

Texture Classification for Fake Indian Currency Detection

¹Mrs. B. Hari Chandana, ²Ms. Lavanya Kandikunta, ³Prof. T. Bhaskar Reddy

^{1,2,3}Department of Computer Science and Technology, Sri Krishnadevaraya University
Anantapur-515003, Andhra Pradesh, India.

Abstract

Currency duplication also known as counterfeit currency is a vulnerable threat on economy. It is now a common phenomenon due to advanced printing and scanning technology. India has always been facing serious problem by the increasing rate of fake notes in the market. To get rid of this problem various fake note detection methods are available around the world and most of these are hardware based and costly. Digital image processing is one of the most common and effective techniques used to distinguish counterfeit banknotes from genuine ones. In the present paper an automated image-based technique is described for the detection of newly issued fake currency by RBI. Security features of banknotes such as watermark, micro-printing etc., are extracted from the banknote images and then detection is performed using Support Vector Machine (SVM). A new approach is presented in this paper using the bit-plane slicing technique to extract the most significant data from counterfeit banknote images with the application of an edge detector algorithm. The results are then compared with genuine banknotes and with other techniques for detecting counterfeit notes. Unlike existing research, it was observed that the edges obtained using bit-plane sliced images are more accurate and can be detected faster than obtaining them from the original image without being sliced. Experimental results confirm the effectiveness of the proposed algorithm

Keywords: Support Vector Machine (SVM), classifier, Texture Classification, Fake Currency Detection, Canny Edge Detection.

INTRODUCTION

The growing menace of counterfeit currency is evident as newspapers and online articles report huge caches of fake currency notes being seized more often. Nowadays all the countries are facing the growing and challenging difficulties of counterfeiting of its banknotes. Since from the invention of currency around the world a global challenge has been started to stop counterfeiting of currency. Though there are several security features has been incorporated to protect the banknotes from counterfeiting, but due to advancement of the printing media technology, it has become an easy task to counterfeit paper banknotes. Hence, fake banknotes' detection is an emergence issue for a country to protect its economy as well as people's faith on currency. The amount of circulation of counterfeit money can threaten the reliability of state currency at any time, which in return has an impact on the stability and value of currency. Different anti-counterfeit approaches and measures have been developed on currency

notes to be able to cope with the act of counterfeiting. Some of the measures available in currency notes include watermarks, security threads, and holograms. However, the constant and rapid improvements in the scanning and printing industries have made it easier for unskilled counterfeiters to reproduce high-quality and close to reality banknotes.

In this work, image processing is used to manipulate the nature of images in order to enhance pictorial information which can be easily interpreted by humans. The images used and analyzed are digital images. A digital image is an image composed of discrete values, which can be considered as an array of discrete dots with their associated brightness. Images of scanned currency notes used in this paper will undergo the following phases: image acquisition, pre-processing an image, bit-plane slicing, edge detection, image segmentation, and feature extraction. Enhancing images may not always be the answer for image analysis, depending on the application. This can be resolved using bit-plane slicing where relative information can be extracted from each bit-plane. This technique extracts security features from the images of a banknote and detects its authenticity using Support Vector Machine (SVM).

Texture analysis refers to the characterization of regions in an image by their texture content. Texture analysis attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities. In this sense, the roughness or bumpiness refers to variations in the intensity values, or gray levels. Texture analysis is used in various applications, including remote sensing, automated inspection, and medical image processing. Texture analysis can be used to find the texture boundaries, called texture segmentation. Texture analysis can be helpful when objects in an image are more characterized by their texture than by intensity, and traditional thresholding techniques cannot be used effectively.

Texture is another feature that can help to segment images into regions of interest and to classify those regions. In some images, it can be the defining characteristic of regions and critical in obtaining a correct analysis. The image of sample set Figures has three very distinct textures: the texture of the tiger, the texture of the jungle, and the texture of the water. These textures can be quantified and used to identify the object classes they represent.

Recently, particular attention has been dedicated to Support Vector Machines as a classification method. SVMs have often been found to provide better classification results than other widely used pattern recognition methods. Thus, SVMs are very attractive for the classification of remotely sensed data. The SVM approach seeks to find the optimal separating

hyperplane between classes by focusing on the training cases that are placed at the edge of the class descriptors. These training cases are called support vectors. Training cases other than support vectors are discarded. This way, not only is an optimal hyperplane fitted, but also less training samples are effectively used; thus high classification accuracy is achieved with small training sets (Mercier and Lennon). This feature is very advantageous, especially for remote sensing datasets and more specifically for Object-based Image Analysis, where object samples tend to be less in number than in pixel-based approaches. Here, the basic principles will be presented and then their implementation and application to Object Based Image Analysis will be evaluated.

SVM method was designed to be applied only for two class problems. For applying SVM to multi-class classifications, two main approaches have been suggested. The basic idea is to reduce the multi-class to a set of binary problems so that the SVM approach can be used. The first approach is called “one against all”. In this approach, a set of binary classifiers is trained to be able to separate each class from all others. Then each data object is classified to the class for which the largest decision value was determined. This method trains N SVMs (where N is the number of classes) and there are N decision functions. Although it is a fast method, it suffers from errors caused by marginally imbalanced training sets. Another approach is similar to the “one against all” method, but uses one optimization problem to obtain the N decision functions. Reducing the classification to one optimization problem may require less support vectors than a multi-class classification based on many binary SVMs. The second approach is called “one against one”. In this, a series of classifiers is applied to each pair of classes, with the most commonly computed class kept for each object. Then a max-win operator is used to determine to which class the object will be finally assigned. The application of this method requires $(N-1)/2$ machines to be applied. Even if this method is more computationally demanding than the “one against all” method, it has been shown that it can be more suitable for multi-class classification problems (Hsu and Lin), thus it was selected for SVM object-based image classification.

At present there are many techniques have been used to detect the fake notes but unfortunately these are expensive, complex, less accurate, not conveniently portable and also not in the range of general people’s ability. To overcome these drawbacks, in this paper an image-based automated fake note detection approach is described. This technique extracts security features from the images of a banknote and detects its authenticity using Support Vector Machine (SVM). Our ultimate goal is to develop an algorithm that will be efficient for the mobile devices such as smart phone, tablets etc.

RELATED WORK

Currency duplication also known as counterfeit currency is a vulnerable threat on economy. It is now a common phenomenon due to advanced printing and scanning technology. In the paper (2016, Mohammad Shorif Uddin, Pronaya Prosun Das, Md. Shamim Ahmed Roney), an image-based methodology has been proposed to identify counterfeit

Bangladesh banknotes of 500 and 1000 BDT. We used SVM classifier after extracting three security features (watermark, latent image and micro-text) from the acquired images of the banknotes. Here we have considered two types of banknotes (500 BDT and 1000 BDT). With limited testing we have got 100% recognition accuracy. However, rigorous testing with diverse situations of currencies is required for full validation of the proposed approach that will be our immediate work. In addition, we are interested to involve more features to detect forgery and also extend the support for all kinds of Bangladesh banknotes. Besides we are going to implement this technique for Android framework that will ensure greater portability[2].

In the paper (Mayur Jayram More, 2016) they developed an automated banknote recognition system which can be very good utility for the fields like Banking operations and other fields of commerce. Our banknote recognition system is robust and effective with the following features: 1) high accuracy, 2) robustness, 3) high efficiency, and 4) ease of use. To make the system robust to a variety of conditions including image of any angle, whether it is rotated or not, doesn’t matter of its background and whether it is worn or wrinkled bills, we propose a component-based framework by using Speeded Up Robust Features (SURF). We also have employed the spatial relationship of matched SURF features to detect if there is a bill in the camera view. This process largely alleviates false recognition and can guide the user to correctly aim at the bill to be recognized. The evaluation of the proposed system (robustness and generalizability) on a dataset including both positive images (with Indian banknotes) and negative images (no Indian banknotes) collected under a variety of conditions. Though in India, automatic banknote recognition is not common, this system is used in many countries. The recognition system takes scanned images of banknotes for recognition. Experimental results are presented which show that this scheme can recognize currently available 10 notes (1, 2, 5, 10, 20, 50, 100, 500, 1000 & 2000) successfully. The proposed algorithm, achieves 100% true recognition rate and 0% false recognition rate[5].

An Efficient Edge Detection Method Based on Bit-plane Slicing for Bacterial Images, (P. KALAVATHI, 2013). In this paper, a simple, automatic and efficient edge detector based on bit-plane slicing is proposed and is applied to detect the edges of the bacterial images. The edges are detected more accurately by the contour method than the existing popular edge detectors. Further, the proposed and the existing method detected the edges more accurately in the bit-plane sliced images than the original image. In future this proposed method maybe extended to detect edges on all kinds of grayscale images.

As mentioned before, SVM classification is essentially a binary (two-class) classification technique, which has to be modified to handle the multiclass tasks in real world situations e.g. derivation of land cover information from satellite images. Two of the common methods to enable this adaptation include the 1A1 and 1AA techniques. The 1AA approach represents the earliest and most common SVM multiclass approach and involves the division of an N class dataset into N two-class cases. If say the classes of interest in a satellite image include water, vegetation and built up areas, classification would be

effected by classifying water against non-water areas i.e. (vegetation and built up areas) or vegetation against non-vegetative areas i.e. (water and built up areas). The 1A1 approach on the other hand involves constructing a machine for each pair of classes resulting in $N(N-1)/2$ machines. When applied to a test point, each classification gives one vote to the winning class and the point is labeled with the class having most votes. This approach can be further modified to give weighting to the voting process. From machine learning theory, it is acknowledged that the disadvantage the 1AA approach has over 1A1 is that its performance can be compromised due to unbalanced training datasets (Gualtieri and Crompton), however, the 1A1 approach is more computationally intensive since the results of more SVM pairs ought to be computed. In this paper, the performance of these two techniques are compared and evaluated to establish their performance on the extraction of land cover information from satellite images.

DESIGN AND SECURITY FEATURES OF INDIAN CURRENCY

In the current Project work, we have used new 500 rupee INR Indian currency.. The current ₹ 500 banknote, in circulation since 10 November 2016, is a part of the Mahatma Gandhi New Series. The previous banknotes of the Mahatma Gandhi Series, in circulation between October 1997 and November 2016, were demonetized on November 8, 2016. On 13 June 2017,. The design is similar to the current notes in the Mahatma Gandhi (New) Series, except they will come with an inset 'A'.

Design

The ₹ 500 banknote of the Mahatma Gandhi New Series is 66mm x 150mm stone grey coloured, with the obverse side featuring a portrait of Mahatma Gandhi as well as the Ashoka Pillar Emblem, with a signature of the governor of Reserve Bank of India. It has the Braille feature to assist the visually challenged in identifying the currency. The reverse side features a motif of the Indian heritage site of Red Fort, and the logo and a tag line of Swachh Bharat Abhiyan.[8]



Figure 1: RBI printed ₹ 500 Rupee INR note front side

Security features

- See through register with denominational numeral 500

- Latent image with denominational numeral 500
- Micro letters 'RBI' and '500' on the left side of the banknote
- Windowed security thread with inscriptions 'भारत', RBI and 500 on banknotes with colour shift. Colour of the thread changes from green to blue when the note is tilted
- Denominational numeral with Rupee Symbol, ₹ 500 in colour changing ink (green to blue) on bottom right
- Ashoka Pillar emblem on the right Mahatma Gandhi portrait and electrotype (500) watermarks
- Number panel with numerals growing from small to big on the top left side and bottom right side.
- For visually impaired Intaglio or raised printing of Mahatma Gandhi portrait, Ashoka Pillar emblem, bleed lines and identity mark
- Horizontal rectangle with ₹ 500 in raised print on the right

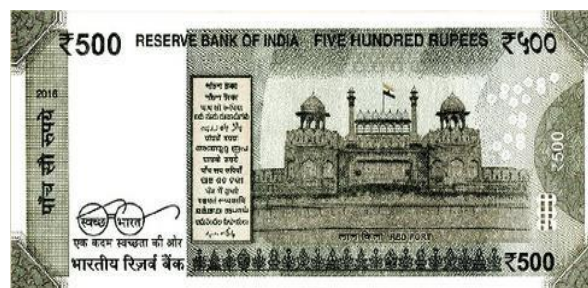


Figure 2: RBI printed ₹ 500 Rupee INR note Backside

Proposed Design and Methodology

Image Extraction and Preprocessing

As mobile camera is used to capture the image, it is evident that there will be some distortion like scale, rotation, skewness etc. The aim of image pre-processing is to suppress undesired distortions and crop the note portion from background using image registration technique. Initially, we use a high-speed corner detector Algorithm to detect important key points from the acquired image.

FAST corner detector uses a circle of 16 pixels (a Bresenham circle of radius 3) to classify whether a candidate point p is actually a corner. Each pixel in the circle is labeled from integer number 1 to 16 clockwise. If a set of N contiguous pixels in the circle are all brighter than the intensity of candidate pixel p (denoted by I_p) plus a threshold value t or all darker than the intensity of candidate pixel p minus threshold value t , then p is classified as corner. The conditions are written as:

- Condition 1: A set of N contiguous pixels S , $\forall x \in S$, the intensity of x (I_x) $> I_p + \text{threshold } t$.
- Condition 2: A set of N contiguous pixels S , $\forall x \in S$, $I_x < I_p - t$

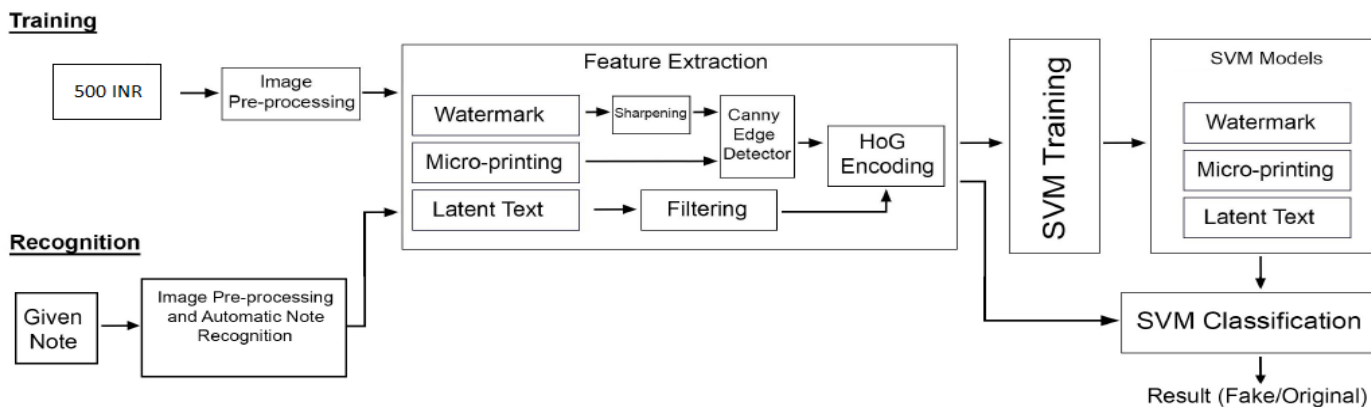


Fig 3: Block Diagram of Proposed Design and Methodology

So when either of the two conditions is met, candidate p can be classified as a corner. There is a tradeoff of choosing N , the number of contiguous pixels and the threshold value t . On one hand the number of detected corner points should not be too many, on the other hand, the high performance should not be achieved by sacrificing computational efficiency. Without the improvement of machine learning, N is usually chosen as 12. A high-speed test method could be applied to exclude non-corner points.

FAST-ER detector is an improvement of the FAST detector using a metaheuristic algorithm, in this case simulated annealing. So that after the optimization, the structure of the decision tree would be optimized and suitable for points with high repeatability. However, since simulated annealing is a metaheuristic algorithm, each time the algorithm would generate a different optimized decision tree. So it is better to take efficiently large amount of iterations to find a solution that is close to the real optimal. According to Rosten, it takes about 200 hours on a Pentium 4 at 3 GHz, which is 100 repeats of 100,000 iterations to optimize the FAST detector.

Then those keypoints are described using FREAK (Fast Retina Keypoint) descriptor.

In order to address the first two weakness points of high-speed test, a machine learning approach is introduced to help improve the detecting algorithm. This machine learning approach operates in two stages. Firstly, corner detection with a given N is processed on a set of training images, which are preferable from the target application domain. Corners are detected through the simplest implementation, which literally extracts a ring of 16 pixels and compares the intensity values with an appropriate threshold.

For candidate p , each location on the circle $x \in \{1, 2, 3... 16\}$ can be denoted by $p \rightarrow x$. The state of each pixel, $S_{p \rightarrow x}$ must be in one of the following three states:

- $d, I_{p \rightarrow x} \leq I_p - t$ (darker)
- $s, I_p - t \leq I_{p \rightarrow x} \leq I_p + t$ (similar)
- $b, I_{p \rightarrow x} \geq I_p + t$ (brighter)

Then choosing an x (same for all p) partitions P (the set of all pixels of all training images) into 3 different subsets, P_d , P_s , P_b where:

- $P_d = \{p \in P : S_{p \rightarrow x} = d\}$
- $P_s = \{p \in P : S_{p \rightarrow x} = s\}$
- $P_b = \{p \in P : S_{p \rightarrow x} = b\}$

Secondly, a decision tree algorithm, the ID3 algorithm is applied to the 16 locations in order to achieve the maximum information gain. Let K_p be a boolean variable which indicates whether p is a corner, then the entropy of K_p is used to measure the information of p being a corner. For a set of pixels Q , the total entropy of K_Q (not normalized) is:

- $H(Q) = (c + n) \log_2(c + n) - c \log_2 c - n \log_2 n$
 - where $c = |\{i \in Q : K_i \text{ is true}\}|$ (number of corners)
 - where $n = |\{i \in Q : K_i \text{ is false}\}|$ (number of non-corners)

The information gain are represented as:

- $H_g = H(P) - H(P_b) - H(P_s) - H(P_d)$

A recursive process is applied to each subsets in order to select each x that could maximize the information gain. For example, at first an x is selected to partition P into P_d , P_s , P_b with the most information; then for each subset P_d , P_s , P_b , another y is selected to yield the most information gain (notice that the y could be the same as x). This recursive process ends when the entropy is zero so that all pixels in that subset are either corners or non-corners.

Notice that the corners detected using this decision tree algorithm should be slightly different from the results using segment test detector. This is because that decision tree model depends on the training data, which could not cover all possible corners.

Euclidian distances between descriptors from acquired and referenced images are calculated. The pair with smallest distance is considered matched point. Then homography matrix is computed from corresponding points where unreliable points are discarded using RANSAC (Random

Sample Consensus) algorithm. The acquired image is registered using homography matrix. There are different kinds of transformations. We use 2D Projective transformation to complete our registration process.



Figure 4: INR 500 note captured by mobile camera



Figure 5: INR 500 Original note scanned copy

New 500 Rupee Bank Note Features – Front Side (obverse)

- See through register in 500 denomination numeral
- Denomination numeral's latent image
- Denomination numeral in Devanagari lipi can be found
- Mahatma Gandhi's portrait orientation and relative position is changed.
- Windowed security thread changes colour from green to blue when you tilt the note.
- Guarantee clause, Governor's signature with premium clause and RBI emblem tilted towards right.
- Electrotpe and Portrait watermarks.
- Number panel with numerals growing from small to large on top left and bottom right sides.
- On the bottom right denomination numerals with rupee symbol in colour changing ink from green to right.
- Ashoka pillar emblem can be seen on the right side.

For Visually Impaired:

Mahatma Gandhi portrait, Ashoka Pillar emblem and identification mark in raised print

- 500 in raised print on the right with circle
- On the left and right five bleed lines in raised print

New 500 Rupee Bank Note Features – Back Side (Reverse)

- Printed year on the left side
- Logo of Swachh Bharat with slogan

- Language panel towards centre
- Red fort image with Indian flag
- Numeral of denomination in Devanagari on the right

Pattern Extraction

As shown in Figure 5, we use pattern extraction methodology to extract watermark. We first get fifth bit-plane of the image. Initially the feature is sharpened using unsharp masking technique. Then Canny-edge detector is used to enhance the edges and it is implemented using the following equations.

$$H_{ij} = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(i - (k+1))^2 + (j - (k+1))^2}{2\sigma^2}\right); 1 \leq i, j \leq (2k+1)$$

The Process of Canny edge detection algorithm can be broken down to 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise.
2. Find the intensity gradients of the image.
3. Apply non-maximum suppression to get rid of spurious response to edge detection.
4. Apply double threshold to determine potential edges.
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

From here, we can intuitively say that edge directions or distributions of intensity gradients are very important in this context. Therefore, it will be convenient to use a kind of encoding that is able to preserve the gradient orientation from the pattern. For this purpose, we can use descriptor like Speeded Up Robust Features (SURF), Scale-Invariant Feature Transform (SIFT), Histograms of Oriented Gradients (HOG), binary descriptors etc. However, SIFT and SURF are patented and computationally expensive. Binary descriptors have some performance issue. That is why we choose to use HOG as a global descriptor to describe the whole image. It produces a vector of oriented gradients that is used to train SVM.

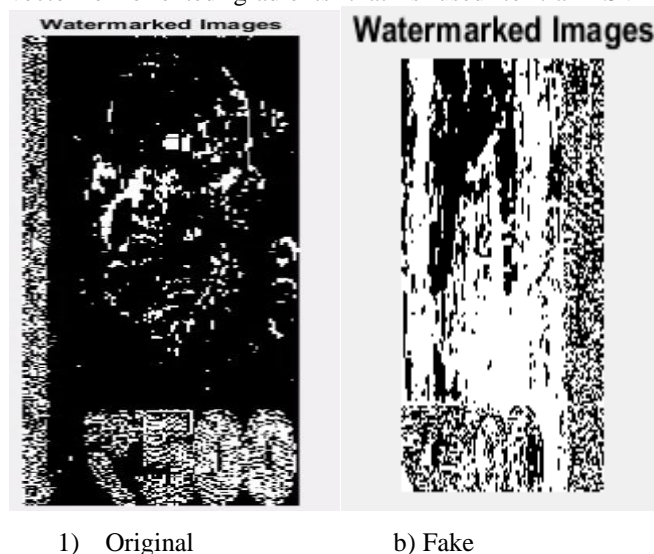


Figure 6: Watermarked Images comparison for both Original and Fake.

Micro Pattern

HOG is used to encode the enhanced image for the same reason as it is used earlier. Then the HOG feature vectors are used as an input for SVM.

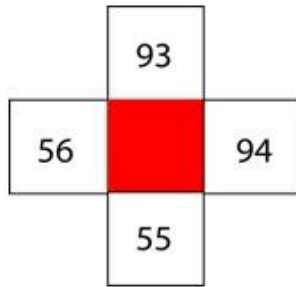


Figure HOG: Pixel value of given input image. Red color means observed pixel

In order to implement this feature descriptor [1], the gradient vector are calculated as follows:

$$\begin{bmatrix} 94-56 \\ 93-55 \end{bmatrix} = \begin{bmatrix} 38 \\ 38 \end{bmatrix} \quad (1)$$

$$\text{Magnitude} = \sqrt{(38)^2 + (38)^2} = 53.74 \quad (2)$$

$$\text{Angle} = \arctan\left(\frac{38}{38}\right) = 0.785 \text{ rads} = 45 \text{ degrees} \quad (3)$$

In order to make this method robust with the variance of contrast, the magnitude feature vector needs to be normalized using the HOG implementation.

HOG and SVM

We use HOG descriptor of cell size 4×4 to encode the patterns (HOG feature vectors) which are illustrated earlier. The HOG feature vectors are fed to SVM. In our work, Support Vector Machine (SVM) is used to perform classification. SVM is trained for three sets of models for 500INR with three different security codes. The main idea behind training of SVMs is to find the separating hyperplane optimally so that the classification error is minimized for the given test samples. Assume a set of M training samples of two separable classes are represented by

$$(x_1, y_1), (x_2, y_2), \dots, (x_M, y_M);$$

Where $x \in R^N$ is an N -dimensional space and class label is denoted by $y, (y_i \in \{-1, 1\})$.

A SVM attain the optimal hyperplane, which linearly classifies (separates) the larger portion of the training data points while maximizing the distance from the hyperplane. Twice of this distance is called the margin. The hyperplane discriminant function is described by the following equation:

$$f(x) = \sum_{i=1}^M y_i \alpha_i \cdot k(x, x_i) + b$$

RESULTS AND DISCUSSION

We have used three different sets of 500 INR notes for both original and Fake. Using image acquisition and extraction we have used 9 point Fast Corner detection technique for every image as shown in the figure 7 & 8.

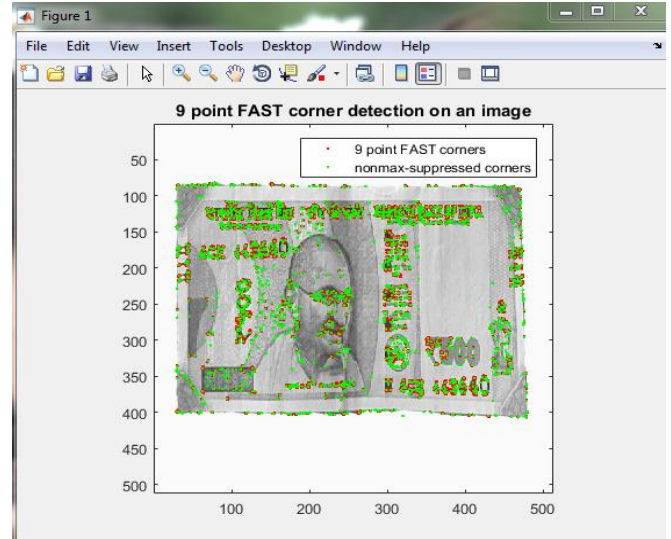


Figure 7: 9 point Fast Corner detection technique for Fake image

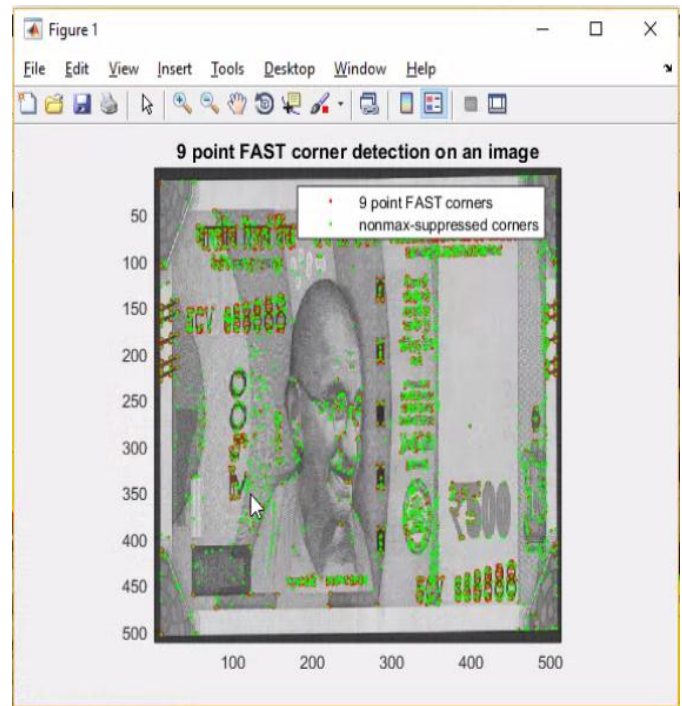


Figure 8: 9 point Fast Corner detection technique for Original image

- 1) First we Run the main program to train the SVM classifier.
- 2) Then run the test_currency to test the images for original or Fake.

By using pattern extraction using SVM technique we have crosschecked the original image with every image of the dataset to identify the image is original or fake.

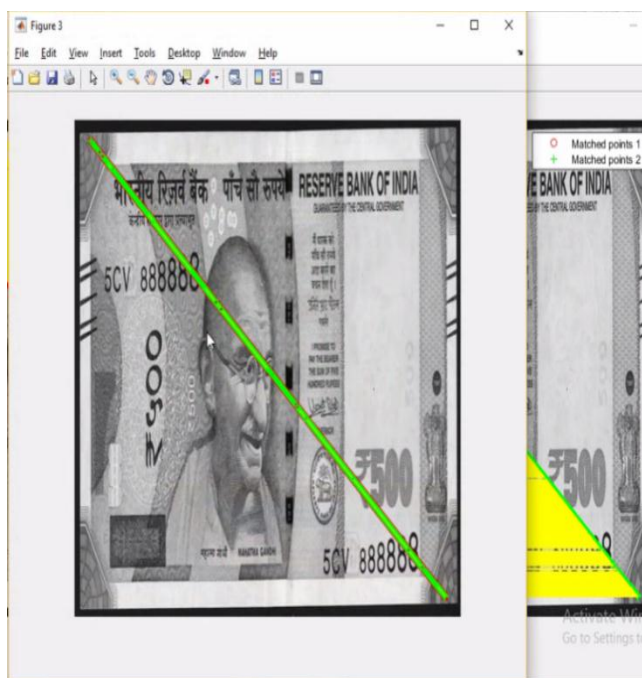


Figure 9: Test results for the image set of Real Currency.



Figure 12: Texture Analysis of Image set



Figure 13: Identification of matching Points

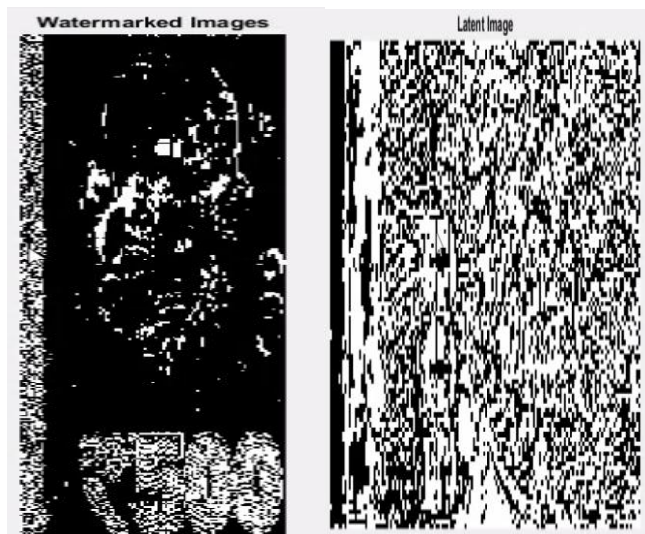


Figure 10: watermark image and latent enhancement image

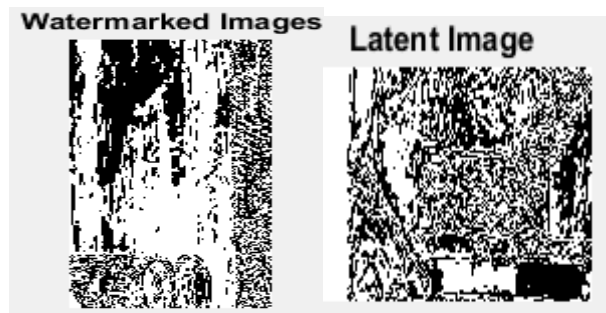


Figure 14: Watermark image and Latent Enhancement Images

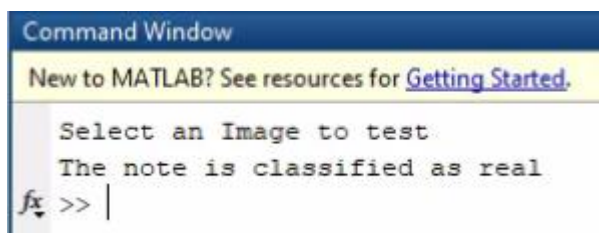


Figure 11: Result obtained as the note is real.

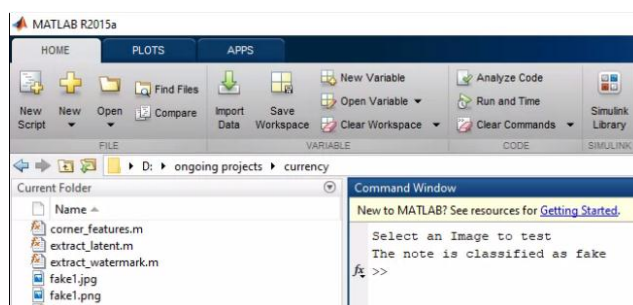


Figure 15: Result obtained a note is Fake.

CONCLUSION

In this paper, an image-based methodology has been proposed to identify counterfeit Indian banknotes of 500 INR. We used SVM classifier after extracting two security features (watermark, and latent image) from the acquired images of the banknotes. Here we have considered the recently issued 500 rupees notes issued by RBI. With limited testing we have got 100% recognition accuracy. However, rigorous testing with diverse situations of currencies is required for full validation of the proposed approach that will be our immediate work. In addition, we are interested to involve more features to detect forgery and also extend the support for all kinds of Indian banknotes.

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