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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)

INTRODUCTION

The need for paper currency recognition system is as follows:

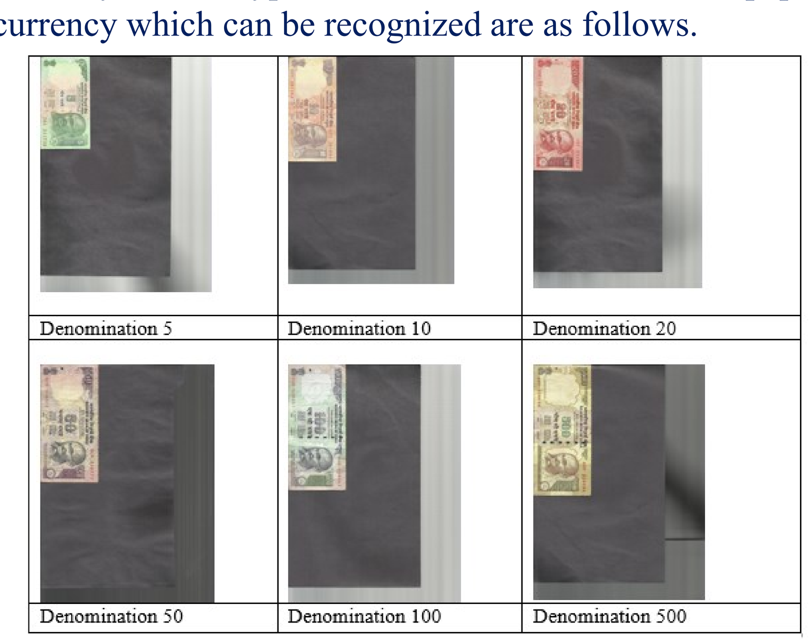
- Counting bulk number of paper notes is time consuming
- To reduce human effort
- Banks need counting machines which can also recognize type of currency

This paper focusses only on the Indian paper currency notes.

OBJECTIVES

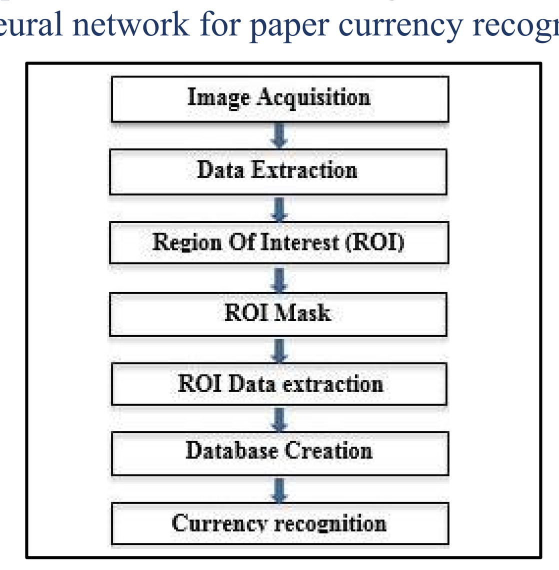
This paper aims to develop a system which can automate this process and is also accurate. Here we make use of single neural network for classification instead of individual neural networks for each currency denomination classification. Backpropagation algorithm and image processing techniques are used for currency recognition.

To develop a system which can recognize Indian paper currency various types. The denomination of Indian paper currency which can be recognized are as follows.



PROPOSED SYSTEM

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.



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).

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

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

B. DATA EXTRACTION

The image of different denomination paper notes are extracted from its background.

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

Dimension of cropped denomination images

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

C.REGION OF INTEREST(ROI)

- Each of the standard images are then further cropped to generate the region of interest containing the face value.
- Dimension of ROI is picked to be 59 x 39 in pixels.
- Initial database of 540 images for training is increased by varying the ROI by introducing marginal error with the help of 21 masking values.

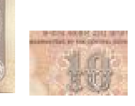
Hence total images obtained is: 21 * 540 = 11340

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]	#7 mask mask = [90 36 58 38] + [-1 2 0 0]	#14 mask mask = [90 36 58 38] + [2 -1 0 0]
#1 mask mask = [90 36 58 38] + [1 1 0 0]	#8 mask mask = [90 36 58 38] + [-1 -2 0 0]	#15 mask mask = [90 36 58 38] + [-2 1 0 0]
#2 mask mask = [90 36 58 38] + [1 -1 0 0]	#9 mask mask = [90 36 58 38] + [2 2 0 0]	#16 mask mask = [90 36 58 38] + [-2 -1 0 0]
#3 mask mask = [90 36 58 38] + [-1 1 0 0]	#10 mask mask = [90 36 58 38] + [2 -2 0 0]	#17 mask mask = [90 36 58 38] + [0 1 0 0]
#4 mask mask = [90 36 58 38] + [-1 -1 0 0]	#11 mask mask = [90 36 58 38] + [-2 2 0 0]	#18 mask mask = [90 36 58 38] + [0 -1 0 0]
#5 mask mask = [90 36 58 38] + [1 2 0 0]	#12 mask mask = [90 36 58 38] + [-2 -2 0 0]	#19 mask mask = [90 36 58 38] + [1 0 0 0]
#6 mask mask = [90 36 58 38] + [1 -2 0 0]	#13 mask mask = [90 36 58 38] + [2 1 0 0]	#20 mask mask = [90 36 58 38] + [-1 0 0 0]

Sample cropped image of denomination 10 of resolution 1074 x 498

Sample standard image of denomination 10 of resolution 250 x 125

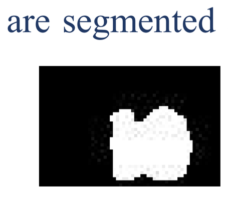


Sample ROI image of denomination 10 of resolution 59 x 39

D.ROI MASK

- The ROI and its masking is found using active contours without edges segmentation by Chan Vese algorithm .
- Segment images whose foregrounds and backgrounds are statistically different and homogeneous.
- It optimally fits a two-phase piecewise constant model to the given image.
- The segmentation boundary is represented implicitly with a level set function , which allows the segmentation to handle topological changes more easily than explicit snake methods.

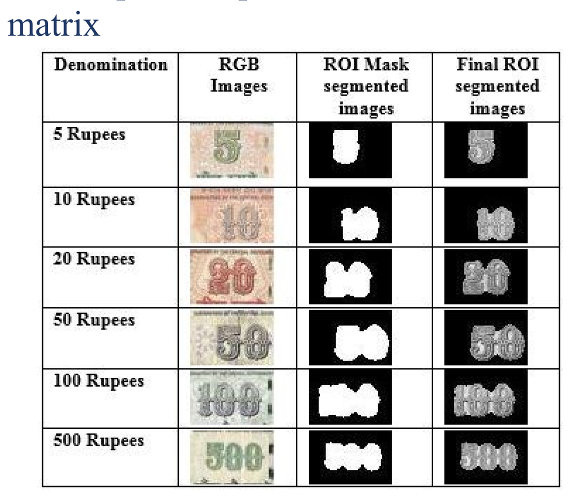
Here ROI images are segmented and the resulting masks are stored



Sample ROI mask image of denomination 10 of resolution 59 x 39

E.ROI DATA EXTRACTION

- Actual data for database is the face value of currency.
- 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.
- Matrices obtained from the above two images operation is scalar multiplied to produce the final ROI segmented image matrix



Results of ROI Data Extraction

F.ROI MASK

Results in stored in database.

- **Training** : variables X and y
- **Testing and cross validation** : variables Xval and yval

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 X matrix contains the pixel values of 'm' images.

F.ROI MASK

- **Training** : variables X and y
- **Testing and cross validation** : variables Xval and yval

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 of the final ROI segmented image are converted to double values and then passed 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.

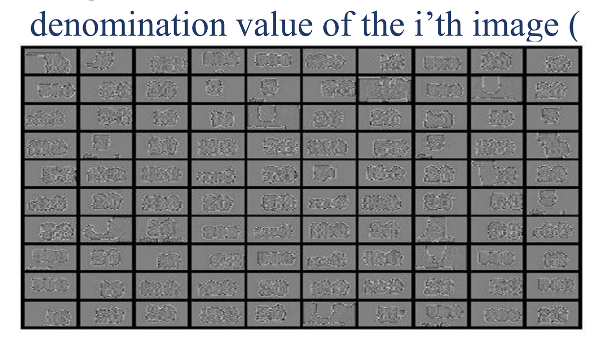
Laplacian filter for four neighbourhood is given by

$$\nabla^2 f = \frac{\partial^2 f}{\partial^2 x} + \frac{\partial^2 f}{\partial^2 y}$$

$$\nabla^2 f = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) - 4f(x,y)$$

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)



Sample 100 images stored in X

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

y values of different denominations

- 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 .
- 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

- The neural network consists of 3 layers with one hidden layer and an input and output layer.
- Here Backpropagation(BP) algorithm is used for recognition of 6 classes of currency.

Cost function

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

Where, input is matrix X and output is vector y

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

L = 3, total no. of layers in network

S_l = no. of units (not counting bias unit) in layer

k = 6, for 6 class currency classification

m = 11340, number of training example

Θ = parameter or weights of neural network layers

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

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

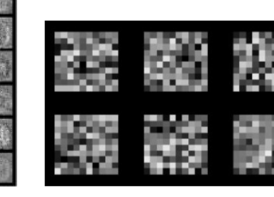
- **Input layer size** = 59 * 39, input image resolution
- **Hidden layer size** = 100, 100 units in hidden layer
- **Number of labels** = 6, from 1 to 6 in output layer

Here we minimize our cost function by updating our weights for the neural network

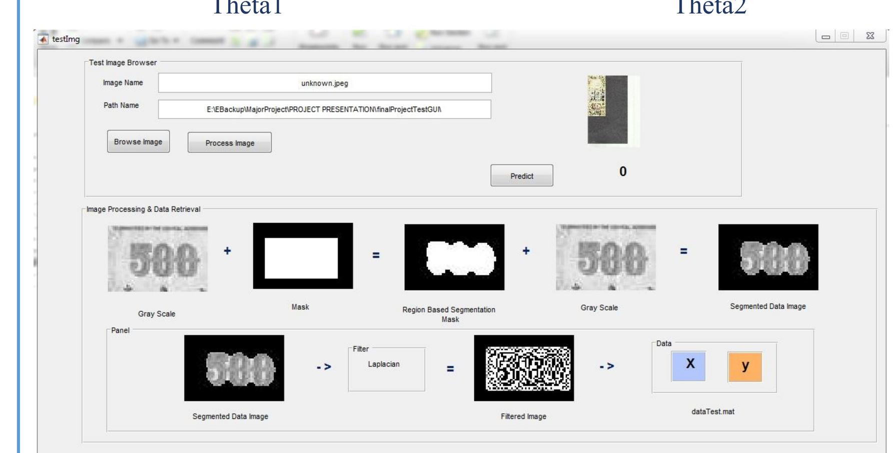
H.LEARNED WEIGHTS

- As the neural network consists of only one hidden layer so we have two weight Theta1 and Theta2 which are matrices after the training process is over for the neural network.
- These matrices are stored in the database and later on used for predicting unknown Indian paper currency note.

Theta1



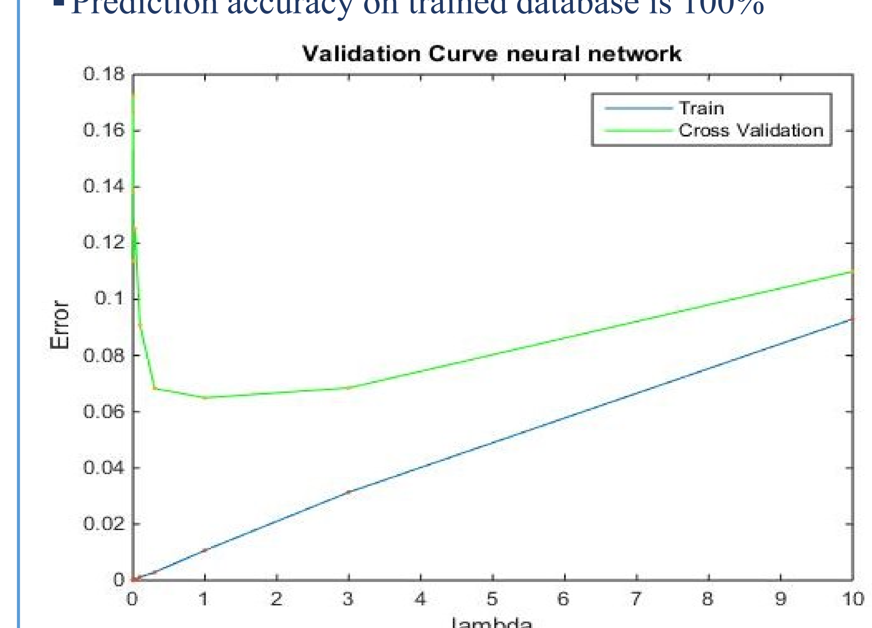
Theta2

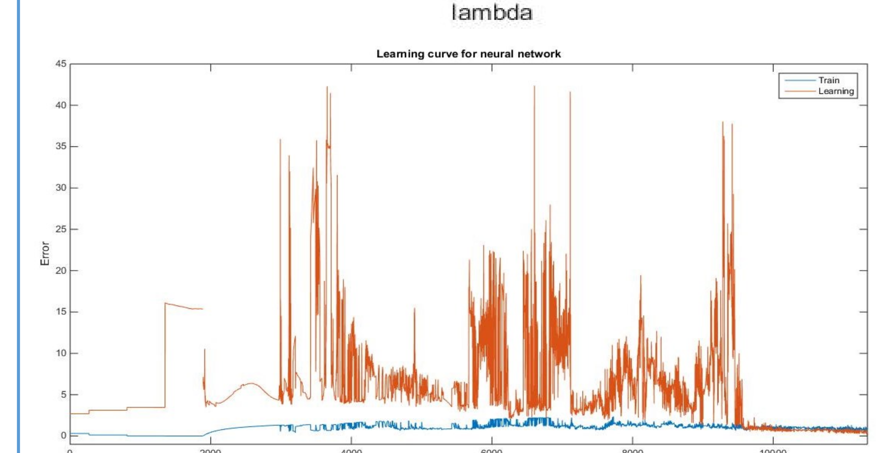


User Interface

EXPERIMENTAL RESULTS

- The λ 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 λ equal to 0.001 and the learning curve is plotted for lambda equal to 0.001
- Prediction accuracy on test database is 97.260274 %
- Prediction accuracy on trained database is 100%





CONCLUSION

- 100% accuracy based on the average quality notes & 97% accuracy for very highly soiled notes.
- Robust system due to its large database based training.
- The segmentation technique and defining the region of interest along with the appropriate standard resolution was based on study to get the best results .
- Chan-Vese active contours without edges algorithm is eliminates background noise.
- Database was increased using Chan-Vese using different masks which various positional masking error.

FUTURE ENHANCEMENTS

- Recognition of currency images which also have random background rather than a standard background
- Recognise images to any degree of orientation and size.
- Counterfeit currency detection can also be incorporated.
- Proposed model can be implemented in hardware for real time currency recognition and counting of currency in paper currency counting machines.

REFERENCES

1. Jae-Kang Lee, Seong-Goo Jeon, and Il-Hwan Kim,"Distinctive point extraction and recognition algorithm for various kinds of Euro banknotes" International Journal of Control, Automation, and Systems vol. 2, no. 2, 2004.
2. Pascal Getreuer, "Chan-Vese region based active contours without edges" Published in Image Processing On Line. ,2012.
3. Shan Gai, Guowei Yang, Minghua Wan ,"Employing quaternion wavelet transform for banknote classification" Neurocomputing vol. 118, pp. 117-178 , 2013.
4. H. Hassanpour , E. Hallajian, "Using hidden Markov models for feature extraction in paper currency recognition" Expert Syst. Appl. , vol. 36 ,pp. 10105-10111 ,2009.
5. Tosihisa Kosaka, Norikazu Taketani, Sigeru Omatu, and Kunihiro Ryo, "Discussion of reliability criterion for US dollar classification by LVQ" ,Proceedings of the SMCid99 1999 IEEE Midnight-Sun Workshop on soft Computing Methods in industrial Applications Kuusamo, Finland, June 16-18, 1999.
6. Chao He , Mark Girolami , Gary Ross, "Employing optimized combinations of one-class classifiers for automated currency validation" Pattern Recognition,vol.37, pp.1085-1096 , 2003.
7. Abbas Yaseri , Seyed Mahmoud Anisheh, " A novel paper currency recognition using fourier Mellin transform, hidden Markov model and support vector machine" International Journal of Computer Applications vol. 61, no.7, pp. 17-22, 2013.
8. García-Lamont, Farid and Cervantes, Jair and Chau, Asdrubal Lopez, "Recognition of Mexican banknotes via their color and texture features" Expert Syst. Appl.,vol.39, pp. 9651-9660, 2012.
9. S. Osher, J.A. Sethian, "Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations,"Journal of Computational Physics,vol.79,no.1,pp.12-49,1988
10. T.F. Chan, L.A. Vese, "Active Contours Without Edges," IEEE Transactions on Image Processing, vol. 10, no. 1, pp. 266-277, 2001.
11. M. Williams and R. Anderson. Currency design in the united states and abroad: counterfeit deterrence and visual accessibility. Federal Reserve Bank of St. Louis Review, September/October 2007, 89(5), pp. 371-414.