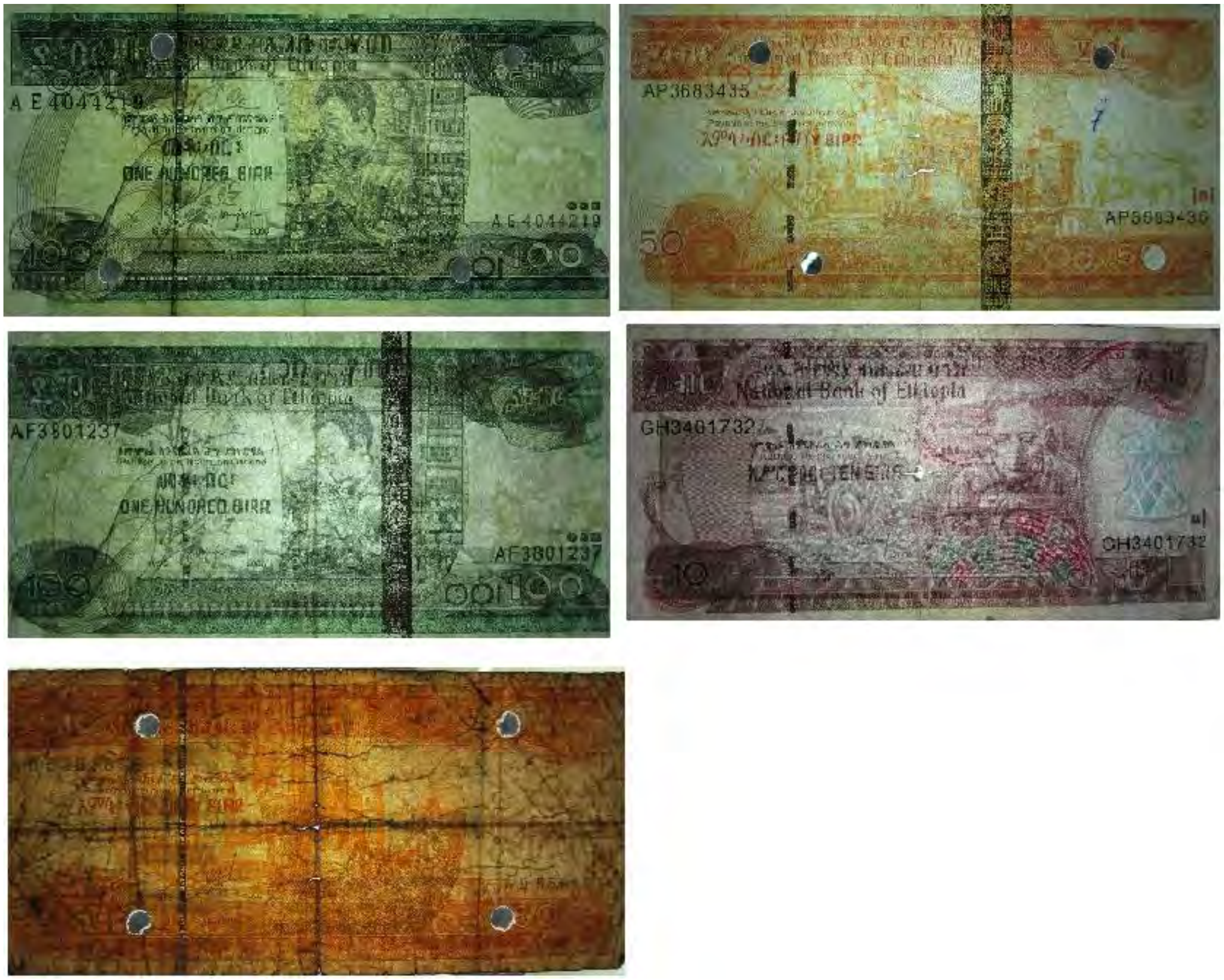
Appendices

Appendix A: Genuine Ethiopian Notes and Their Descriptions [52]



Appendix B: Scanned Image of Counterfeit Ethiopian Notes

Appendix C: Photo Image of Counterfeit Ethiopian Notes



Appendix D: Photo Image of Other Countries' Currencies

Appendix E: List of MATLAB Built-in Function Used

cat ()

imread()

input()

imfilter()

fspecial()

disp()

max()

sum()

corr2()

rgb2grey()

abs()

norm()

imadjust()

detectSURFFeatures()

selectStrongest()

extractFeatures()

matchFeatures()

vpts()

length()

strel()

imclose()

bwareaopen ()

bwlabel()

im2bw ()

Appendix F: Currency Denomination and Recognition Code

Main.m

```
%This is a program that classifies Ethiopian currency into their respective
%denomination and recognize the classified currency whether they are genuine or counterfeit.
clear all
close all
%Store Sample Scanned Image of each Dinomination in an Array
TargetImageArray=cat(3,'scan0040.jpg','scan0052.jpg','scan0067.jpg','scan0078.jpg','scan0083.jp
g');
%Read the Scanned Image
prompt = 'Enter the file name of the scanned image: ';
inputImage = input(prompt,'s');
TestImage=imread(inputImage,'jpg');
%Check Dominant Colour
Dom_Colour=DominatingColour(TestImage);
TestImage = imfilter(TestImage, fspecial('average', [3 2]));
%Check Correlation Cofficient
[Corr_Coefficient,index] = CorrelationCoefficient(TargetImageArray,TestImage,Dom_Colour);
if Corr_Coefficient<0.3
   disp('Not an Ethiopian Currency....Small Corr_Coeffiecent');
    break;
else
%Check Hue Value
   HueValueDiff=FindHueValue(TargetImageArray,index,TestImage);
end
if HueValueDiff>80
```

```
  disp('Not an Ethiopian Currency...Different HueValueDiff');
  break;
else
%Check SURF Feature
    matchpercent=MatchSURF(TargetImageArray,index,TestImage);
end
if matchpercent<20
   disp('Not an Ethiopian Currency...matchpercent less than 20');
   break;
else
  %Display the Classification Result
   switch index
       case 1
       disp('100 Ethiopian Currency');
       %Check Whether the Currency is Geniune or Not
       flag=TwoStripCheck;
          if flag==1;
              disp('Geniune 100Birr');
          else
              disp('Counterfeit 100Birr');
          end
       case 2
       disp('50 Ethiopian Currency');
       %Check Whether the Currency is Geniune or Not
       flag=TwoStripCheck;
          if flag==1;
              disp('Geniune 50Birr');
```

```
        else
            disp('Counterfeit 50Birr');
        end
    case 3
    disp('10 Ethiopian Currency');
    %Check Whether the Currency is Geniune or Not
    flag=OneStripCheck(200,300);
        if flag==1;
            disp('Geniune 10Birr');
        else
            disp('Counterfeit 10Birr');
        end
    case 4
    disp('5 Ethiopian Currency');
    %Check Whether the Currency is Geniune or Not
    flag=OneStripCheck(400,500);
        if flag==1;
            disp('Geniune 5Birr');
        else
            disp('Counterfeit 5Birr');
        end
    case 5
    disp('1 Ethiopian Currency');
    disp(index);
  end
end
```

DominatingColour.m

```
% This function finds the dominating colour of a test image.
function Dom_Colour = DominatingColour(TestImage)
    G = fspecial('gaussian',[3 3], 2.5);
    filteredCurrency = imfilter(TestImage,G,'same');
    colours = 'RGB';
    [~,idx] = max(sum(sum(filteredCurrency,1),2),[],3);
    Dom_Colour = colours(idx);
 end
```

CorrelationCoefficient.m

```
%This function calculates the correlation coefficient between the test image and
%the sample image and returns the correlation coefficient and the index of
%the sample currency.
function [Corr_Coefficient,index] =
CorrelationCoefficient(TargetImageArray,TestImage,Dom_Colour)
    if Dom_Colour=='B'
        TargetImage=imread(TargetImageArray(:,:,4));
        Corr_Coefficient = corr2(TargetImage(:,:,3),TestImage(:,:,3));
        index=4;
    elseif Dom_Colour=='G'
        TargetImage=imread(TargetImageArray(:,:,1));
        Corr_Coefficient1 = corr2(TargetImage(:,:,2),TestImage(:,:,2));
```

```
        TargetImage2=imread(TargetImageArray(:,:,4));
        Corr_Coefficient2 = corr2(TargetImage2(:,:,2),TestImage(:,:,2));
        if Corr_Coefficient1>Corr_Coefficient2
          Corr_Coefficient=Corr_Coefficient1;
          index=1;
        else
          Corr_Coefficient=Corr_Coefficient2;
          index=4;
        end
    else
        TargetImage2=imread(TargetImageArray(:,:,2));
        Corr_Coefficient2 = corr2(TargetImage2(:,:,1),TestImage(:,:,1));
        TargetImage3=imread(TargetImageArray(:,:,3));
        Corr_Coefficient3 = corr2(TargetImage3(:,:,1),TestImage(:,:,1));
        TargetImage4=imread(TargetImageArray(:,:,4));
        Corr_Coefficient4 = corr2(TargetImage4(:,:,1),TestImage(:,:,1));

        TargetImage5=imread(TargetImageArray(:,:,5));
        Corr_Coefficient5 = corr2(TargetImage5(:,:,1),TestImage(:,:,1));
Corr_Matrix=[Corr_Coefficient2,Corr_Coefficient3,Corr_Coefficient4,Corr_Coefficient5];
        Corr_Coefficient=max(Corr_Matrix);
         if Corr_Coefficient==Corr_Coefficient2
            index=2;
         elseif Corr_Coefficient==Corr_Coefficient3
            index=3;
         elseif Corr_Coefficient==Corr_Coefficient4
            index=4;
```

```
        else
            index=5;
        end
    end
end
```

FindHueValue.m

```
 %This function calculates the hue value of a test image returns the hue
% value difference of the test image and its corresponding sample currency.
function HueValueDiff = FindHueValue(TargetImageArray,index,TestImage)
    HSVTest=rgb2hsv(TestImage);
    HSVTarget=rgb2hsv(imread(TargetImageArray(:,:,index)));
    AvgHue = (HSVTest(:,:,1) + HSVTarget(:,:,1))/2;
    HueValueDiff = norm(abs(HSVTarget(:,:,1)-AvgHue));
end
```

MatchSURF.m

```
%This function calculates the feature match percentage of a test image and
% its corresponding sample image.
function matchpercent=MatchSURF(TargetImageArray,index,TestImage)
    I1 = imadjust(rgb2gray(TestImage));
    I2 = imadjust(rgb2gray(imread(TargetImageArray(:,:,index))));
    %Find the feature points
    points1 = detectSURFFeatures(I1);
    points2 = detectSURFFeatures(I2);
    %Select the first 100 Strogest points
    points1=points1.selectStrongest(100);
```

```
    points2=points2.selectStrongest(100);
    %Construct the feature vector
    [f1, vpts1] = extractFeatures(I1,points1);
    [f2, vpts2] = extractFeatures(I2,points2);
    %Construct the index pairs of the match features
    [index_pairs] = matchFeatures(f1, f2,'Metric','SSD','MatchThreshold',50, 'MaxRatio', 0.7) ;
    %Find the match points
    matchedPoints = vpts1(index_pairs(:, 1));
    %Claculate the match percentage
    matchpercent=(length(matchedPoints)/length(vpts1))*100;
end
```

TwoStripCheck.m

```
%This function checks the existence of the thin and thick strip in a test image.
function flag=TwoStripCheck()
    %Read in image
    prompt = 'Enter the file name of the Camera image: ';
    inputPicture = input(prompt,'s');
    TestPicture=imread(inputPicture,'jpg');
    %Pre-analysis
    hsvImage = rgb2hsv(TestPicture);
    for i=180:5:270
        %Segement the thin strip
        croppedImage = hsvImage(:,i:i+5,:);
        satThresh = 0.4;
        valThresh = 0.3;
        BWImage = (croppedImage(:,:,2) > satThresh & croppedImage(:,:,3) < valThresh);
```

```
        %Morphological Analysis
        se = strel('line', 6, 90);
        BWImageClose = imclose(BWImage, se);
        %Area opening
        areaopen = bwareaopen(BWImageClose, 15);
        %Count the number of objects in this strip
        [~,count] = bwlabel(areaopen);
          if count==1
              countWide=WideStrip(TestPicture,450,550);
              if (count==1&&countWide==1)
                  flag=1;
              else
                  flag=0;
              end
              break;
          end
    end
    if count~=1
        flag=0;
    end
end
```

OneStripCheck.m

```
%This function checks the existence of the thin strip in an image.
function flag=OneStripCheck(x,y)
    %Read in image
    prompt = 'Enter the file name of the scanned image: ';
    inputPicture = input(prompt,'s');
```

```
    TestPicture=imread(inputPicture,'jpg');
    %Convert into grayscale
    hsvImage = rgb2hsv(TestPicture);
    for i=x:5:y
        %Segement the thin strip
        croppedImage = hsvImage(:,i:i+5,:);
        satThresh = 0.4;
        valThresh = 0.3;
        BWImage = (croppedImage(:,:,2) > satThresh & croppedImage(:,:,3) < valThresh);
        %Morphological Analysis
        se = strel('line', 6, 90);
        BWImageClose = imclose(BWImage, se);
        %Area opening
        areaopen = bwareaopen(BWImageClose, 15);
        %Count the number of objects in this strip
        [~,count] = bwlabel(areaopen);
          if count==1
              flag=1;
              break;
          end
    end
    if count~=1
        flag=0;
    end
end
```

WideStrip.m

```
 % This function checks the existence of the wide strip and
% returns the number of object in the wide strip.
function countWide=WideStrip(TestPicture,x,y)
   for i=x:20:y
       %Segement the wide strip
       CroppedWideStrip = TestPicture(:,x:y,:);
       %Convert into grayscale
       GreyWideStrip = rgb2gray(CroppedWideStrip);
       %Binarization
       WideStripBW = ~im2bw(GreyWideStrip, 30/255);
       %Area opening
       AreaOpenWide = bwareaopen(WideStripBW, 100);
       %Morphological Analysis
       se = strel('square', 5);
       BWImageCloseWide = imclose(AreaOpenWide, se);
       %Count the number of objects in this strip
       [~,countWide] = bwlabel(BWImageCloseWide);
          if countWide==1
             break;
          end
   end
end
```

Declaration

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

Declared by:

Name: ____

Signature: ____

Date: ____

Confirmed by advisor:

Name: ____

Signature: ____

Date: ____