Design and Development of A Computer Vision Algorithm and Tool for Currency Recognition in Indian Vernacular Languages for Visually Challenged People

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ABSTRACT

God has created this universe and all living and non-living entities. Human is one of the best among His creations and in Human beings, eyes are the best gift of God to see His creations. As of now, humans are considered as the only developed creatures among God's creations and have developed themselves from Stone Age to the Computing Era. As the human civilizations grew up, the transactions have moved from barter system to currency. Every country has its own currency in terms of coins and paper notes. Each of the currency of Individual County has its unique features, colors, denominations and international value. We, all, having been given two beautiful eyes could recognize the currency easily but the same is not easy for blind people. The denomination can easily be recognized for a currency but it becomes difficult to identify a counterfeit currency from the real one. Especially for the blind people, it is a herculean task like finding a needle from haystack. The main motive of this work is to develop and test a robust computer vision algorithm(s) to identify the Indian currency, mainly paper-based currency, in Indian Regional languages.

In order to go ahead with this research, we used feature detector, ORB (Oriented FAST Rotated BRIEF). The reason behind use of ORB is the trade-off in performance of ORB. Among its category, ORB has been proved less accurate than its siblings SIFT and SURF in terms of feature detection, however, it is faster in terms of execution time than the others. As SIFT and SURF are patented technologies and ORB is free and open source, we opted to go with ORB to improve its performance in terms of recognition accuracy. In this direction, first, for preprocessing, we improved the time performance of Grab-Cut algorithm (An algorithm which is used to remove background from the images) for Android based devices, named as *cGrab-Cut*. The output of this algorithm can be used for further processing of image to classify it. For feature detection, we developed two hybrid approaches in order to improve performance of ORB, *HORB* - Histogram based ORB and *ACORB* - ACO based ORB. In order to provide the best performance for image classification, we also developed a three stage hybrid classifier based on the concepts Histograms, ORB and Bag of Visual Words, titled, *HORBoVF* and a two stage ACO, ORB and Bag of Visual Words based classifier, *ACORBoVF*. These algorithms have been developed in

such a way so that they can work in constrained environments like low memory and slow processors. Along with this, we also trained and tested, *TensorCu₹₹ency*, a Transfer learning based image classifier to see the performance of convolutional neural network using TensorFlow technology. To test the effectiveness of our approaches, we developed python and android based test programs. The results also prove that the proposed approaches served the aforementioned purpose and are much better as compared to sole ORB. Thus, taking the advantage of faster execution of ORB, this work tried to improve the performance of ORB with different approaches.

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1 INTRODUCTION

This chapter briefly introduces about the currency across the world and Indian currency. It also tells the motive behind this work, the problem statement and what are the research contributions of this work. At the end, it writes about possible applications of this work based on the research contributions.

1.1 A BRIEF HISTORY OF CURRENCY

From the moment, barter systems ended, currencies came into existence for day to day life. According to definition on Wikipedia [64], the word currency (from Middle English: curraunt, "in circulation", from Latin: currens, -entis), in the most specific use of the word, refers to money in any form when in actual use or circulation as a medium of exchange, especially circulating banknotes and coins. A more general definition is that a currency is a system of money (monetary units) in common use, especially in a nation. It is also referred as banknotes, coins, bills (in US) etc.

It dates back 2000 BC where it used to be in the form of coins. Later, in between 618 AD to 907 AD, in pre-modern china, during Tang dynasty, use of paper-based currencies started. In medieval Islamic world, during 7th-12th Century, the paper based currency was introduced that became base for a stable-high valued currency dinar. Sweden was the first country to introduce paper-based currency in Europe in 1661. Each country in this world has its own currency and each currency has a specific denomination that indicates its monetary value. US Dollars, British Pound, Japanese Yen, EURO are the examples of currencies of different countries. Following is the list of prominent currencies of countries across the world according their market share.

Rank	Currency	ISO 4217 code (symbol)	Rank	Currency	ISO 4217 code (symbol)
1	United States dollar	USD ($)	11	Mexican peso	MXN ($)
2	Euro	EUR (€)	12	Singapore dollar	SGD (S$)
3	Japanese yen	JPY (¥)	13	Hong Kong dollar	HKD (HK$)
4	Pound sterling	GBP (£)	14	Norwegian krone	NOK (kr)
5	Australian dollar	AUD (A$)	15	South Korean won	KRW (₩)
6	Canadian dollar	CAD (C$)	16	Turkish lira	TRY (₺)
7	Swiss franc	CHF (Fr)	17	Russian ruble	RUB (₽)
8	Renminbi	CNY (元)	18	Indian rupee	INR (₹)
9	Swedish krona	SEK (kr)	19	Brazilian real	BRL (R$)
10	New Zealand dollar	NZD (NZ$)	20	South African rand	ZAR (R)

Table 1.1 Currencies of various countries

The next section describes how Indian Rupee came into existence and its growth till date.

1.2 INTRODUCTION TO INDIAN CURRENCY

1.2.1 Rupee

The Indian Rupee is the original official currency of India. Before going into the details about current Indian Rupees, let's go back to the era of 6th century BC when currencies were started in India. It is India who was the first issuer of coins in the world. The word "*Rupee*" is believed to be derived from word Rupaa – a Sankrit name of Silver [65]. So the silver coins which were issued were called "Rupaalu" and gradually all those coins started being called as Rupee. Following image shows the first coins which were issued by Chandragupta Maurya in 3rd century BC.

Figure 1.1. Silver coins of Maurya Empire

Figure 1.2. Silver coins of Rupee Sher Shah Suri

After 18 centuries later, in 1540, Sher Shah Suri issued silver coins, called Rupee, in exchange of 40 copper coins called Paisa. This silver coins remained in use during Mughal and British rule also. British introduced Coinage Act in 1835 and Paper Currency Act in 1861 to have uniform currency throughout India. Since then, a variety of coins were introduced till freedom. In 1950, when India become Republic, Indian government issued first of its coin replacing King's portrait with Ashoka's Lion. Following figures show few currencies introduced by British Empire from Victoria portrait to King George series and other currencies which were used during British Rule.

Figure 1.3. 1 Paisa issued by Sayla State

Figure 1.4. Indian Rupee coins in 1862

Figure 1.5. Half Aana of King George VI series, 1945

Figure 1.6. British India Rupee in 1947

Figure 1.7. Rs. 100 of Hyderabad State

Figure 1.8. Five Rupees, 1922

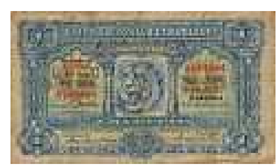


Figure 1.9. Portugese Indian 1 Rupee, 1924

Figure 1.10. French Indian 1 Rupee, 1938

Figure 1.11. George VI Indian 1 Rupee, RBI 1937

Figure 1.12. 1 Rupee, British India

1.2.2 Reserve Bank of India and New Currencies

The Reserve Bank of India, formally started in 1935, is the chief controlling authority for the issuance of the currency. In earlier days, India currency was from 1 Aana to 100 Rupees. The currency had denomination like 1, 5, 10, 20, 25 and 50 in terms of paisa. However, except ₹1 and ₹2 coins, the other coins have been discontinued and new coins of ₹5, ₹10, ₹20, ₹50, ₹100 and ₹500 have been introduced. The currency is available in a denomination value of ₹1, ₹2, ₹5, ₹10, ₹20, ₹50, ₹100, ₹500 and ₹2,000. The symbol for Indian rupee is, ₹, designed by D. Udaya Kumar. On 15 July 2010, Government of India declared it the official sign for Indian Rupee.

The currently running series was introduced in 1996 and is called the Mahatma Gandhi series. Since then every Indian currency notes has Mahatma Gandhi photo on it. These currency notes are printed at the Government of India's Currency Note Press located at Nashik, Dewas, Salboni, Mysore and Hoshangabad. Each banknote has its denomination written in 18 Indian languages of which English, Hindi and Devnagari languages are used on front and back side and other 15 regional languages of India on the back side. New notes of ₹2,000 and ₹500 have different size and security features. Now, in India, the ATMs usually dispense ₹100, ₹500, and ₹2000 currency notes. Following images show sizes of various Indian currencies.

Figure 1.13 Currency Notes of Different Sizes

Figure 1.14. Various Indian Currency Notes

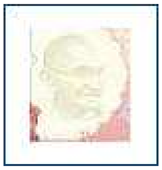
Figure 1.15. Indian Currency Coins

Figure 1.16. The new ₹2,000 Currency, 150X66 mm

Figure 1.17. The new ₹500 Currency, 160X66 mm

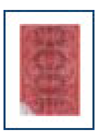
In recent years, the currency notes are slightly modified to include see through register on the left side of obverse. Along with this, the year is now printed on the back side. Since our neighbor countries try to dump the fake currencies, to prevent such fraudulent, the RBI has introduced so many security features in the currency notes to prevent fraud or printing of counterfeit notes. Following section discusses the security features of Indian currencies.

1.2.3 Unique features of Indian Currency notes

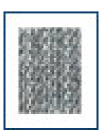


Watermark: The Mahatma Gandhi Series of banknotes contain the Mahatma Gandhi watermark with a light and shade effect and multi-directional lines in the watermark window.

Security Thread: Rs.1000 notes introduced in October 2000 contain a readable, windowed security thread alternately visible on the obverse with the inscriptions 'Bharat' (in Hindi), '1000' and 'RBI', but totally embedded on the reverse. The Rs.500 and Rs.100 notes have a security thread with similar visible features and inscription 'Bharat' (in Hindi), and 'RBI'. When held against the light, the security thread on Rs.1000, Rs.500 and Rs.100 can be seen as one continuous line. The Rs.5, Rs.10, Rs.20 and Rs.50 notes contain a readable, fully embedded windowed security thread with the inscription 'Bharat' (in Hindi), and 'RBI'. The security thread appears to the left of the Mahatma's portrait. Notes issued prior to the introduction of the Mahatma Gandhi Series have a plain, non-readable fully embedded security thread.



Latent Image: On the obverse side of Rs.1000, Rs.500, Rs.100, Rs.50 and Rs.20 notes, a vertical band on the right side of the Mahatma Gandhi's portrait contains a latent image showing the respective denominational value in numeral. The latent image is visible only when the note is held horizontally at eye level.



Microlettering: This feature appears between the vertical band and Mahatma Gandhi portrait. It contains the word 'RBI' in Rs.5 and Rs.10. The notes of Rs.20 and above also contain the denominational value of the notes in microletters. This feature can be seen better under a magnifying glass.

Intaglio Printing: The portrait of Mahatma Gandhi, the Reserve Bank seal, guarantee and promise clause, Ashoka Pillar Emblem on the left, RBI Governor's signature are printed in intaglio i.e. in raised prints, which can be felt by touch, in Rs.20, Rs.50, Rs.100, Rs.500 and Rs.1000 notes.

Identification Mark: A special feature in intaglio has been introduced on the left of the watermark window on all notes except Rs.10/- note. This feature is in different shapes for various denominations (Rs. 20-Vertical Rectangle, Rs.50-Square, Rs.100-Triangle, Rs.500-Circle, Rs.1000-Diamond) and helps the visually impaired to identify the denomination.

Fluorescence: Number panels of the notes are printed in fluorescent ink. The notes also have optical fibres. Both can be seen when the notes are exposed to ultra-violet lamp.

Optically Variable Ink: This is a new security feature incorporated in the Rs.1000 and Rs.500 notes with revised colour scheme introduced in November 2000. The numeral 1000 and 500 on the obverse of Rs.1000 and Rs.500 notes respectively is printed in optically variable ink viz., a colour-shifting ink. The colour of the numeral 1000/500 appears green when the note is held flat but would change to blue when the note is held at an angle.

See through Register: The small floral design printed both on the front (hollow) and back (filled up) of the note in the middle of the vertical band next to the Watermark has an accurate back to back registration. The design will appear as one floral design when seen against the light.

In past, Indian coins were also manufactured with heavy metals. However, these traditional coins of different sizes have been discontinued by RBI. According to the Intelligence Bureau reports, the heavier Indian coins were smuggled across the Bangladesh border where they were melted and were used in creating razor blades and ornaments. This lead to acute shortage of these coins in India and West Bengal was the worst affected state. The beggars who were smuggling the coins used to get a premium of 10-15% on the coins. This was actually an interesting way to make the money out of money. For this reason, the Indian government reduced the size and changed the metal to put an end on this fishy business. Gradually, these and hence the weight of the coins to make this business economically unviable and thereby, gradually, the older coins were discontinued and taken back from the market.

On November 8, 2016, Hon'ble Prime Minister of India declared cancellation of existing currency of ₹500 and ₹1,000. The reasons that Prime Minister told in his Address are to curb the black money, corruption menace, to stop terror funding and Hawala business. The next section briefly discuses motive behind this work.

1.3 MOTIVATION FOR THIS WORK

The seeds for this work were sowed in late 2006, when one of us, was cheated by receiving a counterfeit currency of ₹500 and had to resolve that issue by destroying that currency. This made a loss of ₹500 but sparked a thought, that having been given two eyes, if a person could be cheated then any kind of financial cheating could happen to the blind people! From our own experiences, we learned that the currency, be it a coin or note, identification, is really a herculean task for the blind people. This laid down the foundation for our work.

In addition to this, in earlier days, as the previous section discusses, the coins were of different sizes and shapes and hence the identification was quite easy. Since 2011, as discussed in the previous section, RBI put an end to manufacture the coins of different sizes and introduced coins of almost same size and weight. This made the identification of coins more difficult for the blind people. The mixture of old and new coins makes the task tougher. Following are the new size and weights for the different coins as per the new regulations of RBI.

₹5	23 mm 6 g	₹10	27 mm 5.62 g	₹2	25 mm 4.85 g	₹1	22 mm 3.79 g

The paper based currencies have also been changed in their size along with other features, especially after demonetization which made the life of blind people worse. Like ₹500 and ₹2000 notes are smaller in size than current ₹100 and ₹50 notes. Due to such minor variations in the size of the paper based currency and frequent addition of new features to enhance the security, the identification for the same becomes more difficult than the coins. And when the currency is counterfeit or torn out, the identification becomes, even more, difficult, for the blinds. Money is something for which people are, usually, being cheated. Especially, if the person is blind, there are more chances of him/her being cheated. India, according to WHO reports (March, 2017), has 12 million blind people which is $1/3^{rd}$ of total of 39 million people all over the world. Also, in India, the currency recognition tools are available to the Banks only which are neither affordable nor handy to a common man! In order to prevent the cheating and to serve the unprivileged people of the society, visually impaired people, we thought to do this work. The next section discusses the problem definition, objectives of this work, our research contributions and possible applications of our work.

1.4 PROBLEM STATEMENT, OBJECTIVES, RESEARCH CONTRIBUTIONS AND APPLICATIONS

1.4.1 Problem Statement

To design and develop a computer vision algorithm(s) that can recognize Indian currency denominations and translate it into Indian vernacular language

1.4.2 Objectives

In order to achieve our noble goal, we planned:

1. To design and develop an algorithm(s) that can recognize the denomination of the Indian currencies.
2. To ensure that, along with denomination identification, it also checks if the currency is counterfeit or not.
3. To make the algorithm(s) lighter in terms of memory and time both so as to be usable for handheld devices.
4. To develop the algorithm(s) in such a way so that it/they can survive the events like demonetization and can adapt the new currencies.
5. To develop a test tool for the proposed algorithm(s) so ensure that the objectives are met.

Apart from the main objectives stated above, the other objectives in terms of generic research are:

1. To design and develop the algorithm(s) in such a way so that it/they remain(s) generic and can be used for feature detection and image classification for any images, not only Indian currencies.
2. To improve or fusion any other existing technique(s) or algorithm(s) in order to achieve our goal.

1.4.3 Research Contributions

Any image recognition process contains three phases, mainly: Preprocessing, Feature Extraction and Classification. Through this research, we have contributed for each of the phase with some novel or hybrid approach. Following are our research contributions through this work:

1. A modified and improved Grab-Cut algorithm, *cGrab-Cut* (Compromised Grab-Cut), for background removal in pre-processing stage with 50% reduction in time consumption (Especially for Android devices). This algorithm can be used to remove background from the captured images as a part of preprocessing. *(Paper publication No: 4)*
2. A Histogram and ORB based a novel, generic and improved feature detector, named ***HORB***, to detect image feature in order to improve performance of ORB. The performance of ***HORB*** seemed to be nice with an average increase of 12.862% against ORB and takes an average time of 2.336 seconds for image identification. *(Paper publication No: 5)*
3. In order to further improve the performance of ORB, a heuristic based approach through Ant Colony Optimization has been used. The novel, generic and ACO based ORB feature detector, ***ACORB*****,** is developed and implemented. It has been tested profoundly to prove its competency and shows improvement in performance of ORB. This approach is really promising with an average increase of 13.249% accuracy, consuming less time of 2.174 seconds for image identification.
4. To further improve the performance of the partially visible objects, a novel, generic and three stage hybrid image classifier using Histograms, ORB and Bag of Visual Features has been developed. It has been named as ***HORBoVF***. Along with histograms and ORB feature detector, it uses a dynamic bag of visual features to classify the images. The performance of ***HORBoVF*** is outstanding with an average 91.541% accuracy taking 2.453 seconds and serves our motive of development of this algorithm. *(Paper publication No: 5)*
5. Since we were successful in applying ACO in feature detection using ORB, we deployed the same feature detector with our dynamic bag of visual features to develop another generic, novel and two stage classifier ***ACORBoVF***. This approach uses the same

dynamic bag of visual features. The final performance of the algorithm remains same as ***HORBoVF*** with little less time consumption of 2.287 seconds! Both, ***HORBoVF*** and ***ACORBoVF***, can be used as generic classifiers for any kind of images, once the visual dictionary is created.

6. ***Te₹₹ency***, is a TensorFlow and CNN based trained model and classifier for Indian currencies. This has specifically been developed to evaluate the performance of our other two classifiers and to utilize the power convolutional neural networks, a neural network of millions of images, for image classification. This also gives a promising result of 87.215% accuracy taking 0.11 seconds for the mentioned purpose.

7. In order to carry out the testing for our proposed approaches, a dataset has been created, for each category of Indian currency denomination, consisting of average 455 images for small dataset (total 4552 images) and 1504 images for large dataset (total 15042 images) for training purpose. For testing purpose, for each category of Indian currency denomination, an average 182 fully visible images (total 1819 images) and 228 partially visible images (total 2284 images) have been taken.

1.4.4 Applications

The all algorithms have been designed in such a way so that they work not only for currency recognition but also for any other kind of image recognition and classification. Few possible applications could be:

1. The improved *cGrab-Cut* can be used for Android based vision applications for background subtraction in preprocessing stage.
2. *HORB* and *ACORB* can be used as improved feature detectors for image matching purposes.
3. *HORBoVF* and *ACORBoVF* can be used as improved classifier for image labeling.
4. *Te₹₹ency* can be used for Indian currency recognition

2. LITERATURE STUDY

In terms of currency recognition, the attempts are being made since 1993 to make the life easier for the visually challenged people. The currency recognition is mainly based on object detection and image feature extraction. So, following text discusses the work done till date in the areas of currency recognition and image feature extraction. Next section tells about basics of image processing related to image matching and classification followed by tools and techniques used for our work. Following table 2.1 summarizes the work carried out exclusively for currency recognition across the world, including Indian currency.

Sr. No.	Currency Recognition Approach	Currency	Accuracy	Year
1	Neural Network [1]	USD	98.08	1993
2	Neural Network, Optimized Mask and Genetic Algorithm [2]	USD	>95%	1995
3	Hybrid Neural Network [3]	USD & Japanese	92	1996
4	Multilayered Peceptrons in NN [4]	USD		1996
5	Neural NN with Gaussian Distribution [5]	USD, CA$, AU$, Krone, Franc, GBP, Mark, Pesetas	High	1998
6	Neural NN and axis-symmetrical mask [6]	EURO	97	2000
7	Neural NN and Principal Component Analysis [7][8]	USD	95	2002
8	Back Propagation NN [9]	Chinese Renminbi	96.6	2003
9	Markov Models [11]	USD, EURO, Dirham, Rial	95	2007
10	Ada-Boost Classification [12]	USD	High	2008
11	Neural Network [13]	Malaysian Ringit	High	2008
12	Artificial Neural Network [14]	SL Rupee	High	2008
13	Data Acquisition [15]	Chinese Renminbi	100	2008
14	Bio-inspired Image Processing [16]	EURO	100	2009
15	Image Processing [17]		High	2008
16	Wavelet Transform [18]	Rials	81	2010
17	Ensemble Neural Network with Negative Correlation Learning [19]	Bangladeshi Taka	98	2010
18	Local Binary Patterns [20]	Chinese Renminbi	100	2010
19	Image Processing & Neural Network [21]	Indian Rupee	High	2010
20	Intersection Change [22]	Chinese Renminbi	97.5	2010

21	Support Vector Machine [23]	Chinese Renminbi	87.097	2011
22	Component based framework using SURF [24]	USD	100	2012
23	SIFT and K-means clustering [25]	USD	100	2012
24	Wavelet Transform & Neural Network [27]	Dirham	99.12	2012
25	Local Binary Patterns and RGB Space [28]	Mexican	97.5	2012
26	LBP, Gabour Wavelet Transform, Image subtraction [29]	Indian	High	2012
27	SVM, Neural Network and Heuristic [30]	Indian	High	2012
28	Edge detection, segmentation, feature extraction [31]	Indian	High	2012
29	Localization using color of images [32]	Indian	High	2012
30	Grayscale, linear transformation and edge-detection, 3-layer neural network [33]	Indian	High	2012
31	LBP and neural network [34]	Indian	High	2012
32	LBP and color descriptors [35]	Indian	High	2012
33	Discriminative color [36]	Maxican	High	2013
34	Quaternion Wavelet Transform & Generalized Gaussian Density [37]	USD, Renminbi and EURO	99.68	2013
35	ROI, Pattern Recognition and Neural Network [38]	Indian	High	2013
36	Basic Feature Extraction using Euler Numbers [39]	Pakistani Rupee	High	2013
37	Feature extraction using HSV [40]	Indian	High	2014
38	3X3 grid and neural network [41]	Indian	High	2014
39	Bag of words [42]	Indian	96.7	2014
40	Number Recognition [43]	Chinese Renminbi	95.92	2014
41	Instance Retrieval and Indexing [42]	Indian	96.7	2014
42	Non parametric approach [44]	Saudi Arabia Rial	High	2015
43	Radial Basis Kenrel Function [45][46]	Dirham	91.51	2015
44	2D discrete wavelet transform, Frequency domain extraction [48]	Indian	High	2015
45	Gaussian mixture model, texture and neural network [49]	Indian	High	2015
46	See-through register, thread and identification mark [50]	Indian	High	2015
47	Sobel operator with gradient magnitude [51]	Indian	High	2015
48	Segmentation, feature extraction [52]	Indian	High	2015
49	Categorization and verification [53]	Ethiopian	90.42	2015
50	Region of Interest (ROI), Discrete Wavelet Transform, Linear Regression and SVM [47][55]	Indian Rupee	High	2015
51	Color SIFT and Grayscale SIFT [56]		High	2017

52	HOG and Multiclass SVM [57]	USD, CA$, EURO		2017

Table 2.1 Summary of Currency recognition work across the world

Apart from the afore-mentioned algorithms, there are many tools and Mobile Apps developed for currency recognition in different countries. The following text discusses the same.

Maverick Money Reader [58] is an application developed by Jesse Saitoo and his supervisor Dr Akash Pooransingh to enable visually impaired people to identify the currency of Trinidad and Tobago. It is an automatic money detector developed at University of West Indies.

Money Reader developed by Bishoy Gamal for the currency recognition for the blind and visually impaired people to detect the American Currency. In this, user has to just place the camera and rests of the things are processed by the system automatically. It has around accuracy of nearly to 95%.This project was funded by (Play store).

MoneySpeaker [59] is a mobile application developed by the Human-Machine Interaction Lab. and Computer Science Dept. at the University of Engineering and Technology, Vietnam National University, Hanoi. This app helps visual impaired people to identify Vietnamese banknotes (Play store).

Smart Saudi Currency Recognizer (SSCR) is a smart android application that helps the blind community to handle cash matters efficiently by resolving issues related with Saudi currency recognition being faced by people (Play store) [60].

TalkingMoney is a Money Reader Application and dedicated for the Visual impaired people. It is an Android App and blind people can use their smart phones to recognize the value of paper banknotes. Currently, the application is working for Egypt currency (Play store).

EyeNote [61] is a free mobile device application to identify denominations of Federal Reserve Notes (U.S. paper currency) as an aid for the blind or visually impaired.

LookTel Money Reader instantly recognizes currency and speaks the denomination, enabling people experiencing visual impairments or blindness to quickly and easily identify and count number of currencies of many countries [62].

In US, all the denominations are of same size making it difficult for blind people to identify the correct denomination from another. In such situation, the Governments have provided a way to help them to tell apart the different money denominations. In countries like Australia and Malaysia, every denomination is of distinct width and length making the identification easier for the blind people. In Canada, the currencies have provision of Braille dots representing a specific denomination. Blind people can easily read that Braille dots and know the amount denomination they are holding. In India, the RBI has introduced an embossed pattern for every currency note. But the problem with this embossing is as the currency gets older, the embossed spot gets faded. Apart from these, the blind people themselves uses their own ways like Folding Money, A Wallet with Many Dividers, Scanners and Assistive Technology etc. to identify money. Though the use of scanners or any other assistive aid is an effective way to identify money, it is only possible when you are at home or if such devices are handy [63].

Having discussed all the research works across the world and in India along with the available Apps/Tools, it is concluded that the research work that have been proposed, even for Indian currencies, are not materialized using some standard algorithms in the form a real tool or app in market that can help blind people to identify the Indian currency. Apart from the proposed research works, in India, the real implementations of currency recognition tools are limited to the ATMs and Banks only which are neither affordable nor handy to a common man! Looking towards a need of a standard algorithm(s) and tool that can help the blind people in India to recognize the Indian currencies in their mother tongue (regional languages), this work has been carried out with a noble intention.

3. PROPOSED WORK

In order to achieve our goal, we divided our work into four phases, named, preprocessing, feature detection, classification and text-to-speech conversion. Following figure shows the outline of our work.

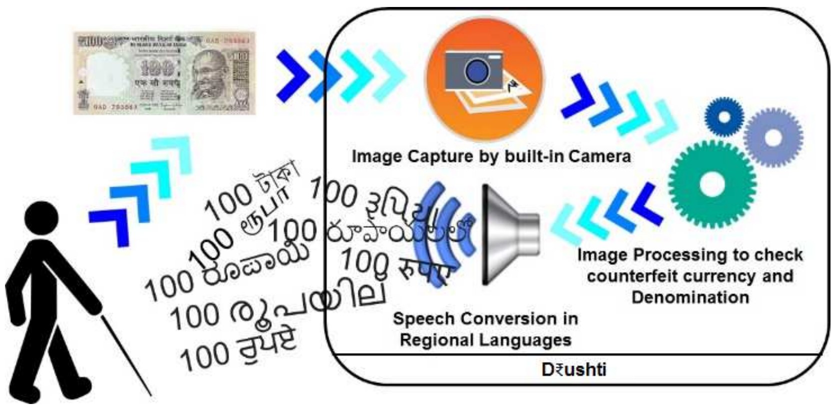


Figure 3.1 An overall view of our system

Here, Text-to-Speech is simply a technology which is being used to convert the output into speech so that blind people can listen to it. Research point of view preprocessing, feature detection and classification are the major phases. This chapter introduces and discusses our proposed approaches in detail. The first section tells about our work for preprocessing of images in terms of *cGrabCut* – An improved background removal algorithm for Android devices. Next section describes our proposed feature detectors, *HORB* and *ACORB*. Finally, it discusses our three different classifiers: a three stage hybrid classifier – *HORBoVF*, a two stage hybrid classifier – *ACORBoVF* and a CNN and TensorFlow based Indian currency classifier – *Te₹₹ency*. The performance evaluation of all the proposed approaches is discussed in next chapter.

3.1 *cGrab-Cut* – A COMPROMISED YET OPTIMIZED GRAB-CUT FOR ANDROID DEVICES FOR PREPROCESSING

Grab-Cut is actually an iterative and interactive background removal algorithm based on Graphcut theory designed to solve Min Cut/Max Flow problem and K-Gaussian model [10]. In their work, Suriya et. al. [42] used Grab-Cut for foreground detection i.e. segmentation. But the implementation of their algorithm on Android device in Java was not found as efficient as it is in C++. The problems which we found, through experiments, with their algorithm are:

1. Resizing of image twice
2. Dynamic calculation of Threshold value based on the resized image, the higher the number of rows and columns, larger the threshold value would be.
3. Larger size of initial rectangle.
4. Repeated masking and Grab-Cut iterations, which are dependent on threshold value. So, if the threshold value is larger the number of iterations will be large.

These factors were consuming more time and memory both. To address these issues, we, experimentally, tried to optimize it in terms of time and memory both. Instead of resizing the image, we started with initially a small rectangle and applied Grab-Cut with binary inverse thresholding and masking. The result was outstanding. Due to calling of Grab-Cut and masking only once along with inverse binary thresholding, the time and memory consumption was considerably low. Meaning of a perfect cut and a rough cut is shown in the below figure.

Figure 3.2 Output of Perfect Gab-Cut and *cGrab-Cut*

Though the output in figure 3.2 is not a perfectly background removed image, yet majority of the background portion is being removed here. Hence, the output is acceptable for further processing. It is a trade-off that is being carried out with a little compromise in output in order to improve performance in terms of time and memory, both. Due to this compromise, it has been named as *cGrab-Cut*.

3.2 FEATURE DETECTION

As mentioned in [54], ORB is faster in execution but SIFT, KAZE and AKAZE outperforms it in terms of feature detection and matching. So to improve the performance of ORB, we propose two hybrid ORB feature detectors.

3.2.1 *HORB* – A Histogram based ORB feature detector

Histogram matching is one of the oldest techniques in image matching. It is actually a transformation of image into histogram in order to match it with other histogram in reference for the purpose of image identification. This is one of the simplest image classification methods. For histogram comparison, there are various methods like histogram intersection, Pearson correlation, Chi-Square, Bhattacharya distance available. It is also possible that a histogram of a banana and green grass field could be same and hence may lead to high intersection value. To address this issue and eliminate such mismatches, we propose a fusion of histogram intersection and ORB for image matching, named *HORB*.

In our algorithm, first, the captured image is converted into histogram and matched with histogram of images in dataset. This is the stage where the histogram intersection is used for finding the closest match. For, the histogram of a banana and a grass-field could have more intersection value and may lead to wrong identification. To filter-out any such Banana-Grassfield combination, the images with top ten histogram intersections are used and corresponding feature subsets are sent for feature matching using ORB. The best matched feature subset passing through a specific threshold value is selected from the top ten images' feature set and retuned as output label.

3.2.2 *ACORB* - ACO based ORB feature detector

In his work, Kwang-Kyu Seo [26] used ACO for content based image retrieval using HSV and RGB color model with Textures. He showed in his work that Ant colony optimization in case of image feature extraction converges quickly. To take the advantage of this, we made an attempt to use ACO for feature detection using ORB, where in along with colors and textures, specific feature vectors of distinguishable features have also been used, named as *ACORB*. ACO has been used to explore the feature subset of a given set. If the selected feature subset is suitable or not is decided using heuristic function. With the collection of feature subsets found, the best is set as output class. The overall accuracy of the proposed work is observed as 65.47% as compared to 52.22% of ORB, 13% more and little bit higher than *HORB*'s 65.08%. It takes average 2.17 seconds per image for feature detection, a bit faster than *HORB*.

3.3 CLASSIFICATION

3.3.1 *HORBoVF* – Histogram, ORB and Bag of Visual Features based Hybrid Classifier

With the same intention of improving performance of ORB, especially for partially visible images, we proposed a three stage classifier which is a fusion of Histogram, ORB feature detector and Bag of visual words. Here, instead of simply creating visual vocabulary, we are creating Bag of Visual Features – A visual dictionary of specific features of image on the fly i.e. dynamically. This visual vocabulary, created using ORB features and K-means clustering, which is used for labeling of image.

First, the captured image is converted into histogram and matched with dataset. Histogram intersection is used for finding the closest match. Here, we follow the *HORB*, proposed in section 3.2.1 and hence, the top ten feature subsets are sent to the next layer for image matching using ORB. The feature extraction and matching for the given subsets and features of the given image is carried out. The output of this layer is sent to the third and final stage of classification for verification purpose. The proposed Bag of Visual Features approach is shown in the figure below with overall dictionary creation process:

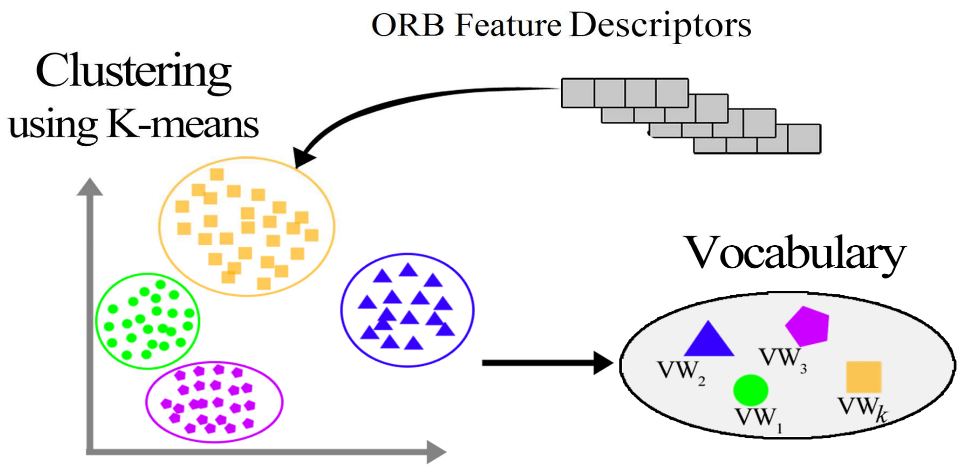


Figure 3.3 ORB based dictionary vocabulary creation process

The whole algorithm has been divided in to three stage Filtered Classification process. The following figure shows structure of *HORBoVF*.

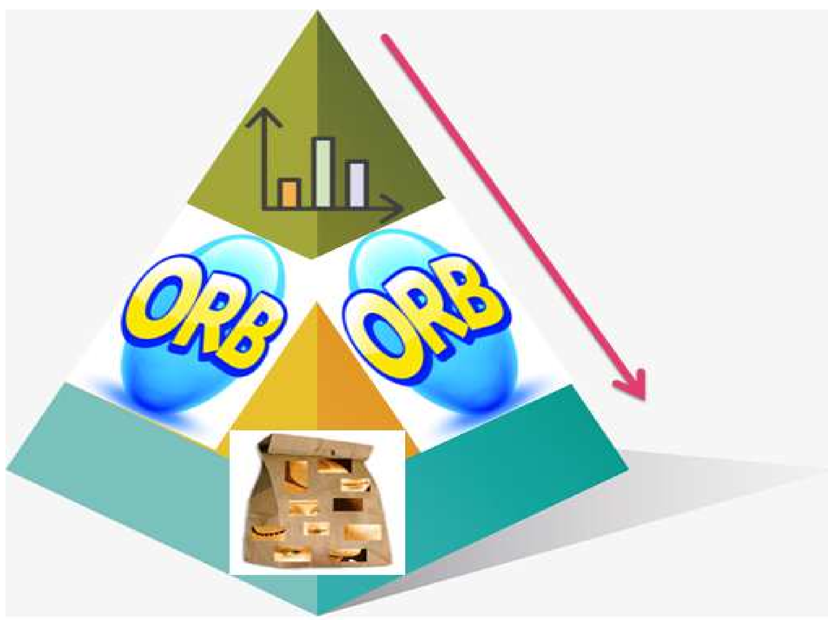


Figure 3.4 *The HORBoVF* Pyramid

3.3.2 *ACORBoVF* – ACO, ORB and Bag of Visual Features based Hybrid Classifier

To take the advantage of fast convergence of ACO in small number of inputs and to beat the issue of misclassification of K-Means, we proposed and experimented one more approach with combination of *ACORB*, proposed in 3.2.2 and ORB based Bag of Visual Features' classifier. This is a two stage classifier in the line of *HORBoVF.* We are using the same dynamic Bag of Visual Features for labeling of image.

In the first stage, the captured image is used as an input to *ACORB* and a closest match is decided. The matched label for the closest image is sent to the next stage of classification for verification purpose. The overall algorithm has been divided into two stage Classification process, one layer less than *HORBoVF*. The following figure shows structure of *ACORBoVF*.

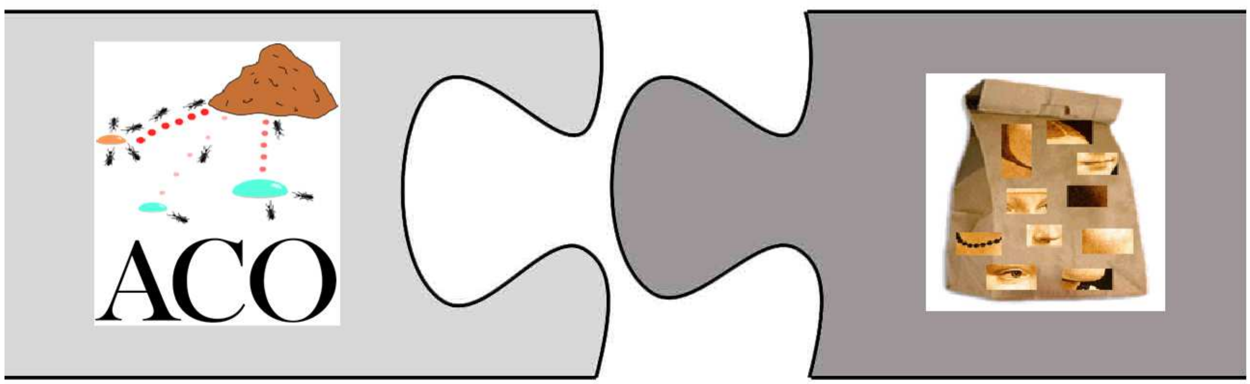


Figure 3.5 *The ACORBoVF* Structure

3.3.3 *Te₹₹ency* – An Image Classifier Using Transfer Learning

Te₹₹ency is a TensorFlow based CNN model which we created specifically for Indian currency identification. TensorFlow is known as transfer learning. In TensorFlow, there are basically two approaches used for transfer learning: build the model or re-use the model. In one approach, based on the source task, a source model is prepared and may be reused for similar task. Many a times the new model is required to be tuned also. In another approach of pre-trained models, an existing model is selected as model and if suits the task then can be retrained and tuned, if needed. This has specifically been developed to evaluate the performance of our other two classifiers and to utilize the power of convolutional neural networks, a neural network of millions of images, for image classification.

4. TESTING AND RESULT ANALYSIS

In order to make sure that we achieved our goal, we performed extensive testing of our all the proposed approaches. This chapter shows result analysis carried out to see the fruitfulness of our research work.

4.1 PERFORMANCE TESTING OF *cGRAB-CUT*

As stated in our proposed approach, in 3.1, *cGrab-Cut* is a trade-off based implementation of Grab-Cut where in, we are giving up some quality in order to achieve faster performance. We tested 100 images (100X2 image captures) to check performance in terms of time and it is observed that average times reduced by *cGrab-Cut* is by 50%. Following graph shows the average time, per image, taken by Grab-Cut, 18.983 seconds, and *cGrab-Cut*, 8.219 seconds, for a set of 100 images.

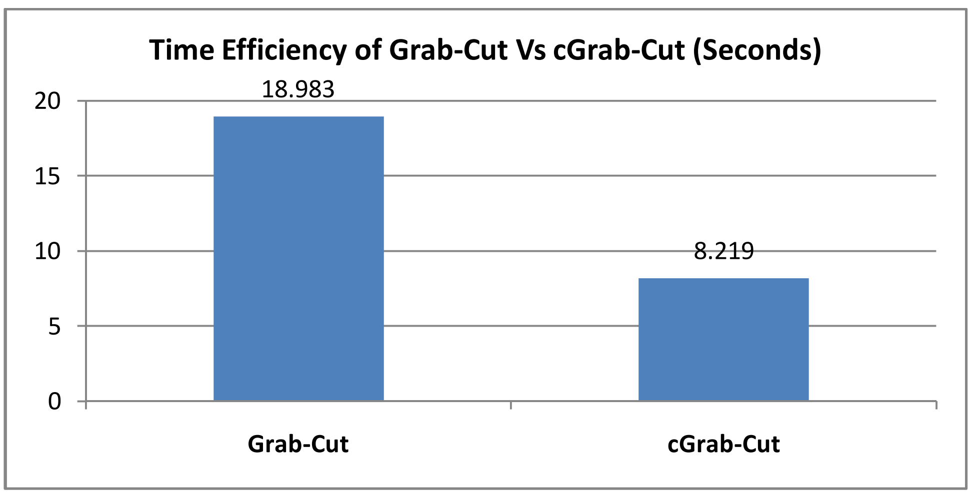


Figure 4.1 Time Efficiency improvement of Grab-Cut

4.2 PERFORMANCE TESTING & ANALYSIS OF *HORB*

In terms of time, *HORB* takes an average 2.333 and 2.339 seconds per image, for recognition of fully and partially visible images, which are almost, double than ORB consuming 1.201 and 1.160 seconds per image. But for improvement in recognition accuracy, this trade-off is necessary.

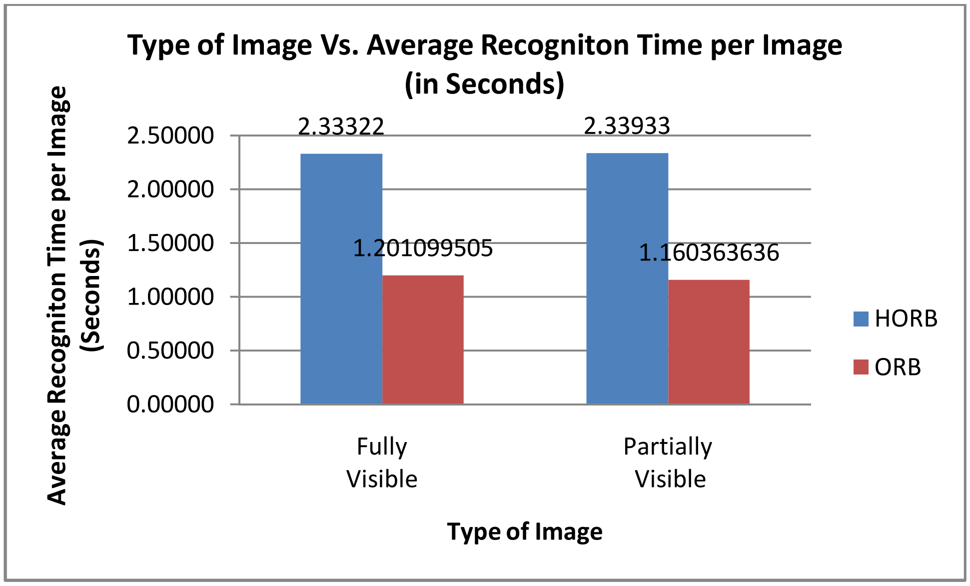


Figure 4.2 Average time taken per image by *HORB* and ORB

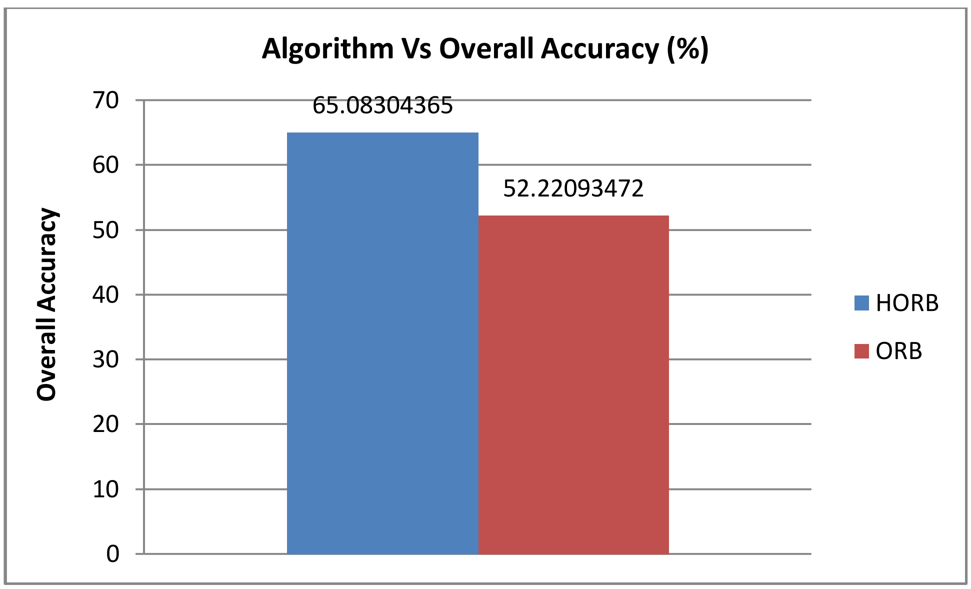


Figure 4.3 Overall performance of *HORB* and ORB

The figure 4.3 shows an overall improvement of around 12.862% of in ORB using the proposed approach. It proves that our approach, *HORB*, has an edge over ORB.

4.3 PERFORMANCE TESTING & ANALYSIS OF *ACORB*

In terms of time, *ACORB* takes an average 2.443 and 1.904 seconds per image, for recognition of fully and partially visible images, higher than ORB consuming 1.201 and 1.160 seconds per image and almost nearby as *HORB*. The average time taken by *ACORB* is 2.174 seconds, which is a bit less than *HORB*'s 2.336 seconds. Time consumption for each denomination and average time taken per image are shown in figure 4.4 and 4.5.

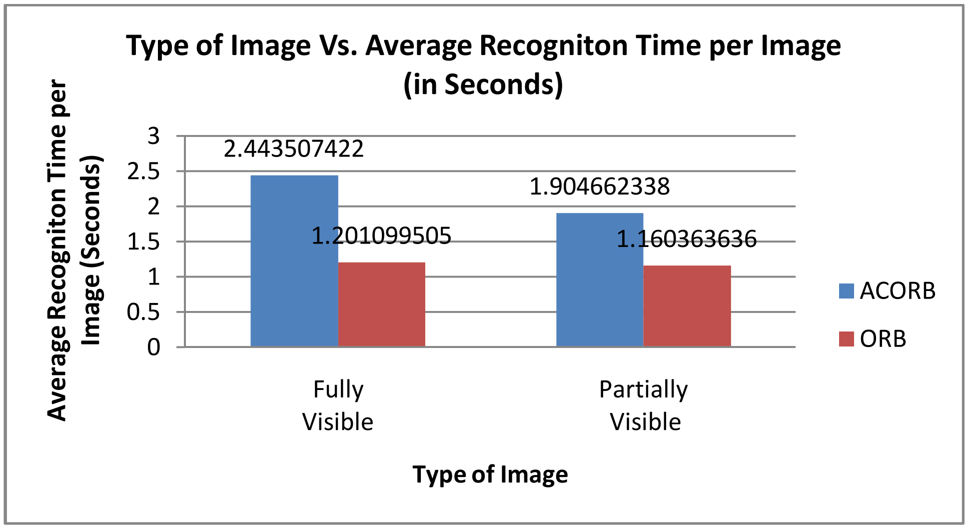


Figure 4.4 Average time taken per image by *ACORB* and ORB

The figure 4.5 shows an overall improvement of around 13.249% in ORB through our approach, *ACORB*. It is also 0.386% higher than *HORB*.

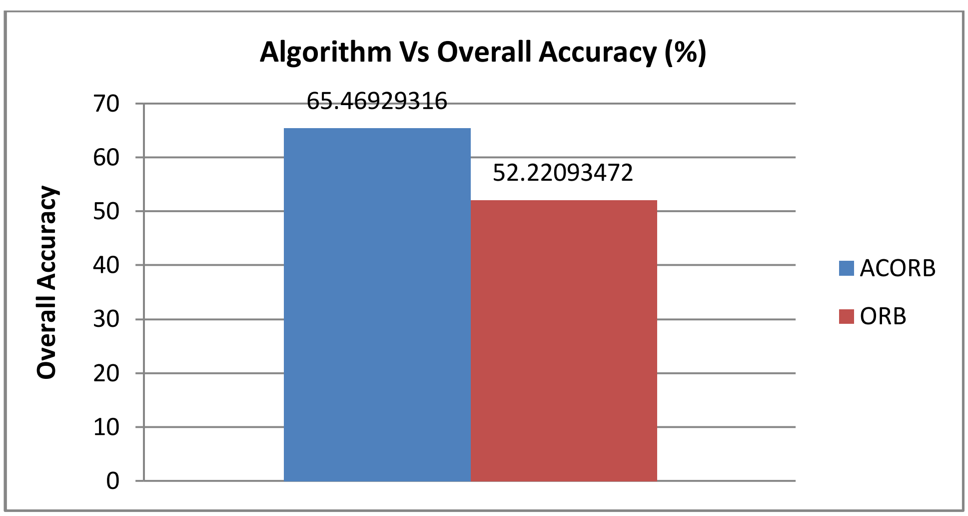


Figure 4.5 Overall performance of *ACORB* and ORB

4.4 PERFORMANCE TESTING & ANALYSIS OF *HORBoVF* & *ACORBoVF*

As observed in sections 4.2 and 4.3, the overall performance of ORB has been improved through *HORB* and *ACORB* but it does not yield better, does not even improve, performance for partially visible images. In order to improve that performance, we introduced *HORBoVF* and *ACORBoVF* based on *HORB* and *ACORB* respectively in combination with a dynamic Bag of Visual Features (BoVF). This section discusses performance analysis of *HORBoVF* and *ACORBoVF* jointly as both of these uses a common classifier, dynamic BoVF in the final stage after feature detection using *HORB* and *ACORB* respectively. We have already discussed the performance analysis of *HORB* and *ACORB* in 4.2 and 4.3, so we will discuss the performance of Bag of Visual Features only in context of different values of K (Number of Clusters) used in K-Means clustering. In order to measure the accurate performance, we took the values of K=10, 15, 20 and K=24. The clusters are created based on the features detected using *HORB* and *ACORB* in order to take the advantage of improved feature detectors discussed in 4.2 and 4.3. The following figures show performance of our algorithms in terms of time and accuracy proving our approaches is outstanding not only for fully visible images but also for partially visible images.

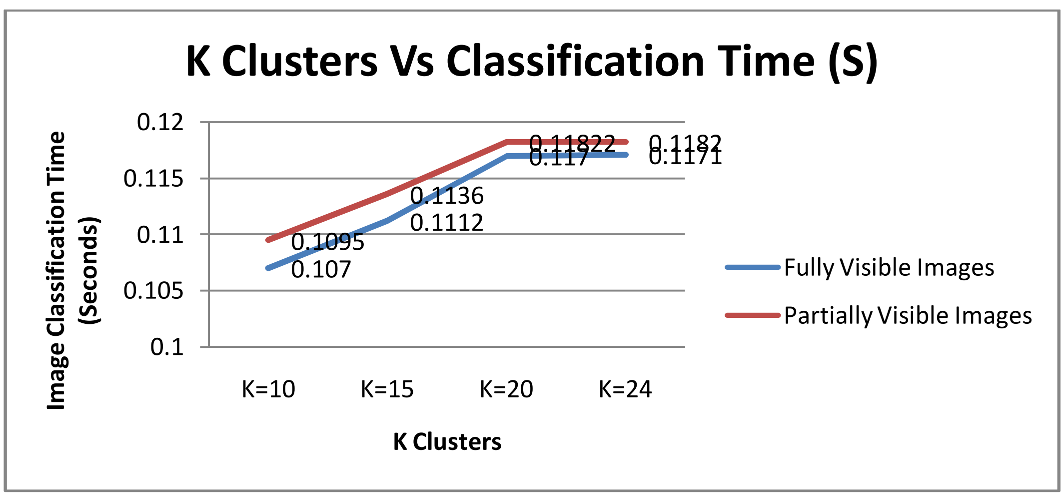


Figure 4.6 Average time taken per image by *HORBoVF* for K clusters

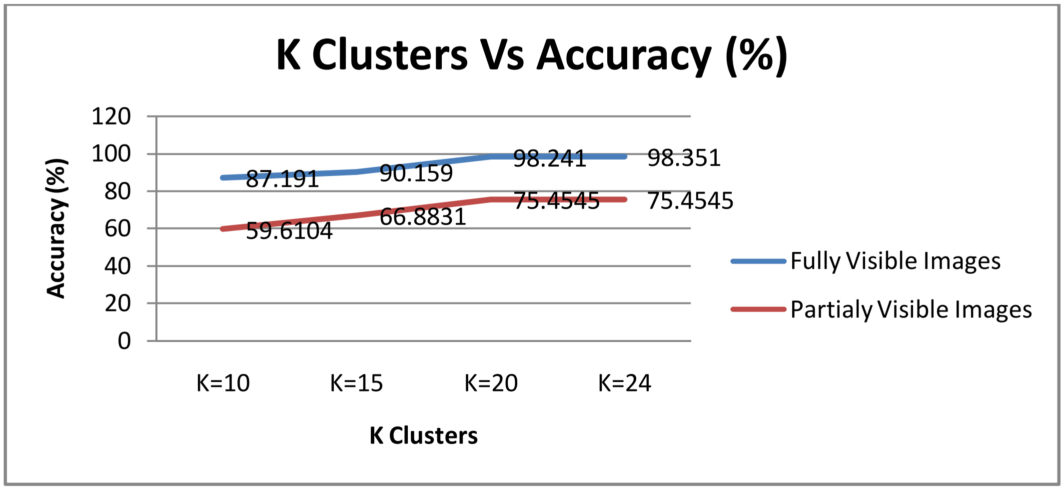


Figure 4.7 Average Classification Accuracy by *HORBoVF* for K clusters

4.5 PERFORMANCE TESTING & ANALYSIS OF *Te₹₹ency*

Te₹₹ency is based on training of TensorFlow model for a specific number of iterations. We tested it for iterations 100, 500, 1000, 2000 and 4000. The following results show performance of *Te₹₹ency*. These results are also far better than traditional ORB but not at par with our classifier *HORBoVF/ACORBoVF*. It shows that our *HORBoVF/ACORBoVF* performs better than *Te₹₹ency*.

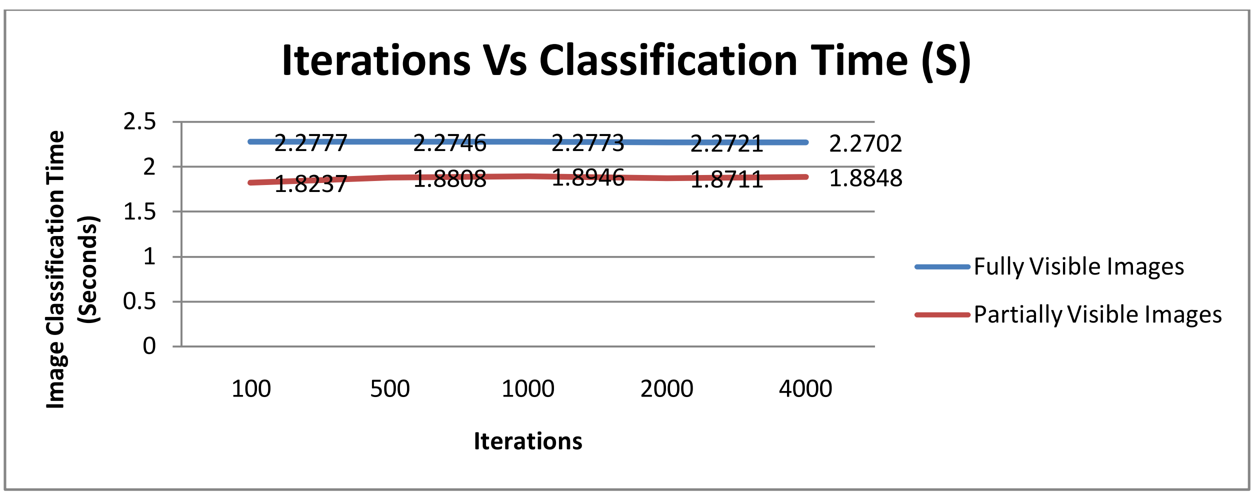


Figure 4.8 Average time taken per image by *Te₹₹ency* for various iterations

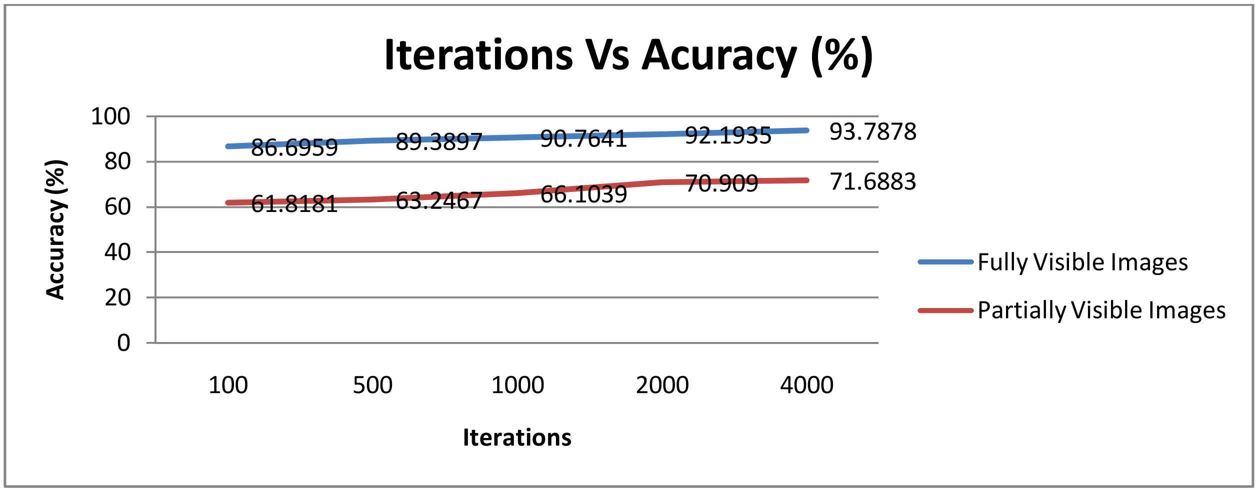


Figure 4.9 Average classification accuracy by *Te₹₹ency* for various iterations

4.6 PERFORMANCE SUMMARY

To summarize the performance of the proposed approaches, for ***HORBoVF*/*ACORBoVF*** and ***Te₹₹ency***, we considered K=24 and 4000 iterations respectively which are giving their best performance in their category for different values of K and iterations. The following figure shows overall accuracy of all our proposed approaches in comparison with ORB. It shows that all our proposed feature detectors outperform ORB with 13% more accuracy and our dynamic bag of visual features beats TensorModel with 4% higher accuracy.

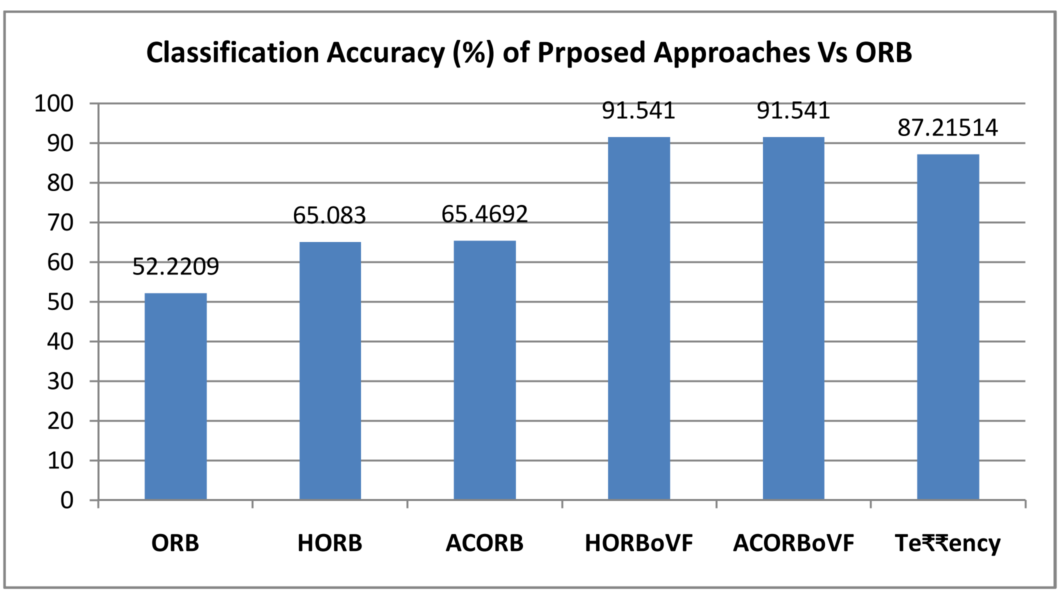


Figure 4.10 Image classification performance of proposed approaches against ORB

Figure 4.11 shows that all our approaches take almost double time than ORB but this difference is compensated by higher accuracy of the algorithms.

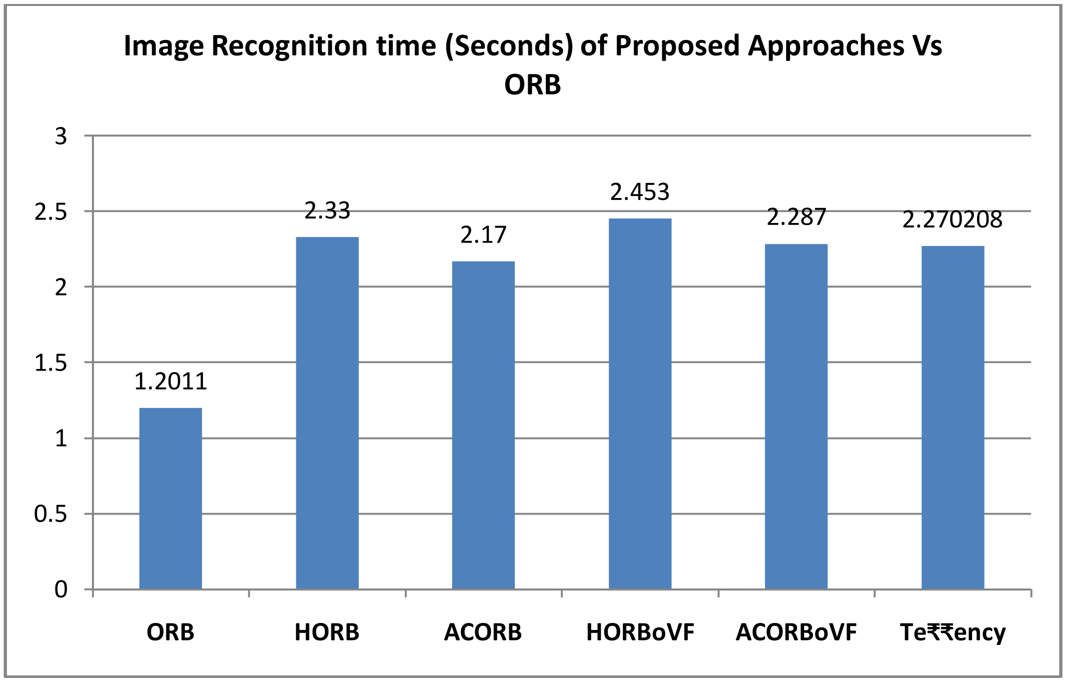


Figure 4.11 Time efficiency of proposed approaches against ORB

5. CONCLUSIONS AND A ROAD-MAP

5.1 CONCLUSIONS

After going through an exhaustive testing and meticulous result analysis we draw the following inferences: First, the hybrid feature detectors, *HORB* and *ACORB*, which we proposed works far better than original ORB and gives better performance. However, in order to improve the recognition performance, we had to apply give-and-take policy wherein the execution time is increased, almost doubled. This increase is due to added layer of histogram generations and histogram intersection process in case of *HORB*. In case of *ACORB* too, the execution time is increased due to pheromone updates, probability calculation for the specific feature being part of the given input image etc. But, this increased time gets compensated by 20% increase in recognition accuracy for fully visible images. Unfortunately, these two proposed approaches could not improve the recognition accuracy for partially visible images keeping it 10% same as ORB. The results of *HORB* and *ACORB* give an inference that "***Feature detectors independently can recognize fully visible images with higher accuracy but are not capable of recognizing partially visible images and gives poorest performance***".

Second, in hunt for an improved classifier for partially visible images, we opted for hybrid classifiers, named *HORBoVF* and *ACORBoVF* and a CNN based classifier - *Te₹₹ency*. We used one of the most widely used approaches called Bag of Visual Words and combined it with our proposed feature detectors to take the advantage of their improved performance. The results were as per the expectations. All our classifiers work fine and show tremendous performance. Our Bag of Visual Features classifier gives 98.351% recognition accuracy for fully visible images whereas it gives 75.454% accuracy in case of partially visible images. This is a huge achievement showing the increase in accuracy by 65% in partially visible images. *Te₹₹ency* also performs similar in case giving 93.787% and 71.688% accuracy for fully and partially visible images respectively. These figures lead us to conclude that "***A classifier, be it a bag of words based or neural network based, can improve accuracy for partially visible images also***".

It is also observed that for K=20 and 24, the performance of the *HORBoVF* and *ACORBoVF* remains steady. The same has been experienced in case of 2000 and 4000 iterations for *Te₹₹ency* where performance was almost same. This infers that "***After certain level of clustering or training, the performance improvement in accuracy is not possible***". We trained 4208 images for *Te₹₹ency*. Since the training dataset is kept smaller, *Te₹₹ency* is not able to perform at par in comparison with *HORBoVF* and *ACORBoVF* and hence it is proved that "***For CNN based models, the larger the number of training images, the better the performance***".

5.2 ROAD MAP FOR FUTURE WORK

All our approaches are feature based i.e. the image recognition and classification is carried out based on certain number of features matching and classification algorithm. For testing, we obtained fake currency images by getting it color photocopied and used some playing currency notes for children etc. Upon testing, the results were accurate and the currencies were recognized as fake. Yet, a lot of work can be done in this direction to detect if the currency is counterfeit or not as we firmly believe that feature detection can help in recognizing the denomination of the currency. It is not sufficient to detect if the currency is fake or real. This has remained, always, a challenging issue for all the researchers and still it is. So a lot of work can be done in this direction.

Apart from recognizing the fake or real currency, another challenging part, which we saw in chapter 4, is recognition of partially visible images. In spite of having 24 clusters in BoVF and 4000 iterations in *Te₹₹ency*, we are not able to achieve 80% accuracy for partially visible images. This is another area where a lot of work can be done to improve the classification accuracy for partially visible images.

In BoVF, we used K-Means clustering and dictionary creation. In order to keep the dictionary updated, as and when new images are added into dataset, we perform clustering from the scratch and a new dictionary is created replacing the existing ones. Instead of this, an incremental clustering approach can be used so that, as and when new images are added into dataset, clustering could be carried out for the new images with reference to the existing clusters and corresponding new visual words can be added into the current dictionary. Along with this, instead of using K-Means, other clustering approaches, if applicable, may also be deployed for clustering the features and building the dictionary to measure the performance of Bag of Visual Features.

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7. PUBLICATIONS

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