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An intelligent system for paper currency verification using support vector machines

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Abstract. In recent years, with the advent of digital imaging technology, e.g., color printers and color scanners, it has become easier for counterfeiters to produce fake banknotes. The spread of counterfeit money causes loss to everyone involved in financial transactions. Therefore, an effective and reliable verification technique is necessary for successful and reliable financial transactions. This paper presents a cognitive computation-based technique for paper currency verification. In this regard, Scanning Electron Microscopy (SEM) and X-Ray Diffraction (XRD) analyses of counterfeit and genuine banknotes were performed. This experimentation confirmed that the materials used in preparation of genuine and counterfeit banknotes were totally different from each other. Based on these findings, a set of discriminative and robust features was proposed to reflect these differences in currency images. The proposed features represented characteristics of the materials of the banknote, such as printing ink, chemical composition, and surface coarseness. With these robust features, Support Vector Machines (SVMs) were employed for classification. In order to evaluate the performance of the proposed technique, experimentations were performed on a self-constructed dataset of Pakistani banknotes, comprised of 195 currency images, including 35 counterfeit banknotes. The results showed that the proposed system achieved 100% verification ability for properly captured images.

1. Introduction

Building systems based on cognitive computing is a necessity in the present time. They can mimic the functionality of the human brain [1,2]; currency verification systems are an instance. Currency verification systems are used to detect counterfeit banknotes. These systems have potential applications in Automated Teller Machines (ATMs), currency exchange agencies, and other organizations involved in financial transactions. The spread of counterfeit currency causes loss to the organization, traders, and individuals. For automated financial transactions, reliable and efficient currency verification systems are inevitable. This is a great motivating factor for researchers around the globe to develop reliable techniques for currency verification. In this context, when developing banknote verification systems, accuracy and performance are to be considered as important parameters.

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In this work, authors performed the XRD analysis and Scanning Electron Microscopy (SEM) of the banknotes. The XRD is a popular analytical technique used by researchers and industry experts to examine the composition of different materials in microscopic level. On the other side, SEM based analysis can reveal detailed information about texture, chemical composition, and material of object under observation. In this technique, high-energy beam of electrons is fired on the surface of the object, which generates a variety of signals at the surface of the specimen. These signals reveal important information regarding the object. Usually, this is performed on selected small areas of the specimen ranging from 1 cm to 5 microns.

In the XRD and SEM imaging analyses, it was verified that counterfeit banknotes were different from genuine ones with respect to the materials used in their preparation. These materials included printing ink and printing paper, which consequently affected printing techniques and textures of banknotes. Based on these analyses, a discriminative set of features was proposed for detecting counterfeit banknotes. These features were extracted from currency images and Support Vector Machines (SVMs) were used for classification. Figure 1 shows the design flow diagram of the proposed technique.

It is important to mention that due to the availability of advanced and sophisticated printing technology, counterfeiters are able to produce currency with almost similar quality to that of genuine banknotes. Due to this, it is really a challenging task to detect the counterfeit banknotes manually, even by the bank personnel, who deal with the cash most of the time. The proposed cognitive computation-based system employs a robust set of features, which enables it to perform better than a manual verification by human. This can be very helpful in financial transaction by detecting the counterfeit currency in real time to save the people from financial loss.

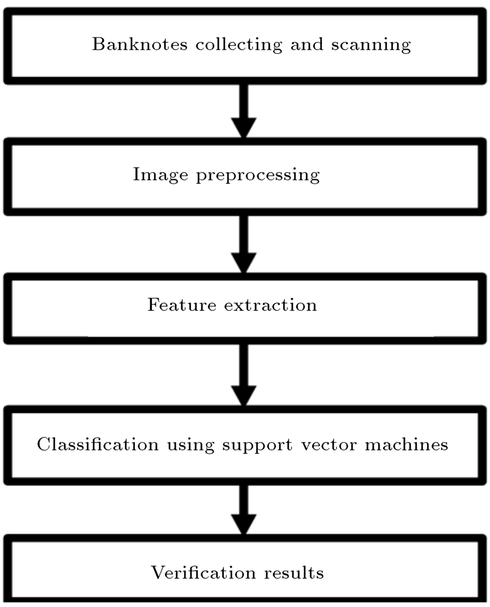


Figure 1. Design flow diagram of currency verification system.

The rest of the paper is organized as follows. Section 2 describes the related work for currency verification. The proposed methodology is presented in Section 3. The experimental verification of the proposed method is discussed in Section 4. The experimental results are presented in Section 5 and the paper is concluded in Section 6.

2. Related work

Different techniques have been proposed by researchers around the globe for object recognition and segmentation [3,4], especially currency recognition and verification [5-11]. In [5], Vila et al. developed a currency verification technique for euro banknotes. This technique was based on the analysis of different parts of the euro banknotes using spectroscopy technique. They acquired the chemical compositions of different parts of the banknote using infrared spectroscopy. This information could only be reproduced if the same formula of material was used. Authors considered €50 and €100 banknotes for evaluating the performance of the system. They used Principal Component Analysis (PCA) for data reduction and GRAMS 32 software (Galactic) for data processing.

Another technique was proposed by Chang et al. [6] for Taiwanese banknotes using SVM. They used three features, namely hidden fluorescent fibers, watermark, and color-changing ink with SVM using n-fold cross-validation method for verification. This method achieved 99.01% accuracy using linear SVM kernel. Yeh et al. [7] also proposed a currency verification technique for Taiwanese banknotes using multiple SVM kernels. They converted RGB image into YIQ color space and used luminance part for further processing. The luminance image was further divided into different parts and each part had a different kernel function. Then, histogram for each part of genuine and counterfeit banknotes was computed and used as input to the verification system. Moreover, different partitioning strategies of 2×2 blocks, 4×4 blocks, and 4×2 blocks were tested and best accuracy was achieved with 4×2 blocks division.

Spagnolo and Simonetti [8] proposed a technique for banknote verification based on 2D infrared barcode. They exposed the banknotes to ultraviolet light for identifying the metallic fibers embedded in the banknotes. Then, each banknote was matched with the template stored in the database for currency verification. Xie et al. [9] proposed a method to identify the authenticity of Chinese currency by using texture roughness of the banknote. They calculated the gray level changes in horizontal and vertical directions in multi-neighborhood of each pixel. From these gray scale changes, they defined the peak and valley points. They evaluated this method for 10 counterfeit and 100 genuine banknotes of 100 Yuan (Chinese currency).

Another method for fake currency detection in real time was proposed by Yoshida et al [10]. This method was based on microcontroller and considered specific features such as micro-printing for Bangladeshi currency. After capturing the microtext using grid scanner, they utilized OCR-based technique to verify the specific characters printed on the banknote using micro printing technique. This technique was tested on 100 and 500 TAKA. Frosini et al [11] used low-cost sensors for feature extraction and then, employed neural network to develop a technique for paper currency recognition and verification for Italian currency. They used photocopies of the currency as counterfeit samples. Sargano et al. [12] developed a currency recognition system for Pakistani banknotes, which was capable of identifying currency denominations; however, this method was not able to detect the counterfeit currency. In addition to this, several other methods were proposed for currency recognition and verification, such as [13,14]. These methods employed hidden currency feature for currency verification.

It is very important for automated financial transactions to have a currency verification method which detects the counterfeit currency in real time. The proposed method addresses this problem effectively with high accuracy and speed of recognition, which make it suitable for real-time applications.

3. Proposed methodology

The conventional methods of currency verification use standard security features indicated by the issuing authorities of the banknotes. These features include watermarking, micro-printing, metallic ink, latent image, and protective fibers. Unfortunately, these features have already been counterfeited and are available in counterfeit banknotes. According to the report published by Central Bank of Russia [15], these security features are counterfeited in most of the cases. In 95% of the cases, watermark and protective fibers features are counterfeited; also, security thread in 75% of the cases and micro-printing in 70% of the cases are counterfeited. Figure 2 shows the genuine and counterfeit banknotes of 5000 PKR; it can be seen that these features are available in 5000 PKR counterfeit banknote as well. Therefore, these features are not reliable to be used for currency verification and some other methods have to be developed for this purpose.

Figure 2. Genuine and counterfeit banknotes of 5000 PKR: (a) Genuine banknote, and (b) counterfeit banknote.

Figure 3. Selected parts of 1000 PKR considered for XRD analysis.

3.1. XRD analysis and SEM imaging

XRD analysis and SEM imaging for two parts of both genuine and counterfeit banknotes were performed, as indicated in Figure 3. The images of flag part are shown in Figure 4(a) and (b), while images of serial number are shown in Figure 4(c) and (d). In order to determine the differences between genuine and counterfeit banknotes at pixel level, the histograms of genuine and counterfeit banknotes were also calculated, as presented in Figure 5.

Figure 5(a) shows the histogram of serial number, where histograms of genuine and counterfeit banknotes are shown in blue and green, respectively. Figure 5(b) shows the histogram of flag portion, where genuine banknote is represented in blue color and counterfeit is shown in green color. Figure 5(c) shows the histogram of flag and serial number portion of the genuine banknote. It can be seen that both histograms have proper relationship, showing almost similar peak and valley points. Figure 5(d) shows the histogram of serial number and flag of counterfeit banknote. Both counter-

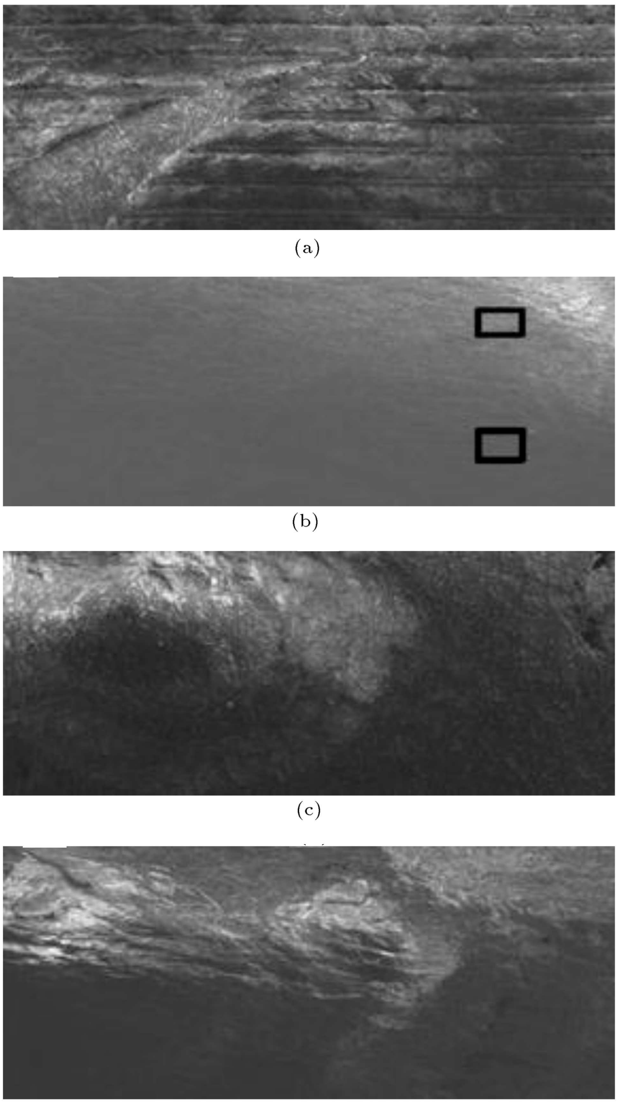


Figure 4. (a) Flag image of genuine banknote, (b) flag image of counterfeit banknote, (c) serial no. image of genuine banknote, and (d) serial no. image of counterfeit banknote.

feit images have almost the same appearance, showing the presence of the same trend over the whole image.

Moreover, authors performed XRD analysis of serial number parts of the banknotes to check their chemical formations. The results are presented in Tables 1 and 2 their graphical representation is provided in Figure 6. The results indicate that genuine banknote is composed of oxygen, carbon, magnesium, sodium, silicon, and iron elements, while counterfeit banknotes are only composed of carbon, oxygen, and a very small quantity of aluminum. This information is only reproducible if the same formula is used for both genuine and counterfeit banknotes, which is quite challenging for the counterfeiters.

The second part of the banknote used for XRD analysis was Pakistani flag. Analysis results are presented in Tables 3 and 4. The results show that banknotes have different chemical compositions. The graphical representation of XRD analysis is provided in Figure 7.

Table 1. XRD analysis of serial no. part of genuine banknote.

Element	Weight (%)	Atomic (%)
C K	52.81	60.91
O K	36.23	31.37
F K	9.29	6.78
Na K	0.54	0.33
Mg K	0.65	0.37
Si K	0.48	0.24
Total	**100.00**	**100.00**

Table 2. XRD analysis of serial no. part of counterfeit banknote.

Element	Weight (%)	Atomic (%)
C K	68.45	74.51
O K	30.65	25.05
Al K	0.90	0.44
Total	**100.00**	**100.00**

Table 3. Flag SEM image analysis of 1000 PKR genuine banknote.

Element	Weight (%)	Atomic (%)
C K	47.17	63.88
O K	27.72	28.18
Na K	0.11	0.08
Mg K	0.45	0.30
Si K	1.40	0.81
Fe L	23.16	6.75
Total	**100.00**	**100.00**

Table 4. Flag SEM image analysis of 1000 PKR counterfeit banknote.

Element	Weight (%)	Atomic (%)
C K	55.77	62.68
O K	44.23	37.32
Total	100.00	100.00

Based on the above analysis results, authors carefully chose a set of statistical features that represented quality of the paper, banknote material, and printing techniques. Then, for representing texture roughness, they found binary value changes in the derivative image with respect to its neighbor pixels in x-axis and y-axis. These points were labeled as peak and valley points. The flow chart is shown in Figure 8 and discussed in detail in the subsequent sections.

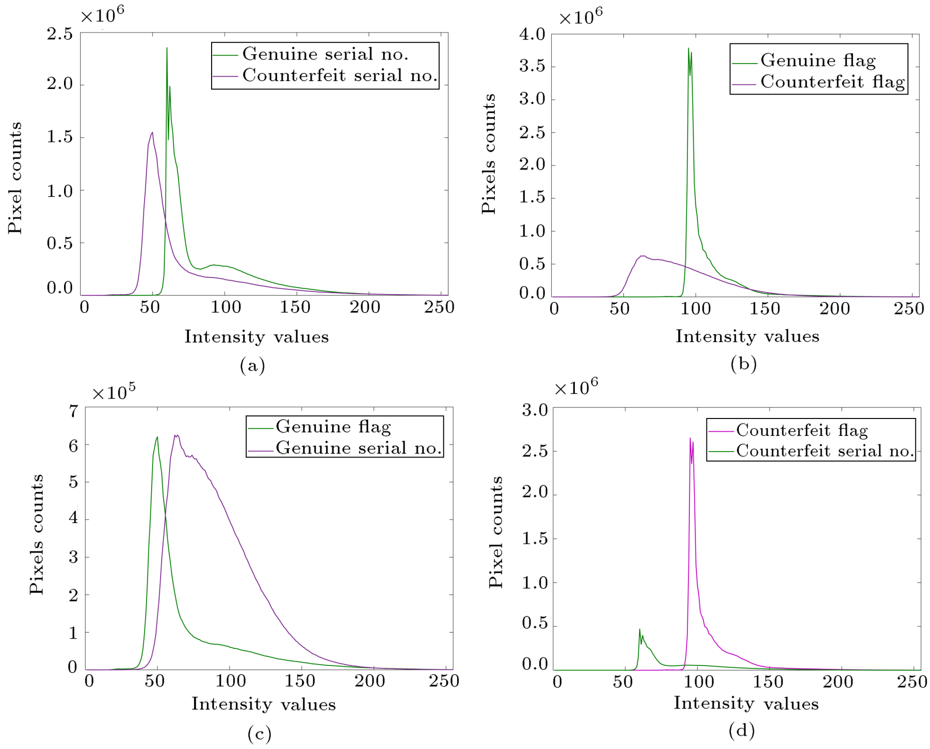


Figure 5. (a) Histogram of serial no. part of counterfeit and genuine banknotes. (b) Histogram of flag part of counterfeit and genuine banknotes. (c) Histogram of serial no. and flag parts of genuine banknote. (d) Histogram of serial no. and flag parts of counterfeit banknote.

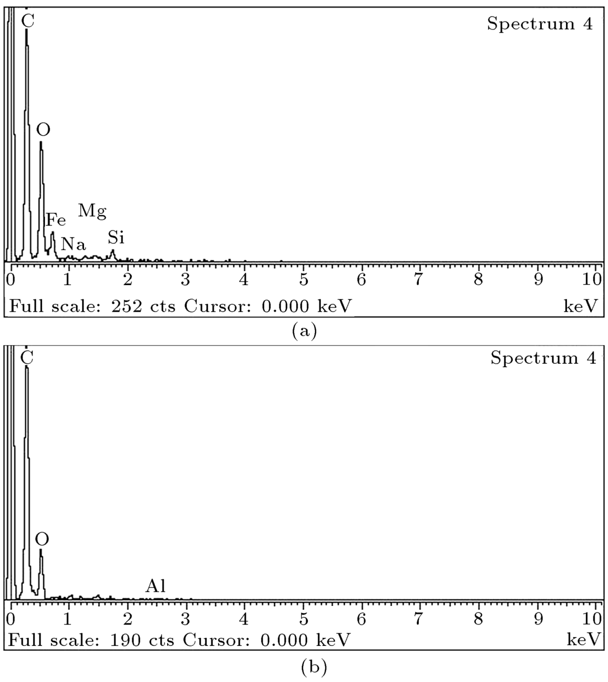


Figure 6. Serial no. XRD analysis: (a) Graphical view of genuine banknote, and (b) graphical view of counterfeit banknote.

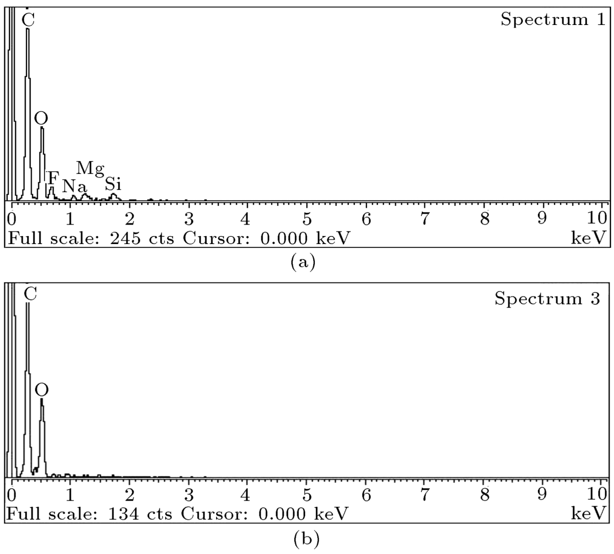


Figure 7. XRD analysis of flag part: (a) Graphical view of genuine banknote, and (b) graphical view of counterfeit banknote.

3.2. Banknote collecting and scanning

All recognition systems require a dataset for training and testing purposes. To this end, public datasets are available to some recognition systems such as face recognition. However, for unlike these systems, to the best of the authors' knowledge, no such benchmark datasets are available for currency recognition and verification. Therefore, authors constructed a dataset of 195 Pakistani banknotes, including 35 counterfeit banknotes (500, 1000, and 5000 PKR).

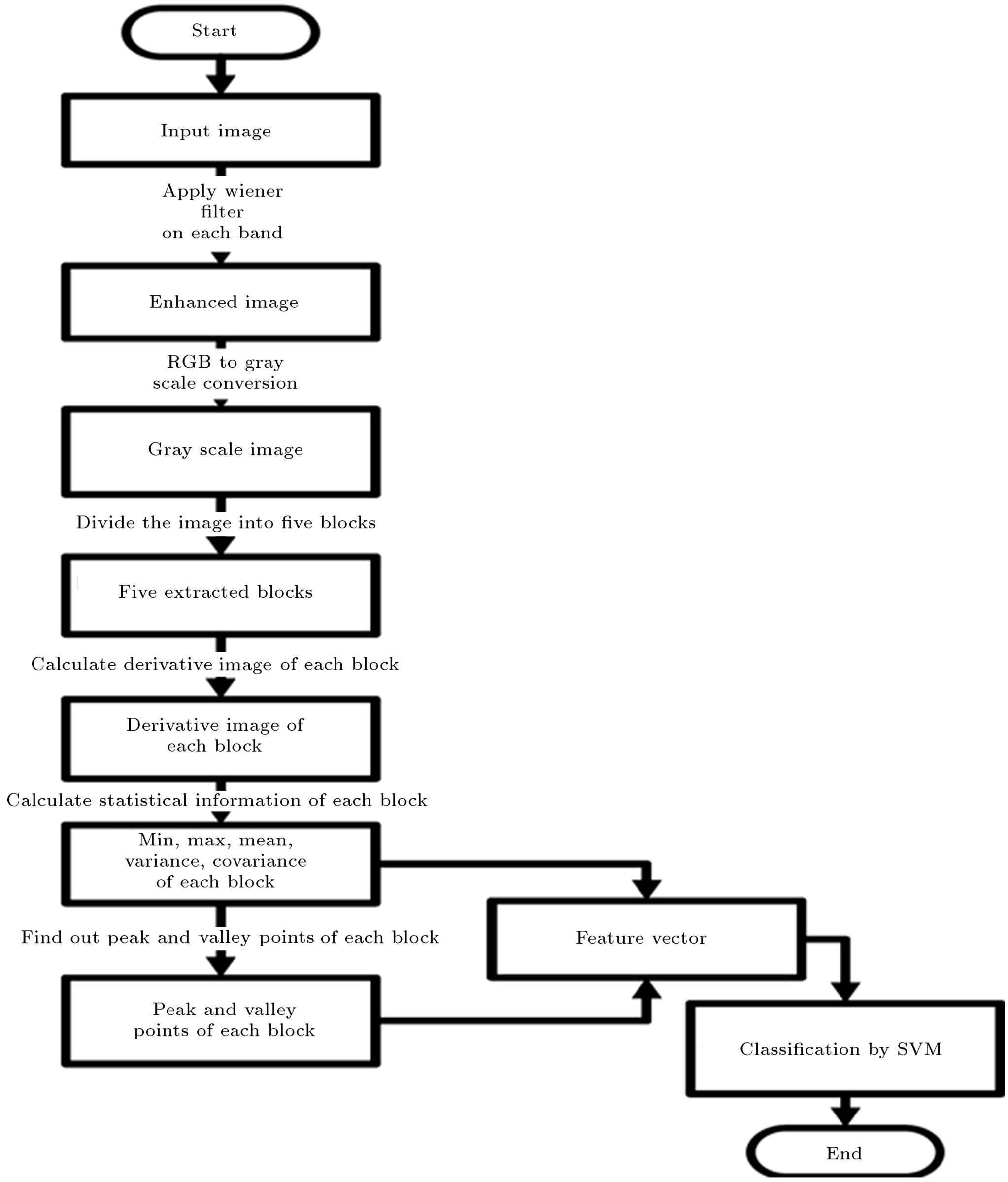


Figure 8. Flow chart of the proposed currency verification system.

3.3. Preprocessing

In some recognition and verification systems, a preprocessing step is required before the feature extraction and representation. This can improve the performance of the verification system. In order to recognize worn, torn, and noisy currency along with the clean banknotes, preprocessing is helpful [16]. During circulation, banknotes become noisy and even worn and torn in some cases. In this regard, authors applied Weiner filter to each band (R, G, and B) of the banknote. The Wiener filter uses adaptive filtering based on the mean and variance estimations of neighborhood of each pixel as stated in Eqs. (1) and (2), respectively. This filter is equally useful for clean and dirty banknotes by preserving the edges and other useful information.

$$\mu = \frac{1}{MN} \sum_{n1,n2 \in \eta} \alpha(n1, n2), \tag{1}$$

$$\sigma^2 = \frac{1}{MN} \sum_{n1,n2 \in \eta} \sigma^2(n1, n2) - \mu^2, \tag{2}$$

where α represents the $N \times M$ neighborhood around each pixel in the image [17]; the Wiener filter is described in Eq. (3):

$$b(n1, n2) = \mu + \frac{(\sigma^2 - \nu^2)}{\sigma^2}(\alpha(n1, n2) - \mu), \tag{3}$$

where ν^2 is the noise variance; if it is omitted, the Wiener considers the average of all local variances.

3.4. Feature extraction

Feature extraction and representation is an important step of any recognition and verification system. Due to the presence of a huge amount of information in an image, it is not desirable to process the whole image. Rather, a selected set of features is extracted from the image. The performance of verification systems is very much dependent on appropriate selection of features and representation process. In this study, two types of important features including statistical features and texture characteristics of the banknote are extracted. They are described in detail in the following sections.

3.4.1. Statistical features of the banknote

When we capture an image using a digital camera, the camera blinks light on the surface of the object. During this process, some part of the light is reflected back, while another part of the light passes through the object with change in direction, which is called refraction of light. In this scenario, the overall intensity of the object can be calculated as follows: If intensity of the incident is I_0 and refracted intensity is I [18], then the relationship among these factors can be calculated as in Eq. (4):

$$I = I_0(1-\eta)e^{-\alpha d}. \tag{4}$$

In Eq. (4), α represents the absorption by the medium, η represents the reflection of light, and d indicates the thickness of the medium. We can understand from Eq. (4) that each pixel is related to refraction coefficients, absorption coefficient, and reflection coefficients of the image. In fact, these coefficients are representatives of the materials used in the banknote. In order to reflect the material-related parameters in digital image, we selected texture roughness and a set of statistical features of the banknote. Moreover, it was observed that some parts of the banknote were more important in terms of these parameters as they reflected the differences between two banknotes more obviously. Therefore, the banknote was divided into five different blocks and derivative image was calculated for each block as shown in Eq. (5):

$$\nabla f(x,y)=f_x(x,y)=\frac{\partial f(x,y)}{\partial x}, \quad f_y(x,y)=\frac{\partial f(x,y)}{\partial y}. \tag{5}$$

We selected five parameters to calculate the statistical features for each block of the banknote, as indicated in Eqs. (6)-(10):

1. **Mean value:** It represents the mean value for each block of the derivative image as shown in Eq. (6):

$$D_{\text{mean}} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} f(i,j). \tag{6}$$

2. **Minimum value:** This is one of the important features, calculated along each row as shown in Eq. (7):

$$D_{\min} = \frac{1}{n}\sum_{i=1}^{n}\min(f(x,i)). \tag{7}$$

3. **Maximum value:** The maximum value of the derivative image along each row is calculated as shown in Eq. (8):

$$D_{\max} = \frac{1}{n}\sum_{i=1}^{n}\max(f(x,i)). \tag{8}$$

4. **Variance:** It is a measure of the dispersion in a set of data, which is calculated as shown in Eq. (9):

$$D_{-var} = \frac{1}{n}\sum_{i=1}^{n} f_i(xi-\mu^2). \tag{9}$$

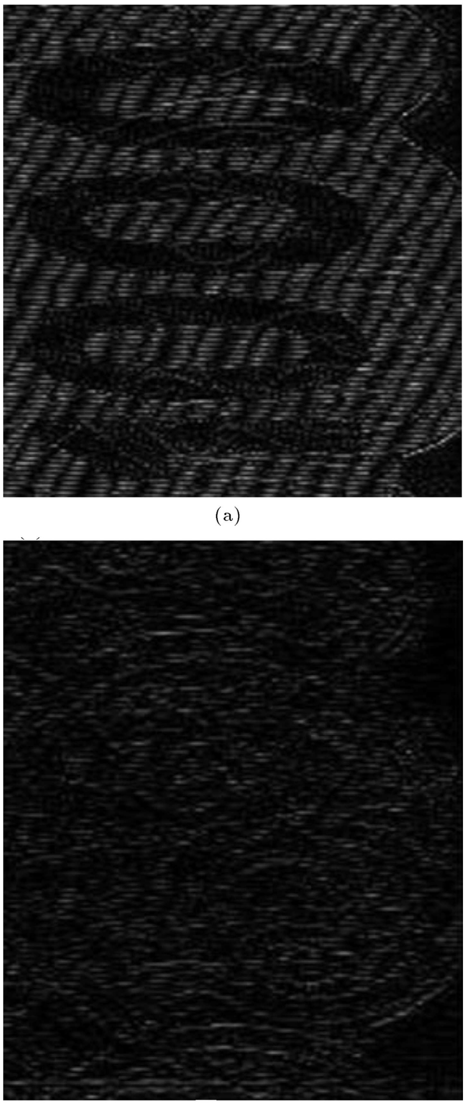
5. **Covariance:** It is the covariance matrix, $cov(X)$, of an image. It can be calculated using Eq. (10):

$$D_{cov} = \frac{cov(Xi,Xj)}{(\sigma i\sigma j)}. \tag{10}$$

3.4.2. Texture roughness of banknotes

Texture of an image is generally reflected as a set of pixels with a particular shape and direction; however, there is no universal definition for a texture. It is helpful in describing the surface roughness of an object. The texture roughness is considered as an important feature and plays an important role in texture analysis [19]. Different algorithms have been proposed over time for analyzing the texture roughness, e.g., the one proposed by Rosenfeld and Troy [20]. This algorithm calculates the mean of the local neighborhood of each pixel. Another algorithm for analysis of texture roughness was proposed by Jain and Karu [21]. This algorithm was an extension to Troy's approach. The basic idea of the algorithm was to calculate the grayscale changes and their mean values in both vertical and horizontal directions [22].

Another concept of surface roughness is used in engineering for assessing the surface quality of the manufactured components. This idea is based on the geometry of the object, which represents the surface roughness as set of peak points, valley points, and the space between these points. There is also a set of parameters listed by ASME and ISO to evaluate the surface roughness of the manufactured components [19]. The proposed method is based on this idea to describe the surface roughness of the banknotes. As per the proposed method, if the changes in the intensity of an image are taken as sine wave, many peaks, valleys, and transition points in the intensity



(a)

(b)

Figure 9. Derivative image: (a) Genuine banknote, and (b) counterfeit banknote.

values are produced. In order to make the surface roughness clearer, we calculated the derivative of each block of the currency image. The derivation was helpful to engrave the embedded features as shown in Figure 9.

There are three groups of pixels in each derivative image: pixel values greater than zero, pixel values less than zero, and some pixels with exactly zero value, as shown in Table 5. The complete process of calculating texture roughness is described in Algorithm 1.

4. Support Vector Machines (SVMs)

After extracting features by Algorithm 1, some classifier has to be used for classification of genuine and counterfeit banknotes. The neural network technology has good generalization and self-organization ability that make it suitable for pattern recognition. However, it has some limitations as well. Firstly, it produces good results only when we have many training samples and does not exhibit good generalization with a limited number of training samples. Secondly, there should be uniformity in training samples; otherwise, results may converge to local optimum solution [6]. As an alternative to NN, there are other powerful classification machines with better generalization ability, called Support Vector Machines (SVMs). This classifier was proposed by Vapnik in the 1990s [23]. The basic idea of SVMs is to differentiate two classes by constructing a hyper-plane between them. By using hyper-plane, the separation margin between two classes is maximized. The structure of the SVM is shown in Figure 10.

Table 5. Peak (P), Valley (V), Partial Peak (PP), Partial Valley (PV), Ramp Up (RU), and Ramp Down (RD) points.

Current pixel $I(r,c)$	**Previous-x** $I(r,c-1)$	**Previous-y** $I(r-1,c)$	**Group name**
Positive	Negative	Negative	P
Positive	Negative	Positive	PP-yx
Positive	Positive	Negative	PP-xy
Positive	Positive	Positive	RD
Negative	Negative	Negative	RU
Negative	Negative	Positive	PV-yx
Negative	Positive	Negative	PV-xy
Negative	Positive	Positive	V

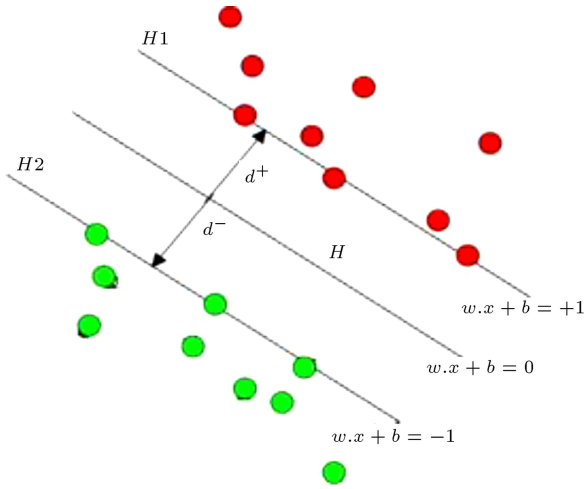


Figure 10. Structure of SVM.

4.1. Support Vector Machines (SVMs) training

In this study, SVM is used for classification. In order to train the system, 125 images for 100 genuine and 25 counterfeit banknotes are used. There are three output classes for three denominations (500, 1000, and 5000 PKR) of banknotes. The complete information regarding input and outputs units is summarized in Table 6.

```
Roughness_Feature_Extraction (I(x,y))
Input: Derivative Image block (I(x,y))
Output: Feature Vector
mean0, mean1, mean2, mean3, mean4, mean5, mean6, mean7←0
count0, count1, count2, count3, count4, count5, count6, count7←0
[M, N]=size (I(x,y))
  for  r←2 to M
       for  c←2 to N
               if (d(row,column)>=0 & (row-1,column)<0 & d(row,column-1)<0)
               columnount0=columnount0+1
               mean0=mean0+d(row,column)
               end if

               if (d(row,column)>=0 & (row-1,column)<0 & d(row,column-1)>=0)
               columncount1=columncount1+1
               mean1=mean1+1
               end if

               if (d(row,column)>=0 & (row-1,column)>=0 & d(row,column-1)<0)
               columncount2=columncount2+1
               mean2=mean2+1
               end if

               if (d(row,column)>=0 & (row-1,column)>=0 & d(row,column-1)>=0)
               columncount3=columncount3+1
               mean3=mean3+1
               end if

               if (d(row,column)<0 & (row-1,column)<0 & d(row,column-1)<0)
               columncount4=columncount4+1
               mean4=mean4+1
               end if

               if (d(row,column)<0 & (row-1,column)<0 & d(row,column-1)>=0)
               columncount5=columncount5+1
               mean5=mean5+1
               end if

               if (d(row,column)<0 & (row-1,column)>=0 & d(row,column-1)<0)
               columncount6=columncount6+1
               mean6=mean6+1
               end if
               if (d(row,column)<0 & (row-1,column)>=0 & d(row,column-1)>=0)
               columncount7=columncount7+1
               mean7=mean7+1
               end if
            end for
  end for
mean0=mean0/columncount0
mean1=mean1/columncount1
mean2=mean2/columncount2
mean3=mean3/columncount3
mean4=mean4/columncount4
mean5=mean5/columncount5
mean6=mean6/columncount6
mean7=mean7/columncount7
End Function
Exit
```

Algorithm 1. Complete process of calculating texture roughness.

Table 6. SVM learning parameters.

Parameters	Value
No. of banknotes	125
Banknote types	3 (500, 1000, 5000)
Genuine	100
Counterfeit	25
No. of inputs	93
No. of outputs	2 (0/1)
Threshold	0.5

5. Experimental results

In order to assess the performance of the proposed method, experiments were performed on 60 genuine banknotes (5000, 1000, and 500 PKR) and 10 counterfeit banknotes. Initially, with the threshold value of 0.5, the system achieved 98.57% ability for 500, 1000, and 5000 PKR banknotes as shown in Table 7. In the case of 500 PKR banknote, the proposed system recognized all counterfeit banknotes correctly, while there was misclassification for one genuine banknote. After analyzing the resulting values of counterfeit and genuine banknotes, we found that all genuine banknotes had values greater than or equal to 0.4, while all fake banknotes fell in the negative range of values. Therefore, we adjusted the threshold value to 0.4, which gave us 100% accuracy on these three denominations of Pakistani banknotes. Verification results are shown in Table 7.

5.1. Comparison with other methods

Our method achieves 100% accuracy; the recognition rates for individual currency denominations are presented in Tables 7 and 8. The results confirm that our method produces results equal to or higher than those of other currency verification methods such as [7,24-31] presented in Table 9. It is important to mention that the currencies used for experimentation in comparison methods are different and different techniques have been used for currency verification. Moreover, most of these methods are not suitable for real-time recognition as they consider the whole image for processing or employ a combination of multiple feature descriptors. The proposed method uses few selected features, which confirms its suitability for real-time currency verification. Moreover, our dataset includes dirty, worn, and torn banknotes, which are quite challenging for any verification system due to the presence of noise and get embedded in the banknote during circulation.

Table 7. Verification results at threshold value of 0.5.

Banknote type (PKR)	No. of banknotes tested, G = genuine, F = fake	No. of banknotes correctly recognized	Recognition ability (%)
500	20 (G)	19	95
500	4 (F)	4	100
1000	30 (G)	30	100
1000	3 (F)	3	100
5000	10 (G)	10	100
5000	3 (F)	3	100
Total	**70**	**69**	**$69/70 \times 100 = 98.57$**

Table 8. Verification results at threshold value of 0.4.

Banknote type (PKR)	No. of banknotes tested, G = genuine, F = fake	No. of banknotes correctly recognized	Recognition ability (%)
500	20 (G)	20	100
500	4 (F)	4	100
1000	30 (G)	30	100
1000	3 (F)	3	100
5000	10 (G)	10	100
5000	3 (F)	3	100
Total	**70**	**70**	**100**

Table 9. Comparison of currency verification results with state-of-the-art methods.

Year	Method	Currency type	Accuracy (%)
	Proposed method	**PKR banknote**	**100**
2017	Pham et al. [24]	Hong Kong Dollar (HKD)	99.38
		Kazakhstani Tenge (KZT)	100.00
		Colombian Peso (COP)	99.72
		United State Dollar (USD)	99.99
2017	Dittimi et al. [25]	Nigerian Naira	99.0
2016	Murthy et al. [26]	Indian paper currency	90.00
2016	Hlaing and Gopalakrishnan [27]	Myanmar banknotes	99.20
2016	Zeggeye and Assabie [28]	Ethiopian currency	96.13
2015	Yan et al. [29]	United States Dollar (USD)	98.60
2014	Singh et al. [30]	Indian paper currency	96.70
2012	García-Lamont et al. [31]	Mexican banknotes	98.95
2011	Yeh et al. [7]	Taiwanese banknotes	96.77

6. Conclusion

In this article, a currency verification technique used for Pakistani banknotes was presented. This technique was based on the statistical information and texture characteristics of the banknotes. In order to select the set of efficient and discriminating characteristics, the authors performed XRD diffraction analysis and SEM imaging of the counterfeit and genuine banknotes. Based on the results of the analysis, a set of features was selected to differentiate genuine banknotes from counterfeit ones. With these features, Support Vector Machines (SVMs) were used for classification. The system was tested on a self-constructed dataset of 195 Pakistani banknotes, including three denominations of 500, 1000, and 5000 PKR banknotes. The results indicated that the proposed system achieved 100% accuracy on this dataset, which was superior to the results of most state-of-the-art currency verification methods.

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