An Automated Recognition of Fake or Destroyed Indian Currency Notes in Machine Vision

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Abstract

Almost every country in the world face the problem of counterfeit currency notes, but in India the problem is acute as the country is hit hard by this evil practice. Fake notes in India in denominations of Rs.100, 500 and 1000 are being flooded into the system. In order to deal with such type of problems, an automated recognition of currency notes in introduced by with the help of feature extraction, classification based in SVM, Neural Nets, and heuristic approach. This technique is also subjected with the computer vision where all processing with the image is done by machine. The machine is fitted with a CDD camera which will scan the image of the currency note considering the dimensions of the banknote and software will process the image segments with the help of SVM and character recognition methods. ANN is also introduced in this paper to train the data and classify the segments using its datasets. To implement this design we are dealing with MATLAB Tool.

Keywords: *Heuristic Analysis, Character Recognition, SVM, NN Tool, Bank Note, Machine fitted with a camera.*

1. Introduction

Automatic methods for bank note recognition are required in many applications such as automatic selling-goods and vending machines. Extracting sufficient monetary characteristics from the currency image is essential for accuracy and robustness of the automated system. This is a challenging issue to system designers. Every year RBI (Reserve bank of India) face the counterfeit currency notes or destroyed notes. The bank staffs are specially trained to detect counterfeit notes but problem begins once such notes are infiltrated into the market and circulated through common people. Even receiving fake notes from ATM counters have also been reported at some places. Although the forensic experts (i.e. the questioned document examiners) are available to trap these forgeries, but the existing method for detecting fake notes is cumbersome as this involves filing a case to the police, sending the document for verification and then waiting for results to come. Handling of large volume of counterfeit notes imposes additional problems. Therefore, it would be of great help if we can involve machines (independently or as assistance to the human experts) for automatic authentication of bank notes.

The Reserve bank of India estimates that there is at least Rs.2 trillion fake rupee notes in circulation throughout India. It is suspected that almost all of these notes originate from security presses located elsewhere. A common person does not know what to do when he gets a fake rupee note. Here are some points to keep in mind while checking the bank note**-** *Paper Quality, Visual Fake Currency Detection, mark printed in intaglio in which the image is in a slightly raised manner, portrait of Mahatma Gandhi***,** *a promise and guarantee clause, the RBI seal, the emblem of the Ashoka Pillar, all***l** *serial numbers[1].*

With that, there are also some techniques for detecting counterfeit currency like -

Varied-Density Watermarks:

Most people are familiar with two types of document watermarks which can be found in banknotes or on checks. In banknotes, these are recognizable designs that are put into the paper on which the documents are printed, whilst in checks they tend to be specific patterns. These watermarks are normally used to prevent people from being able to make fake copies, and, therefore, to be confident that the banknote or document is authentic. By varying the density of the paper a banknote is printed on in a controlled manner, thin watermarks can be applied. These are visible when a bright light shines onto the rear of banknote, and the varied paper density causes varying intensities of light to pass through, causing the watermarked image to appear on the other side of the note.

Fig 1 Indian Currency

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Ultraviolet Fluorescence:

Embedding fluorescent fibre into the paper, or printing ultra-violet ink onto the paper, creates a form of optical verification easily used at counters, checkouts, etc. By exposing the note to ultra-violet light, the ink or fibr fluoresce, revealing a coloured pattern not visible under natural light.

Intaglio Printing:

It is the printing process itself that serves to vouch for the authenticity of the document. The note is subjected to a high-pressure printing process that strengthens and slightly raises the paper's surface structure. Using different alignments of lines printed in this manner, a *latent image* can be produced which changes appearance depending on the angle at which the note is viewed.

Microtext:

Text printed at smaller than 1 point size, readable only with a loupe or magnifying glass. It provides additional security to invoices, coupons, and other fraud-sensitive applications. Compatible with color, monochrome, and highlight color devices.

Fibre-Based Certificates of Authenticity:

Based on the characteristics of fibre-optic light transmission, this method makes use of unique configurations of fibre embedded in the paper

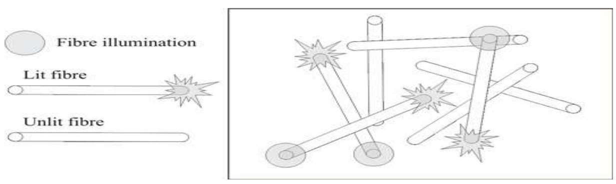


Fig 2 fibre embedded in paper

Colour and Feature Analysis:

There are different algorithms and techniques used to extract the features of banknote and distinguish the patterns of genuine note from the fake note.

2. Approach with main security units

A banknote carries security features mainly on its paper, design and printing process. Examination or verification of currency notes is mostly conducted by checking the following aspects: i) physical dimensions, ii) paper quality, iii) design, and (iv) printing technique. Physical dimension of currency note depends on its cut size of length, width, and thickness of paper. The paper on which currency note is printed carries important level of security. Watermarks and security thread are other important parts of security on currency note paper. Apart from these features, the process used to print banknotes provides important checkup for authentication of the notes. In many cases counterfeiting have been reported even on the paper identical to one as used for genuine notes leaving a very narrow gap to identify the original from the fake. However, the printing technique that is hard to replicate because some of its inherent characteristics. There are numerous printing processes like offset, dry offset, intaglio, letterpress, serigraphy, screen printing, photostat copying, inkjet, bubble-jet, digital printing, etc. that can be used for printing currency notes. But our objective is to deal with the selected security features that are strong enough to determine the genuine banknote or counterfeit banknote. So the units on which we the system will deal is – watermarks, see through register, optically variable link, fluorescence, latent image, readable window security thread[1].

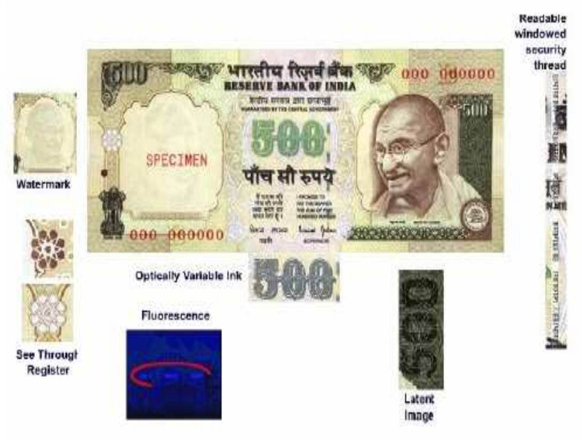


Fig 3 security features

Security Features on Indian Banknote:

1. Watermark-

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

2. Latent Image-

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

3. Fluorescence

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

4. Microlettering-

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

5. Optically Variable Ink-

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

6. See through Register-

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

***7.** Serial Numbers*

*E*very banknote has its own serial number, so it is more important to check whether the number is wrong or repeated.

There were the selected units that will help us to recognize the banknote. The counterfeit currency note first segmented into different parts containing these units and with the NNTOOL and appropriate algorithm processing and feature extraction will be applied with particular segment.

3. Methodology

The main objective of this paper is find out the counterfeit banknotes with the help of hardwares. The system is built in MALAB where different tools and algorithms will help us to process the templates of banknote. Bank notes are available in nominal values of 5, 10, 20, 50, 100, 500 and 1000 rupees and these notes have their own dimensions. So it is very necessary to first calculate the dimensions of each and every note and put their values in database.

This role is played by the machine where a camera is fitted which will scan the whole note at once[6]-[7]. With sharp-eyed sensors, machine will scan the entire banknote in high-resolution detail. This smart machine has qualities to enhance your business and adaptability to ensure trouble free adjustment to your current and future needs. The keen-sighted scanner detect all defective banknotes, in contrast to other low level detector and scanning techniques[2]-[4]. The same high level of precision is maintained whatever the complexity of the sorting criteria you choose. In the market, there are different smart machines available that are best suited for finding the counterfeit currency notes. One of such machine is BAR 5000. The CCD cameras scan the entire banknote from edge to edge in three spectra – visible light, infrared and ultraviolet – providing high precision data for sorting and authentication. You can choose to scan one or both sides of the note, selecting the combination of spectra best suited to your needs. The three spectra we are using only to detect the watermarks, latent images, optically variable ink, microletting etc.

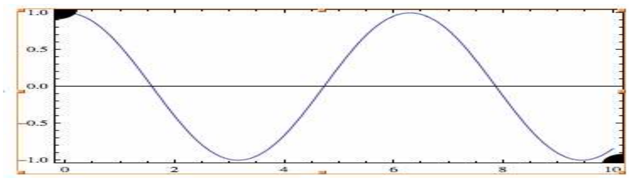
Table1 - Counting pixel value

S. NO.	value	dimensions
1	Rs 10	--*-- px
2	Rs 20	--*-- px
3	Rs 50	--*-- px
4	Rs 100	--*-- px
5	Rs 500	--*-- px
6	Rs 1000	--*-- px

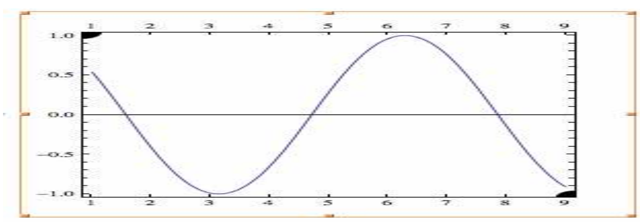
Above is the database that contains the dimensions of different Indian currency notes that will make the work easy to match the dimension and recognize the note.

The coordinates of the upper left corner of the frame are always Scaled[{0,1}]. The coordinates of the lower right corner of the frame are always Scaled [{1,0}].Let's place large points at the upper left and lower right corners:

Plot[Cos[x], {x, 0, 10}, Frame -> True, Epilog -> {PointSize[.08], Point[Scaled[{0, 1}]], Point[Scaled[{1, 0}]]}]



Plot[Cos[x], {x, 1, 9}, ImageSize -> 300, AspectRatio -> 1, Frame -> True, ImagePadding -> 30, FrameTicks -> {Range[9], Automatic}, Epilog -> {PointSize[.08], Point[Scaled[{0, 1}]], Point[Scaled[{1, 0}]]}]



1. Documentation states that ImagePadding "is defined within ImageSize".
2. The image shown above has a width and height of 300 pixels.
3. There is a 30 pixel margin drawn around the frame; this corresponds to 10% of the width and height.
4. So the frame corners should be, starting from the origin, at ImageScaled[{.1,.1}], ImageScaled[{.9,.1}, ImageScaled[{.9,.9}] & ImageScaled[{.1,.9}].

SVM (Support Vector Machine) and ANN

Support Vector machines (SVM) are a new statistical learning technique that can be seen as a new method for training classifiers based on polynomial functions, radial basis functions, neural networks, splines or other functions. Support Vector machines use a hyper-linear separating plane to create a classifier[10-[11]. For problems that can not be linearly separated in the input space, this machine offers a possibility to find a solution by making a non-linear transformation of the original input space into a high dimensional feature space, where an optimal separating hyperplane can be found. Those separating planes are optimal, which means that a maximal margin classifier with respect to the training data set can be obtained. Here support vector machines (SVM) are used aiming at determining the location of decision boundaries that produce the optimal separation of classes. Two types of common non-linear kernel functions namely, polynomial and radial basis function (RBF) are considered. The whole sample set consisting of genuine as well as duplicate samples is divided into four subsets. A fourfold test is conducted so that each subset appears at least once as in training, validation and testing. The proportion in which samples appear in training, validation and test data is 2:1:1 (training: 50%, validation: 25% and testing: 25%).

As it is well known, SVMs are trained through the following optimization procedure by using the equations ,

Polynomial: $K(x, x') = (x.x' +1)\ d$
RBF: $K(x,x')= exp(-\gamma\ lx\text{-}x'l2)$ *for* $\gamma > 0$

where $K(.)$ is called the kernel function . The value of the kernel equals the inner product of two vectors, xi and xj, in the feature space $\Phi(xi)$ and $\Phi(xj)$; that is $K(x\ \&\ x') = \Phi(xi)\cdot \Phi(xj)$. In this work the RBF is used.. Training was carried out using first the ANN and then the same experiments were repeated with the SVM using both constant width RBF functions[12]. The classification accuracy is also checked with a Neural Network (NN)-based classifier[13]. An MLP (Multi-Layer Perceptrons) consisting of 9 input nodes correspond to nine dimensions of a feature vector is used. The output consists of only one node to gives binary output (genuine or duplicate). Hidden layer, in the present experiment, contains 2 nodes. A logistic function as explained in the next section is used as the activation function of the network. Like SVM-based classifier a four-fold test is conducted for NN-based classification [10]. Samples appear in training, validation and test data following the ratio 2:1:1. The final decision about whether the printing technique of a currency note is genuine does not depend on checking of a single character image. As there are many character images on a note, therefore, printing technique is authenticated for number of character images all of which should pass the authenticity criteria. Failure for one image mark the banknote questioned. The decision making process is intentionally made very stringent to reduce false acceptance rate to almost zero.

4. Experimental Result

In this section, we test and compare the performance of the proposed method with other methods on a set of some Indian banknotes. In these banknotes some are genuine and some are forged. We randomly chose few genuine notes and few forged ones as training patterns, and the others as testing patterns. For convenience, we call the SVMs of Eq.

$$\min_{\mathbf{w},b} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l}\xi_i$$
$$\text{s.t.} \quad y_i(\langle \mathbf{w}, \phi(\mathbf{x}_i)\rangle + b) \ge 1 - \xi_i, \xi_i \ge 0, i = 1, 2, \ldots, l,$$

standard SVMs. In the following experiments, we use C = 1 for standard SVMs and C = 2l+ for our proposed SVMs of eqn

$$\min_{\mathbf{w},b} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\left(\sum_{\{i|y_i=+1\}} d_i^+\xi_i + \sum_{\{i|y_i=-1\}} d_i^-\xi_i\right)$$
$$\text{s.t.} \quad y_i(\langle \mathbf{w}, \phi(\mathbf{x}_i)\rangle + b) \ge 1 - \xi_i, \xi_i \ge 0, i = 1, 2, \ldots, l$$

First of all, we compare the performance of our proposed SVMs with that of standard SVMs. A single kernel is used. No partitioning is done, i.e., the whole image of each banknote constitutes one partition. Table 1 presents the results obtained with different hyperparameters.

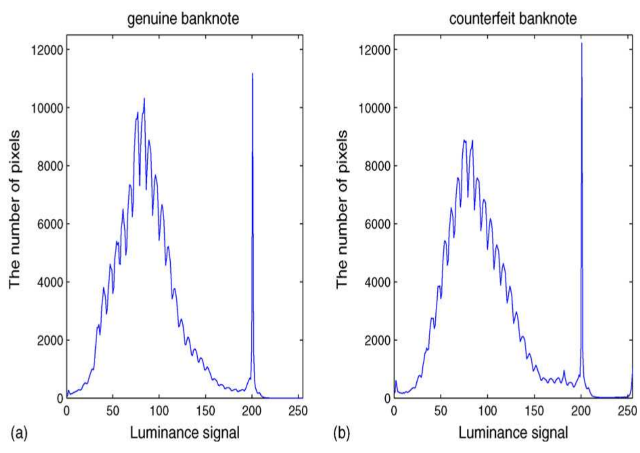


Fig 4 genuine currency vs counterfeit currency

Note that in the table, Sd-Sk indicates that it is standard SVM with single kernel. Op-Sk stands for our proposed SVM with single kernel. FPR stands for false positive rate. FNR stands for false negative rate. ACC stands for accuracy.

Table 2-

Kernel	Sd-Sk ACC (%)/FPR (%)/FNR (%)	Op-Sk ACC (%)/FPR (%)/FNR (%)
$\gamma = 0.01$	67.742/90.909/0.000	70.968/45.455/20.000
$\gamma = 0.1$	74.194/54.546/10.000	77.419/36.364/15.000
$\gamma = 0.05$	74.194/54.546/10.000	74.194/45.455/15.000
$\gamma = 0.5$	**80.645** /45.455/5.000	**80.645** /45.455/5.000

After this step, we will move forward to investigate the effect of applying on the partition of banknote. The banknote is divided into 3 or 4 partition based on the more accuracy and robustness.

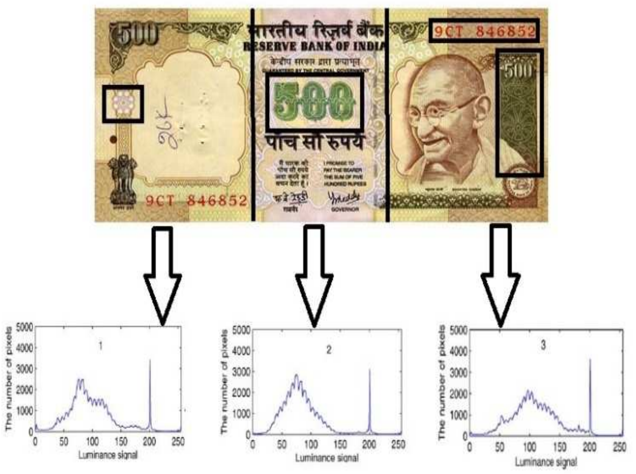


Fig 4 partition of banknote

In this experiment, we investigate the effect of applying the strategy of partitioning. Tables 3 and 4 present the results for two sets of kernels, _ = [0.050.55]T and _ = [0.010.050.10.51]T , respectively. In these tables, Op-Mk-Tr-Pa and Op-Mk-Id-Pa stand for Op-Mk- Tr and Op-Mk-Id, respectively, with partitioning. Clearly, different ways of partitioning may result in different performances. For example, partition 2 × 2 gets 100% in accuracy for Op-Mk-Id-Pa with 3-kernels, while partition 2 × 4 gets a poor performance, only 80.645% in accuracy. Also, a partition may behave differently with different sets of kernels. For example, partition 4 × 2 gets 96.774% in accuracy for Op-Mk-Id-Pa with 3-kernels, while it gets 100% in accuracy for Op-Mk-Id-Pa with 5-kernels. The variation in performance indicates the variation in histogram distribution due to different ways of partitioning.

Table 3- Results obtained from partitioning for _ = [0.05 0.55]T .

Results obtained from partitioning for $\gamma = [0.05\,0.5\,5]^T$.

RBF kernel	$\gamma = [0.05\,0.5\,5]^T$	
Methods / Partitions	Op-Mk-Tr-Pa ACC (%)/FPR (%)/FNR (%)/time (s)	Op-Mk-Id-Pa ACC (%)/FPR (%)/FNR (%)/time (s)
2 x 2	**96.774** /9.091/0.000/17.271	**100.000** /0.000/0.000/11.025
2 x 4	80.645/54.546/0.000/21.683	80.645/54.546/0.000/12.270
4 x 2	**96.774** /9.091/0.000/22.974	96.774/9.091/0.000/12.139
4 x 4	90.323/27.273/0.000/35.968	93.548/18.182/0.000/14.138
8 x 8	77.419/63.636/0.000/93.182	96.774/9.091/0.000/31.559
8 x 16	87.097/36.364/0.000/218.608	**100.000** /0.000/0.000/71.629

Table 4- Results obtained from partitioning for _ = [0.01 0.05 0.10.51]T .

Results obtained from partitioning for $\gamma = [0.01\,0.05\,0.1\,0.5\,1]^T$.

RBF kernel	$\gamma = [0.01\,0.05\,0.1\,0.5\,1]^T$	
Methods / Partitions	Op-Mk-Tr-Pa ACC (%)/FPR (%)/FNR (%)/time (s)	Op-Mk-Id-Pa ACC (%)/FPR (%)/FNR (%)/time (s)
2 x 2	93.548/18.182/0.000/18.806	**100.000** /0.000/0.000/11.815
2 x 4	87.097/36.364/0.000/24.418	80.645/54.546/0.000/13.403
4 x 2	**100.000** /0.000/0.000/26.111	**100.000** /0.000/0.000/13.656
4 x 4	93.548/18.182/0.000/39.462	93.548/18.182/0.000/16.878
8 x 8	80.645/54.546/0.000/177.823	90.323/27.273/0.000/53.398
8 x 16	90.323/27.273/0.000/497.102	93.548/18.182/0.000/149.829

Character Recognition

With all the appropriate results, there is one more attribute used to recognize the currency notes and that are characters. The currency notes contain their unique serial numbers and this is what we are going to deal with. Here will discuss the method used to classify and recognize the characters in banknote.

Heuristic analysis[14][16] of characters is done for this purpose to get the accurate features of characters before feature extraction in currency recognition. The system is designed by applying image Processing toolbox and other related MATLAB toolboxes[15]. This system is divided into some section in order to support the feature extraction process. The various processing steps for analysis are pre- processing, binarization, morphological filtering, heuristic analysis and segmentation and feature extraction etc.

In addition, the heights of detected segments are same for all characters. The sequence of steps can be assembled as follows:
1. Segment the serial number (see fig.3).
2. Analyse the brightness and contrast of segments and exclude faulty ones.
3. Analyse the hue and saturation of segments and exclude faulty ones.

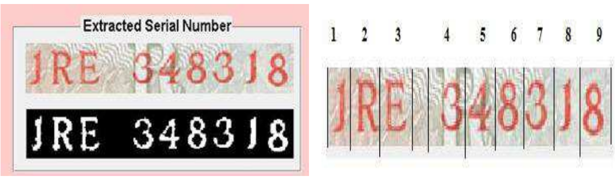


Fig 5 processing with serial numbers

The various properties helps in eliminating the invalid characters that are not useful in feature extraction .The relationship between various properties is also shown

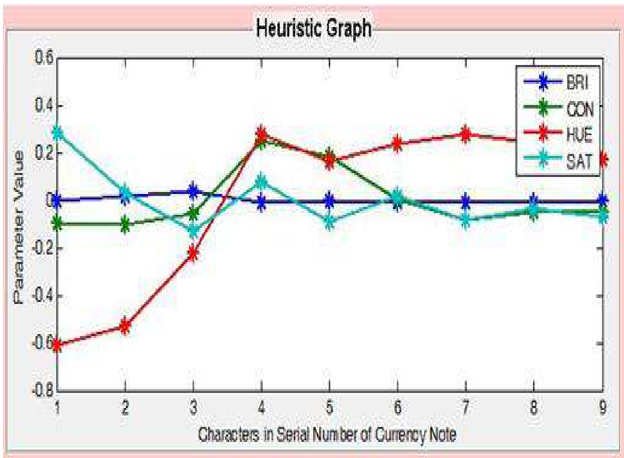


Fig 6 heuristic graph

Feature extraction or selection is a pivotal procedure considerably for currency recognition, which effects on design and performance of the classifier intensively. There below are some categories which is important for the feature extraction on characters like- ***Structural features***, ***Statistical features***, **and *Global transformation***

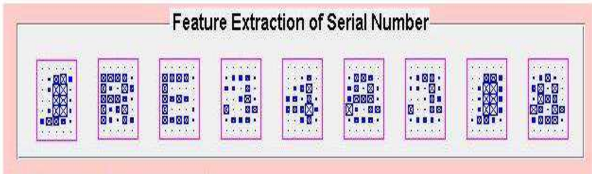


Fig 7 feature extraction

Artificial Neural Network for Classification

The intelligent simulation environment utilizes Artificial Neural Network (ANN)[13] to simulate and optimize a complex queuing system. The integrated simulation ANN model is a computer program capable of improving its performance by referring to production constraints, system's limitations and desired targets. It is a goal oriented, flexible and integrated approach and produces the optimum solution by utilizing Multi Layer Perceptron (MLP). The properties and modules of the prescribed intelligent simulation ANN are: 1) parametric modeling, 2) flexibility module, 3) integrated modeling, 4) knowledge-base module, 5) integrated database and 6) learning module.
A multilayer perceptron (MLP) is used to design a Neural Network-based classifier. Well-known back propagation algorithm is used to train the network. The network does use of the following logistic function as transfer or activation function.

$$f(x) = e^{x} / (1 + e^{x})$$

Complexity of training
The parameters of neural classifiers are generally adjusted by gradient descent. By feeding the training samples a fixed number of sweeps, the training time is linear with the number of samples. SVMs are trained by quadratic programming (QP), and the training time is generally proportional to the square of number of samples. Some fast SVM training algorithms with nearly linear complexity are available. So the gradient decent method is –

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

Where α is the learning parameter, β is known as the momentum and E is the error term
In the present experiment, α is set to 0.9 and β is assigned 0.1. The same dataset as used for the SVM based classifier is also used here to train and test the MLP.

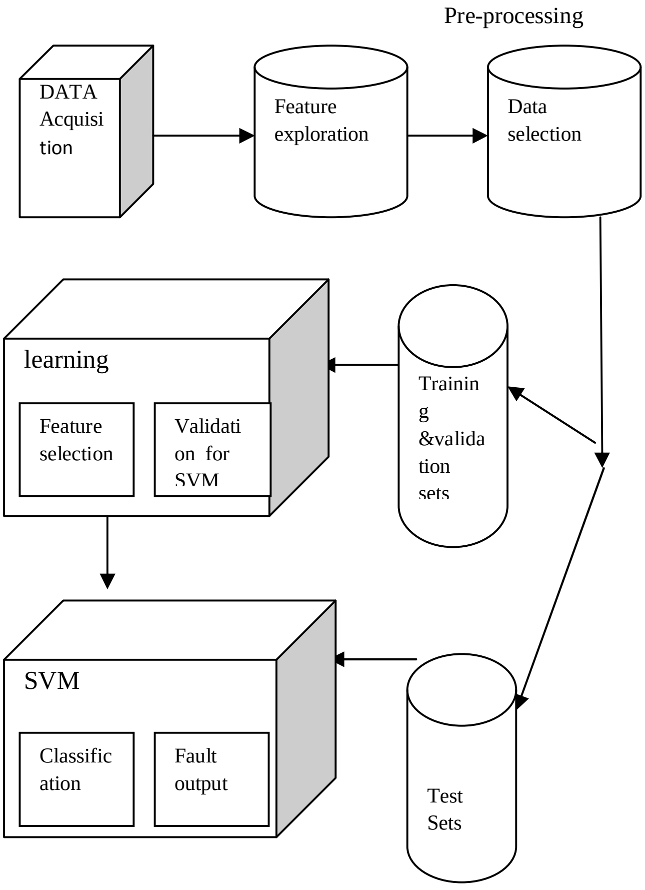


Fig 8 ANN train and test data

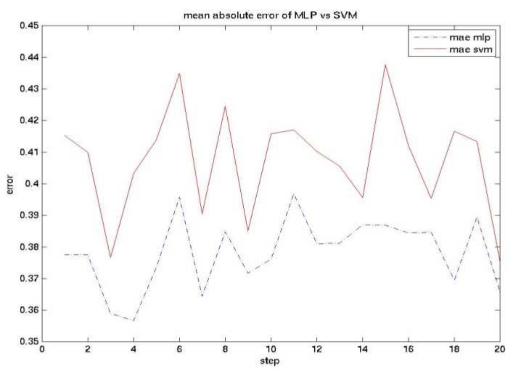


Fig 9 error graph

This graph represents the error line if there is any counterfeit currency note present.

5. Conclusion

Our main motive behind this paper was to present the system based on recognition of counterfeit currency banknotes to avoid frauds. This system is also interfaced with the machine having CCD and advanced feature of UV and infrared red light system to detect the watermarks, latent images etc. For image processing, we have partition the banknote in some parts and process each part individually. For this technique we adopted SVM method that is well suited for such kind of processing. With this thing there is also another feature add of character recognition with the help of heuristic analysis to check the serial numbers of banknote whether they are repeated of misprinted. The whole system is trained and tested with Artificial Neural Network (ANN).

This technique is very adaptive to implement in real time world. Not only in banks, such type of appliances could also be used in shops or some other places. It will be quite beneficial for the person to check their banknotes and avoid to be fool.

References

[1] http://www.rbi.org.in/currency/Security%20Features.html

[2] Rui Lia, Thomas Türkeb, Johannes Schaedeb, Harald Willekec, " FPGA-based Multi-sensor Real Time Machine Vision for Banknote Printing, IT-Institute Industrial IT, Ostwestfalen-Lippe University of Applied Sciences, Liebigstr. 87, D-32657 Lemgo, Germany; vol- 7251 72510S-(8-10).

[3] Mehmet Sevkli, Ali Türkyilmaz M. S. Aksoy, " BANKNOTE RECOGNITION USING INDUCTIVE LEARNING", Fatih University, Faculty of Engineering, Department of Industrial Engineering, Buyukcekmece, 34900, Istanbul, Turkey, pp. 2-3, 1997.

[4] J. Sauvola, M. PietikaKinen, "Pattern Recognition 33 , Adaptive document image binarization", Machine Vision and Media Processing Group, Infotech Oulu, University of Oulu, P.O. BOX 4500, FIN-90401 Oulu, Finland, pp. 225-236, 2000.

[5] Narahari kenkare and Traci may- Plumee, "Fabric Drape measurement: Digital image processing", College of textiles, North Carolina State University, Raleigh, N.C. 2769, vol 4, pp. 3-4.

[6] Automated Visual Inspection Systems Help Ensure Quality and Security of U.S. Currency The U.S. Department of the Treasury's Bureau of Engraving and Printing (BEP).

[7] Elias N. Malamas, Euripides , G.M. Petrakis2, Michalis Zervakis, " A SURVEY ON INDUSTRIAL VISION SYSTEMS,

APPLICATIONS AND TOOLS", Department of Electronic and computer engineering technical university of crete Chania crete Greece,pp 7-18

[8] C. Cortes, V. Vapnik, Support-vector network, Machine Learning 20 (3) (1995) 273–297

[9] M. Pontil, A. Verri, Support vector machines for 3D object recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence 20 (6) (1998) 637–646.

[10] C.-F. Lin, S.-D. Wang, Fuzzy support vector machines, IEEE Transactions on Neural Networks 13 (2) (2002) 464–471.

[11] J.C. Platt, Fast training of support vector machines using sequential minimal optimization, in: B. Schölkopf, C.J.C. Burges, A.J. Smola (Eds.), Advances in Kernel Methods: Support Vector Learning, MIT Press, Cambridge, MA, USA, 1999, pp. 185–208

[12] Chi-Yuan Yeh, Wen-Pin Su, Shie-Jue Lee, Employing multiple-kernel support vector machines for counterfeit banknote recognition, Department of Electrical Engineering, National Sun Yat-Sen University, Kaohsiung 804, Taiwan

[13] www.cse.msu.edu/~cse802/notes/ArtificialNeuralNetworks.pdf

[14] Daniel Kahneman, Amos Tversky and Paul Slovic, eds. (1982),″ Judgment under Uncertainty: Heuristics & Biases.″ Cambridge, UK, Cambridge University Press ISBN 0-521-28414-7.

[15] A.Mc Andrew,”Introduction to Digital Image Processing With MATLAB”,by Cenage Learning,2004

[16] Gerd Gigerenzer, Peter M. Todd, and the ABC Research Group (1999), ″Simple Heuristics That Make Us Smart″ Oxford, UK, Oxford University Press. ISBN 0-19-514381-7.

[17] Dewi Nasien , "The Heuristic Extraction Algorithms for Freeman Chain Code of Handwritten Character", Faculty of Computer Science and Information System (FSKSM) University Teknologi Malaysia Skudai, 81310, Malaysia.

[18] Wing-Soon Wilson Lian, Dr. Diane P. Pozefsky, "Heuristic-Based OCR Post-Correction for Smart Phone Applications", THE UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL DEPARTMENT OF COMPUTER SCIENCE, 2000.