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An efficient Feature Extraction Algorithm for Multi-Font Numeral Recognition system in Images

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ABSTRACT

The current research wok will help to speed up the cheque processing in banking industry where tremendous volumes of the cheque leaves are submitting every day. Feature extraction, as a key element of optical character recognition, has been analyzed across the past several years, and a number of algorithms have been offered. In this paper, a new feature extraction algorithm for recognizing printed off-line multi-font numeral is proposed. The proposed method consists of five different phases, namely, data collection, pre-processing, segmentation, feature extraction, and recognition. The numeral samples used here are the scanned image where the account number has been printed on the bank cheque leaves from various Banks in India. Each numeral from the account number is cropped individually, and must be performed size normalization with aspect ratio, this image is equally divided into n matching zones. For classification and recognition, Euclidean distance classifier is used. The recognition accuracy of 77.57% is obtained in average for multi-font multi-size numerals.

INTRODUCTION

Tremendous volumes of the cheque leaves are submitting in all the banks regularly. This research wok will help to speed up the banking industry by the automatic reading of the account number from the bank cheque leaf. Literature survey shows that different banks in India use different fonts and sizes to print the account number on the cheque leaf as shown in Table 1. Table 2 depicts the five common fonts used in the current research works. Various algorithms have been invented and enforced which recognize the numerals by manipulating distinct characteristics of the numbers insert to them. It uses feature extraction algorithm to extract the features and classification algorithm to detect the numerals using features extracted. The objective of this research work has to be recognizing multi-font multi-size numerals from an image which is machine-written.

The organization of this paper is as below. In section 2 an overview of numeral recognition is yielded and in section 3 database collection and pre-processing multi-font multi-size numerals are given. Section 4 says about proposed methodology which describes feature extraction algorithm follows by classification and recognition. The experimental results are discussed and the conclusion of the work is given in section 6.

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Table 1: Different fonts used by different banks in India

Sl. No	Name of Banks	Font face
1	Allahabad Bank	Arial
2	The South Indian Bank Limited	Arial
3	Federal Bank| Savings	Verdana, ML1-TTRevathi
4	HDFC Bank	Arial, Arial Rounded MT Bold
5	ICICI Bank	ISFOC-TBorder-1
6	State Bank Of India	Arial black
7	Standard CharteredBank	Arial
8	Citi Bank	Arial
9	Lakshmi Vilas Bank	Arial Narrow

Table 2: Selected fonts used in the current research work

Sl. No	Font Face
1	Arial
2	Arial Rounded MT Bold
3	ISFOC-TBorder-1
4	Verdana
5	Courier New

Review of Literature:

There are innumerable approaches that come up to the difficulty of numeral recognition contingent on features extracted and the ways of extracting those features. There remain many algorithms for feature extraction which have its own advantages or disadvantages over other algorithms. Many different important touchstones of feature extraction algorithms required being looked at for higher rate of recognition.

Cruz R. M., Ren, T. I, & Cavalcanti G. D. proposed a total of six feature extraction algorithms. The methods are Multi Zoning , Gradient Directional, Structural Characteristics, Modified Edge Maps, Concavities Measurements and Projections. A strategy using neural networks as a combiner achieved 99.68 % of recognition rate as the highest one on the MNIST database Rajashekararadhya and Ranjan (2009). Saravanan K.N, & Anitha R proposed an algorithm for feature extraction with the relative density to recognize handwritten numerals which is unconstrained single connected irrespective of the languages. For the recognition of numerals the minimum distance classifier technique has been employed. The method yielded a satisfactory accuracy rate of recognition 92.85%, 99.28%, 98.95%, 98.72%, 99.48%, and 99.29%for Latin, Assamese, Devanagari, Manipuri, Oriya and Malayalam Handwritten Numerals respectively Saravanan and Anitha (2014). Lee J. S., Bang S. Y and Kwon recognize a presented input by recognizing the character type and then identifying its component graphemes. They introduced three new ideas: the elaboration of the sub image areas applied by the grapheme classifiers, an algorithm to exactly divide the vowel’s sub image areas horizontally, and a substantiation process to assess the result of the type classifier (Lee *et al*., 1999). Dhandra B. V., Hangarge M and Benne R. G used features like global and local structural identical to water reservoirs, maximum profile distances, directional density estimation and fill hole density. A PNN classifier is used for the recognition and the overall accuracy of 97.20% is obtained (Dhandra *et al*., 2010). Pal and Chaudhuri (Pal and Chaudhuri, 2004) have done a entire detailed survey on Indian script and the methodologies used to recognize these. Hanmandlu et.al (Madasu *et al*., 2004) has reported a fuzzy based method to recognize multi-font numerals. Firstly the numeral image is submitted to preprocessing and then subdivides into constant number of sub-images called boxes then normalized vector distance of foreground pixels are calculated and utilized as features. Madasu, Yusof and Hanmandlu M proposed a method to recognize unconstrained, isolated multi-font machine printed numerals and characters are recognized with the help of fuzzification function. In this paper they started an implementation with a binary image of a numeral is partitioned fixed number of sub-images called boxes. The fuzzy sets consists of features like normalized vector distance and angles from each box and they gained 96% of recognition rate (Madasu *et al*., 2004). V chandran , S Slomka depicts that the trispectral features are finer than moment invariants and affine moment invariants. Here they gained 95% of classification accuracy as to about 81% for Hu's moment invariants and **39%** for Flusser/Suk using a **1-NN** classifier (Chandran *et al*., 1997). This paper introduces a Hybrid, fuzzy rule base and HMM method for numeral recognition both Urdu and Arabic in unconstrained surroundings from both offline and online area. Basically offline area is implied for preprocessing normalization, slant normalization. The approach gives accuracy of 97.1% (Razzak *et al*., 2009). Ying Wen, Pengfei Shi demonstrates a pattern classification method with improved LDA and Bhattacharyya distance based classification for recognition of numerals. Improved LDA is utilized as a dimensionality diminution technique and Bhattacharyya distance uses the distribution features of the samples in apiece class to refine the recognition rate. The recognition rate was good in improved LDA melded with Bhattacharyya distance process(Ying Wen *et al*., 2008). Ketan S. Machhale , Pradnya and Pravin Zode proposed an adaptive template matching and feature extraction manipulating curvelet transform for the numerals recognition. The average recognition accuracy achieved is about 97% (Machhale *et al*., 2012). Akhilesh Pandey and et. al the proposed an approach which utilizes simple profile and contour base triangular area representation method for obtaining back propagation, feature extraction, and for classification cascade feed forward neural network. The overall recognition rate of this method obtained is 94.16% (Pandey and Kumar). Ting-ting Zhao and *et al*. proposed BP artificial neural network depend on genetic algorithm training approach to solving Renminbi number recognition. The Back Propagation artificial neural network focused on genetic algorithm that merges the global search ability of genetic algorithm and local search ability of Back Propagation algorithm (Zhao *et al*., 2010). Avi-Itzhak proposed a neural network method to execute eminent recognition rate on multi-font and size characters. A new centroid-dithering training procedure with a less noise-sensitivity normalization process is manipulates with two different component. The first component concentrate on single size and font characters and the second component deals exactness for extra added font and size capability, each a two-layered neural network is edified to identify the complete group of 94 ASCII character pictures in 12-pt Courier font and a greater two-layered neural network is instructed to identify the complete set of 94 ASCII character figures from 8 to 32 point sizes and for 12 commonly used fonts(Avi-Itzhak *et al*., 1995). Cao J., Shridhar & Ahmadi introduced a hierarchical architecture of neural network for recognizing handwritten numerals. They have proposed a Bayes incremental learning neural network classifier for the recognition of handwritten numerals. Feature extraction sub-not used with a Principal Component Analysis neural network, the proportion of the input vector is importantly diminished and the de-correlation of data vector is calculated expeditiously (Cao *et al*., 1997). B V Dhandra, Benne R G., & Hangarge M proposed a method based on single Euler number feature without thinning and normalization of size for multi-font size Kannada numeral recognition system. A nearest neighbor classification with Euclidian distance has been employed for classification of Kannada numerals and the overall classification accuracy is found to be 99.00% (Dhandra *et al*., 2011). Kumar, K. P used the innovation in segmentation of the number into four identical element and using one of these element like left bottom portion to extract recognition features. This algorithm also proposed a single conflict resolution method to sort out struggle while conflicting features are come across they achieved 98% accuracy. Here only eight values function as an indicator to apiece candidate image, other than two numerals which are decided by the equivalent approach using conflict resolution incorporated in the algorithm Kumar K. P (2012). Rajashekararadhya & Ranjan presented zone and distance metric build feature extraction algorithm. The centroid is determined for each character and the image is further separated into n identical zones. Later average distance from the centroid of a character to the apiece pixel present in the zone is calculated. This step is iterated for all the zones exist in the numeral image. At last for the classification and recognition, n such features are extracted. For the classification support vector machine is applied and obtained 97.75% recognition rate for Kannada numerals Rajashekararadhya and Ranjan (2009). Binu P. Chacko, Babu Anto P adhibited both statistical and structural features and the rate of recognition obtained was 93.3% and 95.7% respectively. They have applied thinning algorithm to take out features and represented the image in a 4 * 4 grid Chacko and Anto (2007). Hanmandlu M., Kumar & Mohan have proposed a back propagation neural network which is used for the identification of handwritten characters. Here feature extraction is performed using three various methods i.e. hybrid, sector and ring. The features include of normalized vector angles and distance. The hybrid approaches combine the ring and sector methods which give better result (Hanmandlu *et al*., 1999). Lee S. W presented a novelty approach for off-line identification of totally unconstrained handwritten numbers making a simple multilayer cluster neural network drilled with the back propagation algorithm. Even Lee S. W proposed a method with genetic algorithms eludes the problem of determining local minima in training the multilayer cluster neural network with gradient descent approach, and better the accuracy. For classifying similar numerals efficiently five independent sub networks is developed with a three-layer cluster neural network and Kirsch masks are acquired for extracting feature Lee S. W., (1996). Kawatani, T. proposed new techniques by applying the LDA process to the quadratic discriminant function and MQDF2. Experiments are carried out for hand printed numeral recognition and the better result gained by MQDF2; the accuracy obtained is 99.67%. The LDA method decreases the misread rate by 30% Kawatani T, (1993). G G R.Rajeswari, H. and Sidramappa C presented a novel method which first converts numeral image into binary and size normalized to 40 x 40 pixels. After tracing the boundary of the number the chain code of the image is decided and these codes are symbolized in a complex plane and calculate the ten dimensional Fourier descriptors that generate the feature vector. The ten-dimensional Fourier descriptors are given to multi-class SVM classifier as input to identify the numeral. The experiment is conducted through five-fold cross-validation approach and afforded identification accuracy of 97.76% G G, (2014). Britto, A. S combined features grounded on foreground and background information to recognize handwritten digits using an HMM-based classifier. Here the author divides the digit into zones based on column and row it allows us to avoid the numeral normalization. Recognized accuracy rates obtained were around 98% using 60,000 numeral samples of the NIST SD19 database (Britto, A. S., 2003). Majumdar A & Chaudhuri B. B proposed a method to normalize features based on the pixel into 4 X 4 blocks in which each numeral is partitioned into bounding-box and the features used here are the normalized position of radius of curvature of strokes, intersections, end-points and holes developed in individual block. To recognize printed and handwritten numerals a multi-layer neural network classifier is used. They have obtained a maximum recognition rate of 95.7% for handwritten numbers and recognition rate of 99.2% for recognizing printed numerals Majumdar and Chaudhuri, 2006). Zhu X, Geoger C, Shi Q, & Cheng M have suggested a classification with two separate stages , like coarse and detailed. The former employs an inference approach showed on the local structure and fuzzy pre-classifier used for recognition. They grouped three different categories of primary features which are: boundary distances, pixel densities and line distances from centroid in a segment. The latter apply distance matching on a subset of prototypes, the distinct wavel*et al*ters on local curve segments and a single-layered Back propagation network on the binary image, which decreases the number of prototypes to be cope with the given input and the system obtained a final result (Zhu *et al*., 1998). Hegadi, R. S., & Kamble, P. M proposed an approach to identify the Marathi handwritten numbers through multilayer feed-forward neural network. Firstly pre-process the scanned image, segmented and it is resized to 7 × 5 pixels applying cubic interpolation. The overall accuracy rate obtained using this approach is 97% (Hegadi and Kamble, 2014).Sazal *et al*., proposed a new method deep belief network (DBN), which is a probabilistic generative model, that capture the raw character images as input and learning progresses in two different steps - an unsupervised feature learning succeeded by a supervised fine-tuning of the network parameters. They demonstrate unsupervised feature learning via the experimental studies keep on the Bangla basic characters and numerals and attained 91.3 % accuracy (Sazal *et al*., 2014).Akhand and *et al.*, proposed a CNN based BHNR which normalizes the written numeral images and then employs CNN to classify individual numerals for recoganizing(Akhand *et al*., 2015). Arun K Pujari, and C Dhanunjaya Naidu (Pujari *et al*., 2004) implemented a method which employs wavelet multi-resolution analysis for extracting features and the system identifies the font style and font face from the document and it identifies the characters present in the document. It prevents the occurrence of feature extraction method and it extracts the invariant features of the characters. It has achieved 93.46 % success rate.

Table 2: Comparison of results with other methods

SL.NO	Features used	Classifier	Accuracy
Saravanan and Anitha (2014)	relative density feature extraction algorithm	Minimum distance classifier	Latin 92.85%, Assamese 99.28%, Devanagari 98.95% Manipuri 98.72%, Malayalam 99.29% Oriya 99.48%
(Dhandra *et al*., 2010)	Directional density estimation features Profile distance features, fill hole density feature, and Water Reservoir principle based features	Probabilistic neural network	99.40% for kannada, 99.60% for Telugu, and 98.40% for Devanagari numerals
(Ying Wen *et al*., 2008)	Linear discriminant analysis	Improved LDA and Bhattacharyya Distance	96.93%
(Cao *et al*., 1997)	Local histogram of the chain codes	Statistical and neural network	96.02%
(Dhandra *et al*., 2011)	Foreground features namely, transitions from background to foreground, Background features based on concavity information	HMM	99%
Chacko and Anto (2007)	Statistical and structural features	Neural network	95.7%
(Hanmandlu *et al*., 1999)	Structural features like the number of branches, junction points and end points ; local features such as normalized vector lengths and angles are used.	back propagation neural network	
G G, (2014)	Chain code, Fourier Descriptors	Support vector machine (SVM)	97.76 %
Majumdar and Chaudhuri, 2006)	the normalized position of holes, radius of curvature of strokes and endpoints, intersections	Multi-layer neural network classifier	95.7% for handwritten numerals and 99.2% for printed numerals
(Pujari*et al*., 2004)	Wavelet Analysis	DNN	93.46 %

Research in numeral recognition has several practical applications such as reading assistances for the blind, bank cheques, number plates of vehicles and automatic pin code reading to sort postal mail. Here we introduce an efficient feature extraction algorithm for multi-font multi-size numerals. There are five major stages in the numeral recognition which as shown in Figure 1. Preprocessing has two different stages: firstly it removes noise from the scanned object and secondly it converts the colored image into grayscale and then into a binary image.

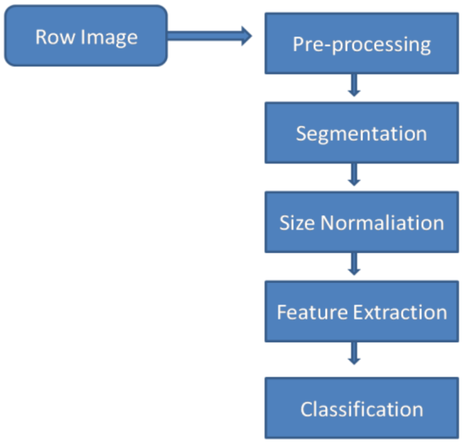

Fig. 1: Different stages of the Numeral Recognition Process.

Data collection and pre-processing:

The main method of data acquisition is through scanning the bank cheque leaves using the digitized scanner at 300 dpi and stored as color images. MatLab program modules were developed for segmentation of numerals from the scanned images. Database of 3700 numeral images with different fonts and sizes are stored in the .tif format in ten different folders [0-9]. Sample data set which is scanned is shown in Figure 2. To take uniformity amidst the numerals, the cropped images are size with respect to aspect ratio, and the aspect ratio obtained here is 1.56.

Most of the data collection is done through bank cheques and with the help of bond paper with the same thickness as the normal bank cheque paper that is 100gsm. The numerals printed on these papers are in multi-font and multi-size. Mainly five different fonts such as Arial, Arial Round MT, Courier New, ISFOC, and Verdana are used here because my literature survey shows many banks are using these fonts, the same is shown in Table 2. Out of these data 75 percentage employed for the training set and the left over 25 percentage used for testing purpose.

Fig. 2: Sample data set

Sample data set which is scanned is shown in Figure 2. All the scanned images have a group of numerals, to get these numerals individually crop the image into sub-images as each numeral should fit in minimum rectangle box using labeling connected component. Later the same sub-images are subjected to size normalization; it is essential due to the multi-font face and size, which leads to various fluctuations in the shapes and sizes of numerals. Therefore, to take uniformity amidst the offline machine printed numerals all the images should be made of the same size and this is achieved by size normalization with respect to aspect ratio. These images later used to extract the features Rajashekararadhya and Ranjan (2009).

Proposed Methodology:

The proposed methods use the zone based pixel density as the feature in the classification process. After the size normalization, the entire image has grouped into 80 X 128. This image is subdivided into 5/8 sub-images and calculated the density features from all the four sides of each sub-image individually. These features are clustered for all 0-9 digits and the mean value is stored as feature to recognize the numerals.

Feature Extraction:

Feature extraction algorithm is an important stage in offline numeral recognition as each numeral is distinct and distinguishing each numeral with others are quite difficult. Therefore it is significant to extract the correct features in such a way that the recognition of numerals which is in multi-font and multi-size becomes more easygoing on the basis of each feature of the individual numeral. In feature extraction algorithm the bounding box of a numeral image is segmented and the directional pixel densities are calculated for all four sides in each of these zones.

Fig. 3: Original datset after cropping

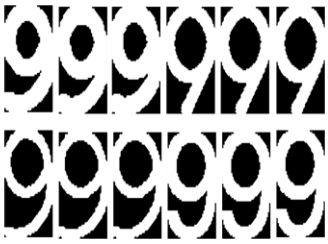

Fig. 4: Normalized image

Figure 3 shows the original dataset immediately after cropping; later the same images are subjected to size normalization the same is shown in Figure 4. Size normalization is done with respect to aspect ratio, which is calculated with the height and width of the trained data set.

Fig. 5: Zone-Based Directional Pixel density from all sides of bounding box

The pixel density is numerated row/column wise till it meets the outer border of each zone in the four directions of a numeral that is through left, right, top and bottom directions as shown in Figure 5.

Algorithm for training multi-font numerals

Step 01: Read the scanned image if not found then go to Step 10

Step 02: Convert the colored image into gray scale image and later to binary image

Step 03: Crop the image into sub-images as each numeral should fit in minimum rectangle box using labeling connected component.

Step 04: Do size normalization using aspect ratio calculated with the images received from Step 3 as each numeral image has different size, the aspect ratio obtained here is 1.56, and the resized numeral image has to be saved.

Step 05: Divide the image into 8/5 equal zone.

Step 06: For each zone calculates the pixel density features from four sides.

Step 07: Apply single linkage clustering for grouping the features.

Step 08: Get the average density of clustered features and save into the library.

Step 09: Repeat step 5 to step 8 for each individual numeral.

Step 10: stop.

Algorithm for testing multi-font numerals:

Step 01: Read the scanned image if not found then go to Step 09

Step 02: Convert the colored image into gray scale image and later to binary image

Step 03: Crop the image into sub-images as each numeral should fit in minimum rectangle box using labeling connected component.

Step 04: Do size normalization using aspect ratio for each cropped image and save.

Step 05: Divide the image into 8/5 equal zones

Step 06: For each sub-image calculates the density features from four sides of each zone.

Step 07: Find the Euclidean distance between the input features and the features stored in the library.

Step 08: Get the minimum distance from step 7 and return the digit.

Step 09: stop.

Classification and Recognition:

The extracted features have to be clustered and calculate the mean value later these values are saved as features in the library. The extracted features stored in the library are used to identify multi-font numerals. The training set algorithm is used to in classification phase, to extract the features from the testing samples. Then the Euclidean distance has been used to find the minimum distance from new vector obtained with respect to features stored in the library.

Table 4: Total number of clusters created for each digit from training features.

Digits	Clusters formed	Total training dataset
0	93	296
1	105	296
2	87	296
3	85	296
4	80	296
5	84	296
6	116	296
7	95	296
8	76	296
9	41	296

Table 5: Recognition Rate

Numeral	Recognition Rate
0	39.19
1	100
2	100
3	6.75
4	100
5	86.49
6	44.59
7	100
8	100
9	98.64

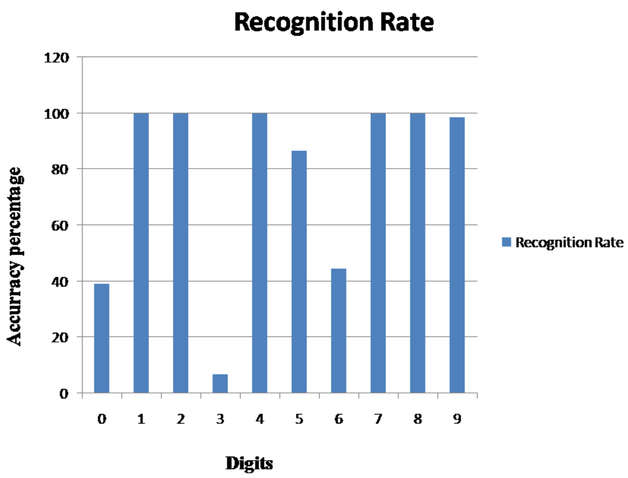

Fig. 6: Performance graph

The accuracy rate of numerals from 0-9 is shown in Table 5 and Figure 6 shows the performance graph of the same. The graph contains accuracy rate in the Y axis and numerals in X axis. The performance of any recognition system could be evaluated through several factors, such of the size of the numeral, font style used, etc.The new algorithm is tested with the testing dataset containing 740 digits from 0 to 9. The average recognition rate obtained was 77.57%.

Conclusion:

A new feature extraction algorithm is proposed in this research work for multi font and multi size numerals. This method acquires the group of numerals as image from the cheque leaf, crop individual digit and does the size normalization. Thinning is not applied in this method. The efficiency of numerals 1,2,4,7 and 8 is 100 % and the numerals 0, 3, 5, 6 and 9 are 56%. The efficiency of these numerals can be increased by including more features.

Table 5: sample confusion matrix for multi font multi size numerals

	0	1	2	3	4	5	6	7	8	9	%
0	29								45		39.18919
1		74									100
2			74								100
3			69	5							6.756757
4					74						100
5						64	7		3		86.48649
6							33		41		44.59459
7								74			100
8									74		100
9									1	73	98.64865
										Total	77.56757

Limitations and Future Enhancement:

The number of features generated using this algorithm is more and it occupies more space to store the floating point values. Our future work aims at decreasing the number of features which are generated using the proposed algorithm to reduce the space and combine other feature set to improve the recognition rate. As well as the algorithm will be modified to deal with more fonts and to other language numerals. The recognition rate for the digits 0, 3 and 6 needs to be improvised.

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REFERENCES

Akhand, M.A.H., M.M. Rahman, P.C. Shill, S. Islam and M.H. Rahman, 2015. Bangla handwritten numeral recognition using convolutional neural network. In *Electrical Engineering and Information Communication Technology (ICEEICT), 2015 International Conference on* pp: 1-5.

Avi-Itzhak, H.I., T.A. Diep and H. Garland, 1995. High accuracy optical character recognition using neural networks with centroid dithering. IEEE Transactions on pattern analysis and machine intelligence, 17(2): 218-224.

Britto, A.S., 2003. Complementary features combined in an HMM-based system to recognize handwritten digits. In Image Analysis and Processing, 2003. Proceedings. 12th International Conference on pp: 670-675.

Cao, J., M. Ahmadi and M. Shridhar, 1997. A hierarchical neural network architecture for handwritten numeral recognition. Pattern recognition, 30(2): 289-294.

Chacko, B.P. and P.B. Anto, 2007. Comparison of Statistical and Structural Features for Handwritten Numeral Recognition. In *Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on* 2: 296-300.

Chandran, V., S. Slomka, M. Gollogly and S. Elgar, 1997. Digit recognition using trispectral features. In *Acoustics, Speech, and Signal Processing, 1997. ICASSP-97., 1997 IEEE International Conference on* 4: 3065-3068.

Cruz, R.M., G.D.C avalcanti and T.I. Ren, 2010. Handwritten digit recognition using multiple feature extraction techniques and classifier ensemble. In *17th International Conference on Systems, Signals and Image Processing* pp: 215-218.

Dhandra, B.V., R.G. Benne and M. Hangarge, 2010. Kannada, Telugu and Devanagari handwritten numeral recognition with probabilistic neural network: a novel approach. International Journal of Computer Applications, 26(9): 83-88.

Dhandra, B.V., R.G. Benne and M.H angarge, 2011. A single euler number feature for multi-font multi-size Kannada numeral recognition. arXiv preprint arXiv:1111.4290.

GG, R., H. Rajeswari and C. Sidramappa, 2014. Printed and handwritten mixed kannada numerals recognition using svm.

Hanmandlu, M., K.M. Mohan and H. Kumar, 1999. Neural based handwritten character recognition. In *Document Analysis and Recognition, 1999. ICDAR'99. Proceedings of the Fifth International Conference on* pp: 241-244.

Hegadi, R.S. and P.M. Kamble, 2014. Recognition of marathi handwritten numerals using multi-layer feed-forward neural network. In*Computing and Communication Technologies (WCCCT), 2014 World Congress on* pp: 21-24.

Kawatani, T., 1993. Handprinted numeral recognition with the learning quadratic discriminant function. In *Document Analysis and Recognition, 1993., Proceedings of the Second International Conference on* pp: 14-17.

Kumar, K.P., 2012. Optical Character Recognition (OCR) for Kannada numerals using Left Bottom 1/4th segment minimum features extraction. International Journal of Computer Techology & Applications, 3(1): 221-225.

Lee, J.S., O.J. Kwon and S.Y.B ang, 1999. Highly accurate recognition of printed Korean characters through an improved two-stage classification method. Pattern recognition, 32(12): 1935-1945.

Lee, S.W., 1996. Off-line recognition of totally unconstrained handwritten numerals using multilayer cluster neural network. IEEE Transactions on Pattern Analysis and Machine Intelligence, 18(6): 648-652.

Machhale, K.S., P.P. Zode and P.P. Zode, 2012. Implementation of number recognition using adaptive template matching and feature extraction method. In *Communication Systems and Network Technologies (CSNT), 2012 International Conference on* pp: 194-197.

Madasu, V.K., M. Hanmandlu and M. Yusof, 2003. Fuzzy based approach to the recognition of multi-font numerals. In The Second National Conference on Document Analysis and Recognition, pp: 118-126.

Majumdar, A. and B.B. Chaudhuri, 2006. A MLP classifier for both printed and handwritten Bangla numeral recognition. In Computer Vision, Graphics and Image Processing, pp: 796-804.

Pal, U. and B.B.C haudhuri, 2004. Indian script character recognition: a survey. pattern Recognition, 37(9): 1887-1899.

Pandey, A., A. Kumar, R. Kumar and A. Tiwari, Handwritten Devanagri Number Recognition using Majority Voting Scheme. *International Journal of Computer Science and Information Technology & Security (IJCSITS), ISSN*, 2249-9555.

Pujari, A.K., C.D. Naidu, M.S. Rao and B.C. Jinaga, 2004. An intelligent character recognizer for Telugu scripts using multiresolution analysis and associative memory. Image and vision computing, 22(14): 1221-1227.

Rajashekararadhya, S.V and P.V. Ranjan, 2009. HANDWRITTEN NUMERAL/MIXED NUMERALS RECOGNITION OF SOUTH-INDIAN SCRIPTS: THE ZONE-BASED FEATURE EXTRACTION METHOD. Journal of Theoretical & Applied Information Technology, 6(3).

Rajashekararadhya, S.V. and P.V. Ranjan, 2009. Support vector machine based handwritten numeral recognition of Kannada script. In Advance Computing Conferen Shridhar, ce, 2009. IACC 2009. IEEE International., pp: 381-386.

Razzak, M.I., S.A. Hussain, A. Belaïd and M. Sher, 2009. Multi-font numerals recognition for urdu script based languages. International Journal of Recent Trends in Engineering (IJRTE).

Saravanan, K.N and R. Anitha, 2014. Zone Based Relative Density Feature Extraction Algorithm for Unconstrained Handwritten Numeral Recognition. Journal of Theoretical and Applied Information Technology, 64(1).

Sazal, Md Musfiqur Rahman, *et al*. 2014. "Bangla handwritten character recognition using deep belief network." *Electrical Information and Communication Technology (EICT), 2013 International Conference on*. IEEE.

Ying Wen, Pengfei Shi, 2008. An approach to numeral recognition based on improved LDA and Bhattacharyya distance. In Communications, Control and Signal Processing, 2008. ISCCSP 2008. 3rd International Symposium on pp: 309-311.

Zhao, T.T., J.Y.Z hao, R.R. Zheng and L.L. Zhang, 2010. Study on RMB number recognition based on genetic algorithm artificial neural network. In *Image and Signal Processing (CISP), 2010 3rd International Congress on* 4: 1951-1955.

Zhu, X., C. Geoger, Q. Shi and M. Cheng, 1998. An off-line system for recognition of free written zipcodes. In *Signal Processing Proceedings, 1998. ICSP'98. 1998 Fourth International Conference on* 2: 1253-1256.