Handwritten Digit Recognition System Using FLDA and Support Vector Machines

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Abstract- Handwritten Character Recognition (HCR) is the task of recognizing the characters which are present in a digital image of handwritten text. The present paper proposes a novel approach for handwritten digit recognition system. The present paper extracts digit image features based on Fisher Linear Discriminant Analysis (FLDA) and derives classify the digit images using Support Vector Machines (SVM). The present paper mainly concentrates on extraction of features from digit image for effective recognition of the numeral. To find the effectiveness of the proposed method it is tested on MNIST database, CENPARMI, CEDAR and newly collected data. The proposed method is implemented on more than one lakh digit images and gets good comparative recognition results. The percentage of the recognition achieved is about 96.97%.

Keywords—Handwritten digit recognition, SVM, FLDA, MNIST Database, image features.

I. INTRODUCTION

Machine learning, usually refers to changes in the system that perform tasks associated with Artificial Intelligence (AI). A major focus of machine learning research is to automatically produce models, such as rules and patterns, from the data. Hence, machine learning is closely related to the fields of data mining, statistics, inductive reasoning, pattern recognition, and theoretical computer science **[1**]. A variety of practical applications of machine learning research is emerging due to recent advances in hardware and software [**2**]. Some of the practical applications include Natural Language Processing (NLP), medical diagnosis, bio-informatics, speech and handwriting recognition, object recognition etc. The present focuses on handwritten digit recognition.

The origin of character recognition was found in 1870 when Carey invented the retina scanner-an image transmission system using a mosaic of photocells [**3**]. Nipkow invented the sequential scanner, which was a major breakthrough both for modern television and reading machines, in the year 1890. Russian scientist Tyurin in 1900 initially made a successful attempt to develop an aid to the visually handicapped through character recognition. Handwritten Character Recognition (HCR) is a subset of OCR, which is a process of classifying written characters into its appropriate classes based on the features extracted from each character. The study of handwriting covers a very broad field dealing with numerous aspects of very complex task. It involves research concepts from several disciplines; experimental psychology, computer science, physics, forensic document experiments, anthropology, etc. [**4, 5**]. Simulating the human reading is a challenging task needs intensive research effort in the field of character recognition and it also provides efficient applications in Writer identification, Forensic analysis of handwriting, Postal automation, Bank cheque recognition, Reading aid for blind, Language processing etc.

The offline handwritten character recognition system typically consists of the following processing steps. [**6, 7**]:

(1) Gray level scanning at an appropriate resolution, typically 400-200 dots per inch (dpi).
(2) Preprocessing
(a) Binarization (two-level Thresholding), using a global or a locally adaptive method.
(b) Segmentation to isolate individual characters.
(c) (Optional) conversion to another character representation (e.g. skeleton or contour curve).
(3) Feature extraction.
(4) Recognition using one or more classifiers.

(5) Contextual verification or post processing.

C.Y et alin 2003[8] proposed a system for recognition of handwritten scripts used in China, Japan and Korea. The paper summarizes the research activities of features extraction, databases used and classification schemes. In addition, it includes a description of the performance of numerous recognition systems found in both academic and industrial research laboratories. The scheme consists of two stages: a feature extraction stage for extracting multi resolution features with wavelet transform, and a classification stage for classifying unconstrained handwritten numerals with a single multilayer cluster neural network. Work on multiwavelets and neural networks can also be seen in [**9**]. An unconstrained offline handwriting recognition system is described in **[10**]. The scheme consists of seven main modules: skew angle estimation and correction, printed-handwritten text discrimination, line segmentation, slant removing, word segmentation, and character segmentation and recognition. The system is tested on standard NIST, IAM-DB, and GRUHD databases.

[**1**Pixel-based and shape-based features [11] are chosen for the purpose of recognition. Multi-layer neural network architecture was chosen as classifiers of the mixed class of handwritten and printed numerals. Handwritten character recognition of popular south Indian script is described in [**12**]. The features used are mainly obtained from the directional information. For feature computation, the bounding box of a character is segmented into blocks and the directional features are computed in each block. Quadratic classifier is used for classification purpose.

From the above literature survey, it is clear that, most of the work has been done on English, Chinese, and Arabic and few on Indian scripts but all are have time complexity was somewhat high and extraction of features is also difficult. Most of the work has been concentrated on numerals and basic characters.

The paper considers only the Basic English numerals for recognition purpose. The dataset for the experiment was collected from different individuals of various professions in the states of Andhra Pradesh and Telangana. The proposed method overcome the disadvantages of various techniques and finds the effective feature extraction process for the recognition handwritten digits of different databases in an effective manner.

The paper is organized as follows: Section 2 contains database creation and the preprocessing. Section 3 describes feature extraction methods and the proposed algorithm is presented in Section 4. The experimental details and result analysis is presented in Section 5. Section 6 contains the conclusion part.

II. PROPOSED METHODOLOGY

The proposed method is mainly consists of 4 steps. In the first step, collecting the numerals data from various data bases and gathering images from various people in AP and Telangana state. After collecting the numeral data preprocess data i.e. elimination of noise and conversion of gray scale images into binary images and also the normalization of the binary images by using the normalization techniques. In the third step, extract the features of the each digit image using image Fisher Linear Discriminant Analysis (FLDA). In step 4, classification of digits by using Support Vector Machines (SVM). The block diagram of the proposed method is shown below figure 1

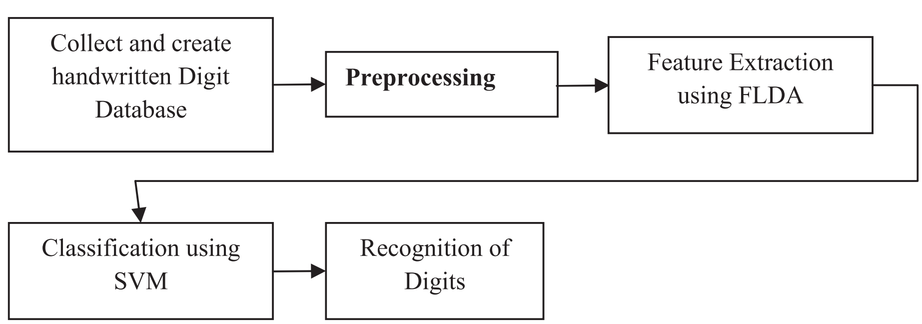

Figure 1: Block diagram of the proposed system

Step 1: Collection of numeral image database

Several standard datasets of digits are found in English. Some of them are CENPARMI, CEDAR, and MNIST datasets. The CENPARMI (Centre for Pattern Recognition and Machine Intelligence) digit dataset [**9**] is available from CENPARMI, Concordia University. In this dataset 4000 images (400 samples per class) are specified for training purpose and 2000 images are used for testing purpose. These digit datasets were collected from United States Postal Service (USPS). The Center of Excellence for Document Analysis and Recognition (CEDAR) digit dataset is available from CEDAR, The State University of New York, Buffalo. The training and test sets contain 18468 and 2711 digits, respectively. The number of samples in both training and test sets differ for each class. The Modified National Institute of Standards and Technology (MNIST) dataset [10] was extracted from the NIST datasets SD3 and SD7. The training and test sets are composed of both SD3 and SD7. Samples are normalized into 20×20 grayscale images with aspect ratio reserved, and the normalized images are located in a 28×28 frame. The number of training and test samples is 60,000 and 10,000 respectively. The sample images of the MNIST dataset is shown in fig.2.

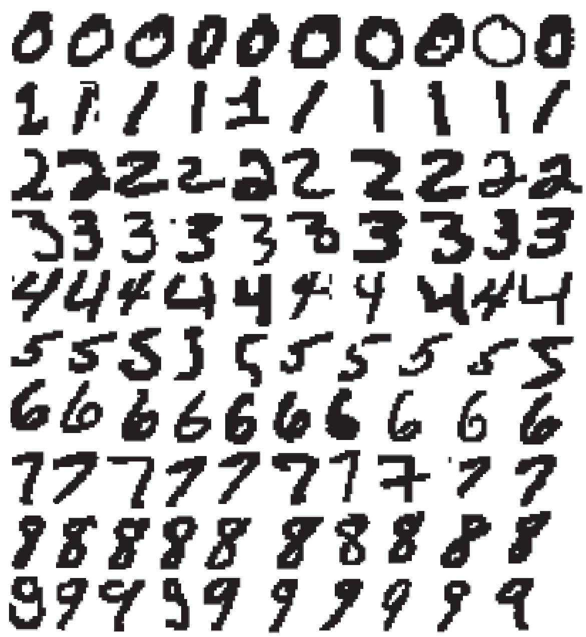

Figure 2: Sample images of the Digit Database

The plain paper was used for data collection. Each person was instructed to write the digits (fully unconstrained) along the vertical direction. The dataset contains about 100 isolated samples each of 10numerals written by 1000 native writers including university graduates, high school children, and adults. Around fifty percent data is from high school children. A flatbed scanner was used for digitization, with images in gray tone at 300 dpi. These were stored has Bit Map File (BMP) format using a standard technique for converting them into monochrome images. Data was manually extracted from scanned images and normalized into 50×50 size using a standard bi-cubic approach. After processing scanned images about digits and a total of 100000 (100×1000) images of numerals are obtained. Dataset developed planned to be made available publicly for research purpose. Some of the sample images after extracting from the scanned image are shown in figure 3.

Figure 3: Sample Scanned document of digit images

Step 2: Digit Image Preprocessing

Data capture of documents by optical scanning or by digital video yields a file of picture elements, which is the raw input to document analysis process. The first step in document analysis is to perform a preprocessing on this image to prepare it for further analysis. Such processing includes Thresholding to convert a gray scale (or color image) to a binary image, reduction of noise to reduce extraneous data, skew estimation of a document image if document suffers from tilt (skewed), thinning, enable subsequent detection of pertinent features of the object of interest and then segmentation of text line to individual digit character. It is assumed that characters are already isolated and preprocessing steps such as Binarization, noise removal, normalization and thinning are to be done. Initially, the document is captured using gray level mode. Character extraction from the scanned document is done manually. Then Otsu's histogram-based global threshold approach is applied for digit image Binarization. Figure 4 shows the gray level picture of the character and resultant of global Thresholding approach.

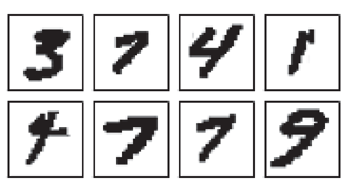

Figure 4: Results of Binarization

The next step is to normalize the given character image into a standard size. For that, a standard nearest neighbor interpolation method is used. Figure 5 shows some sample images after applying normalization technique.

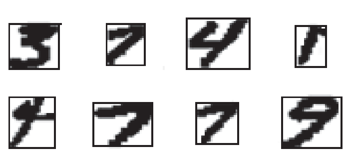

Figure 5: Samples of Digit Images after Normalization

III. FEATURE EXTRACTION TECHNIQUE USING FISHER LINEAR DISCRIMINANT ANALYSIS (FLDA)

The objective of the FLD [**Fisher R. A., 1936, Belhumeur P. N et al, 1997**] is to investigate differences among multivariate classes, to determine which attributes discriminate between the classes, and to determine the most parsimonious way to distinguish among classes. Similar to the analysis of variance for single attribute, the intra-class variance to evaluate the dispersion within classes can be computed and inter-class variance to examine the differences between the classes. Steps involved in the feature extraction using FLD for a set of images are as follows. Suppose that there are *M* training samples A_k *(k=1, 2… M)*, denoted by m by n matrices, which contain *C* classes, and the i^{th} class C_i has n_i samples. For each training character image, define the corresponding character image as follows:

- Calculate the within class scatter matrix (S_w) for the i^{th} class, a scatter matrix (S_i) is calculated as the sum of the covariance matrices of the centered images in that class

$$S_i = \sum_{x \in X_i} (x - m_i)(x - m_i)^T \tag{1}$$

Where, m_i is the mean of the images in the class. The intra class scatter matrix (S_w) is the sum of all the scatter matrices.

$$S_w = \sum_{i=1}^{c} S_i \tag{2}$$

- Calculate the inter class scatter matrix (S_b): It is calculated as the sum of the covariance matrices of the differences between the total mean and mean of each class.

$$S_B = \sum_{i=1}^{c} n_i (m_i - m)(m_i - m)^T \tag{3}$$

Where n_i is the number of images in the class, m_i is the mean of the images in the class and m is the mean of all the images.

- Solve for the generalized eigenvectors (v) and eigenvalues (λ) of the intra class and inter class scatter matrices: $S_B V = \lambda S_W V$

The digit image is first partitioned into non-overlapping regions (sub patterns) and FLD is applied to the portioned image.

Image Partition:

Suppose that there are *N* training samples $\mathbf{A_k}$= (k=1, 2…*N*), denoted by *m* by *n* matrices, which contain *C* classes, and the i^{th} class C_i has n_i samples. Now, an original whole pattern $\mathbf{A_k}$ denoted by a vector **V** is partitioned into *K* d-dimensional sub pattern's in a non-overlapping way and reshaped into *d*-by-*K* matrix $X_i = (X_{i1}, X_{i2}, ..., X_{iK})$ with X_{ij} being the j^{th} sub pattern of X_i and $i = 1,..N,\ j = 1,..K$. Now to form the j^{th} training sub pattern set $\{TS_j\}_{dxN}$, j^{th} sub pattern of X_i and $i = 1,..N,\ j = 1,..K$ are collected respectively. In this way, *K* separate sub patterns are formed.

Apply PCA on *K* Sub patterns:

Now according to the second step, conventional PCA is applied to the j[th] subpattern set TS_j to seek corresponding projection sub vector $U_j = (u_{j1}, u_{j2}, .., u_{jq})$ by selecting first q eigen vectors corresponding to q largest eigenvalues based on maximizing the total scatter in the projected space. Define the j[th] total sub-scatter matrix C_j as follows:

$$C_j = \frac{1}{N}\sum_{i=1}^{N}(X_{ij} - \overline{X}_j)(X_{ij} - \overline{X}_j)^T \qquad (4)$$

Where $\overline{X}_j = \frac{1}{N}\sum_{i=1}^{N} X_{ij} \quad j = 1,..,K$ are sub pattern means

After obtaining all individual projection sub vectors from the partitioned sub patterns, extract corresponding sub features Y_j from any sub pattern of a given whole pattern $Z = (Z_1, Z_2, .., Z_K)$ using the following equation:

$$Y_j = U_j^T Z_j \qquad (5)$$

Now synthesize them into a global feature as follows:

$$Y = (Y_1^T, Y_2^T, ..., Y_k^T)^T = (Z_1^T U_1, Z_2^T U_2, .., Z_k^T U_k)^T$$

In this process, in order to classify an unknown character image **P**, the image is first vectorized and then partitioned into K sub-patterns $[p_1, p_2, .., p_K]$ in the same way as explained above. Using the projection sub vectors extracted, sub features of the test sample **P** is extracted as follows:

$$F_j = U_j^T p_j \quad \text{where j=1…}K \qquad (6)$$

Since one classification result for the unknown sample is generated independently in each sub pattern, there will be total K results from K sub patterns. To combine K classification result from all sub patterns of this character image **P**, a distance matrix is constructed and denoted by $D(P) = (d_{ij})_{NxK}$, where d_{ij} denotes the distance between the corresponding j[th] patterns of **P** and the i[th] character, and d_{ij} is set to 1 if the computed identity of the unknown sample and the i[th] character's identity are identical, 0 otherwise. Consequently, a total confidence value that **P** finally belongs to the i[th] character class is defined as

$$TC_i(P) = \sum_{j=1}^{K} d_{ij} \qquad (7)$$

And the final identity of this P is determined by

$$Identity(P) = \arg\max_i (TC_i(P)) \; 1 \le i \le N \qquad (8)$$

For each sample Y in training set, extract the feature $Z = Y^T * W$

In the next step, conventional FLD is applied to the j[th] sub pattern set [TS_j] to seek corresponding projection sub vectors $U_j = (U_{j1}, U_{j2}, U_{j3}, ..., U_{jq})$ by selecting q eigenvectors corresponding to q largest eigenvalues based on maximizing the ratio of the determinants of the inter-class and the intra-class scatter matrices of the projected samples. Analogues to the fisher face method, define the j[th] inter-class and intra-class sub scatter matrices, Gb_j and Gw_j respectively as follows:

$$Gb_j = \sum_{i=1}^{C} n_i (\overline{X}_{ij} - \overline{X}_j)(\overline{X}_{ij} - \overline{X}_j)^T \tag{9}$$

$$Gw_j = \sum_{i=1}^{C} \sum_{X_k \in C_i} (X_{kj} - \overline{X}_{ij})(X_{kj} - \overline{X}_{ij})^T \tag{10}$$

Here, $\overline{X}_j = \frac{1}{N}\sum_{i=1}^{N} X_{ij}$ j=1,2,...,K are sub pattern means, $\overline{X}_{ij} = \frac{1}{n_i}\sum_{i=1}^{n_i} X_{ij}$ is i[th] class j[th] sub pattern mean and X_{kj} is the j[th] sub pattern of k[th] sample belonging to the i[th] class.

After obtaining all individual projection sub vectors from the partitioned sub patterns, extract corresponding sub features Y_j from any sub pattern of given whole pattern $Z = (Z_1, Z_2, .., Z_K)$ using the following equation:

$$Y_j = U_j^{\,T} Z_j \tag{11}$$

Now synthesize them into a global feature as follows:

$$Y = (Y_1^T, Y_2^T, ..., Y_k^T)^T = (Z_1^T U_1, Z_2^T U_2, .., Z_k^T U_k)^T \tag{12}$$

After extraction of the features from each digit image, classification is applied for feture vecor. The present paper utilizes the support vector machines for classification.

IV. CLASSIFICATION USING SUPPORT VECTOR MACHINES (SVM)

SVM represent a new pattern classification method which grew out of some of the recent work in statistical learning theory. SVM were proposed by Vapnik in [**Vapnik, 1995**] and they perform structure risk minimization. SVM uses a linear separating hyper plane to create a classifier even when the distribution of the objects in the space is not linearly separable. In this case SVM can transform the original space into a higher dimensional feature space where the regions can be linearly separable.

Consider a two-class problem where the class labels are denoted by +1 and -1. Given a set of *l* labeled patterns, ς = (xi , yi), 1 ≤ i ≤ l, xi ∈ d , yi ∈ −1, +1, the hyper plane represented by (w, b) where w ∈ d represents the normal to the hyper plane and b ∈ the off set, forms a separating hyper plane if the following separability conditions are satisfied

$$(w \cdot x_i) + b \geq +1 \ \ if \ y_i = +1 \tag{45}$$

$$(w \cdot x_i) + b \geq +1 \ \ if \ y_i = -1 \tag{13}$$

The constraints Eqs (45) and (46) are equivalent to:

$$y_i[(w \cdot x_i) + b] \geq 1 \Rightarrow [(w \cdot x_i) + b]y_i - 1 \geq 0, i = 1, ..., l \tag{14}$$

This however is not the optimal hyper plane, because some points may be very close to it and points near them could easily be mis-classified. The best solution is a hyper plane with the largest possible margin. It can be noted that the points for which Eq (45) holds lie on the hyper plane $w \cdot x + b = 1$ and their distance from the origin is $\frac{|1-b|}{\|w\|}$, similarly the points for which equation 46 holds lie on the hyper plane $w \cdot x + b = -1$ and their distance from the origin is $\frac{|-1-b|}{\|w\|}$. The pair of hyper planes can be found by giving maximum margin by minimizing the Eqs (45) and (46) subject to the constraints of Eq (47).

$$\Phi(w) = \frac{1}{2}\|w\|^2 \tag{15}$$

The training points for which the equality Eq (47) holds and whose removal would change the solution found, are called support vectors. The solution to the maximization problem is found by the saddle point of the Lagrange function:

$$L(w, b, \alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i [x_i \cdot w + b] y_i - 1 \tag{16}$$

Where, $\alpha \geq 1$ is the Lagrange multiplier. By differentiating and equating to zero three properties of the optimal hyper plane is obtained:

$$\sum_{i=1}^{l} \alpha_i^0 y_i = 0, \alpha_i^0 \geq 0, i = 1, \dots, l \tag{17}$$

The vector w is the linear combination of the examples in the training set:

$$w^0 \sum_{i=1}^{l} \alpha_i^0 y_i x_i, \alpha_i^0 \geq 0, i = 1, \dots, l \tag{18}$$

Only the support vectors can have non-zero coefficients α_i in Eq 18

$$w^0 = \sum \alpha_i^0 y_i x_i, \alpha_i^0 \tag{19}$$

Substituting these results in Eq (49), the function W (α) is obtained:

$$w(\alpha) - \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \tag{20}$$

Maximizing it with the constraints of Eq 50, a solution vector $\alpha 0 = (\alpha 1, ..., \alpha l)$ is fond and defines the discriminative function:

$$f(x) = sign\left(\sum_{support\ Vectors} y_i \alpha_i^0 (x_i \cdot x) - b^0\right) \tag{21}$$

Where, x_i are the support vectors, α_i is the optimal Lagrange multipliers and b^0:

$$b^0 = \frac{1}{2}\left[\left(w^0 \cdot x^*(1)\right) + \left(w^0 \cdot x^*(-1)\right)\right] \tag{22}$$

The $x*$ (1) is for any support vector such that y = 1 and $x*$ (−1) such that y = -1.

In order to relax the constraints Eqs (45) and (46) positive slack variables ξ, i = 1, ..., *l* is introduced in the constraints:

$$(w \cdot x_i) + b \geq +1 - \xi_i \ if \ y_i = +1 \tag{23}$$

$$(w \cdot x_i) + b \geq +1 - \xi_i \ if \ y_i = -1 \tag{24}$$

$$\xi_i \geq 0 \forall_i \tag{25}$$

The function to minimize changes to:

$$\phi(w) = \frac{1}{2}\|w\|^2 + C(\sum_i \xi_i)^k \qquad (26)$$

Where *C* is a parameter to be chosen by the user, high values of *C* assign a higher penalty to errors. For K = 1 the ξi parameters appear in Lagrangian as a different constraint for $\alpha_i \mid 0 \le \alpha_i^0 \le C$.

To sum up, the SVM method for learning two classes classier is as follows: a kernel function and some value for the constant *C* in Eq (59) are chosen. Then solve its dual, which is same as Eq (50) except that the variable α_i also has an upper bound, namely *C*. Using this, given a feature vector x, the output of SVM is calculated, namely f (x). The classification of x would be +1 if the output of the SVM is positive; otherwise it is -1.

V. RESULTS AND DISCUSSION

The proposed feature extraction methods are experimentally evaluated with the dataset containing various handwritten numerals collecting from MNIST data base, CENPARMI data base, CEDAR data base and most of the images from scanned images. Collectively, the data base contains 176000 digit images. No method has tested using such type of large database. In this paper, Nearest Neighbor Classifier (NNC) is used for classification purpose**.** All experiments are carried out on a PC machine with i5 processor 2.7GHz CPU and 4 GB RAM memory under MatLab 10.0 platform. 20 percentage of the each data base is used for training and remaining 80 percentage images are used for testing purpose i.e. 35200 images are used for training purpose and 140800 images are used for testing purpose. The percentage of recognition of the proposed method when two-step method is applied is listed out in tables 1, 2, 3 and 4. The Recognition percentage of MNIST database is 96.67, CENPARMI data base is 96.72, CEDAR data base is 96.06 and Scanned digit Database is 97.13 and the overall percentage of recognition is 96.91. The consolidated percentage of recognition of the whole database which is used in this paper is listed out in table 5 and recognition graph of the each database is shown in table 6.

Table 1: Recognition percentage of MNIST data base of the proposed Method

Digit	Total no of Digits	correctly classified	Not Correctly Classified	% Recognition
0	6573	6336	237	96.39
1	6715	6474	241	96.41
2	6580	6368	212	96.78
3	6600	6382	218	96.70
4	6442	6186	256	96.03
5	6575	6384	191	97.10
6	6705	6393	312	95.35
7	6715	6498	217	96.77
8	6605	6438	167	97.47
9	6490	6344	146	97.75

Table 2: Recognition percentage of CEPARMI data base of the proposed Method

Digit	Total no of Digits	correctly classified	Not Correctly Classified	% Recognition
0	320	310	10	96.88
1	320	311	9	97.19
2	320	309	11	96.56
3	320	304	16	95.00
4	320	308	12	96.25
5	320	307	13	95.94
6	320	312	8	97.50

7	320	311	9	97.19
8	320	310	10	96.88
9	320	313	7	97.81

Table 3: Recognition percentage of CEDAR data base of the proposed Method

Digit	Total no of Digits	correctly classified	Not Correctly Classified	% Recognition
0	160	156	4	97.50
1	160	153	7	95.63
2	160	155	5	96.88
3	160	153	7	95.63
4	160	150	10	93.75
5	160	151	9	94.38
6	160	155	5	96.88
7	160	157	3	98.13
8	160	154	6	96.25
9	160	153	7	95.63

Table 4: Recognition percentage of Scanned data base of the proposed Method

Digit	Total no of Digits	correctly classified	Not Correctly Classified	% Recognition
0	7985	7832	153	98.08
1	8025	7808	217	97.30
2	8123	7838	285	96.49
3	7816	7603	213	97.27
4	7923	7755	168	97.88
5	8050	7779	271	96.63
6	8023	7769	254	96.83
7	8075	7823	252	96.88
8	8115	7849	266	96.72
9	7865	7646	219	97.22

Table 5: Considered database percentage of recognition when the proposed method applied

Digit	Total no of Digits	correctly classified	Not Correctly Classified	% Recognition
0	15038	14634	404	97.31
1	15220	14746	474	96.89
2	15183	14670	513	96.62
3	14896	14442	454	96.95
4	14845	14399	446	97.00
5	15105	14621	484	96.80
6	15208	14629	579	96.19
7	15270	14789	481	96.85
8	15200	14751	449	97.05
9	14835	14456	379	97.45

Table 6: Percentage of recognition of the individual database

Database	% of Recognition
CEPARMI	96.67
CEDAR	96.72
MNIST	96.06
Scanned Images	97.13

VI. COMPARISON OF THE PROPOSED METHOD WITH OTHER EXISTING METHODS

The efficiency of the proposed method is compared with other existing methods like twin minimax probability machine (TWMPM) proposed by Zhijie et.al [13], transformation based features proposed by Syed et.al [14], Back Propagation with Neural Network approach[15] and selection, reproduction, mutation and crossover methods with Genetic Algorithm (GA) proposed by Devikanniga et.al[16]. The TWMPM method generates two hyper-planes of the digit images and it also avoids making distributional assumptions about the class-conditional densities of the digit. The performance of the TWNPM method is evaluated on two data sets only i.e UTC and MNSIT and the overall percentage of the proposed method 88.07%. The method proposed by the Syed utilizes the Discrete Cosine Transform (2D-DCT) for feature extraction and Hidden Markov models (HMMs) used for classification. The syed proposed method is applied on only MNIST database and got 95.95% if feature vector size is more. More feature vector causes more computational cost. Sakshica proposed to classify the handwritten digits by using the features and their spatial relationship in the pattern with Hopfield Neural Network. A small number of images are tested by using this method and got 90.23% only. Devikanniga proposed a method to classify the handwritten digit using GA and got the overall performance is only 87%. The performance evolution of the proposed method with other existing methods is listed out in table 7 and the classification graph is represented in figure 6. From table 7, it is clearly evident that, the proposed method exhibits a high recognition rate than the existing methods.

Table 7: Overall percentage of the Different Recognition systems

Data Base	TWMPM method [17]	2d-DCT with HMM Approach [18]	NN with Back propagation [19]	different NN Approaches [20]	proposed method
CEPARMI	87.18	95.28	85	89.23	96.67
CEDAR	91.23	96.45	89	90.24	96.72
MNIST	88.73	95.92	91	91.27	96.06
Scanned Images	85.15	96.18	84	90.87	97.13

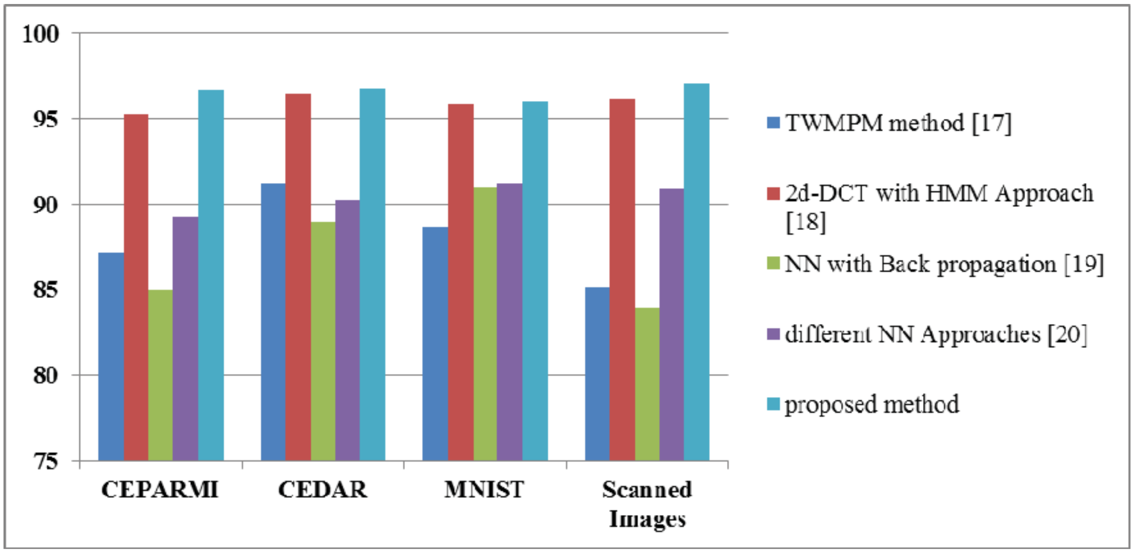

Figure 6: Graphical representation of the percentage of recognition of the proposed method and other existing methods

VII. CONCLUSION

In this paper a very large database of unconstrained handwritten digit images for experiment purpose was introduced. No author tested with such a large data base. It is proposed to make this database available for research purpose. 100000 handwritten characters collected from 1000 different individuals of different age groups and different areas. No author has attempted to such collection. The proposed method utilizes a small algorithms for preprocessing such as Binarization, normalization and thinning algorithms. The proposed method takes very less amount processor time for recognition of digit image. The main object of the proposed method is an efficient feature extraction method is derived for handwritten digit recognition. The overall percentage of the proposed method achieves 96.91%.

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