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# A Novel Method for Counterfeit Banknote Detection

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***Abstract—*** The objective of this work is to detect counterfeit banknotes using image pattern classification techniques. The color scanner makes it easier to produce counterfeit banknotes. So it is important to find an efficient method to detect counterfeit banknotes. In this work, a method for automated banknote authentication is proposed, which segments the whole banknote into many regions, and then builds individual classifiers on each region. Firstly, the banknote is segmented into different number of partitions. Then the luminance histogram and texture features are extracted from each partition of the banknote. The features extracted from each partition are then used to classify the banknotes using multiple support vector machines. The result is whether the currency is genuine or counterfeit.

***Keywords—***Support Vector Machine, Counterfeit Banknote, Luminance Histogram, Texture Features

## I. Introduction

The large number of counterfeit banknotes in circulation causes profit loss to traders and banks. Therefore, finding an efficient method to detect counterfeit banknotes is an important and demanding task for business transactions in our daily life. Several approaches have been proposed for counterfeit banknote recognition. Takeda et al. [1] proposed a mask optimization technique using genetic algorithms (GA) and neural networks to detect counterfeit banknotes. Frosini et al. [2] employed neural networks to develop a paper currency recognition and verification system.

He et al. [3] presented one-class classifiers for counterfeit banknote recognition. Each banknote is divided into m × n partitions. An individual classifier is constructed for each partition, and then these classifiers are combined to make the final decision. Ionescu and Ralescu [4] also proposed one-class classifiers for counterfeit banknote recognition. Support vector machines (SVMs) have been proven to be an effective and efficient tool for solving classification problems [5–8]. The paper currency verification using the support vector machines has been proposed in the papers [9–10].

## II. Outline of the Work

The system will be programmed based on MATLAB and includes a user-friendly interface. The main steps in the system are reading image, segmentation, feature extraction, classification and result .There are 7 denominations of Indian Paper currency. Each note has different size and different color. A Genuine 500 INR and a counterfeit 500 INR banknotes are shown in the figure 1 & 2 respectively.

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Fig. 1. A Genuine 500 INR Banknote


Fig. 2. A Counterfeit 500 INR Banknote

The block diagram of the proposed work is shown in the figure 3 which involves four major steps of image acquisition, image segmentation, feature set extraction and classification. Then the results are found.

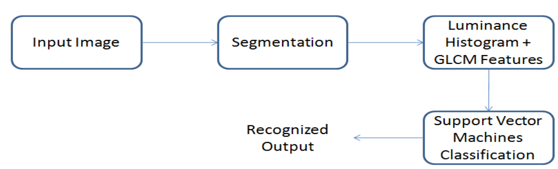

Fig. 3. Block diagram of the proposed work

## III. Methodology

*A. Image Acquisition*

The system database is based on data collected from various websites. And also the banknote images are acquired through scanner.

*B. Segmentation*

The banknote is segmented as 2×2, 3×3 and 4×4 partitions. The original image is segmented into overlapping frames of equal sized partitions. One of the partitions contains the face value of the currency. Each region of interest provides specific weighted control over the model accuracy. The banknote is partitioned before the features are extracted. For a 2×2 partition, 4 normal partitions and 1 overlapping frame partition is made. Likewise for a 4×4 partition, 16 normal partitions and 9 overlapping frames partitions are made. And for a 3×3 partition, 9 normal partitions and 4 overlapping frame partitions are made.

Fig 4. 2×2 Partition with 1 overlapped frame.

*C. Feature Extraction*

A feature set is computed for each partition of the banknote image. The luminance histogram of each partition is found out and then the texture feature of each partition is found out from the gray level co-occurrence matrix. By combining both these features a feature set is computed for each partition. By converting the RGB Image to YIQ, the luminance histogram of 256 values is derived.

*1. Luminance Histogram*

Luminance histograms are accurate than gray level histograms at describing the luminosity or the perceived brightness distribution within an image. Hence the color intensities are distributed over the 3-planes in RGB image representation, the histogram for representing the color cannot be calculated for RGB. Thus the image is transformed from RGB to YIQ color plane where Y represents the luminance part, and I & Q represent the chrominance part. Primary and secondary colors such as R, G, B, C, M & Y colors are distributed on the luminance plane whereas B & W information are distributed over the chrominance planes. Thus these six pixel color groups are captured and are utilized in plotting the histogram of the image.

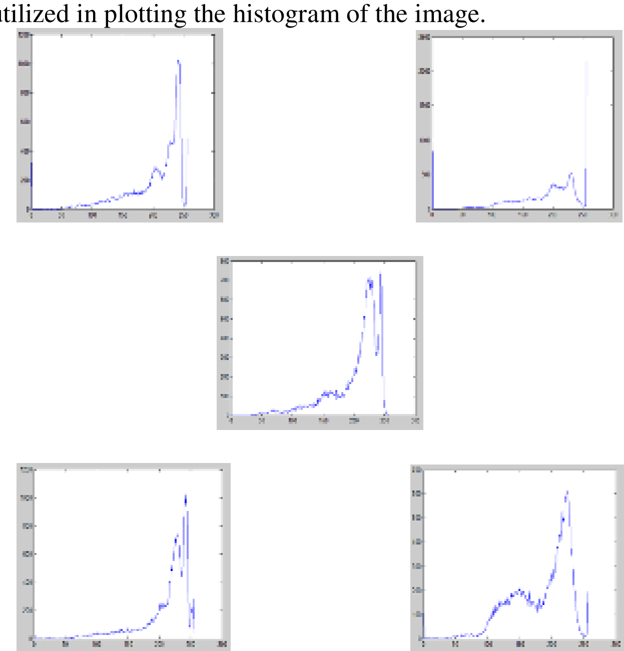

Fig. 5. Luminance Histogram of the Genuine 500 INR Banknote (2×2 partition)

The Figure 5 shows the luminance histogram of all the five partitions from the 2×2 partition of 500 INR Genuine Indian banknote.

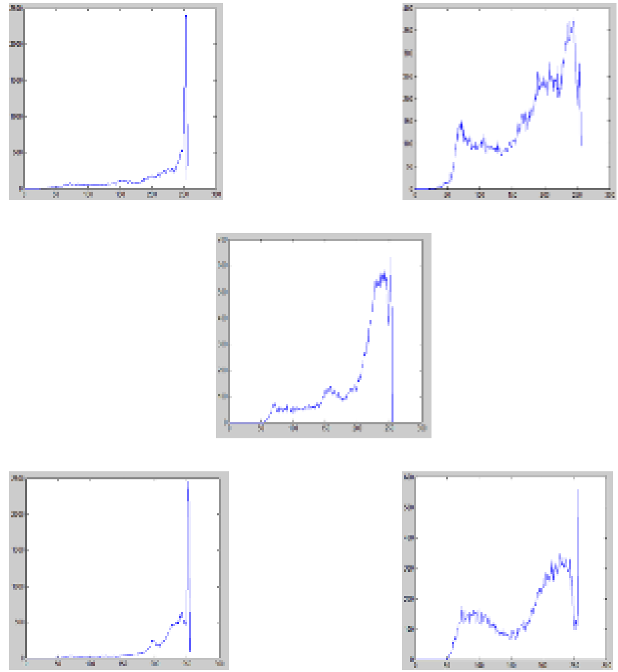

Fig. 6. Luminance Histogram of a counterfeit 500 INR Banknote (2×2 partition)

The Figure 6 shows the luminance histogram of all the five partitions from the 2×2 partition of 500 INR Counterfeit Indian banknote.

*2. Gray Level Co-Occurrence Matrix*

It represents the co-occurrence of the intensity value of pixels in an image. The texture features derived from the GLCM are Contrast, Correlation, Energy, and Homogeneity.

i. Contrast

Contrast is a measure of the intensity contrast between a pixel and its neighbor over the entire image.

ii. Correlation

Correlation is a measure of how correlated a pixel is to its neighbor over the entire image.

iii. Energy

Energy is the sum of the squared elements in the GLCM.

iv. Homogeneity

Homogeneity is a value that measures the closeness of the distribution of elements in the Gray Level Co-Occurrence Matrix to the GLCM diagonal.

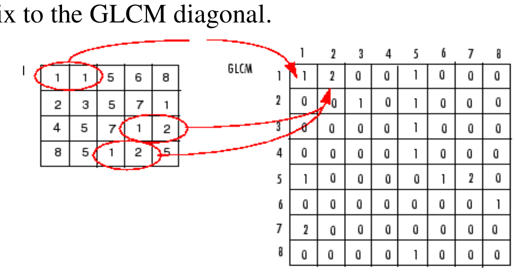


Fig. 7. Process used to create the gray level co-occurrence matrix

 

For each partition, 256 features of luminance histogram and 4 features of GLCM are derived. Combining these features, a feature set of 260 features is found for each partition.

### *D. Classification using Support Vector Machines*

The support vectors are training samples which define the optimal separating hyper plane between two classes. The support vectors are (equally) close to hyper plane. The goal of a SVM is to find the particular hyper plane for which the margin of separation p is maximized. We use 256 bins for each histogram and 4 texture features for GLCM. In this way, an input vector of size 260 is formed. From each partition of the banknote, 260 features are extracted and given as an input to svm classifier. Multiple svm classifiers are used for training and testing, based on the number of partitions made.

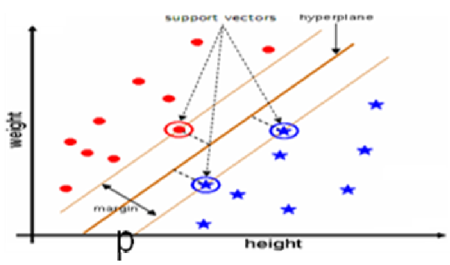


Fig. 8. Support vector machines

Each partition has specific weighted control over model accuracy. In our work, each region segmented is given different weightage. The result is whether the currency is genuine or counterfeit.

## IV. Experimental Results And Analysis

In this work, we compared our recognition system with multiple-SVM classifiers. In a multiple-SVM classifier, each banknote is divided into m × n partitions. A single-kernel SVM was constructed for each partition. Note that the same kernel was used for all partitions of a banknote. By varying the no. of partitions of a currency, the accuracy of the model is tabulated at each level.

Table. 1. Accuracy with three different partitions.

| Indian Currency | Accuracy | | |
|---|---|---|---|
| | 2×2 | 3×3 | 4×4 |
| 5 INR | 75.00 | 87.50 | 75.00 |
| 10 INR | 87.50 | 75.00 | 75.00 |
| 20 INR | 85.71 | 71.42 | 71.42 |
| 50 INR | 91.66 | 83.33 | 91.66 |
| 100 INR | 85.71 | 85.71 | 92.85 |
| 500 INR | 83.33 | 75.00 | 91.66 |
| 1000 INR | 86.60 | 93.54 | 86.60 |

As it has shown in the table 1, 4×4 partition achieves better accuracy for the denominations 50 INR, 100 INR AND 500 INR. And the 3×3 gives better accuracy for 5 INR and 1000 INR. Then the 2×2 partition provides good accuracy for the denominations 10 INR and 20 INR.

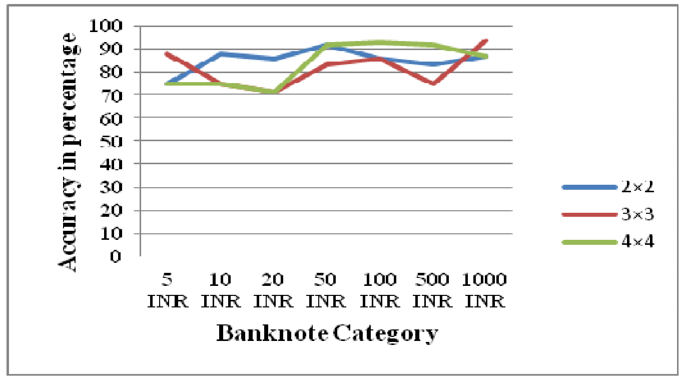


Fig. 9. Performance of multiple SVM with 3 different partitions

## V. Conclusion

Most of the existing systems of counterfeit detection being hardware related and costly, this work provides a reliable solution in detecting the counterfeit banknotes in a cost effective soft computing way. The system achieves the overall performance of 87.85%. Our system has one big advantage. Suppose if more counterfeit preventive features are added as safety features to the banknotes, our system will still be able to distinguish between genuine and forged banknotes without any modification.

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