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Machine Assisted Authentication of Paper Currency: an Experiment on Indian Banknotes

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Abstract Automatic authentication of paper money has been targeted. Indian bank notes are taken as reference to show how a system can be developed for discriminating fake notes from genuine ones. Image processing and pattern recognition techniques are used to design the overall approach. The ability of the embedded security aspects is thoroughly analysed for detecting fake currencies. Real forensic samples are involved in the experiment that shows a high precision machine can be developed for authentication of paper money. The system performance is reported in terms of both accuracy and processing speed. Comparison with human subjects namely forensic experts and bank staffs clearly shows its applicability for mass checking of currency notes in the real world. The analysis of security features to protect counterfeiting highlights some facts that should be taken care of in future designing of currency notes.

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1 Introduction

The problem of large scale counterfeiting paper currency poses a serious threat to our society as large amount of fake notes causes economic instability. Counterfeiting of currency notes affects the existence of the monetary equilibrium as its value, velocity, output and welfare may get affected. Most countries that use paper currency for transactions are plagued by this problem. Several media [1] [2] reports highlight the alarming rate at which this counterfeits are increasing, the seriousness of the issue, as well as the continuous government efforts to curb this problem [3]. Unfortunately counterfeiters also adapt to the new security features that are incorporated. Criminals continue to find ways to replicate the currency despite the new banknote security features in place. There have been leaps and bounds in the technical field of counterfeit currencies, and this together with the recent advances in the digital scanning and copying techniques has been an indomitable force. This has moved the European Union legislators to draft new guidelines so that computer and software manufacturers are to be forced to introduce new security measures to make it impossible for their products to be used to copy banknotes [4]. However, it is almost impossible to track and stop all of the counterfeiting efforts and hence, we need to deploy better authentication systems that carefully scrutinize notes before allowing them to circulate.

The bank staffs are specially trained to detect counterfeit notes and so far they do it manually as the sorting machines are not able to do this job. The technology based on which sorting machines work is limited to image based scanning, which is not foolproof when it comes to detection of fake currencies. The technology for sorting banknotes does not take into consid-

eration the high intricacies involved into security features, physical and chemical properties of papers, inks, resins, chemical, etc. used to print the currency notes and therefore, they are often unable to distinguish the slight discrepancies between fake and genuine notes.

Sometimes the forensic experts (i.e. the questioned document examiners) are involved to give their opinions on suspected notes. Existing methods for detecting and confirming the fake notes is too cumbersome as this involves filing a case to the police, sending the document for verification and then waiting for results to come. On the other hand, the vast traffic actually calls for the introduction of machine authentication of currency notes [5], [6]. Forensic agencies are always on the lookout for systems that track these forgeries using automated techniques and give a complete analysis of the error report of the note in question. This analysis is of particular interest to the community as they would understand the robustness of the security features and on which features to work on in future note design. Further the speed introduced to the process due to automation will help in handling the huge volume of paper currencies. Machine authentication technique could also ensure that fraudulent samples are not passed via ATMs and other cash delivery systems [7]. Even currency note counting or sorting machines may have such equipment installed that looks to trap the counterfeit currency note that might appear. This would trap the fake notes that are circulated in the public directly by the counterfeiters.

Our research is directed to this end. It attempts to provide a complete automated approach for detection of counterfeit currency notes. Also a thorough analysis is provided that explores the performance of the embedded security features and their sensitivity. This analysis helps the regulatory bodies understand which security feature are under what kind of threat of breach and what modifications could be done to improve the design, making it less vulnerable to counterfeiting. Detailed experiments were done with real data to support the claim. A comparative study is also reported, involving forensic document experts and bank staff to show the applicability and robustness of the system at a grass root level.

1.1 Previous Work

Research on manufacturing secure currency notes is indeed an old subject. Because of the commercial nature of this research lots of research studies were patented rather than published in scientific journals. U.S. Patent issued in 1857 [8] may be the earliest attempt of an optical method of manufacturing secure paper money. It

involved using paper tinted to absorb light, and printing ink that also absorbed light rather than reflecting it so that clear photographic copies could not be made. Many researchers assumed that the embedded watermark and security thread are hard to duplicate and filed patents on how to authenticate the watermark and or security thread [9], [10] and [11]. The patent in [12] described an approach that is based on the reflective property of the bank notes in question. A series of light source is placed that provides wavelength of varying illumination, which is used to measure the reflective and refractive response of the currency note images. This data is then compared with the pre-calculated data on original and fake notes to report the authenticity of the notes. On the other hand, the patent in [13] proposed a method to verify US currency notes by analysing different aspects of the ink used for printing.

Because of the commercial interest, the patents express little technical and experimental details and this has restricted the research community to judge the performance of the systems. On the contrary, the researchers reporting details of their methods and experiments have so far dealt with recognition of currency notes. They address the problem of recognizing currency of different countries (U.S. dollars, Euro notes, etc.), and different denominations for a given currency. For this purpose, Neural Networks [4], [8], [9], [14], [15], and [16]; Genetic Algorithm [17] and Hidden Markov Model [18] have so far been used. These studies have successfully addressed the currency or denomination recognition problem but did not consider whether the input bank note is genuine or fake. There are a few studies which address this problem and give details about their methods and experiments. The paper in [19] is an example. In this article, the authors proposed a semi-automatic approach for characterizing and distinguishing original and fake Euro notes. Their method is based on the analysis of several areas of the banknotes using a Fourier transformed infra-red spectrometer with a microscope with an attenuated total reflectance (ATR) objective. They considered four different regions of a note and observed that fake notes are easily identifiable from the analysis of the spectra corresponding to the four regions. However, the authors did not propose any automated scheme for authentication.

Later on, the authors in [20] describe another system for authenticating Bangladeshi Bank Notes. They assume that original currencies under test have the bank name printed in micro letter print. They scan this part (the region where the bank name should be) using a grid scanner and the textual images are fed in an optical character recognition engine that matches characters with prototypes. Since the fake currencies are as-

sumed not to have the text they show very low matching percentage. The algorithm is heavily dependent on one feature which makes the system very sensitive. The system would fail miserably if the counterfeiters happen to develop means of duplicating the feature in question.

Very recently, a commercial system [21] is available in the market for detecting fake notes. In order to authenticate a paper currency, the system makes use of several hardware components like light intensity compensation circuits, magnetic level circuits, visual light sensors, Infra-Red ray sensors, Ultraviolet Ray Sensors and many other technical light sensors. These hardware components function simultaneously and compare crucial security features like ones from the based materials like paper, ink, security thread, fluorescent resins, micro prints, secret watermarks, intaglio patterns, etc., against the data stored in standard memory bank. The memory bank keeps information about the characteristics of genuine and counterfeit notes. For a given note, if the features match to those of the real ones, the system passes the note as genuine. If any difference is spotted, the machine saves the features match those of counterfeits and these notes are rejected. In case of no match either with genuine note or with counterfeit notes, the notes should be identified as genuine but worn out and hence machine passes it as genuine in case of normally worn out notes.

1.2 Contribution of our Work

After reviewing the literature we find that there have been little studies reporting technical and experimental details on how to automatically authenticate currency notes. Many studies rely on one or two features that also can be duplicated using today's high end technology. As there are so many security features in the currency notes, analysing only a certain aspect of the note security may not be a good choice. A complete integrated framework has been missing that looks into many aspects like security features in printing, ink, background artwork, watermark, security thread, etc. Another general shortcoming in the existing studies is the use of synthetic data. Many authors generate samples at lab to test their algorithms. Therefore, performances of these algorithms on real forensic samples are yet to be explored.

Earlier, we provided conclusive evidence of decision making using printing techniques [22], but the approach looked only on the printing process and dealt with a small database to test the initial system performance. In this paper, we have incorporated several other security aspects based on ink, security thread and an

art work based feature set that supplements the printing style based approach. A large dataset comprising of 1000 notes (500 for each genuine (G) and fake (F) class) has been used to test the system performance and a thorough analysis is provided by comparison with real forensic document examiners to show the applicability of our research in the real world scenario. Analysis is also done to report the speed of the system. Popular pattern recognition tools like the k-means, neural network and support vector machines are used to demonstrate the system performance. We have also shown the robustness of each feature in tackling the problem and thus pointing out the sensitivity of the features. The feature level analysis brings out important views that the note designing agencies could keep in mind regarding the susceptibility of the features to be duplicated. A sequential ordering of security features is also suggested that should be maintained while testing to maximize the performance accuracy. Involvement of real forensic samples is another significant aspect of this study. Indian bank notes are taken as a reference. In fact, because of highly heterogeneous concepts involved with Indian currencies, authentication of these notes poses a big technical challenge.

2 Security features of Indian Bank Notes

The impact of the document and its mobility as a transaction medium determines the amount of security in place for its protection. There have been a lot of research studies for providing security in paper documents [23]. Bank notes being the principal monetary exchange medium do have a lot of security features to prevent counterfeit [24]. The Apex bank of every country is responsible for placing these security features to prevent forgery. In India it is the responsibility of the Reserve Bank of India (RBI) [25]. The security features in a currency note are mainly on its paper, design and printing. Authentication of currency notes is thus refer to authentication of the following areas: i) Currency notepaper, ii) Currency note printing technique, iii) Ink used for currency note printing, iv) Currency note design, v) Other security features (e.g. the thread, the registration mark, and many others) that are intentionally incorporated to check the authenticity. These security features provide a tough challenge to the counterfeiters who attempt to replicate them. Important security features are associated with the currency notepaper itself. Physical features of currency note are based on its cut size of length, width, grammage and thickness of paper. The paper has a unique feel, crackling sound and it is constituted of high quality with 100% cotton or wood pulp lending a particular color, a unique

fiber length, surface finish, a typical opacity, and its capacity of extra strength of folding. Watermarks and security thread are another important parts of security aspect of paper money. Important property of watermark is that it cannot be replicated on scanning or by photocopy equipment. Examination of watermarks checks its design, size and thickness using transparent light. The security thread appears to the left of the Mahatma Gandhi portrait is partially embedded and partially visible. On seeing this thread with an ultraviolet light exposure the thread appears in a single line. This is also a proof of the registration of the note that both the sides of the note are properly aligned. This thread has the writings of “RBI” and “Bharata” (India) in Devanagari alternatively written on it. Denomination of a note (e.g. 500, or 1000) is also embedded in the thread. Fig. 1 shows the significant security features embedded in both sides of a 500 Rupee note (source: Reserve bank of India).

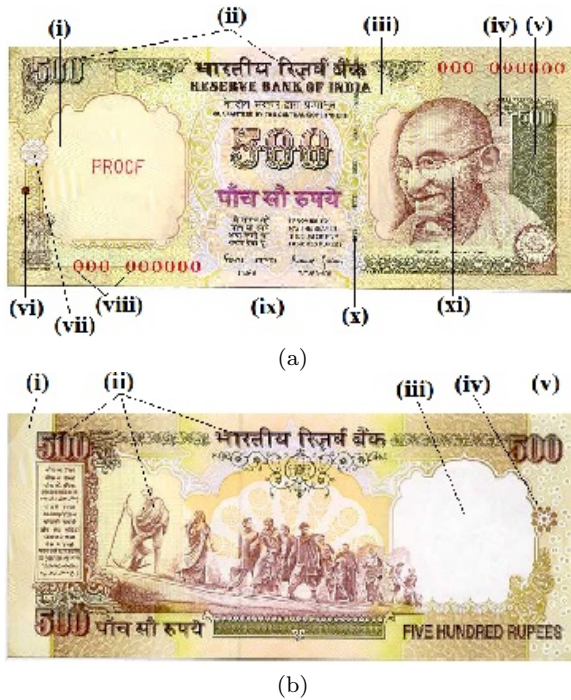


Fig. 1 Significant security features in Indian banknote: (a) Front side features: (i) Multidirectional artisan lines, (ii) Intaglio printing, (iii) OMR, (iv) Micro text, (v) Latent image, (vi) Blind mark, (vii) See through, (viii) Fluorescent ink numbers, (ix) Optically variable ink, (x) Security thread with clear text, and (xi) Hand graved portrait; (b) Back side features: (i) Multi-directional artisan lines, (ii) Intaglio printing, (iii) Gandhi water mark, (iv) See through, and (v) OMR features.

A lot of important security features are involved in the design of currency note. The Guilloche design, portrait design, micro lettering, type face, font size, color,

see through register, anti-scan lines, Braille mark, rainbow effect, layers of CYMK, bleeding effects, latent image effects, etc. all are involved as part of security design. Another level of distinction of currency notes is the printing process. Among the numerous printing processes that can be used for printing currency note only a few processes are used for printing of Indian currency notes. Among them intaglio printing is of prime importance because of the typical signature it leave and it being hard to duplicate. The basic components of printing ink are pigment, solvent, and drier. Where ink pigment is responsible for color effect on substrate, drier is responsible to bind ink pigment to substrate and solvent is responsible for solubility of ink pigment and drier. Examination of final printing effect is an important aspect for verification of security document authenticity. Final effects on currency note are defined by unique color, impression, water resistance, line work (width, thickness, sharpness, etc.), halftone effect, digitized patterns and also reflectivity and feel/tactility.

3 Overview of the proposed method

The proposed method is based on image processing [26] and pattern recognition principles [27]. The feature extraction in this experiment is largely dominated by the input from the forensic experts making sure that every aspect of the security features is considered when choosing features. As all the features used by the experts [28] cannot be captured computationally, a subset of the features is used. Some new features which are effective for detecting fake notes, but are difficult to check manually, are also added. The feature space is analysed and visualized by using clustering technique. The decision making process is built using two different classifiers: i) Artificial Neural Networks (ANNs) ii) Support Vector Machines. Furthermore, a Linear Discriminate Analysis is used to measure the performance of each feature. Our feature extraction process considers four different security aspects of the banknote: i) printing technique, ii) Ink property, iii) Thread and (iv) the Art work used in designing the note. The features and rationales behind choosing them are explained below.

3.1 Preprocessing

Different security features are available at different parts of the banknote image. So the initial scanned image needs to be divided into distinct ROIs. The image of the currency note is registered using Hough Transform on a Canny edge detected image (Fig. 2(a)). Template matching of the denomination (“500”/“1000”) and the

Mahatma Gandhi portrait generates two fixed positions as reference around which the rest of the ROIs are extracted (Fig. 2(b)).



Fig. 2 Preprocessing steps: (a) Image registered using Hough Transform (b) Extracted ROI (i) matched portrait(red)(ii)matched denomination(red) (iii) ROI from latent image(blue) (iv) microprint lines(blue) (v) Intaglio print(blue) (vi) Central pattern(blue) and (vii) Security thread(blue).

The horizontal strip just above the registered portrait of Gandhi is used to segment the intaglio fonts. Text extraction from this part is done using the vertical and horizontal pixel projection techniques (Fig. 3). The biggest black pixel blob in the image is the area to be focussed for the extracting features using latent scan. A vertical strip just beside the denomination is used for the security thread based measures and finally the region between the registered Mahatma Gandhi portrait and the largest black blob is used for the micro-print line features.



Fig. 3 Text extraction using pixel projection: (top) Black pixel projection on x-axis, (bottom) the horizontal strip used to separate Intaglio fonts in English.

3.2 Features

3.2.1 Printing Technique

Intaglio printing is used for printing currency notes in India. The denomination of the note and “Reserve Bank of India” are printed on the face of the notes and are always printed using the Intaglio method. This method of printing leaves several signatures that are hard to replicate [28]. We have analysed some of the features and tried to differentiate the fake notes from the genuine ones based on printing technique detection. Following are the features used in detecting printing technique.

Dominant intensity (f_p^1) is used to capture slight difference in brightness (or glossiness) of banknotes. Mathematically this is represented as follows,

$$f_p^1 = x : f(x) = \max(\text{intensity histogram}). \quad (1)$$

The feature, Hole count (f_p^2) checks the textural similarity of the printed character strokes in a note by counting the number of eight connected white pixel cluster (defined as hole) divided by the area of the character stroke as shown in Eq.(2),

$$f_p^2 = \frac{\#8 \text{ connected white patch in char strokes}}{\text{Area of character stroke}}. \quad (2)$$

Average hue (f_p^3) gives an assessment of the quality of color. This feature is computed in HSV space on the Hue (H) stream as follows,

$$f_p^3 = \text{Average}(H). \quad (3)$$

R.M.S. contrast (f_p^4) in Eq.(4) measures the varying difference in brightness of the two classes (Genuine/Fake) of notes. Mathematically it is expressed as follows (where I_i and \bar{I} denote the intensity of the i -th pixel and the mean intensity, respectively),

$$f_p^4 = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (I_i - \bar{I})^2}. \quad (4)$$

The key tone (f_p^5) value gives us the information about the intensity zone where most of the information is stored by calculating the mean of the intensity profile of the character stroke after masking as given below,

$$\text{Image} \rightarrow \text{Masked character} \rightarrow f_p^5 = \text{Mean}(\text{Intensity}). \quad (5)$$

Average color (f_p^6) assesses a reconstituted color matrix based on a scalar parameter (p). This checks the color composition of the print according to the note issuing authority of India. For instance, the principal streams in Intaglio character stroke are blue and black in 500 denominations. The average color is computed as below,

$$f_p^6 = \frac{\sum s(i)}{N} \quad (6)$$

where $s(i)$ is defined as

$$s(i) = pB_{\text{blue}}(i) + (1 - p)B_{\text{black}}(i), 0 < p < 0.5$$

and B_{blue} and B_{black} correspond to blue and black strokes, respectively.

Along with these six features, three other features are extracted: edge roughness E_{PBER} , (f_p^7) (Eq. 7), area difference (f_p^8) (Eq. 8) and correlation coefficient (f_p^9). These features are computed based on the work of Breuel et al. [29], [30]. The edge roughness is computed as

$$f_p^7 = E_{\text{PBER}} = (p_a - p_b)/p_b \quad (7)$$

where p_a is the perimeter of the original image, p_b is perimeter of the filtered (median filter) binary image and E_{PBER} is the perimeter based edge roughness. In calculating this feature, the character image is first binarized using Otsu threshold value (say, T) (A_{otsu}) and then the same image is again binarized using a different threshold value that is calculated by adding a normalized parameter sc to T ($A_{\text{otsu}+sc}$). The area difference is computed as

$$f_p^8 = \text{Area Difference} = \frac{|A_{\text{otsu}+sc} - A_{\text{otsu}}|}{A_{\text{otsu}}}. \quad (8)$$

The correlation coefficient is computed as

$$f_p^9 = \frac{\sum_{(i,j) \in \text{ROI}} (A(i,j) - \bar{A})(B(i,j) - \bar{B})}{\sqrt{\sum_{(i,j)} (A(i,j) - \bar{A})^2} \sqrt{\sum_{(i,j)} (B(i,j) - \bar{B})^2}} \quad (9)$$

where $(i,j) \in \text{ROI}$, A is the original gray value image, B is the corresponding binary image, \bar{A} and \bar{B} are the mean of A and B , respectively.

Based on the above nine features, classifiers are trained to identify fake notes based on printing technique.

3.2.2 Ink Properties

The reaction of the ink on a particular substrate is different for different inks. This difference actually lends a typical signature indicating the authenticity of a note.

CCRatio (f_i^1) Colour composition of the central zone (Fig. 4) of a note is analysed by doing an independent component analysis. This was followed by a filtration method that keeps those pixels ON where the green component index in the RGB color space is higher than the blue component index which is in turn higher than the red component index to generate a mask. Computationally it is represented by color composition ratio (*CCRatio*) feature which is defined as

$$f_i^1 = \frac{\# \text{ON Pixel in mask}}{\# \text{Pixels in mask}}. \quad (10)$$

The number of pixels are fixed as the images are registered using a 4-point registration prior to processing.

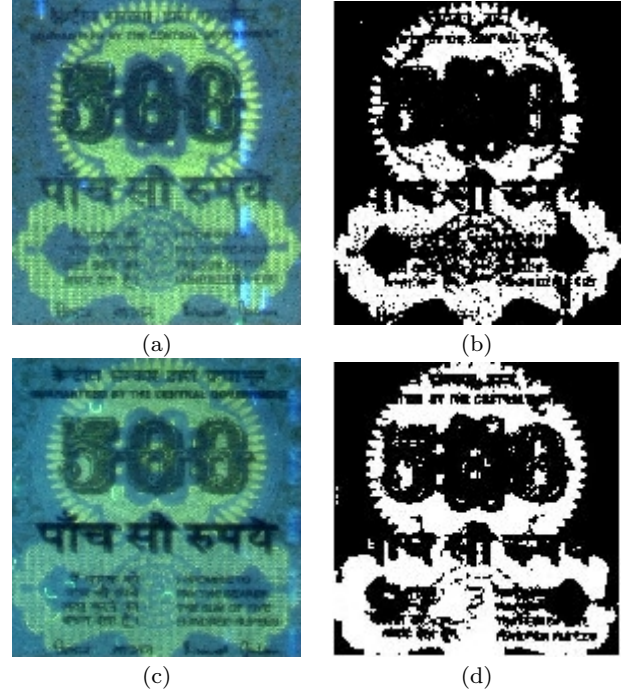


Fig. 4 Analysis of colour composition: (a) and (c) UV scans of fake and original image; (b) and (d) are resultant images from the left hand side counterparts after filtration to check colour composition.

Micro letter (f_i^2) This feature appears between the vertical band and Mahatma Gandhi portrait in the notes. In notes of denominations 20 and above, the denominational value and “RBI” constitute the micro letters. In our study, we have looked into the colour of these micro letters. The RGB values are first transformed to a specific absolute colour space. This adjustment makes the resulting data device independent. The masked image was changed from RGB to $L^*a^*b^*$ colour space using the CEILAB Illuminant D65 as a reference [31]. The resultant distribution of b^* index is plotted in Fig. 5. The difference (visually) between genuine and fake notes is seen. Computationally, spread of the index distribution is captured as the feature f_i^2 by calculating the standard deviation (spread) values of the b^* index distribution as formulated below,

$$f_i^2 = \text{Spread} = \sqrt{\frac{\sum_{i=1}^N b_i^* - \bar{b}^*}{N - 1}}. \quad (11)$$

Ink Fluidity (f_i^3) It is observed that the ink used to print genuine currency notes blot considerably greater than the counterfeit ink. The study of fluidity of ink as a vision based feature was done by K. Franke et al. [32]. Following this study we developed a feature that would computationally help in decision making about the ink

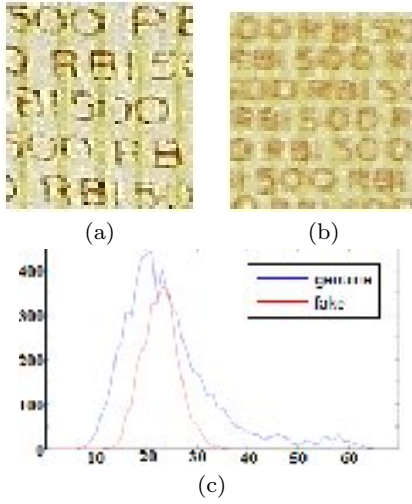


Fig. 5 Analysis of micro lettering: (a) genuine banknote, (b) fake banknote; (c) b^* stream index plot of genuine (blue line) and fake (red line).

authenticity. Edges of the print were taken and the intensity profile was plotted (Fig. 6). We then normalise the curve using an averaging kernel. A steady value is computed in Eq. 12 as follows. Let $f(x)$ be the *number of pixels having intensity x* , $\forall x \in X = \{x_1, x_2, \dots, x_n\}$, where x_1 refers to the intensity value corresponding to maximum pixel count and $x_k = x_{k-1} + 1$. We define $\nabla f(x)$ as $\nabla f(x) = f(x_{k+1}) - f(x_k)$, $0 < k < n - 1$ where $x_n > x_{n-1} > x_{n-2} > \dots > x_2 > x_1$.

The $\nabla f(x)$ vector would always start with a negative quantity as the very first value in this vector is the difference from the highest pixel count. The first positive entry is found (x_p) and the steady value is generated as follows,

$$steady = \frac{\sum_p^n f(x)}{n + 1 - p} \quad (12)$$

where p is the position of the 1st positive entry.

The percentage overshoot is then recorded as a feature using the steady value in Eq.(13) and computed as follows,

$$f_i^3 = \frac{overshoot}{steady} = \frac{max}{steady} - 1. \quad (13)$$

3.2.3 Thread

Two security thread related features are considered: the registration of the notes and the text in the security strip.

Registration (f_t^1) The thread should always appear as a single line. This is a way to test of the registration of the notes. We check this using a binary feature, f_t^1 ,

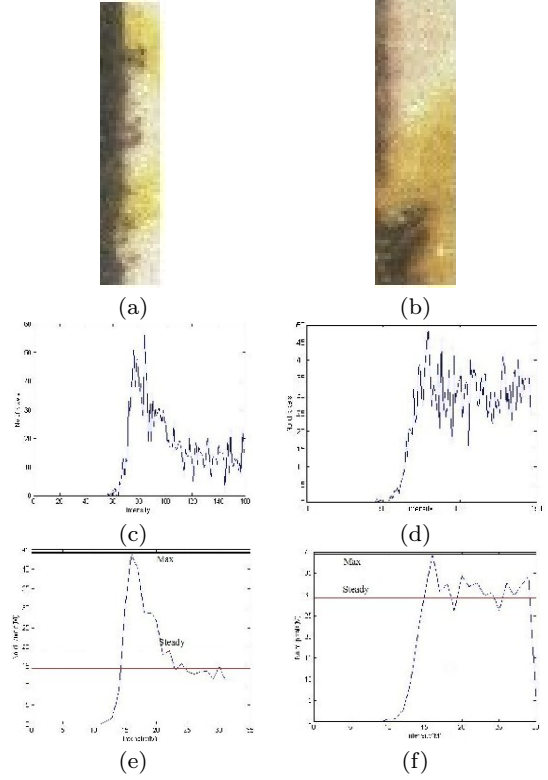


Fig. 6 Ink analysis: (a) Genuine ink spread, (b) Fake ink spread, (c) Histogram of genuine ink, (d), Histogram of fake ink, (e) Normalized graph with steady value (genuine ink), and (f) Normalized graph with steady value (fake ink).

which decides whether a note is genuine ($G = 1$) or fake ($D = 0$). Two sets of thick blobs are found (refer Fig. 7(i)b), one represents the thread parts seen from the front while the other represents the thread parts on the back of the note. Two lines, one for the front and the other for the back, are fit through the centroid (c_x, c_y) points of the corresponding blobs. The centroid of a blob is calculated using the following formulae where A be the area of the blob.

$$c_x = \frac{\sum_{i=0}^{n-1} (x_i + x_{i+1})(x_i y_{i+1} - y_i x_{i+1})}{6A}$$

$$c_y = \frac{\sum_{i=0}^{n-1} (y_i + y_{i+1})(x_i y_{i+1} - y_i x_{i+1})}{6A}$$

This is followed by a distance check of the lines using a threshold distance t , empirically computed from 100 note samples.

$$d(t_f, t_b) < t, \quad \text{Genuine,} \\ >= t, \quad \text{Fake.} \quad (14)$$

where t_f = foreground line points, t_b = background line points.

The feature, f_t^1 is a binary feature which generates a decision based on Eq. 14. Fig. 7(i) shows the registration problem of thread in a fake note.

Text in Thread (f_t^2) This is another binary feature that checks whether thread texts exist. The texts RBI and “Bharat” (Hindi for India) in Devanagari script are written on original notes where these two words appear alternatively. We extracted the text portion from the threads and then used conventional pattern matching tools to compare. There were only 4 such texts patterns as shown in Fig. 7(ii)(a-d) to compare so the templates were extracted from the original image and then used to as ground truth data for pattern matching. Majority of fake notes showed negligible matching because they do not have any text as shown in Fig. 7(ii)(f).

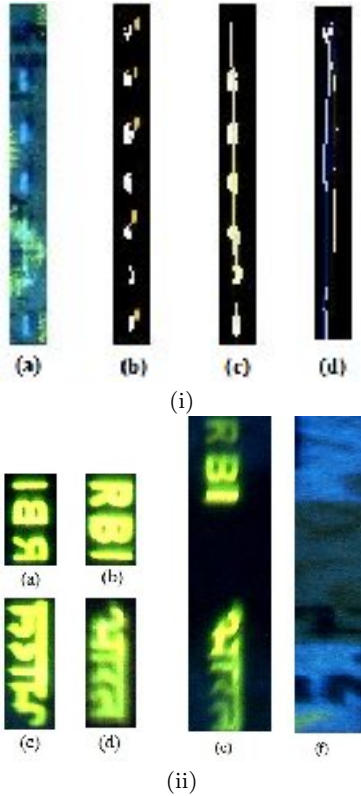


Fig. 7 Analysis of security thread: (i) Security Thread: (a) fake note image (b) thick blobs representing the thread on the front (c) line in front (d) two lines which do not overlap; (ii) Text in Security Thread: (a)-(d) four occurring patterns (e) original note (f) fake note.

3.2.4 Art Work

This section deals with printing patterns that are intricately introduced in note design to prevent the counterfeiters from replicating them. Initially the image is passed through a median (3×3 sub window) filter to remove impulsive noise. Next, the centroid of each dot is mapped as shown in Fig. 8. The three features described below are extracted and analysed.

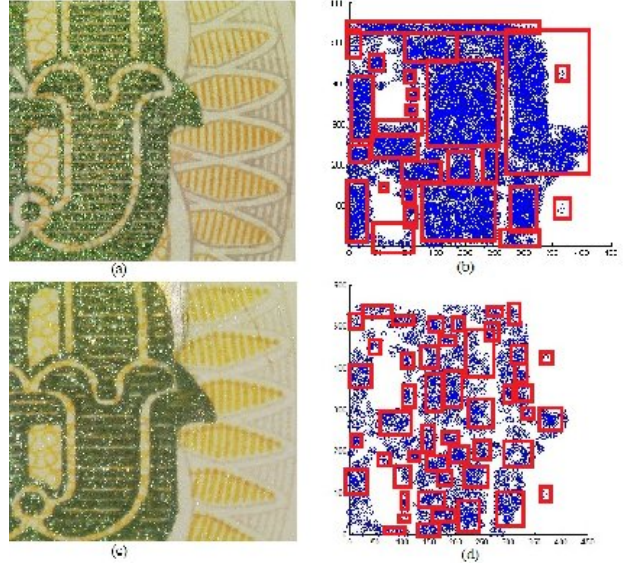


Fig. 8 Analysis of dot distribution: (a) Genuine note (b) distribution of dots centroids for the genuine note (c) Fake note (d) distribution of dot centroids for the fake note.

Dot distribution (f_a^1) The distribution of the dot centroids gives us the impression that in the fake note the distribution of the dots are far less uniform when compared to the genuine notes. Entropy count provides a measure of this randomness. The entropy (H) is calculated as a feature, f_a^1 , and the following equation measures it as

$$f_a^1 = H = - \sum_{i=1}^n p(x_i) \log p(x_i) \quad (15)$$

where n is the number of dots.

Cluster distribution and dot density features (f_a^2 and f_a^3) We also compute the number of clusters occurring at the character strokes of the letters. An unsupervised agglomerative hierarchical clustering scheme is used with a Euclidean distance check to calculate the number of clusters. Let C_1 and C_2 be the two clusters and d is the distance matrix, then $\max\{d(x, y) : x \in C_1, y \in C_2\}$. An iterative process continues until the separation of the clusters exceeds a threshold (indicated by a Euclidean distance). Cluster density f_a^2 is defined as

$$f_a^2 = \frac{\# \text{Clusters}}{\text{Area of Character Stroke}}. \quad (16)$$

From the Fig. 8 it is evident that the original notes have a more even distribution of dots and far more dots in the character stroke. This difference in the dot count is used as another simple feature which gives the dot density, f_a^3 as,

$$f_a^3 = \frac{\# \text{dots}}{\text{Area of Character Stroke}}. \quad (17)$$

Adaptive Otsu threshold removes most of the background leaving only the character stroke whose area is calculated.

Reading Latent Denomination (f_a^4) When viewing the strip left to the Mahatma Gandhi's picture, the denomination of the note is seen engraved quite distinctly. The machine readability of these denomination digits is measured in Eq. 18. This zone comprises of two sets of lines- horizontal and vertical. The vertical lines represent the text part. The sharpness of the lines is different in the two categories of notes (genuine vs. fake) lending them different readability index f_a^4 which is defined as $f_a^4 = \text{Score of NN classifier}$. (18)

An MLP-NN classifier was trained with digit samples taken from the genuine notes. The vertical lines need to be extracted for the text to be read properly so we use a 3×3 convolution matrix (CM)

$$CM = \begin{bmatrix} -2 & 4 & -2 \\ -2 & 4 & -2 \\ -2 & 4 & -2 \end{bmatrix}$$

that reduces the number of horizontal lines in the image and strengthens the vertical lines.

The image that results from this operation has a lot of clutter and noise (Fig. 10(b)). A particular component tag is assigned to each 8-connected cluster and the number of pixels in each cluster is recorded. Fig. 9 shows the histogram of component size vs. component tag. A threshold is selected from this histogram to eliminate most of the clutter. This method brings out the latent information from the image. Fig. 10(c) shows the resultant image after thresholding.

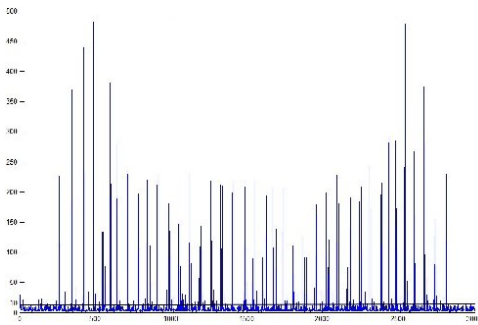


Fig. 9 Component size (along the y-axis) vs. Component tag (along the x-axis).

4 Experiment

Experiment is conducted to check the validity of the proposed approach. Real life forensic samples are con-

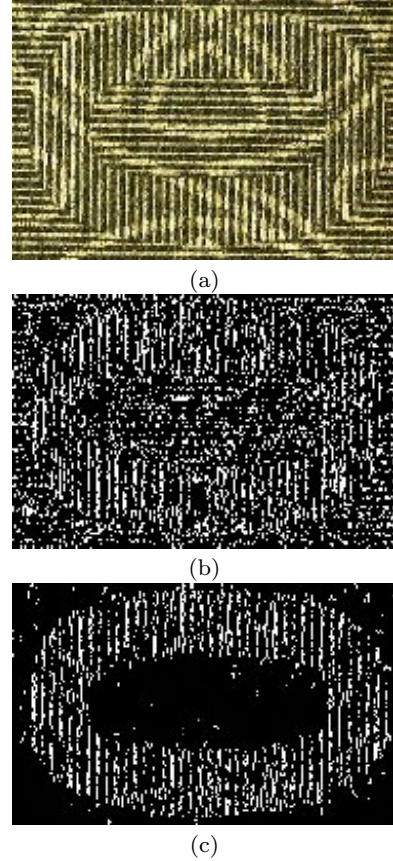


Fig. 10 Analysis of latent image: (a) Image of genuine note, (b) after convolution, (c) after filtration.

sidered in this experiment. This section explains the data set, the capturing conditions, our experimental strategies, and finally, the results.

4.1 Dataset

This work considers the real data that was collected from the forensic department of India. The dataset has a total of 500 original and 500 fake note images scanned into jpeg format. The scanning involves different medium as explained in the next section. Forensic experts received the fake notes at different times and from different groups. From their experience they note that a particular group shows a particular kind of proficiency making fake notes. Therefore, only few fake note samples were considered for a particular group. Fake note samples from any such groups are considered so that samples show a wide variety and diversity in counterfeiting features. Two denominations namely 500 and 1000 (1000 being the highest denomination for Indian bank notes) are considered as fake note makers mostly target these two denominations. The experts encounter the highest number of fake notes for denomination of

Table 1 Capturing Conditions

Condition	UV Scan	Latent	Flood	
			I	II
Light Source	365nm UV	Co-axial	100%	100%
Long pass	VIS	VIS	VIS	VIS
Band pass	OFF	OFF	OFF	OFF
Magnitude	2.069	9.64	29.97	40.08
Gain	12dB	1 dB	0 dB	2 dB
Iris	73%	50%	64%	64%
Integration	$\frac{1}{4}$	$\frac{1}{8}$	$\frac{1}{8}$	$\frac{1}{8}$

500. The dataset also considers 500 and 1000 denominations in a ratio of 7:3.

The entire dataset is divided into two sets. The **Set 1** consists of 500 fake notes and 500 original notes. This was used to train, test and validate the system performance and analyse the accuracy of the features. **Set 2** consisting of 200 fake notes and 200 original notes randomly selected from the **Set 1** and were used to test the system in comparison to forensic experts and bank staff. Since forensic experts were involved the set was deliberately kept small as it took quite some time for them to deliver results by following the existing manual process.

4.2 Capturing conditions

In our experiment, four different scanning techniques: (i) UV Scan, (ii) Latent, (iii) Flood I and (iv) Flood II, are used to get image of a currency note. Different regions of a note are scanned under different techniques. For example, the central design of the note appears prominent under ultraviolet (UV) ray, hence, this region is scanned with UV ray. There are latent marks on the side of a note. The parameters of the cameras used for imaging are given in Table 1. As explained in Section 3, the proposed method captures several features in order to authenticate a note. All these features are not extracted from the same type of scanning medium. Four different scans give different features as listed in Table 2. It is noted that while scanning different regions of a note under different capturing conditions, we have used only one wave length of the light source. This would lead to a relatively low cost adaptation of our proposed method as most of the commercial systems and patents (as discussed in Sec. 1) have extensively used high cost multiple light sources of different wavelengths.

4.3 Experimental Strategies

The authentication of notes is modeled as a 2-class classification problem: discrimination of genuine (denoted

Table 2 Source of features

	Features	Captured from
INK features	CC ratio, f_i^1	UV Scan
	Micro letter, f_i^2	Flood I
	Ink fluidity, f_i^3	Flood II
Thread features	Registration, f_t^1	UV Scan
	Thread text, f_t^2	UV Scan
Artwork features	Dot distribution, f_a^1	Flood I
	Cluster distribution, f_a^2	Flood I
	Dot density, f_a^3	Flood I
	Latent denomination, f_a^4	Latent
Printing features	All the nine features related to printing techniques	Flood II

by **G**) vs. fake (denoted by **F**). Different groups of features are taken into account to accomplish this classification task. The feature groups, as discussed in the previous section, are based on Ink, Thread, Artwork and Printing technique. Each feature group is used in a bi-clustering of the feature vectors to visualize their distribution in the feature space and then again for classifying the samples by Support Vector Machines (SVM) and Artificial Neural Network (ANN) scheme. Four-fold cross validation method is followed using both the SVM and ANN based classification. The data set is divided into 2:1:1 ratio to generate training, validation and test sets. The relative robustness of the individual features is measured and Linear Discriminant Analysis (LDA) is used to provide a comparative performance analysis of the feature groups.

Classification with SVM makes use two kernels (polynomial kernel and RBF kernel). Mean squared error (MSE) is computed as follows: $MSE = \frac{\sum_{j=1}^T \sum_{i=1}^V (d_{ij} - y_{ij})^2}{V \times T}$, where V and T are the number of support vectors and test samples, respectively, d_{ij} and y_{ij} are the desired output and the SVM output, respectively for the i -th support vector and the j -th test sample. The neural network used for classification consists of three input nodes and 2 output or decision nodes with 1 hidden layer. Normal back propagation algorithm has been used for training with an activation function given by $f(x) = \frac{e^x}{1+e^x}$. A gradient descent method is used to find the optimized set of connection weights that are updated as per the following equation,

$$W_{t+1} = W_t + \alpha * \left(\frac{\partial E}{\partial W} \right) |_{W(t)} + \beta * (W_t - W_{t-1}). \quad (19)$$

Next, we use Fisher linear discrimination analysis (LDA) [33] to study the performance of individual features. Suppose ω is the normal to the discriminating hyper plane, $\mu_{y=0}$, $\mu_{y=1}$, are the sample means, $\sum_{y=0}$ and $\sum_{y=1}$ are the covariance matrices of the two classes (*genuine* and *fake*). Now we can consider that for one

class, $y = 0$ for $\omega^T.X + b \geq 0$ and for the other class, $y = 1$ for $\omega^T.X + b < 0$. From these equations, parameter vector ω is computed to maximize class separability criterion and b is the bias, which lies in between the means of the training samples projected onto this direction. The separation between these two distributions is to be the ratio of the variance between the two classes and is given by

$$S = \frac{\sigma_{\text{between}}^2}{\sigma_{\text{within}}^2} = \frac{(\omega \cdot \mu_{y=1} - \omega \cdot \mu_{y=0})^2}{(\omega^T \sum_{y=1} \omega + \omega^T \sum_{y=0} \omega)}. \quad (20)$$

For Fisher LDA, this separation achieves maximum when

$$\mathbf{w} = \left(\sum_{y=1} + \sum_{y=0} \right)^{-1} (\mu_{y=1} - \mu_{y=0}). \quad (21)$$

Finally, the cumulative accuracy taking all the features into consideration is computed and a study is conducted to find out a proper sequence in which the features are to be tested. This is important as this reduces the load of the machine if at various stages the number of notes to be checked could be reduced without sacrificing the accuracy.

4.4 Experimental Results

At first, results are reported based on individual feature groups. The capacity of these features are then analysed in the context of detecting fake notes. Finally, results are reported considering all the features and a sequence by which features are to be checked is highlighted in order to authenticate a bank note in question.

Accuracy of Ink Based Features. There are three ink based features: f_i^1, f_i^2 and f_i^3 . The bi-clustering results on **Set 1** using these three features are shown in Table 3. Table 4 reports the classification results when SVM and ANN, respectively are used as classifiers.

Table 3 Bi-Clustering using Ink Based Features

	#Samples of Genuine (G)		#Sample of Fake (F)		Clustering Accuracy
	G	D	G	D	
Iteration1	478	11	22	489	967 (96.7%)
Iteration2	471	18	29	482	953 (95.3%)
Iteration3	464	22	36	478	942 (94.2%)
Avg.					95.4%

Accuracy of Art Work Based Features. There are four features which are captured from the note artwork: $f_a^1, f_a^2,$

Table 4 Ink Features based classification of Currency Notes using SVM and ANN on Test set

	SVM				ANN
	%Correct		MSE		
	Poly	RBF	Poly	RBF	
Fold1	100.0	94.0	0.491	0.530	100.00%
Fold2	98.0	94.0	0.217	0.219	99.30%
Fold3	98.0	92.0	0.103	0.199	98.50%
Fold4	98.0	98.0	0.064	0.256	96.00%
Avg.	98.5	94.5	0.219	0.301	98.45%

f_a^3 and f_a^4 as discussed in Section-3. Bi-clustering results using these features are shown in Table 5. Classification accuracies by SVM and ANN are reported in Table 6.

Table 5 Bi-Clustering using Artwork Based Features

	#Samples of Genuine (G)		#Sample of Fake (F)		Clustering Accuracy
	G	D	G	D	
Iteration1	476	15	24	485	961 (96.10%)
Iteration2	474	14	26	486	960 (96.00%)
Iteration3	478	18	22	482	960 (96.00%)
Avg.					96.0%

Table 6 Art work based classification of Currency Notes using SVM and ANN on Test set

	SVM				ANN
	%Correct		MSE		
	Poly	RBF	Poly	RBF	
Fold1	99.00	98.00	0.011721	0.00527	100.0%
Fold2	100.00	100.00	0.018473	0.008652	98.0%
Fold3	100.00	99.00	0.012698	0.006285	99.0%
Fold4	98.00	99.00	0.010526	0.008807	99.0%
Avg.	99.25	99.00	0.0133545	0.007253	99.0%

Accuracy of printing based features. A comprehensive study of the printing based features ($f_p^1-f_p^9$) is presented in Table 7.

Table 7 Printing Technique based classification of Currency Notes using SVM and ANN on test set

	SVM				ANN
	%Correct		MSE		
	Poly	RBF	Poly	RBF	
Fold1	100	100.00	0.000121	0.00527	100.00%
Fold2	100	100.00	0.000873	0.008652	99.30%
Fold3	100	100.00	0.01028	0.006285	98.50%
Fold4	100	99.00	0.000205	0.008807	98.00%
Avg.	100	99.75	0.002869	0.007253	98.95%

In spite of the high accuracy of the individual feature group more than one feature group makes the system more robust. This makes it more immune to the counterfeiter's effort, even if the fake note generators happen to develop means to surpass the security measures of any particular feature set. Use of other features would help in maintaining the high performance of the system.

With currency notes we are extra careful in making the system conservative so that no fake currency passes through the system. The two thread based features (f_t^1, f_t^2) are therefore used upfront that are binary in nature and discriminate notes based on either the presence or absence of two features (namely registration (f_t^1) and text(f_t^2) as defined in Sec.3.2.3) into Genuine (G) and Fake (F). This reduces the processing time too which we have analysed next.

Recognition accuracy of the complete system. The performance of individual feature group is quite good but not perfect. Now all the features are taken together to test the system. Individual feature groups are selected in different sequence in order to optimize the performance of the system in terms of accuracy, speed and computational overhead. The Table 8 shows that the system operates fastest if the thread based features is placed in the beginning. A total of 1000 notes (500:G, 500:F) were used to compute the speed of the system. The time reported here comprises the time required to scan the notes using the four scanning methods mentioned in Table 1, for registration to figure out which part of the image should be fed to which module and finally to execute the authentication framework. With an improved scanner this time would certainly go down.

Table 8 Processing time under different ordering of security features

Ordering of features	Test Set G:Genuine F:Fake	Accuracy	Time (Mins)
1.Thread 2.Ink 3.Printing Technique 4.Art Work	(F:500 G:500)	100%	160
1.Ink 2.Thread 3.Printing Technique 4.Art Work	(F:500 G:500)	100%	222
1.Ink 2.Printing Technique 3.Thread 4.Art Work	(F:500 G:500)	100%	271
1.Ink 2.Printing Technique 3.Art Work 4.Thread	(F:500 G:500)	100%	324

It is also noted that all the features are needed to make the system as accurate as possible. The final system integrates the two classifiers (SVM and ANN) that are used for discrimination between genuine and fake currencies. A majority vote approach is followed in integrating results from these two classifiers. A note is rejected if a tie occurs during majority voting. This makes the system conservative but reduces the risk of accepting a fake sample as genuine.

Comparison with Respect to Human Experts. We conducted a comparative study to check the system's performance with respect to human experts. Two categories of people were involved in this experiment. The first group consisted of trained forensic experts and the other group referred to bank employee who were the first in line to receive the bank notes from circulation. The result is tabulated in Table 9. At every run the notes were selected at random from **Set 2** of the database as mentioned in Sec. 4.1.

Forensic experts analyse each note individually using various optoelectronic devices which takes quite some time. So, the dataset was kept deliberately small to account for this long process. The bank staff has a reasonable speed of producing results but there accuracy suffers mainly because of the qualitative aspect involved in the authentication process. Bank staffs generally authenticate notes by feeling the currency paper and quick checking the note under light. They go for further verification only if any suspicious note is encounter but then again the lack of sophisticated machines hampers the overall accuracy.

Table 9 Performance with respect to human subjects (accuracies are reported for detection of fake notes).

Testing Method	Samples	Test Result	Accuracy (%)	Time (min)
Forensic Experts	F:50, G:25	F:50, G:25	100	124
	F:50, G:50	F:50, G:50	100	166
	F:25, G:100	F:25, G:100	100	204
Bank Employees	F:50, G:25	F:46, G:25	92	28
	F:50, G:50	F:47, G:50	94	36
	F:25, G:100	F:23, G:100	92	41
Our System	F:50, G:25	F:50, G:25	100	12
	F:50, G:50	F:50, G:49	100	16
	F:25, G:100	F:25, G:97	100	20

Relative performance of the feature group The ability of the three feature groups, namely Ink, Artwork and Printing technique based features, in detecting fake currency notes is analysed using Fisher linear discrimination analysis (LDA) [33]. The previous sub-section (4.3)

highlights how we use LDA for this purpose. The projection of the individual feature groups are taken on the best discriminant plane and further mapped to show the separability of the feature groups in a 2-D plot. Fig. 11 shows the results. Finally, performance of the individual features on a 0-100% accuracy scale is reported in Fig. 12. The relative performance of the features gives vital information to the note designers as to which feature is performing the best and which feature is more susceptible to counterfeiting attack.

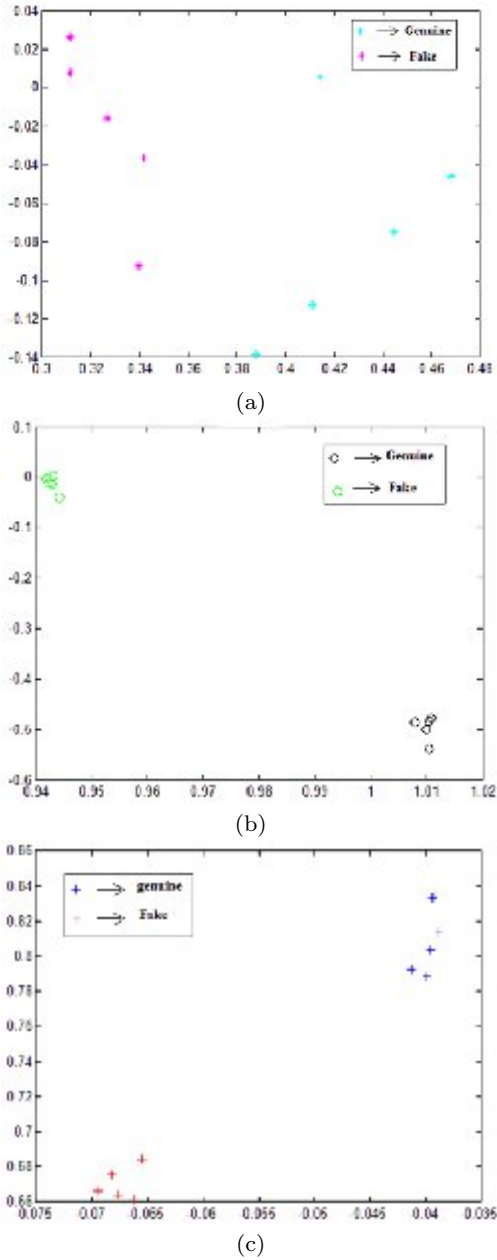


Fig. 11 Separability of notes in feature space using: (a) ink features, (b) artwork features, and (c) printing technique based features.

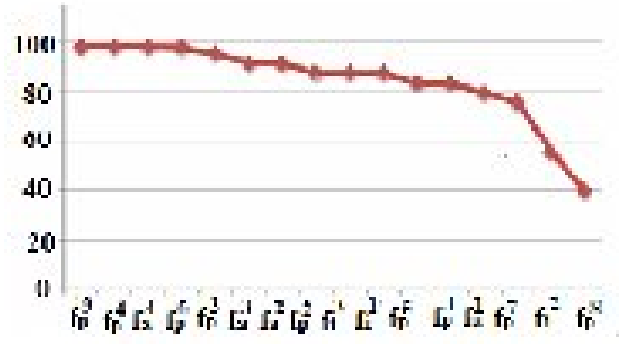


Fig. 12 Performance of individual features. The features are along the x -axis and the corresponding accuracies (%) are along the y -axis.

5 Conclusion

An automatic method for authentication of currency notes is explored. This research is particularly important when the problem of fake bank notes is considered as a serious problem in many countries. The present experiment considers Indian bank notes as reference. This study investigates how the security features can be computationally captured in order to automate the authentication process. Exhaustive evaluation of the method using real life samples brings out the potential of the approach.

The complexity of the overall system is kept optimal so that a low cost hardware realization of the proposed method is feasible. A low cost system is in demand so that a large scale deployment of such a system becomes possible. For this purpose, we are in touch with a few companies who are interested in prototyping such a system. Some algorithmic optimization may be needed for embedded realization of the present system.

Another immediate extension of this study is to evaluate the method on a different test collection. We are in process of collecting a new set of samples from another laboratory (different from the one from which we received the current data set) of the Department of Forensic Sciences. Exploiting new features and method for authentication is indeed needed to make the system robust against future counterfeiting efforts. In fact, the present study does not consider one important security feature, namely the watermark feature of the currency notes. The reason behind this refers to the strange habits of Indian people scribbling by ink pen over the blank region on the note where watermark is embedded. Such scribbling marks make the use of the watermark feature very sensitive in authenticating bank notes. Our future effort will explore how to get rid of such scrib-

bling marks and use the embedded watermark as one of the security features.

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