ISSN 2347 - 3983
Volume 11. No.6, June 2023
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter051162023.pdf
https://doi.org/10.30534/ijeter/2023/051162023

Feature Based Indian Currency Detection Using Minimum Weight Distance Classifier

B. Subbarayudu[1], T.Yesaswini[2], C.Sireesha[3], M.Vaishnavi[4]
[1]Assistant Professor, Electronics & Communication Engineering, Madanapalle Institute of Technology and Sciences, Madanapalle, India, Mail: subbarayudub@mits.ac.in
UG Scholars, Electronics and Communication Engineering, Madanapalle Institute of Technology and Sciences, Madanapalle, AP, India
20690A0413@mits.ac.in, 20690A0407@mits.ac.in, 19699A04A5@mits.ac.in.

Received Date: April 29, 2023 Accepted Date: May 20, 2023 Published Date : June 07, 2023

ABSTRACT

The Automated Currency Recognition is of great interest as a number of automated banking systems used by financial institutions make use of it as their main function. A review of the literature on banknote recognition, however, reveals that there are no methods that have been proposed or put into practice for the identification of recently issued bank notes. Real-time applications can benefit from the suggested approach's excellent performance and relative time efficiency. We believe that the composite feature described in this thesis which combines elements of both color and texture is a first in the field of banknote identification. Our contribution is that this research initiative and the suggested technology have made real-time recognition of recently released ultimate development of real-time multi-currency recognition is made feasible by banknotes.

Key words : Back Propagation Neural Network Classifier, F-measure network, HSV color quantization, Real time bank note recognition, Serial Indian paper currency, The Minimum Distance Classifier, Uniform LBP.

1. INTRODUCTION

Thousands of years ago, currency was developed to replace the antiquated barter system, in which any item may be exchanged between two traders with their consent.. Even now, money continues to be an essential part of contemporary life as a measurement unit for the price of a transaction. For instance, it can be utilized to pay off debt and serve as a value store for savings [1]. Cash, including coins and banknotes, cashless money, such as bank checks, and even digital information that represents money in bank accounts have all been added to the monetary form. When banknotes, known as "Jiaozuo," first made their formal appearance in China in the year 1023, they were known as "Jiaozuo." were eventually brought to the western. Hemisphere by American colonists for organized use [5]. Despite having a lengthy history, the global market for printing banknotes is still somewhat secretive, which is often justified by the desire to safeguard the secure environment for the manufacture of this distinctive good. The general public is unfamiliar with printing equipment, security inks, fully automated technology for extremely accurate banknote analysis, or highly secure shredder equipment for spent notes.

A significant amount of research is beginning to shed light on the inner workings of the banknote, particularly in the area of banknote identification, despite limited disclosure of the methods used to produce banknotes. Recent security analysis has led to the development of numerous paper currency recognition systems that are used in a variety of settings for instance, Sorting of banknotes and automated teller machines (ATM's).

2. LITERATURE REVIEW

Numerous paper currency recognition systems, such as automated teller machines (ATM's) and note sorting, have been created as a result of recent security analysis.

2.1 MDC

A trustworthy prototype was made using a Smartphone camera to assist those who are blind distinguishing U.S. paper money being used [18] reported on Ecuador. The aural message representing. The value of the note in front of the camera, as it appeared on the subject's face, was produced by closely examining each shot. In the system, Minimum distance-based MDC and Eigen values based on PCA were combined. Seven frames per second as the minimal processing speed was demonstrated by the prototype, an ideal recognition rate of 99.838%, a recognition rate of 99.156% inside, and a recognition rate of 95.223% outdoors [3]. In their 2014 study, Vishnu and Oman suggested a PCA based framework for recognizing Indian banknotes. They conducted their study using the latent image, micro letter, and RBI seal. Five security measures, including the Reserve, Shape, and Centre Number. The Minimum distance from the primary components of the banknote characteristics was constructed to establish the weight vector similarities [2]. The collection of artificial neural network (ANN) classifiers, which also includes the template-matching classifiers and the radial basis function network (RBFN), learning LVQ stands for vector quantization and BPNN, has also been frequently used to recognize paper cash [10].

2.2 BPNN Classifier

There were 16, 16, and 12 nodes in each of the three planned BPNN tiers. Additionally, they proposed the random masks approach and demonstrated its efficiency by employing Fourier power spectra and time series data as the network's primary inputs. The recommended technique resulted in an identification rate of more than 92% and a recognition rate of at least three notes per second. Another BPNN-based banking system that is appropriate for the US was developed a few years later employing evolutionary algorithm-optimized neural weights and mask sets.

2.3 Digital Image Processing

Many scientific and technical fields, including computer vision, have used pattern recognition. The use of pattern recognition and computer vision in tandem is well covered in literary works. The combined usage has led to a subfield of signal processing that originated in electrical engineering. Digital image processing is one of the most active research fields today. Digital image processing is focused on gathering data, measurements, or information from an image using arrays of numbers obtained by spatially sampling points of a physical image.

3. COLOUR FEATURE EXTRACTION

When a banknote uses a dominant colour to distinguish itself from others, the colour feature can be used to help identify banknotes as a solo feature or as a component of a composite feature [15].
A variety of distinctive elements, including the proportions of each colour and the locations of the color, are included in an image's colour information. Each of these traits may be seen as a distinct colouring feature. The ability to collect statistics for each colour in an image regardless of where it is placed geographically makes a colour histogram an effective feature extraction method.

3.1 Texture Feature Extraction

A common technique for describing texture and a kind of visual descriptor used in computer vision for classification is the local binary pattern (LBP). Ocala, Perikhanian, and Harwood, who drew their inspiration the texture of a texture picture is determined by a model of texture analysis spectrum may be used to describe it, formally introduced the first LBP operator in 1994. The foundation of LBP is the idea that small patterns can be seen in Figure 1 image Edge and other local feature distribution in a photograph is then revealed by a histogram of the micro-patterns, and Patterns created by concatenating the binary gradient directions are called LBP's, or low-order binary patterns.

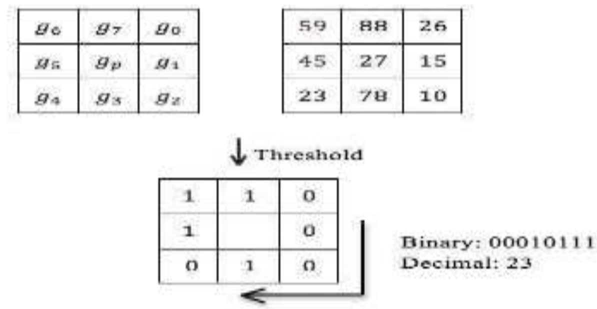


Figure 1: An example of LBP operator

The texture is only applied to a tiny portion of the surface by the first LBP operator, fixed-radius areas, making it appear that it is unable to calculate textures of different sizes and frequency [8] and [9]. Regarding the textures at various sizes, the original LBP operator was changed to expand a 3*3 neighbourhood to any neighbourhood, leading to the creation of a circular local binary pattern [4]. It uses bi-linear interpolation at non-integer pixel coordinates and a circular neighbourhood to enable any neighbour pixels, regardless of their size and radius as shows in Figure 1.
The LBP operators can be used to make a feature vector's dimensions smaller in addition to rotation invariant LBP. In order to be considered uniform, a local binary pattern must only experiences 0 to 1 or 1 to 0 is the result of two bit wise shifts. The patterns 10000110 (4 transitions) and 10101010 (8 transitions), for instance, are uniform, although the patterns 11111111 (0 transition), 00000001 (2 transitions), and 00000110 (2 transitions).In Figure 2 and Figure 3 the Fourier features are based on uniform local binary pattern histograms.

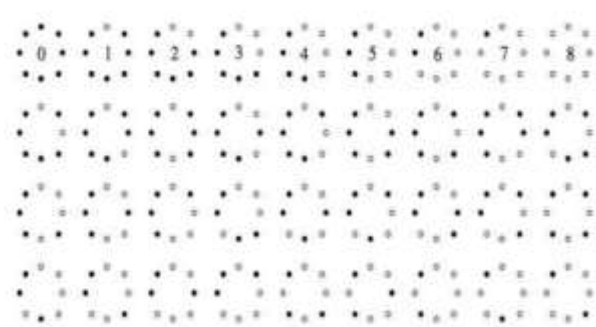


Figure 2: 36 binary patterns with rotational in variance

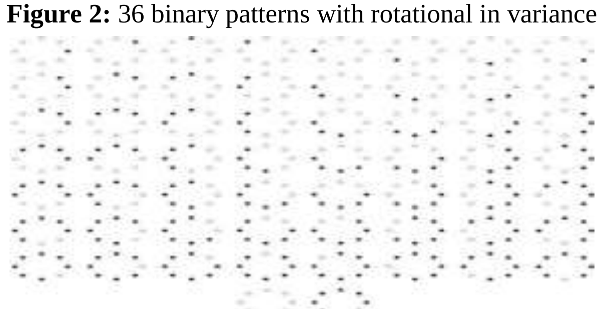


Figure 3: A circle with a one-pixel radius and a neighbor set of eight members as its foundation, uniform LBP

3.2 PCA

It is also known as the Hostelling transform or the Karenina-Love transform, according to [14] particular that inter-correlated variables commonly represent PCA is frequently used to choose the most significant basis to define a certain data-set, even for observations with substantial noise enabling the identification of hidden structure and the filtering of data set noise. Particularly, principal component analysis (PCA) determines principle a group of fresh, orthogonal variables called components created by linearly combining the initial variables. In order to convert the n-dimensional vector to a one-dimensional vector, the image's pixel rows should be arranged in Image Vector $= \{x_1 x_2 \ldots x_{N^2}\}$ where the first N components, x1 through xn, represent the first row of the picture, the following n elements, the second row, and so on.

3.3 LDA

Another linear projection-based method for lowering the dimensionality of the data in a training data set is LDA. Instead of looking for vectors in the underlying space that best describe the data, it looks for those that best discriminate between classes [7]. The comparison unsupervised learning and supervised algorithm. Given a few independent characteristics that each separately define the data set, LDA performs a linear adjustment to them in accordance with the mathematical reason, resulting in the Most significance mean differences existed between the target classes.

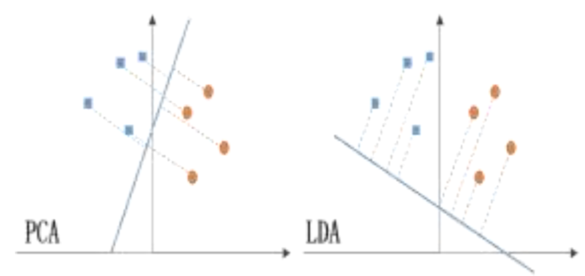


Figure 4: Comparing the mapping outcomes of PCA and LDA

Therefore, even though PCA makes data representation easier by reducing dimensionality and keeping as much of the original data as feasible, it may make categorization challenging. LDA, in contrast, makes the most of the dataset's previously known category information shows in Figure 4. To make the data more easily discernible, it translates the dataset to a different axis.

4. CLASSIFICATION OF ALGORITHMS

Classifier design has long piqued the interest of the pattern recognition community, and in recent years, significant progress has been achieved in this field.

4.1 Minimum Distance Classifier

The accuracy of the MDC is equivalent to that of other, more computationally costly methods like maximum likelihood despite being simple to implement and computationally simple. Compared to in respect to its mean, the randomness of each class, the MDC performs well in practice when the distance between means is large. This could be this classifier's limitation. Typically, three different There are three types of distance measurements: the Euclidean, Manhattan, and Chebyshev used in the minimum distance classification process.

4.2 Back Propagation Neural Network Classifier

McCullough and Pitts developed the first threshold logic-based computational model of an ANN in 1943. This model was based on mathematics and algorithms. It paved the way for a study on ANN to be divided into two approaches, one concentrating on the biological functions of the second on ANN's use in artificial intelligence. According to the particular algorithm employed, neural networks used in ANN models are composed of numerous neurons that can be joined in a number of ways and are organized in layers. Sensors that detect their environment activate input neurons, while additional neurons are activated by weighted links from previously active neurons [6]. Each neuron is capable of delivering a succession of real-valued activation's.

4.3 KPI

Today, multi-class classification systems make usage of the F-measure, which was first constructed in the area of information retrieval. Numerous studies on the recognition of banknotes use the accuracy to calculate the proposed method's recognition rate; this accuracy is determined as the total number of recognition times divided by the accurate recognition times. In Figure 5 shows the diagram of the BPNN.

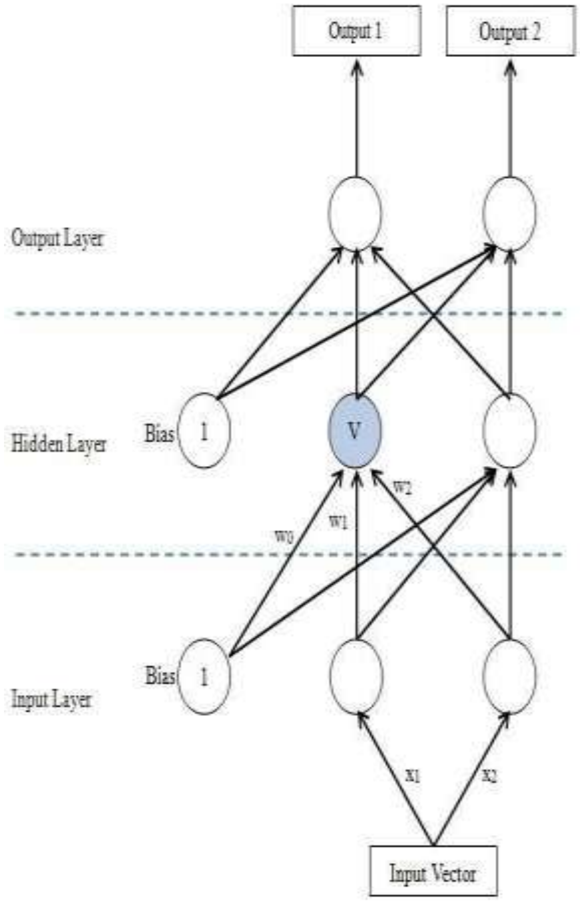


Figure 5: A Schematic diagram of BPNN

4.4 Experimental Platform

MATLAB is selected as the platform for researching automated real-time banknote identification for Series India banknotes due to its integrated graphics and matrix-based language, which naturally express computational mathematics. The research will be carried out on a Lenovo S145 laptop running Microsoft Windows 7 64-bit and the MATLAB student version R2022a software. The laptop has an 8GB of RAM and a 2.50GHz Intel Core i7-4710MQ CPU are used that shows in Figure 6 and Figure 7.

4.5 Flowcharts

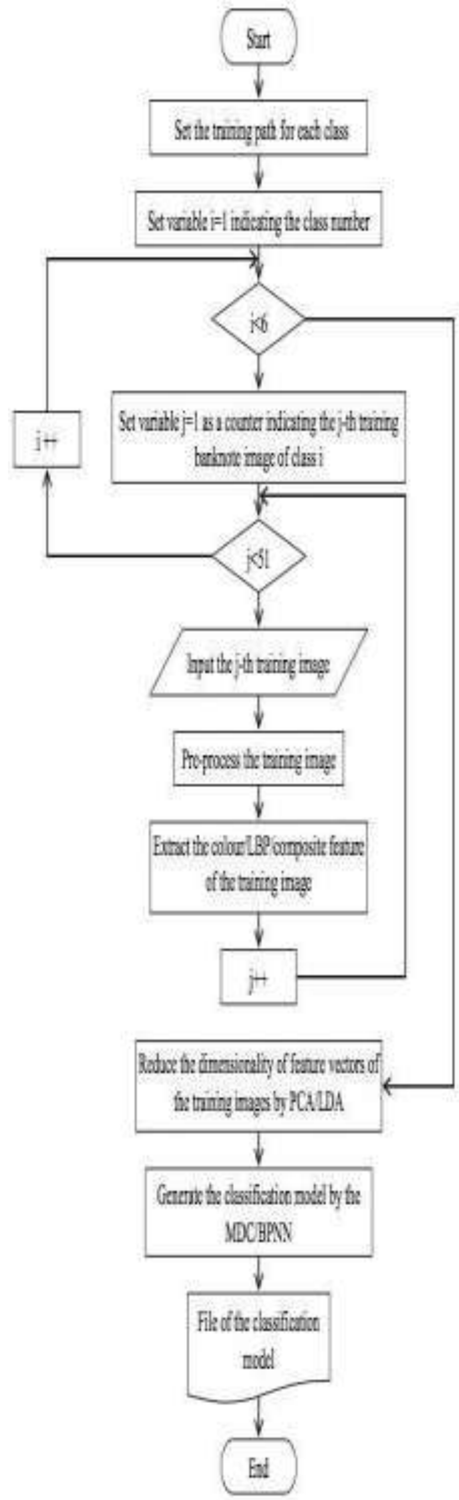


Figure 6: Flowchart of a Training Procedure.

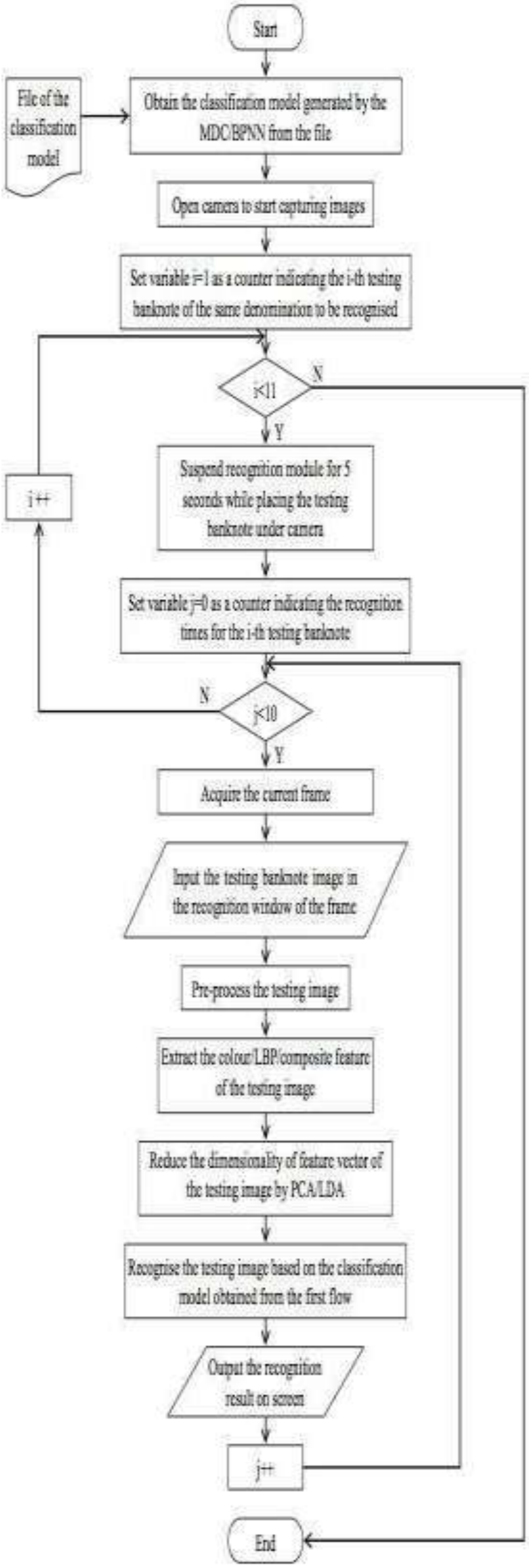
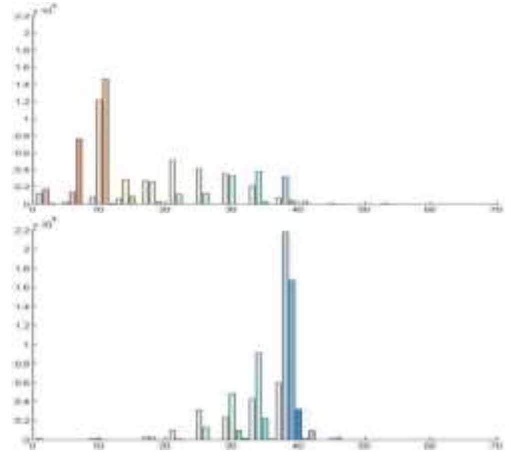


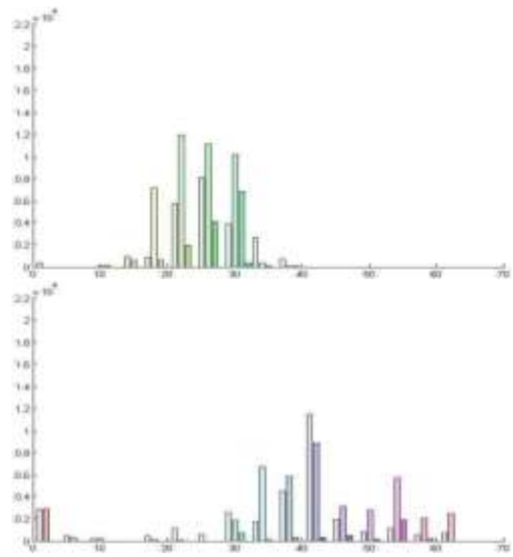
Figure 7: Flowchart of a Testing Procedure.

4.6 Extraction of color features

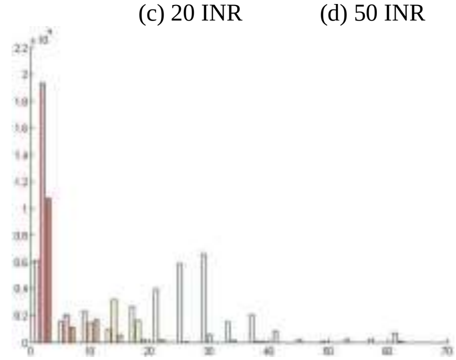
The input picture in MATLAB is changed from RGB to HSV mode. The value relating to a color's brightness is omitted in order to ensure PCA's stability because it is light-sensitive, making it one of the dimensionality reduction techniques to be utilized in the tests.



(a) 5 INR (b) 10 INR



(c) 20 INR (d) 50 INR



(e) 100 INR

Figure 8:16-bit color scanned banknote pictures histograms.

In training, the color Histogram Matrix is generated to store the extracted color features of all training images. As there are 50 training samples for each of the five different denominations, and each training sample is represented by a color histogram with 16 bins, the dimension of the Color Histogram Matrix is 250×16 shows in Table 1.

The input image is converted to a Grey-scale image in MATLAB. To enhance the contrast of the Grey levels, the Grey-scale image is passed through histogram equalization in MATLAB as shows in Figure 9. The default function transforms an intensity image to an image with 64 discrete Grey levels. By histogram equalization, the histogram of an image is equalized, and frequencies of intensity are uniformly distributed over the whole intensity.

The banknotes within the recognition window are captured as frames, and each frame serves as the testing image to be analyzed. Subsequently, the testing image is processed in the same way as processing the training images, including pre-processing, feature extraction and dimensionality reduction. Finally, the processed banknote image being tested is then sent to the classification model generated in the training stage for denomination recognition. During testing, taking a 5 INR testing banknote as an example, after 10 times of recognition of a 5 INR testing note, a five-second intermission is given to place another 5 INR for testing within the recognition window. Thus, it is noteworthy that 50 testing samples eventually generate a total of 500 recognition results, with each testing sample generating 100 recognition results [12]. The recognition result of each time is shown above the recognition window, highlighted by a red color as shows in Figure 8 and the Combination will be shows in Figure 9 and also the real time examples of Indian notes shows in Figure 10.

Table1: The F-Measure of each combined method for recognizing each denomination when used scanned bank note images for training.

Combination No.		Denomination class				Average
	Rs5	Rs10	Rs20	Rs50	Rs100	
1	0.9049	1	0.8827	1	1	0.9575
2	0	0.475	0.8718	0	0.7609	0.4216
3	0.9901	1	0.9899	1	1	0.9960
4	0.7663	1	0.6014	1	0.9796	0.8695
5	0.9529	1	0.9569	1	1	0.9820

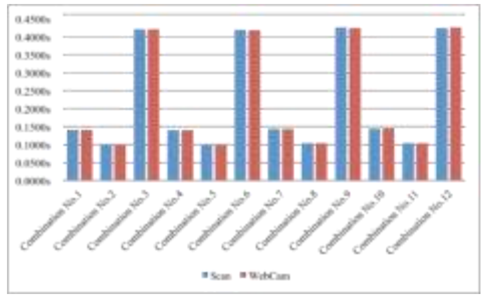


Figure 9: Matlab's testing window

a) 10 INR Real Note

b) 20 INR Real Note

c) 200 INR Fake Note

Figure 10: Real Time example of Indian Notes

5. RESULTS

As we analyze the initial hypothesis in light of the research findings in this chapter, we will present the experimental outcomes.

5.1 **Experimental Results**

Table 2: The F-measure of each combined training approach when utilizing webcam photos of currency to distinguish between each denomination.

Combination No.	Training sets	
	Scan	Webcam
1	0.9575	0.9940
2	0.4216	0.9133
3	0.9960	0.9960
4	0.8695	0.9920
5	0.9820	0.9920
6	0.7994	0.9441
7	0.9759	0.9940

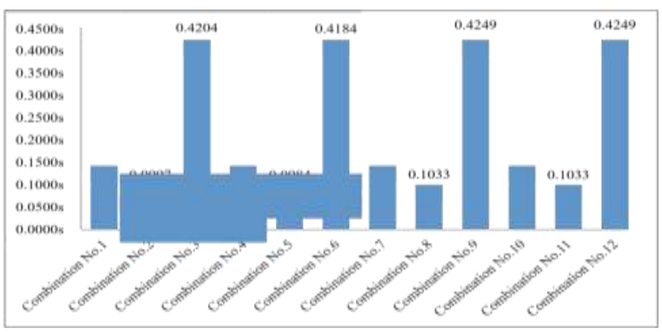


Figure 11: The typical recognition time required by each method when used together.

6. CONCLUSION

By summarizing the current research, highlighting its novelty, highlighting its importance, this chapter will support the thesis, noting its strengths and weaknesses, and recommending additional study.

Summary

Answering the question of how to use digital image processing Real-time identification of the new Series India banknotes in front of a camera is challenging. It depends on a variety of variables, including the make-up of the training set, the features that need to be gleaned, and the classifiers that need to be applied [16] and [17]. This thesis offers empirical methods for Series India banknote real-time recognition based on the analysis of the banknote recognition literature. For training, 250 samples of various denominations of banknotes, including 50 each of 5, 10, 20, 50, and 100 Indian rupees, respectively [11] and [13] shows in Table 2. Two groups of training sets are produced once the training has been processed in Figure 11.

REFERENCES

1. Aasma, S., & Asma, N. (2016). India Currency Denomination Recognition by Image Processing. International Journal for innovations in Engineering, Science and Management.

2. Hungarian, F.P, Mohammad pours, T., & Kianisarkaleh, A. (2012). Persian banknote recognition using wavelet and neural network. In International Conference on Computer Science and Electronics Engineering, (Vol. 3, pp. 679684). IEEE.

3. Ali, A., & Manzoor, M. (2013). Recognition System for Pakistani Paper Currency. World Applied Sciences Journal.

4. Althafiri, E., Sarfraz, M., & Alf arras, M. (2012). Bahraini paper currency recognition Journal of Advanced Computer Science and Technology Research, 2(2), 104-115.

5. Bender, K. (2006). Money makers. Berlin: John Wiley and Sons. Bezek, J. C. (2013). Pattern recognition with fuzzy objective function algorithms.

6. Springer Science & Business Media. Barked A. A. S. S. (2013). Survey of currency recognition system using image processing. International Journal of Computational Engineering Research, 03(7).

7. Bishop, C. M. (2006). Pattern recognition and machine learning: springer. Bow, S. T. (Ed.). (2002). Pattern recognition and image pre-processing. CRC Press.

8. Chae, S. H., Kim, J. K., & Pan, S. B. (2009). A study on the Korean banknote recognition using RGB and UV information. Communication and Networking, 477-484.

9. Chakraborty, T., Nala wade, N., Manjra, A., Sarangi, A., & Chaudhari, P. P. (2016). Review of various image processing techniques for currency note authentication. Int. J. Compute. Eng. Res. Trends, 3(3), 119-122.

10. Chambers, J. (2012). Digital currency forensics Master Thesis, Auckland University of Technology.

11. Chapelle, O., Zine, A., & Schoellkopf, B.(Eds.) (2006). Semi-supervised learning. Cambridge, MA: MIT Press.

12. Cherkasky, V., Friedman, J. H., & Wechsler, H. (Eds.). (2012). From statistics to neural networks: theory and pattern recognition applications (Vol. 136). Springer Science & Business Media.

13. Choi, E., Lee, J., & Yoon, J. (2006). Feature extraction for bank note classification using wavelet transform. In 18th International Conference on Pattern Recognition, (Vol 2, pp. 934937). IEEE.

14. Coos, K. J., Wieniawski, R. W., Petryks, W., & Kurgan, L. A. (2007). Feature Extraction and Selection Methods. In Data Mining (pp. 133-233). Springer US.

15. Cristea, P. D. (2009). Application of neural networks in image processing and visualization. In Geo Spatial Visual Analytics (pp. 59-71). Springer Netherlands.

16. De Sa, J. M. (2012). Pattern recognition: concepts, methods and applications. Springer Science & Business Media.

17**.** Devi, O. R., Prasad, J., Rao, B., Babu, M., Kumar, L., Prakash, P., Rani, K. (2016). Survey on paper currency recognition system. Int. J. Emerge. Trends Technol. Compute. Sci, 5(2), 105108.

18. Dittmar, T. V., Hood, A. K., & Suen, C. Y. (2017). Multi-class SVM based gradient feature for banknote recognition. In IEEE International Conference on Industrial Technology , (pp. 10301035).