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A Survey on Handwritten Digit Recognition

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ABSTRACT

Handwritten digit recognition is considered to be well known and significant problem in pattern recognition and computer vision. Handwritten digits are different in terms of their size, style, orientation, position and thickness. It is the challenging part of recognition problem, so the best feature extraction method is used to solve this issue. The goal of this paper is to survey various feature extraction techniques in combination with the classifiers, so that accuracy and recognition rate is maximized and computational cost and complexity is minimized.

Keywords: *Handwritten digits, feature extraction, recognition ,classification.*

1. INTRODUCTION

The method of identifying and organizing the handwritten digits (0-9) through intelligent program/machine is known as Handwritten Digit Recognition. Basic goal of handwritten digit recognition problem is to make the intelligent machine or program that is able to receive the handwritten digit input from different sources like touch screens, paper documents, photographs and many other devices; and intelligently recognize that input. In real world, it has many applications like identifying postal addresses and automatic processing of bank cheques, tax forms, data entry form etc.

Performance of handwritten digit recognition depends on three important operations i.e. segmentation, feature extraction and classification. Figure 1 shows the general flow chart of recognition process. Basic goal of preprocessing is to discard irrelevant information from the input data. It consists of sampling, normalization, smoothing, digitization and noise reduction. Then the input is divided into the best segments and the useful features are extracted from the input. The processed data is trained and classified using different classifiers i.e. k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Neural Networks (NN) etc.

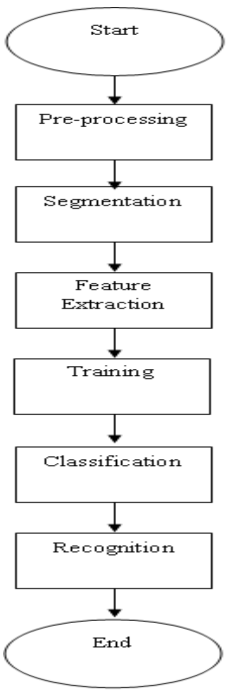

Fig. 1 Recognition process

Data set is the important factor for the recognition process. Data sets are available in different formats like images, attribute files, binary files etc. Various data repositories are available like UCI, Mixed National Institute of Standards and Technology (MNIST), CEDAR, NIST, US Postal Service. Liu *et al* [1] apply state of the art techniques for feature extraction and classification on well known data sets e.g. MNIST, CENPARMI and CEDAR.

The aim of this paper is to survey different feature extraction and classification methods and evaluate the performance in terms of complexity, computational cost, accuracy, speed, rejection and recognition rate. Section II contains the related work; section III summarizes different techniques and their performances; and in the last section, we conclude the paper.

2. RELATED WORK

Handwritten digit recognition is well known established problem in pattern recognition. Many researches on classification algorithm as well as enhancing feature extraction methods have been carried out. Figure 2 shows different classifiers that are used for handwritten digit classification. This section categorizes different classification algorithm to classify handwritten digits while enhancing different feature extraction techniques. Variants of classifiers are also discussed in this section.

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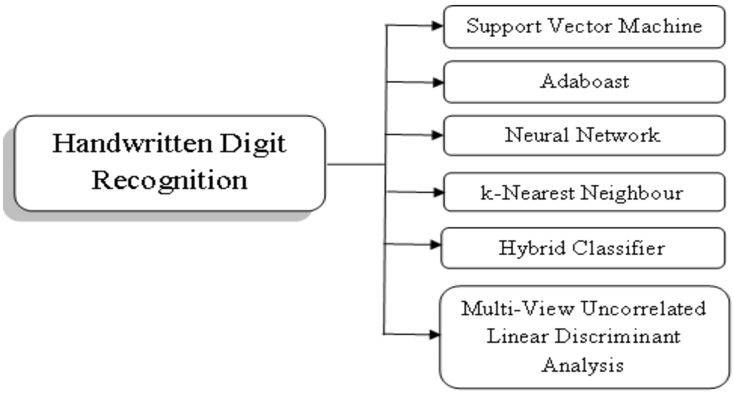

Fig.2 Classifiers for Handwritten digit Recognition

A. Neural Network (NN)

Neural Networks are considered to be the best classifier for many recognition problem.

- Pattern Transformations for feature extraction: Alenso *et al* [2] proposed standard back propagation in neural network with transformation so that error rate is minimized. MNIST Patterns transform by reduction of input size and additive input noise which keeps away from local minimum and stop during learning process. Training dataset and use of noisy input data are the two important issues in this approach. Mean error rate on MNIST data set is 0.46% while overall error rate is 0.34 %. Ranked multilayer perceptron (MLPs) and displacement schemas improved the performance of recognition problem.

- Variant of Convolutional Neural Network (CNN): Wu *et al* [3] proposed a cascade CNN on heterogeneous data. Each CNN recognizes the input data with high confidence and rejected data feed forward to next CNN. Experiment shows that this method achieves 0.23% error rate by using 5 CNN.

- Self Organizing Map: Different classification algorithms are used to solve the problem of handwritten digit recognition. Self Organizing Map (SOM) is one of the data mining tool in which high dimensional data are visualized into two dimensions. Mohebi *et al* [4] proposed a modified version of SOM (MSOM) which initializing the neurons and a topology in which neurons don't adopt from the similar high dense region. It uses Split and Merge algorithm which reduces the quantization error by finding optimal local minimum. For training purpose, authors proposed the recursive version of MSOM (R-MSOM) so that new styles and shapes of input images can be learned. Efficiency of learning algorithm is determined on the unseen data, so convolutional structure cope up with this issue. Hence, Convolutional R-MSOM (CR-SOM) gives 93.03 % accuracy as compared to Convolutional R-SOM (CR-SOM) gives 97.75 % accuracy.

Table 1 discussed variants of neural network with different feature extraction technique on MNIST dataset. Cascade CNN outperform as compared to other techniques and gives accuracy of 99.77 %.

TABLE 1.Comparison of Neural Network

Reference	Technique	Data set	Accuracy (%)
[2]	Ranked multilayer perceptron, Displacement Schemes for feature extraction	MNIST	99.66
[3]	cascade CNN	MNIST	99.77
[4]	Modified version of SOM with recursive and Convolutional property	MNIST	99.03

B. Multi-view Uncorrelated Linear Discriminant Analysis (MULDA)

Multi-view learning is a rapid growing learning technique in machine learning. The basic idea is to combine different learning techniques that improve the performance. A critical issue in this approach is the effective utilization of information that is gathered from multiple sources. Information fusion is an effective method used to resolve this issue.

First time, Hotelling [5] proposed Canonical Correlation Analysis (CCA) which is famous feature extraction technique in multi-view learning. It takes two data sets and finds their linear transformations such that these transformations are correlated to each other. With the passage of time researchers proposed variants of CCA like Kernel CCA [6], Locality Preserving CCA [7] etc. since all are unsupervised methods that don't enhance the performance of recognition.

In past year, many supervised learning methods proposed to overcome this issue. First time, [8] proposed Linear Discriminant Analysis (LDA), which finds optimal linear transformation such that maximum discriminant achieved by minimizing intra-class distance and maximizing inter-class distance. For assurance of recognition performance, it is important to save the discriminant structure in feature extraction process. For this reason many improved algorithms

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of LDA proposed like Discriminant LDA [9], Random Correlation Ensemble (RCE) [10].

[11] combines the CCA with Uncorrelated LDA (ULDA) and propose a new algorithm Multi-view Uncorrelated Linear Discriminant Analysis (MULDA). It eliminates the redundancy in the original features by extracting uncorrelated feature vectors from each set. On problem of handwritten digit recognition, this algorithm gives the best results but for large data sets, computational cost is very expensive as for each feature vector, it calculates eigenvalue.

C. Support Vector Machine (SVM)

SVM are supervised learning methods used for classification and regression. It based on Vapnik-Chervonenkis dimension and the statistical learning theory. Followings are different feature extraction technique that used with SVM classifier. Figure 3 represents different feature extraction methods that are used with svm classifier.

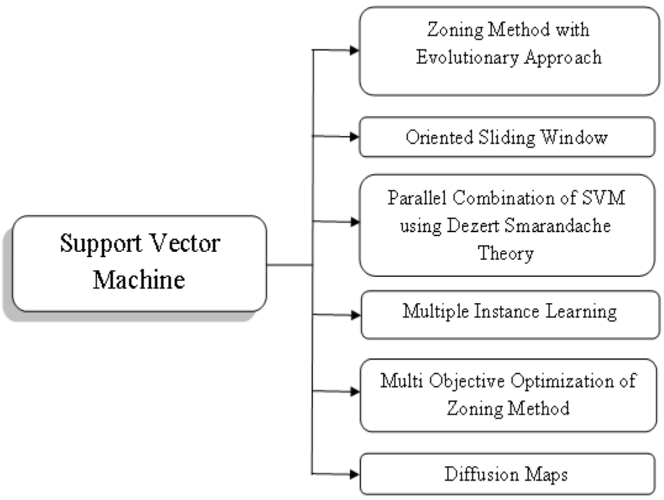

Fig.3 Feature Extraction methods with SVM

- Zoning method with evolutionary approach: Zoning is the popular technique used for feature extraction to improve the accuracy of classification. [12] Proposed zoning technique is based on Voronoi tessellation. Optimal zoning distribution finds through evolutionary strategy. It extracts features from MNIST and USPS data and classified using linear, polynomial and radial base SVM. Experimental results show that recognition rate on MNIST dataset is 99.23% and 97.01% on USPS datasets.

- Multi-Objective Optimization of Zoning Methods: For optimal zoning [13] presented multi objective optimization method in which a number of zones, their positions and shapes are found using the genetic algorithm. Non-Dominant Sorting Genetic Algorithm II (NSGA II) is used in which initial population is evaluated through non-dominance, 1-Point cross-over and non uniform mutation used. Zoning elitism approach is used to save the best zone and removes the insignificant zones. Significance of zones depends on how much features are used in the current zone, more features mean more significant and vice versa. Basic goal of this technique is to minimize the total number of zones so that cost of the classification is reduced. Two Cost functions are used in proposed method that is originally proposed by [14]. Experiment shows that optimization method for single-objective produces 14% error rate while multi-objective dwindle down to error rate of 6%.

- Oriented Sliding Window: Handwritten recognition problem is one of the most challenging machine learning problems. Accuracy of recognizing connected digits depends on best segmentation strategy. [15] proposed a segmentation technique which is based on the sliding window that finds the best cutting position of isolated adjacent digits. This window rotates according to vertical axis and finds the optimal location of connected digits for correct segmentation. For classification multiclass SVM (1-against all) with the kernel trick is used. Experiments show that the best segmentation techniques reduce the rejection and confusion rates between digits which enhance the overall recognition performance.

- Parallel Combination of SVM using Dezert-Smarandache theory (DSmT): Performance of handwritten digit recognition problem enhances using training the dataset through different SVM classifiers and combining the outputs. But different classifier results the conflicted output. [16] proposed the technique for parallel use of two SVMs to managing the conflicts of their outputs. In this paper, author used Dezert-Smarandache theory (DSmT) for combining the conflicted outputs. Sigmoidal transformation is used for estimation of recognition problem. Experimental results prove that proposed technique gives better results even conflicted output produce by the SVM classifier.

- Diffusion Maps: Different dimension reduction techniques are used to find better classification. For high dimensional dataset, diffusion maps save the local approximation between data point and reduced the dimension [17]. SVM is simple and easy classifier, [18] combines diffusion maps with SVM to improve performance of recognition.

- Multiple Instance Learning: In real world for multiple instance tasks, data is coming from different feature spaces [19] named as Heterogeneous multiple instance learning (HeterMIL). It states that a bag holds the handwritten digits data from various feature spaces and classification algorithms (heterogeneous baseline method (HB) and Heterogeneous Heuristic MIL (HHMIL)) correct classify these digits. The basic idea of these classification algorithms is to divide the original bag into many small bags according to instance modality. Three types of decision rule made i.e. DS1, DS2 and DSs.

Experiments shows that HHMIL gives the better results than HB.

Table 2 discussed different feature extraction technique with SVM classifier. SVM (Linear, Polynomial, Radial base function) with zoning method that based on Voronoi tasselation better performs rather than other feature extraction methods and gives 99.23 % accuracy on MNIST dataset [12] .

Reference	**Technique**	**Data set**	**Accuracy (%)**
[12]	Zoning technique with evolutionary approach based on Voronoi tasselation, SVM(Linear, Polynomial, Radial base function)	MNIST USPS	MNIST= 99.23 USPS= 97.01
[13]	Non-Dominance Genetic Algorithm used for zoning	CEDAR	94
[15]	RBF kernel in SVM, Oriented sliding window for segmentation	NIST	94.57
[16]	SVM, Propotional Conflict Redistribution (PCR6) used that based on DSmT	USPS	98.45
[20]	SVM, Wavelet transformations.	MNIST	89.51
[20]	SVM, Wavelet packets transformations.	MNIST	97.04

D. Adaboast Classifier

Every classification problem depends on efficiently selection of features from datasets. The goal of feature selection is to reduce total number of features in such a way that performance of recognition at least maintained as well as improved by the classifier. Feature selection methods have some limitation like complexity, relationship between features, feature dependency, what features are best for evaluation by the classifier, and so on. To overcome these limitations, [21] proposed a feature selection method that selects the feature by using genetic algorithm. Fitness function of genetic algorithm is based on the combination of feature classifier. For classification Adaboast classifier with the method named as Aggregation Weight Functional Operators (AWFO) is used. In comparison with Wrapper_SVM, proposed technique is 125 times faster because 69.9% less feature used in this technique.

E. K-Nearest Neighbour

Classification methods are used to classify the input data set. Nearest Neighbour (k-NN) is well-known classification method for pattern recognition [22]. Feature extraction and the classifier selection are key issues for recognition problem. [23] extracts ten feature set i.e. 4 features sets are based on water reservoirs principal [24], 1 number of holes, 1 fill hole density and the 4 maximum profile distance [25]. For finding minimum distance, Euclidian minimum distance function used while K-NN classifier is used for classification purpose. On MNIST dataset, proposed technique gives 96.94 % recognition rate with the value of k is equal to 1. Figure 4 represent different methods that are used in combination with k-NN.

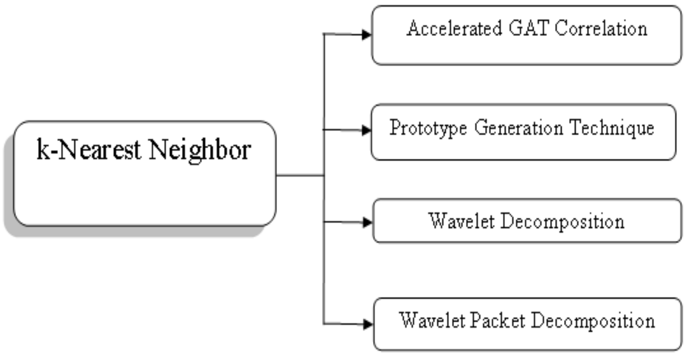

Fig.4 Feature extraction method with k-NN

- Accelerated GAT correlation: K-NN classifier is powerful and straightforward but it takes too much time. [26] combines the K-NN classifier with Global Affine Transformation (GAT) to reduce the computational cost. For optimal transformation, reformulated the GAT that separates the variables and 8 directional GAT generated and lookup tables generate to reduce the computational load. Evaluate this transformation on IPTP CDROM1B dataset which gives the recognition rate of 98.70% and computation cost is 6% of original GAT correlation. In high dimensional feature space, [27] achieved 99.49 % recognition rate on the same data set by modifying the function of discriminant.

- Wavelet Decomposition and Wavelet Packet Decomposition: Handwritten digits are different from each other in terms of their shape, size, orientation, thickness and style. [20] proposed a novel technique that is based on wavelet and wavelet packet. In wavelet transformation, input data is decomposed into two parts which contains the high level details

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and low levels approximation. In this paper this approximation is further decomposed which improves the recognition rate. Wavelet packets hold the more information that offers better data analysis. By using these two methods feature set extracted that are more representative and highly qualitative. For classification SVM and KNN are used. Accuracy of wavelet transformed data using KNN classifier is 84.53% while SVM classifier is 89.51%. Similarly, accuracy of wavelet packets transformed training data using KNN classifier is 96.24% while SVM classifier is 96.29%.

- Prototype Generation Technique: [28] presents a novel prototype technique with k-NN classifier for handwritten recognition problem. Prototype selection and generation of the prototype are the two categories. First involves merging the input images into smaller groups so that k-NN performance will optimize. Learning vector quantization and K-means algorithm are the examples of this approach. While recent work on this technique done by the [29] and [30]. Second strategy reduces the number of initial training dataset and increase the capability of classifier. This paper uses Adaptive Resonance Theory 1 (ART 1) for finding the number of prototypes and selects initial prototype then naïve evolutionary approach used final output. Combination of these approaches with k-NN gives the recognition rate of 98.773%.

Table 3 discussed k-NN classifier with different feature extraction techniques proposed in research. Adaptive Resonance Theory 1 (ART 1) with k-NN gives high accuracy rate of 98.73% on MNIST dataset . It is used for finding the number of prototypes and selects initial prototype then naïve evolutionary approach used final output.

TABLE 3.Comparison of k-NN

Reference	**Feature extraction Technique**	**Data set**	**Accuracy (%)**
[23]	Maximum profile distance, Water reservoir, Filling hole density	MNIST	96.94
[26]	Accelerated GAT correlation	IPTP CDROM1B	98.70
[20]	Wavelet transformations.	MNIST	84.53
[20]	Wavelet packets transformations.	MNIST	96.24
[28]	ART1 based algorithm	MNIST	98.73

F. Hybrid CNN–SVM

Different classifiers are used to solve the recognition problem like SVM, NN,CNN, KNNs etc. [31] proposed a novel hybrid technique that combines the CNN and SVM which gives the better results in terms of accuracy and reliability performance. CNN automatically extract feature while SVM is used for classification. Experimental result shows that this hybrid technique gives error rate of 0.19 % without rejection and 100% reliability with 0.56% of rejection rate.

3. PERFORMANCE EVALUATION

In previous section, different techniques have been discussed for recognition. Evolutionary approach improved the efficiency of algorithm. So feature extraction techniques improved with evolutionary strategy. Every classifier has significant advantages but some limitation, combination of two classifiers gives the improvement in performance because hybrid technique has advantages of both classifiers. Table 4 presents many classification and feature extraction methods with their limitation and performance.

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TABLE 4. Comparison of feature extraction and classification algorithm

Ref:	Feature Extraction / Classification Algorithm	Data Set	Nature of Input Data	Compared with	Key Points of Techniques / Advantages	Drawbacks / Key issues	Performance
[2]	Ranked multilayer perceptron, Displacement Schemes for feature extraction	MNIST	Digitized 70000 handwritten numbers. 60000 images for training and 10000 images for testing		Avoid local minimum, Stop during the learning process	Key issues: Adequate training set and use of noisy input data	Mean error = 0.46 %. Over all Error =0.34%
[4]	Modified version of SOM with recursive and Convolutional property	MNIST	Gray level images of 28 * 28 Pixel	CR-SOM	In identical higher dense area, restrict to adapt the neurons. Local minima achieved on quantized error		Accuracy: 99.03%
[11]	CCA and ULDA	UCI repository; Dutch utility map	Six feature set extracted from data set	DCCA, KNN	Reduced dimension	Computationally expensive if data set is high dimensional and large.	
[12]	Zoning technique with evolutionary approach based on Voronoi tasselation, SVM(Linear, Polynomial, Radial base function)	MNIST USPS	Gray scale images of 28*28 pixel (MNIST) And 16*16 pixel (USPS)	Regular square zoning	Find Optimal zoning distribution	If feature sets size is larger than classification time will be increase.	Accuracy: 99.23% on MNIST 97.01% on USPS
[13]	Non-Dominance Genetic Algorithm used for zoning	CEDAR	9 feature sets used	Single objective optimization method	Find optimal number of zone using GA. Minimized the number of zones.		Error rate= 6%
[15]	RBF kernel in SVM, Oriented sliding window for segmentation	NIST	5000 digits used for learing 600 digits used for testing		Finds Optimal position between connected digits for separating them from each other. Reduce the rejection rate by classifier. Reduce confusion rate between similar digits.		
[16]	SVM, Propotional Conflict Redistribution (PCR6) used that based on DSmT	USPS	4 feature set		Combination of SVM used. Better accuracy rate when SVM produces the conflicted outputs		Error rate : 1.55 %
[21]	Feature selection using Genetic algorithm, Adaboost classifier, AWFO combination methods.	MNIST	5 feature sets used	Wrapper_SVM Two Filters: SAC and Relief	69.9% features reduced so speed increased. Robustness		Time: In Worst case 125 times Faster, In best case: 250 times faster
[31]	Hyrid CNN-SVM	MNIST		CNN	Automatically extract features. Advantages of both CNN and SVM. Not too much increased in terms of complexity.	Choosing the number of layers. Which kernel function used , parameters of kernel functions	Error rate=0.19% without rejection. Reliability=100% with 0.56 rejection rate
[19]	HHML, SVM	UCI	5 different data set generated using random sampling	HB	Multiple instace learning for heterogeneous data. Bag constraint is under consideration so accuracy rate is improved.		
[23]	K-NN, Euclidean minimum distance formula,	MNIST	Training= 50000 images Testing= 5000 images		Find minimum distance between stored vectors and feature vectors. Classify using K-NN on basis of minimum distance.		Recognition rate= 96.94%
[26]	K-NN, Accelerated GAT correlation	IPTP CDRO M1B	Binary Format. Training= 17985 Testing= 17916	simple correlation. Tangent distance	Optimization process is iterative. 8 directional GAT correlation generated. Generate the lookup tables		Recognition rate=98.70%. Computational cost=6% of simple GAT correlation
[20]	KNN, SVM, Wavelet and Wavelet packets transformations.	MNIST	28*28 pixels of images. 6 feature sets used		Using wavelet and wavelet packets, six different feature sets extracted i.e.; skewness, sum, standard deviation, entropy, energy, mean absolute deviation.	Key issue in the selection of features that extracted from data set.	Wavelet Transformation: KNN=84.53% SVM=89.51%. Wavelet Packet Transformation: KNN=96.24% SVM=97.04%
[28]	k-NN. ART1 based algorithm	MNIST	28*28 pixel of images	If new prototype learned, then accuracy rate will be decreased	Initial training set is reduced. Generalization capability of classifier increased.		Accuracy rate= 98.73%

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4. CONCLUSION

Handwritten digit recognition is significant problem in pattern recognition. Digits are unique in terms of their style, position, thickness, orientation and size. This depends on different factors like age and qualification of the writer, quality of the ink and pen etc. Recognition process depends on three main operations: Preprocessing, feature extraction and classification. This paper provides a survey on different feature extraction and classification techniques in terms of their performance and limitation.

REFERENCES

[1] C. l liu, K. Nakashima, H. Sako, and H. Fujisawa, "Handwritten digit recognition: benchmarking of state-of-the-art techniques," Pattern Recognit., pp. 2271–2285, 2003.

[2] J. M. Alonso-weber and M. P. Sesmero, "Handwritten Digit Recognition with Pattern Transformations and Neural Network Averaging," ICANN, Springer-Verlag Berlin Heidelb., pp. 335–342, 2013.

[3] C. Wu, W. Fan, Y. He, J. Sun, and S. Naoi, "Cascaded Heterogeneous Convolutional Neural Networks for Handwritten Digit Recognition," no. Icpr, pp. 657–660, 2012.

[4] E. Mohebi and A. Bagirov, "A convolutional recursive modified Self Organizing Map for handwritten digits recognition," Neural Networks, vol. 60, pp. 104–118, 2014.

[5] H. Hotelling, "Relations between two sets of variates," Biometrica, vol. 28, pp. 321–377, 1936.

[6] N. C. J. Shawe-Taylor, "Kernel Methods for Pattern Analysis," Cambridge Univ. Press, 2004.

[7] T. Sun and S. Chen, "Locality preserving CCA with applications to data visualization and pose estimation," Image Vis. Comput., vol. 25, pp. 531–542, 2007.

[8] F. K, "Introduction to Statistical Pattern Recognition," Acad. Press, 1990.

[9] T. Sun, S. Chen, J. Yang, and P. Shi, "A novel method of combined feature extraction for recognition," Proc. Int. Conf. Data Min., pp. 1043–1048, 2008.

[10] J. Zhang and D. Zhang, "A novel ensemble construction method for multiview data using random cross-view correlation between within-class examples," Pattern Recognit., vol. 44, pp. 1162–1171, 2011.

[11] M. Yang and S. Sun, "Multi-view uncorrelated linear discriminant analysis with applications to handwritten digit recognition," 2014 Int. Jt. Conf. Neural Networks, pp. 4175–4181, Jul. 2014.

[12] S. Impedovo, F. Mangini, and G. Pirlo, "A New Adaptive Zoning Technique for Handwritten Digit Recognition," Image Anal. Process. …, vol. 19, pp. 91–100, 2013.

[13] S. Impedovo, G. Pirlo, and F. M. Mangini, "Handwritten Digit Recognition by Multi-objective Optimization of Zoning Methods," 2012 Int. Conf. Front. Handwrit. Recognit., pp. 675–679, Sep. 2012.

[14] G. Pirlo and D. Impedovo, "Voronoi-Based Zoning Design by Multi-objective Genetic Optimization," 2012 10th IAPR Int. Work. Doc. Anal. Syst., vol. 2, pp. 220–224, Mar. 2012.

[15] A. Gattal and Y. Chibani, "Segmentation and recognition strategy of handwritten connected digits based on the oriented sliding window," 2012 Int. Conf. Front., 2012.

[16] N. Abbas, Y. Chibani, and H. Nemmour, "Handwritten Digit Recognition Based On a DSmT-SVM Parallel Combination," pp. 241–246, 2012.

[17] R. Coifman and S. Lafon, "Diffusion Maps," Appl. Comput. Harmon. Anal. Spec. issue Diffus. maps wavelets, vol. 21, pp. 5–30, 2006.

[18] R. A. Kambli, Y. K. Ankurkar, and A. Mane, "Handwritten Digit Recognition with Improved SVM," vol. 1, no. 4, pp. 483–487, 2014.

[19] W. Peng, "Handwritten Digits Recognition Using Multiple Instance Learning," pp. 408–411, 2013.

[20] M. S. Akhtar and H. A. Qureshi, "Handwritten Digit Recognition Through Wavelet Decomposition and Wavelet Packet Decomposition," pp. 143–148, 2013.

[21] H. Chouaib, F. Cloppet, and N. Vincent, "Fast Feature Selection for Handwritten Digit Recognition," 2012 Int. Conf. Front. Handwrit. Recognit., pp. 485–490, Sep. 2012.

[22] B. O, S. E, and I. M, "In defense of nearest-neighbor based image classification," IEEE Conf. Comput. Vis. Pattern Recognit., pp. 1–8, 2008.

[23] U. R. Babu, Y. Venkateswarlu, and A. K. Chintha, "Handwritten Digit Recognition Using K-Nearest Neighbour Classifier," 2014 World Congr. Comput. Commun. Technol., pp. 60–65, Feb. 2014.

[24] U. Pal and P. Roy, "Multi-oriented and curved text lines extraction from indian documents," IEEE trans Syst. Man Cybern., vol. 34, pp. 1667–1684, 2004.

[25] B. . Dhandra and R. . Benne, "Handwritten Kanada Numeral recognition based on Structural features," Int. Conf. Comput. Intell. Multimed. Appl., 2007.

[26] T. Wakahara and Y. Yamashita, "k -NN classi fi cation of handwritten characters via accelerated GAT correlation," vol. 47, pp. 994–1001, 2014.

[27] M. shi, Y. Fujisawa, T. Wakabayashi, and F. Kimura, "Handwritten numeral recognition using gradient and curvature of gray scale image," Pattern Recognit. 35, pp. 2051–2059, 2002.

[28] S. Impedovo, F. M. Mangini, and D. Barbuzzi, "A novel prototype generation technique for handwriting digit recognition," Pattern Recognit., vol. 47, no. 3, pp. 1002–1010, 2014.

[29] U. Garain, "Prototype reduction using an artificial immune model," Pattern Anal. Appl., pp. 3–4, 2008.

[30] L. Nanni and A. Lumimi, "Particle swarm optimization for prototype reduction," Neurocomputing 72, 2009.

[31] X. Niu and C. Y. Suen, "A novel hybrid CNN – SVM classifier for recognizing handwritten digits," Pattern Recognit., vol. 45, no. 4, pp. 1318–1325, 2012.

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