Neural Network Approach for Indian Currency Recognition

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***Abstract*—It is very difficult to count currency notes of different denominations in a bundle. We propose a system which can be implemented in paper currency counting machines to count Indian currency notes of different denominations efficiently and accurately. The system takes an image of standard orientation in upright position of Indian currency notes and detects its denomination accordingly. It makes use of image processing technique and artificial neural networks.**

Keywords-- Chan-Vese segmentation, backpropagation, masking, cropping, laplacian filter, ROI(region of interest)

I. INTRODUCTION

Currency counting in banks is mostly done by counting machines which can count the paper currency when the banker inserts paper currencies of single denomination type, which is both time consuming and laborious.

Various approaches have been used for currency recognition like distinctive point extraction [1] ,making use hidden Markovian models [4],[7] , quaternion wavelet transform [3], classification by linear vector quantization (LVQ) network [5], combinations of one-class classifiers for automated currency validation[6], recognition by color and texture features [8]. Different countries have various paper currency designs [11], this paper focusses only on the Indian paper currency notes.

This paper aims to develop a system which can automate this process and is also accurate. It is similar to that of [1] but only makes use of single neural network for classification instead of individual neural networks for each currency denomination classification. Backpropagation algorithm and image processing techniques are used for currency recognition.

II. PROPOSED SYSTEM

To achieve the objective of developing a system which can recognize Indian paper currency various steps are followed. The images are acquired, required data is extracted and the region of interest is defined which contains the relevant data to be used for recognition. Then various other steps are followed like making database and making use of neural network for paper currency recognition.

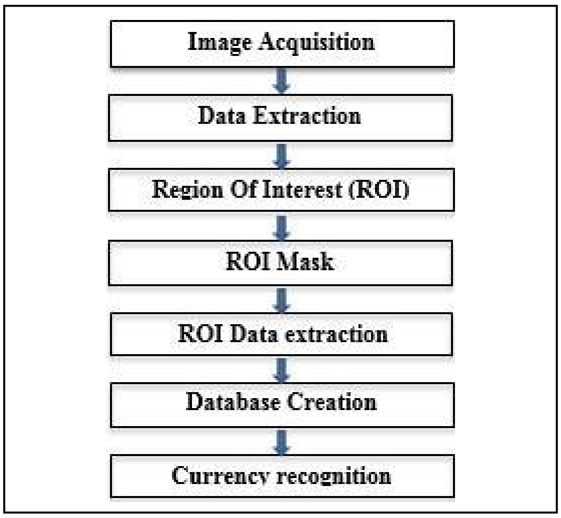


Fig. 1. Proposed system model for currency recognition

A. Image Acquisition

The images are taken through scanner for detection purpose.

Scanner details: HP Deskjet 1050 J410 series

Scanned image DPI: Resolution is 1700 x 2338 with 200 dpi. Background for the image is provided with the help of an A4 size black paper to reduce initial noise while capturing image.

Total scanned images: 613 (100 scanned images for each denomination of 5,10,20,50,100,500 paper rupee notes) and furthermore 13 heavily soiled note images of 5 rupees denomination are taken so total 613(6 * 100 +13).

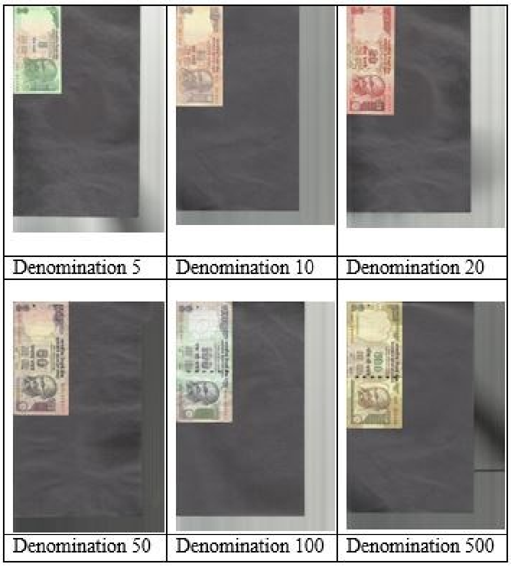


Fig. 2. Scanned images of 6 different denominations

10 random images from each denomination is used for the purpose of testing plus 13 extra heavily soiled paper images and the rest 90 images are used for training.
No of scanned images used for training = 90 * 6 = 540
No of scanned images used for testing = 10 * 6 +13 =73

B. Data Extraction

Required data extraction is the key in a currency recognition system, which influences the accuracy of the system significantly. This is a very critical stage. Here the image of different denomination paper notes are extracted from its background.

TABLE 1. Dimension of cropped denomination images

DENOMINATION	DIMENSION
5 Rupees	915x498
10 Rupees	1074x498
20 Rupees	1155x498
50 Rupees	1145x572
100 Rupees	1233x772
500 Rupees	1313x574

These cropped images of various resolution are converted to standard images of resolution of 250x125.

C. Region Of Interest :

The region of interest is the region containing the face value of the paper currency note. Each of the standard images are then further cropped to generate the region of interest. The dimension of the region of interest after thorough study has been taken to be 59 x 39 in pixels. We have increased the initial database of 540 images for training by varying the region of interest by introducing marginal error with the help of 21 masking values.
Hence total images obtained is: 21 * 540= 11340
The 21 masks which are used on the original
ROI [90 36 58 38] on the standard image found by study are

#0 mask
mask = [90 36 58 38] + [0 0 0 0]

#1 mask
mask = [90 36 58 38] + [1 1 0 0]

#2 mask
mask = [90 36 58 38] + [1 -1 0 0]

#3 mask
mask = [90 36 58 38] + [-1 1 0 0]

#4 mask
mask = [90 36 58 38] + [-1 -1 0 0]

#5 mask
mask = [90 36 58 38] + [1 2 0 0]

#6 mask
mask = [90 36 58 38] + [1 -2 0 0]

#7 mask
mask = [90 36 58 38] + [-1 2 0 0]

#8 mask
mask = [90 36 58 38] + [-1 -2 0 0]

#9 mask
mask = [90 36 58 38] + [2 2 0 0]

#10 mask
mask = [90 36 58 38] + [2 -2 0 0]

#11 mask
mask = [90 36 58 38] + [-2 2 0 0]

#12 mask
mask = [90 36 58 38] + [-2 -2 0 0]

#13 mask
mask = [90 36 58 38] + [2 1 0 0]

#14 mask
mask = [90 36 58 38] + [2 -1 0 0]

#15 mask
mask = [90 36 58 38] + [-2 1 0 0]

#16 mask
mask = [90 36 58 38] + [-2 -1 0 0]

#17 mask
mask = [90 36 58 38] + [0 1 0 0]

#18 mask
mask = [90 36 58 38] + [0 -1 0 0]

#19 mask
mask = [90 36 58 38] + [1 0 0 0]

#20 mask
mask = [90 36 58 38] + [-1 0 0 0]

The images generated in each step are stored for processing.

Fig. 3. Sample cropped image of denomination 10 of resolution 1074 x 498

Fig. 4. Sample standard image of denomination 10 of resolution 250 x 125

Fig. 5. Sample ROI image of denomination 10 of resolution 59 x 39

D. ROI Mask

The region of interest and its masking is found out using active contours without edges segmentation by Chan Vese algorithm [2],[10]. It is used for segmentation of the face value of denomination. It is a nice way to segment images whose foregrounds and backgrounds are statistically different and homogeneous. The method optimally fits a two-phase piecewise constant model to the given image. The segmentation boundary is represented implicitly with a level set function [9], which allows the segmentation to handle topological changes more easily than explicit snake methods.

Here ROI images are segmented and the resulting masks are stored

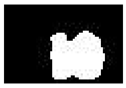


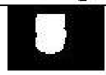
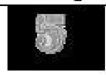
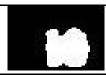
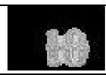
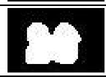
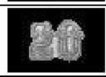
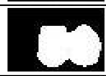
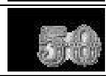
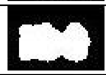
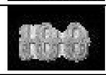
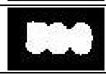
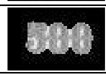
Fig. 6. Sample ROI mask image of denomination 10 of resolution 59 x 39

E. ROI Data Extraction:

Here the actual data to be used for making the database is extracted which is the face value paper currency which show denomination. The RGB values of the ROI images are converted to grayscale values and the ROI Mask segmented images pixel values are divided by 255 to convert the image to binary mask image.

The matrix obtained from the above two images operation is scalar multiplied to produce the final ROI segmented image matrix.

TABLE 2. Results of ROI data extraction

Denomination	RGB Images	ROI Mask segmented images	Final ROI segmented images
5 Rupees			
10 Rupees			
20 Rupees			
50 Rupees			
100 Rupees			
500 Rupees			

F. ROI Mask

The database consists variables X and y used for training and variables Xval and yval used for testing and cross validation purpose.
X is an m x n matrix where, 'm' is the total no of images in the database and 'n' is the total no. of pixels values in an image.
Each row contains the complete pixel values of an image and similarly this matrix contains the pixel values of 'm' images.

The pixel values to be stored are obtained by converting the pixel values of the final ROI segmented image to double values and then passing it through a 3-by-3 filter approximating the shape of the two-dimensional Laplacian operator. The parameter alpha is used to control the shape of the Laplacian and must be in the range 0.0 to 1.0.The suitable value of alpha is found to be 0.08 after testing.

Laplacian filter for four neighbourhood is given by

$$\nabla^2 f = \frac{\partial^2 f}{\partial^2 x} + \frac{\partial^2 f}{\partial^2 y} \quad (1)$$

$$\begin{aligned}\nabla^2 f &= f(x+1,y) + f(x-1,y) + \\ &f(x,y+1) + f(x,y-1) - 4f(x,y)\end{aligned} \quad (2)$$

Where,

f is a 2-dimensional image

y is an m x 1 matrix vector where, 'm' is the total no of images in the database. Each row of the matrix stores the denomination value of the i'th image (1<= i <= m).

TABLE 3. y values of different denominations

Denomination	y value
10 Rupees	1
20 Rupees	2
50 Rupees	3
100 Rupees	4
500 Rupees	5
5 Rupees	6

Similarly variables Xval and yval are made for the 73 test images where only original ROI is used with mask 0 to find the final ROI segmented image and Xval value is used to predict denomination which then is compared with yval to check if our prediction is correct or not.

G. Currency recognition:

Currency recognition is the last phase in currency recognition system. This stage will involve neural network system to recognize the test images of different Indian currency.
The neural network consists of 3 layers with one hidden layer and an input and output layer.
Here Backpropagation(BP) algorithm for artificial neural network is used for recognition of 6 classes of currency.

Cost function:

$$J(\Theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{k=1}^{K} y_k^{(i)} \log\left(h_\Theta\left(x^{(i)}\right)\right)_k + \left(1-y_k^{(i)}\right)\log\left(1-\left(h_\Theta\left(x^{(i)}\right)\right)_k\right)\right] + \frac{\lambda}{2m}\sum_{l=1}^{L-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_l+1}\left(\Theta_{ji}^{(l)}\right)^2 \quad (3)$$

Where,
The input is matrix X and output is vector y.

$$\left\{\left(x^{(1)}, y^{(1)}\right), \left(x^{(2)}, y^{(2)}\right), \ldots, \left(x^{(m)}, y^{(m)}\right)\right\}$$

L = 3, total no. of layers in network
S_l = no. of units (not counting bias unit) in layer

m = 11340, number of training examples

Θ = parameter or weights of neural network layers

$h_\Theta(x) \in \mathbb{R}$, it is the sigmoid function for input x .

k = 6, for 6 class currency classification

$\left(h_\Theta(x)\right)_i = i^{th}$ layer output

To overcome the problem of over fitting and under fitting in neural network regularization is used.
The value lambda λ is used to assign penalty in neural network to the cost function which is given by

$$\frac{\lambda}{2m}\sum_{l=1}^{L-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_l+1}\left(\Theta_{ji}^{(l)}\right)^2$$

Setup parameters for neural network having 3 layers are
Input layer size = 59 * 39, 59x39 input image resolution
Hidden layer size = 100, 100 hidden units in hidden layer
Number of labels = 6, 6 labels, from 1 to 6 in output layer
Here we minimize our cost function by updating our weights for the neural network.

III. EXPERIMETAL RESULTS

The lambda values for which the validation curve is plotted are 0, 0.001, 0.003, 0.01, 0.03, 0.1, 0.3, 1, 3, 10.

Error is minimum for lambda equal to 0.001 and the learning curve is plotted for lambda equal to 0.001.

For λ = 0.001

Prediction accuracy on test database is 97.260274

Prediction accuracy on trained database is 100%

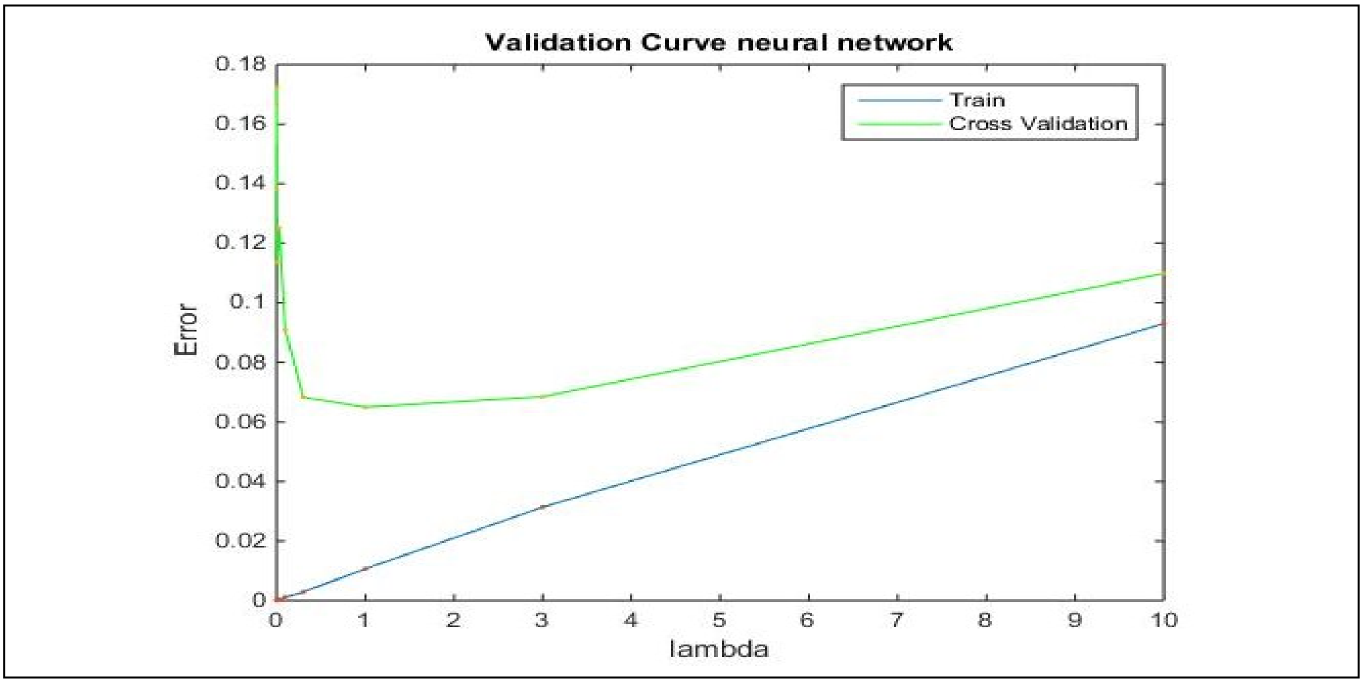


Fig. 7. Validation Curve for different lambda values

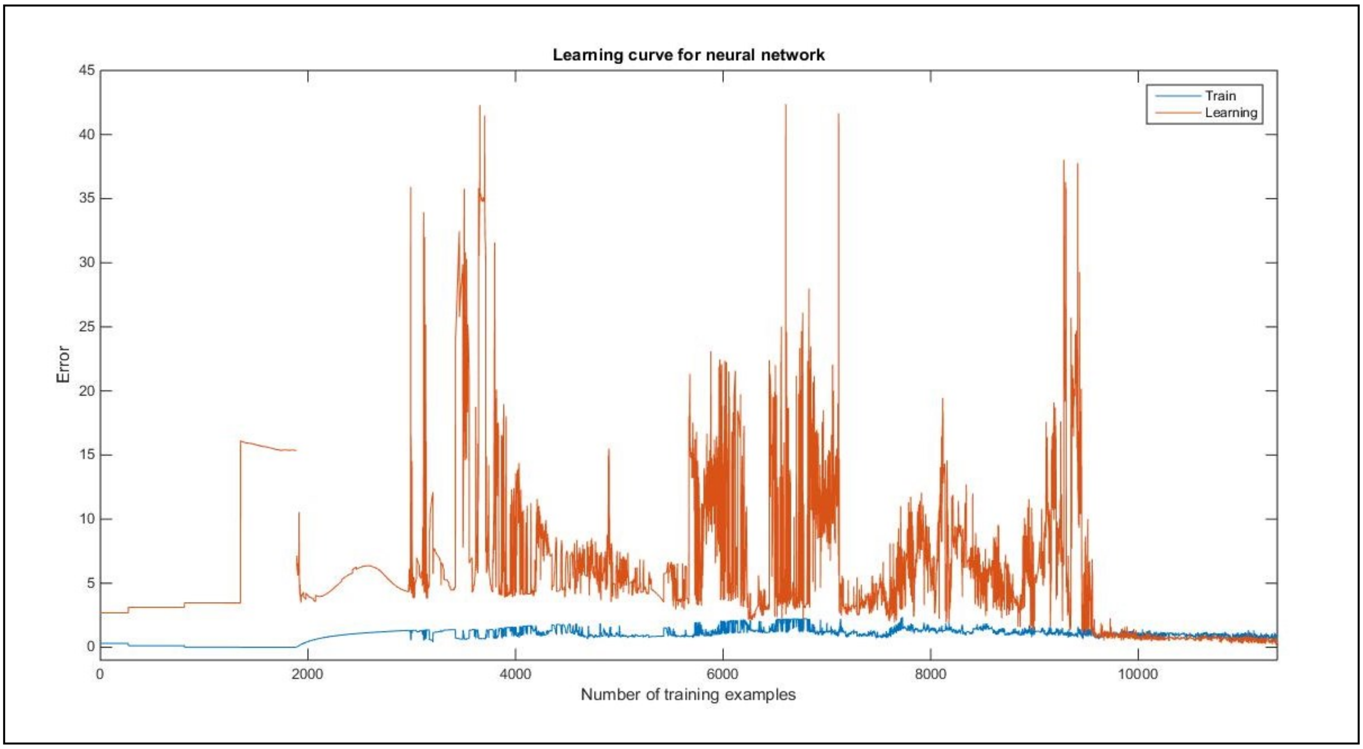


Fig. 8. Learning Curve for neural network for λ = 0.001

CONCLUSION

The proposed system shows high accuracy percentage and is able to recognize cramped as well as soiled notes also. It has 100% accuracy based on the average quality notes and approximately 97% accuracy for very highly soiled notes. The system is also robust due to its large database from where all the training is done for the neural network. The segmentation technique and defining the region of interest along with the appropriate standard resolution was done on trial and error basis to get the best results as possible for extraction of data features. The Chan-Vese active contours without edges algorithm is very much efficient and it also helps to almost eliminate the background along with it the noise there by increasing the quality of the database for training. Moreover, the initial problem of low database for training purpose was solved in an intelligent manner by taking different region of interest masks with little positional co-ordinate difference. This resulted in different image databases after implementing Chan-Vese, as a result the database was increased.

The future enhancements that can be made are as follows.

- Improvements can be done so as to recognize currency images which also have random background rather than a standard background.
- Moreover, certain improvements can be done to recognize currency images to any degree of orientation and any resolution.
- Counterfeit currency detection can also be incorporated.

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