

Isolated Handwritten Digit Recognition using Adaptive Unsupervised Incremental Learning Technique

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ABSTRACT

This paper presents a new approach to off-line handwritten numeral recognition. From the concept of perturbation due to writing habits and instruments, we propose a recognition method which is able to account for a variety of distortions due to eccentric handwriting. The recognition of handwritten numerals is a challenging task in the field of image processing and pattern recognition. It can be considered as one of the benchmarks in evaluating feature extraction methods and the performance of classifiers. The performance of character recognition system depends heavily on what kind of features are being used. The objective of this paper is to provide efficient and reliable techniques for recognition of handwritten numerals. In this paper we propose Zoning based feature extraction system which calculates the densities of object pixels in each zone. Firstly the whole image is divided into 4×4 zones. Further in order to gain more accuracy these zones are divided into 6×6 zones. The division of zones carried out up to 8×8 zones. Hence 116 features are extracted in all. Nearest neighbour classifier is used for subsequent classification and recognition purpose.

1. INTRODUCTION

Optical character recognition, usually abbreviated to OCR is the mechanical or electronic translation of images of handwritten, typewritten or printed text (usually captured by a scanner) into machine-editable text or computer process-able format, such as ASCII code. Whenever a page is scanned, it is stored as a bit-mapped file. When the image is displayed on the screen, we can read it. But it is just a series of dots for the computer. The computer does not recognize any "words" on the image. OCR makes the computer read these words. It looks at each line of the image and determines which particular character is represented by dots.

OCR is a field of research in pattern recognition, artificial intelligence and machine vision. Optical character recognition (using optical techniques such as mirrors and lenses) and digital character recognition (using scanners and computer algorithms) were originally considered separate fields. Because very few applications survive that use true optical techniques, the OCR term has now been broadened to include digital image processing as well.

The recognition of handwritten characters by computer has been a topic of intensive search for many years. Handwritten numeral recognition is always the research focus in the field of image process and pattern recognition. The numeral varieties in size, shape, slant and the writing style make the research harder. The numeral character recognition is the most challenging field, because the big research and development effort that has gone into it has not solved all commercial and intellectual problems. Handwritten numeral character recognition is an important step in many document processing

applications. Digital document processing is gaining popularity for application to office and library automation, bank and postal services, publishing houses and communication technology. The complexity of the problem is greatly increased by noise in the data and infinite variability of handwriting as a result of mood of writer and nature of writing. Recognition of handwritten digits has been popular topic of research for many years. The recognition of handwritten numeral character has been considerable interest to researchers working on OCR.

For the testing purpose an Award List has been used. Data has been collected from 200 users and extracted individual digits from these forms. These forms are filled out from different users in order to take different samples of handwriting. This Award List has 4-digit Roll no, 4-digit Code no and 3-digit Marks. The outcome of the research will be an automated system for recognition of awards. This automated system will recognize only digits. This procedure can also be done manually, but that is a tedious task and prone to error. This system's complexity lies in the different handwriting styles which vary from human to human. Thus automated system provides better recognition accuracy than manual system. The award list which is used in the automated system is shown below:

The rest of the paper is organized into five sections. In the Section 2 we will briefly explain about the review of literature in which the feature extraction technique along with the classifier is discussed. Section 3 describes the proposed system. In section 4 we will discuss about Recognition Result and Comparisons among Different Zoning Techniques and finally conclusion is given in section 5.

2. REVIEW OF LITERATURE

The recognition of handwritten numerals is a challenging task in pattern recognition. It can be considered as one of the benchmarks in evaluating feature extraction methods and the performance of classifiers. P.Zhang, T.D.Bui, C.Y.Suen [1] have proposed a new character recognition algorithm using MAT based Directional Features, Binary Gradient Directional Features, and, Image Thinning Distance Feature.

M. Ziaratban, K. Faez, F. Faradji [2] presents an innovative approach for character recognition called Template Matching. This technique extracts features by searching the special templates in input images. For each template, the position of the best matching in an image is found and saved. The amounts of matching can also be used as a feature.

Hu and Yan [3] presented a structural method for describing both printed and handwritten characters. The character is decomposed into primitives, and each primitive is described by a primitive code. The topological information of a character is represented by a global code. The global code and the primitive

codes describe each character clearly and effectively. Heutte [4], present a new feature vector for the recognition of handwritten characters which combines the strengths of both statistical and structural feature extractors and provides a wide range of identification clues.

Y. Hamamoto , S. Tomita, M. Koga and H. Fujisawa [6, 7, 8] presents a 2D Gabor filter which is a band-pass spatial filter and selective to both orientation and spatial frequency. A Gabor filters extract the orientation-dependent frequency contents, i.e. edge like features, from as small an area as possible.

F. Kimura and U. Pal [9] have proposed a new character recognition algorithm using Gradient filter which are applicable to gray-scale images to obtain a normalized image, and are immune to image noise. A Roberts filter is applied on the normalized image to obtain gradient image.

DDD (Directional Distance Distribution), proposed by Oh and Suen [10], is based on the distance information computed for both black pixels and white pixels in 8 directions. Structural representation may also encode some knowledge about the shape and structure of the character or about various components that form the character. Some feature which could check number of horizontal and vertical line, end points, presence of loops, number of loops, position of loop, and number of intersections and junctions.

The performance of a character recognition system depends on what kinds of features are being used to recognize handwritten numerals. Selection of a feature extraction method is probably the single most important factor in achieving high recognition. Since we have been used Zoning feature extraction method for recognition of handwritten numerals. Zoning is a Distance metric based feature extraction system [5].

In the first type of zoning method features are extracted for each zone by dividing the whole image into equal number of zones. The number of zones is fixed in this method and they are 6×6 . The densities of object pixels in each zone are calculated. Density is calculated by finding the number of object pixels in each zone and dividing it by total number of pixels. Densities are used to form a representation. For binary images, a value of each pixel is either 1 or 0. We have considered pixels having value BLACK (0) as object pixel.

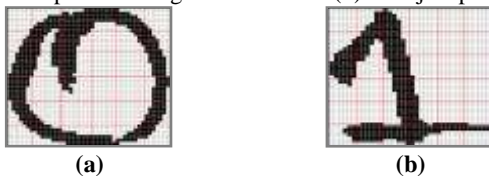


Figure 1: Original Matrix for Numeric Digits 0(a) and 1(b)
In the next zoning method a frame containing the numeral whose centroid is computed and then image is divided into 6×6 equal zones. Compute the distance between the image centroid to each pixel present in the zone using Euclidean Distance method. Then compute the average distance between these points. This procedure is sequentially for the entire zone present in the numeral image.

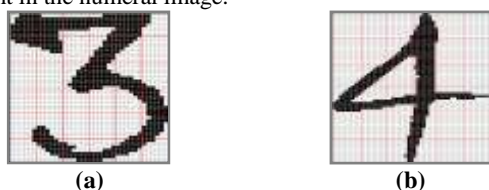


Figure 2: Original Matrix for Numeric Digits 3(a) and 4(b)
These zoning methods can also be combined in order to gain more recognition accuracy. Finally the extracted features from the feature extraction stage are passed to classification stage to identify the text segment. The objective of the classifier is to provide efficient and reliable techniques for recognition of unconstrained handwritten numerals. The classifier is used to make a final decision according to extracted features. The classifier is used to solve the complex problem of digit recognition. The classification phase uses the features extracted from the previous stage to identify the text segment according to preset rules.

Neocognitron is a multi-layered neural network with a property of being able to recognize patterns with deformation, changes in size or shift in position [11, 12, 13,]. There are pairs of layers, S-layers with S-cells and C-layers with C-cells. S-cells receive their inputs from previous C-layer except for the first layer which is connected to the input image. S-cells in the same S-plane extract the same feature at slightly different location to allow for positional shift tolerance in the features represented by these S-cells. The whole recognition process is conducted from layer to layer where local feature extracted in the lower layers are passed onto upper layers for more complex feature extraction until one of the C-cells in the final C-layer produces the response to the input pattern.

SVM (Support Vector Machine) is a useful technique for data classification [15, 16, 17]. The Support Vector Machine (SVM) is learning machine with very good generalization ability, which has been applied widely in pattern recognition, regression estimation, isolated handwritten character recognition, object recognition speaker identification, face detection in images and text categorization. SVM implements the Structural Risk Minimization Principal which seeks to minimize an upper bound of the generalization error rather than minimize the training error.

The best known classifier is KNN (K- Nearest Neighbor). It does not require prior information about the data. An incoming pattern is classified using the cluster, whose center is the minimum distance from the pattern over all the clusters. The task here is to design a model using training data which can classify the unknown patterns based on that model. For the training purpose, we have used 10000 numeric digits. Firstly feature vector for all training data is produced and stored in files.

3. PROPOSED SYSTEM

For extracting the feature, the zone based feature extraction method is purposed. The most important aspect of handwriting recognition scheme is the selection of good feature set, which is reasonably invariant with respect to shape variations caused by various writing styles. Zone based feature extraction method provides good result even when certain preprocessing steps like filtering, smoothing and slant removing are not considered. In this section, we explain the concept of feature extraction method used for extracting features for efficient classification and recognition.

Before extracting features using feature extraction method segmentation is performed on the training form for extract isolated handwritten numeral images. Segmentation is an operation that seeks to decompose an image of sequence of characters into sub images of individual symbols. Segmentation is the first and most important step towards automated recognition of any handwritten or printed data. Here

in the training phase training form has been used; from which isolated handwritten numeric digits, using horizontal and vertical projection are extracted. Features are extracted using reference points, which diagnose from where to start extracting features. It starts diagnosing from top left reference point to bottom right reference point to extract isolated numeric digits. For extracting features it first creates horizontal profiles after these vertical profiles are created on horizontal profiles.

For the training purpose sample form has been used. 200 forms for sample and image data collection has been used. 200 training sets of such images, each one containing 50 characters are used for training. Each set of character images varies for handwriting styles. The training sets of characters are shown in tables 3.1 to 3.10. Adaptive Unsupervised Incremental Learning Technique has been used for Training purpose. A file database has been created which contains isolated images of handwritten numeric digits which are collected using a form containing 5-sets of all the 10 digits of decimal number set. Each user will fill these set of forms in his/her own handwriting. The following paragraph explains in detail about the feature extraction methodology. The sample form for collecting data is as below.

Sample Form for Training:

The form includes fields for 'Name', 'Male' (checkbox), and 'Female' (checkbox). Below these is a grid with 5 rows and 10 columns. Each row is labeled with a digit from 0 to 9, and each column is labeled with a digit from 0 to 9. The grid is currently empty.

Figure 3: Sample data collection form

The sample of collected data is:

The form is filled with the name 'Deepika', 'Male' (checkbox) is unchecked, and 'Female' (checkbox) is checked. The grid contains handwritten examples of the digit '2' in each cell, with the digit '2' written in the top-left corner of each cell.

Figure 4: Example of a sample form with collected data

Zone based feature extraction method is purposed in this paper. In this zoning method again features are extracted for each zone by dividing the whole image into number of zones, but here the numbers of zones are not fixed. Firstly the whole image is divided into 4×4 zones. Further in order to gain more accuracy these zones are divided into 6×6 zones. The division of zones carried out up to 8×8 zones. Again the density is calculated by finding the number of object pixels in each zone and dividing it by total number of pixels.

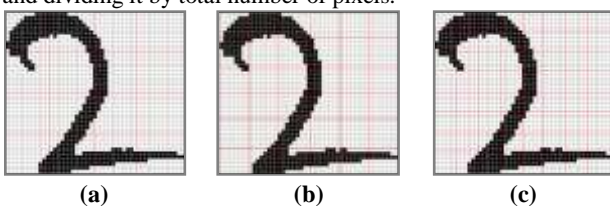


Figure 5: Original Matrices for Numeric Digit (2)

This procedure is sequentially for the entire zone present in the numeral image. Finally 116 such features are extracted for classification and recognition. For classification and recognition NNC classifier is used.

Offline isolated handwritten image samples are extracted using zoning feature extraction method. These are the original image drawn by user by free handwriting that stores in a file databases. This file database makes an image model library in which different types of binary images drawn by different users using different styles of handwriting are stored. The following are the image samples of Numeric characters:-

Table 1: Sample of Offline Handwritten Digits Images 0-9

Digit	Collected samples							
0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7	7
8	8	8	8	8	8	8	8	8
9	9	9	9	9	9	9	9	9

The final stage is testing phase which actually recognize the isolated handwritten numeric images using the k-nearest neighbor classifier with the value of $k=1$. For the testing purpose an Award List has been used, which contains 4-digit Roll no, 4-digit Code no and 3-digit marks which is as below:

Award List					
Class		Subject		Paper	
Session		M. Marks		Pass Marks	
Actual Roll no.	Code No.	Marks	Actual Roll no.	Code No.	Marks
	1001			1031	
	1002			1032	
	1003			1033	
	1004			1034	
	1005			1035	
	1006			1036	
	1007			1037	
	1008			1038	
	1009			1039	
	1010			1040	
	1011			1041	
	1012			1042	
	1013			1043	
	1014			1044	
	1015			1045	
	1016			1046	
	1017			1047	
	1018			1048	
	1019			1049	
	1020			1050	
	1021			1051	
	1022			1052	
	1023			1053	
	1024			1054	
	1025			1055	
	1026			1056	
	1027			1057	
	1028			1058	
	1029			1059	
	1030			1060	

Pass Fail Pass Fail

Figure 6: A Sample award list form

Segmentation is a kind of phase which has been adopted in both the training and testing phase. Segmentation is an operation that seeks to decompose an image of sequence of characters into sub images of individual symbols. Character segmentation is a key requirement that determines the utility of conventional systems. Different methods used can be classified based on the type of text and strategy being followed like straight segmentation method, recognition-based segmentation and cut classification method.

Segmentation is the first and most important step towards automated recognition of any handwritten or printed data. Classification is performed on these segmented characters without further interaction with the segmentation process. Dissection is an intelligent process in which analysis of the image is carried out.

Horizontal Projection: For a given binary image of size $M \times N$, where M is the height and N is the width, the horizontal projection is defined as:

$$HP(i), i = 1, 2, 3 \dots M.$$

Where $HP(i)$ is the total number of black (object) pixels in the i_{th} horizontal row.

Vertical Projection: For a given binary image of size $M \times N$, where M is the height and N is the width, the vertical projection is defined as:

$$VP(j), j = 1, 2, 3 \dots M.$$

Where $VP(j)$ is the total number of black (object) pixels in the j_{th} horizontal row.

Zoning feature extraction algorithm along with the k-nearest neighbor classifier has been adopted, which provides the best recognition accuracy rate. The best recognition rate is provided

by first type of zoning feature extraction algorithm with the value of $k=1$.

The KNN classifier is an extension of one nearest neighbor (1NN) classifier. The K nearest neighbor (KNN) method is a classification method and the principle based on the best distance measurement. It only needs reference data points for both classes [14, 15]. A test sample is then attributed the same class label as the label of the majority of its K nearest (reference) neighbors. We calculate the Euclidean distance between the test point and all the reference points in order to find K nearest neighbors, and then rank the obtained distances in ascending order and take the reference points corresponding to the k smallest Euclidean distances. The k-nearest 30neighbor approach attempts to compute a classification function examining the labeled training points as nodes or anchor points in the n-dimensional space, where n is the feature vector size. Rather than using a 1-nearest 30neighbor classifier, we choose a k-NN classifier to reduce the effect of mislabeled training data and to get a better estimate of Input feature vector. Euclidean distance, used in k-NN finding the nearest 30neighbor, is the straight line distance between two points in an n-dimensional space. The Euclidean Distance between an input feature X and a library feature vector C is given by following equation:

$$D = \sqrt{\sum_i^N (c_i - x_i)^2}$$

Where c_i is the i_{th} library feature and x_i is the i_{th} input feature and N is the number of feature used for classification. The class of library feature vector producing the smallest Euclidean Distance, when compared with the library input feature vector, is assigned to the input character. The k-NN is more general than nearest neighbor. Putting it other way, nearest neighbor is a special case of k-NN, where $k=1$. For the testing purpose the value of $k=1$ has been selected.

Award List					
Class		Subject		Paper	
Session		M. Marks		Pass Marks	
Actual Roll no.	Code No.	Marks	Actual Roll no.	Code No.	Marks
30001	1001	47	3011	1031	93
30002	1002	68	3012	1032	39
30003	1003	74	3013	1033	83
30004	1004	93	3014	1034	62
30005	1005	23	3015	1035	71
30006	1006	07	3016	1036	72
30007	1007	45	3017	1037	64
30008	1008	65	3018	1038	23
30009	1009	97	3019	1039	46
30010	1010	13	3020	1040	65
30061	1011	84	3051	1041	93
30062	1012	79	3052	1042	80
30063	1013	84	3053	1043	70
30064	1014	76	3054	1044	76
30065	1015	54	3055	1045	74
30066	1016	45	3056	1046	46
30067	1017	68	3057	1047	48
30068	1018	79	3058	1048	76
30069	1019	80	3059	1049	83
30070	1020	90	3060	1050	84
3021	1021	93	3041	1051	78
3022	1022	94	3042	1052	76
3023	1023	82	3043	1053	38
3024	1024	79	3044	1054	09
3025	1025	62	3045	1055	63
3026	1026	61	3046	1056	83
3027	1027	07	3047	1057	93
3028	1028	84	3048	1058	59
3029	1029	36	3049	1059	39
3030	1030	16	3050	1060	99

Pass Fail Pass Fail

Figure 7: A filled award list form

Table 2: Ground Truth Table for Form given in figure 7

Actual Roll No.				Code No.				Marks	
3	0	0	1	1	0	0	1	4	7
3	0	0	2	1	0	0	2	6	8
3	0	0	3	1	0	0	3	7	4
3	0	0	4	1	0	0	4	8	3
3	0	0	5	1	0	0	5	2	3
3	0	0	6	1	0	0	6	0	7
3	0	0	7	1	0	0	7	4	5
3	0	0	8	1	0	0	8	6	5
3	0	0	9	1	0	0	9	9	7
3	0	1	0	1	0	1	0	1	3
3	0	6	1	1	0	1	1	8	6
3	0	6	2	1	0	1	2	7	9
3	0	6	3	1	0	1	3	8	4
3	0	6	4	1	0	1	4	7	6
3	0	6	5	1	0	1	5	5	4
3	0	6	6	1	0	1	6	4	5
3	0	6	7	1	0	1	7	6	8
3	0	6	8	1	0	1	8	7	9
3	0	6	9	1	0	1	9	8	0
3	0	7	0	1	0	2	0	9	0
3	0	2	1	1	0	2	1	9	3
3	0	2	2	1	0	2	2	9	4
3	0	2	3	1	0	2	3	8	2
3	0	2	4	1	0	2	4	7	9
3	0	2	5	1	0	2	5	6	2
3	0	2	6	1	0	2	6	6	1
3	0	2	7	1	0	2	7	0	7
3	0	2	8	1	0	2	8	8	4
3	0	2	9	1	0	2	9	3	6
3	0	3	0	1	0	3	0	1	6
3	0	1	1	1	0	3	1	9	3
3	0	1	2	1	0	3	2	3	9
3	0	1	3	1	0	3	3	8	3
3	0	1	4	1	0	3	4	6	2
3	0	1	5	1	0	3	5	7	1
3	0	1	6	1	0	3	6	7	2
3	0	1	7	1	0	3	7	6	4
3	0	1	8	1	0	3	8	8	3
3	0	1	9	1	0	3	9	4	6
3	0	2	0	1	0	4	0	6	5
3	0	5	1	1	0	4	1	9	3
3	0	5	2	1	0	4	2	8	0
3	0	5	3	1	0	4	3	7	0
3	0	5	4	1	0	4	4	7	6
3	0	5	5	1	0	4	5	7	4
3	0	5	6	1	0	4	6	4	6
3	0	5	7	1	0	4	7	4	8
3	0	5	8	1	0	4	8	7	6
3	0	5	9	1	0	4	9	8	3
3	0	6	0	1	0	5	0	8	4
3	0	4	1	1	0	5	1	7	8
3	0	4	2	1	0	5	2	7	6
3	0	4	3	1	0	5	3	3	8
3	0	4	4	1	0	5	4	0	9
3	0	4	5	1	0	5	5	6	3

3	0	4	6	1	0	5	6	8	3
3	0	4	7	1	0	5	7	9	3
3	0	4	8	1	0	5	8	5	9
3	0	4	9	1	0	5	9	3	9
3	0	5	0	1	0	6	0	9	9

4. RECOGNITION RESULT AND COMAPRISONS AMONG DIFFERENT ZONING TECHNIQUES:

We have experimented the system on handwritten numerals. The system is analyzed using different zoning feature extraction methods discussed in section 2 and 3. The percentage accuracy is given in table 11. The percentage accuracy is calculated by dividing correctly recognized digits by total number of digits which are actually present.

Confusion Matrix: Confusion Matrix provides an easy and complete way to describe the knowledge about a classification result. The confusion matrix structure depends on the classifier performance and on consistence of utilized test set. The results of your confusion matrix highly depend on the selection of ground truth / test set pixels. *Rows* correspond to classes in the ground truth map (or test set). *Columns* correspond to classes in the classification result. The *diagonal elements* in the matrix represent the number of correctly classified pixels of each class, i.e. the number of ground truth pixels with a certain class name that actually obtained the same class name during classification. The *off-diagonal elements* represent misclassified pixels or the classification errors, i.e. the number of ground truth pixels that ended up in another class during classification.

Table 3: Confusion Matrix with K=1 (Zoning1)

	0	1	2	3	4	5	6	7	8	9
0	1251	0	0	0	0	0	0	0	0	0
1	0	1088	0	0	1	0	0	0	0	0
2	0	0	426	0	0	0	0	0	0	0
3	0	0	0	496	0	0	0	0	0	0
4	0	0	0	0	471	0	0	0	1	0
5	0	0	0	1	0	471	0	0	0	0
6	0	1	0	0	0	0	269	0	0	0
7	0	1	0	0	0	0	0	286	0	0
8	0	0	0	0	0	0	0	0	302	0
9	0	0	0	0	0	0	1	0	0	334

Table 4: Digit wise recognition accuracy with k = 1 (Zoning1)

Digit	Total	Correct	Percentage
0	1251	1251	100
1	1089	1088	99.91
2	426	426	100
3	496	496	100
4	472	471	99.79
5	472	471	99.79
6	270	269	99.63
7	287	286	99.65
8	302	302	100
9	335	334	99.7
Total	5400	5394	99.89

Table 5: Confusion matrix with k = 1 (Zoning2)

	0	1	2	3	4	5	6	7	8	9
0	1225	4	0	0	0	1	16	1	4	0
1	0	961	3	115	1	1	2	6	0	0
2	0	1	399	11	0	3	0	2	2	8
3	0	0	6	471	0	3	0	15	0	1
4	0	1	1	0	466	0	0	0	1	3
5	0	1	0	3	1	456	2	0	2	7
6	0	2	0	0	3	3	262	0	0	0
7	0	0	0	3	0	0	0	278	0	6
8	0	0	2	4	1	4	0	0	289	2
9	1	0	1	1	4	0	1	3	3	321

Table 6: Digit wise recognition accuracy with k = 1 (Zoning2)

Digit	Total	Correct	Percentage
0	1251	1225	97.92
1	1089	961	88.25
2	426	399	93.66
3	496	471	94.96
4	472	466	98.73
5	472	456	96.61
6	270	262	97.04
7	287	278	96.86
8	302	289	95.7
9	335	321	95.82
Total	5400	5128	94.96

Table 7: Confusion matrix with k = 1 (Zoning3)

	0	1	2	3	4	5	6	7	8	9
0	1223	2	0	9	1	0	13	0	2	1
1	0	1082	1	0	1	0	3	1	1	0
2	0	3	405	4	0	0	0	6	3	5
3	0	0	7	461	0	12	0	4	11	1
4	0	0	1	0	465	2	0	2	0	2
5	0	2	5	12	2	445	0	0	6	0
6	8	2	1	0	6	4	245	0	3	1
7	0	1	1	13	0	1	0	266	1	4
8	3	0	11	28	3	4	2	0	248	3
9	0	2	1	4	3	0	1	10	1	313

Table 8: Digit wise recognition accuracy with k = 1 (Zoning3)

Digit	Total	Correct	Percentage
0	1251	1223	97.76
1	1089	1082	99.36
2	426	405	95.07
3	496	461	92.94
4	472	465	98.52
5	472	445	94.28
6	270	245	90.74
7	287	266	92.68
8	302	248	82.12
9	335	313	93.43
Total	5400	5153	95.43

Table 9: Confusion matrix with k = 1 (Zoning All)

	0	1	2	3	4	5	6	7	8	9
0	1225	1	0	9	1	0	13	0	2	0
1	0	971	1	112	1	0	3	0	1	0
2	0	3	408	3	0	0	0	6	3	3
3	0	0	8	461	0	11	0	4	11	1
4	0	0	1	0	465	2	0	2	0	2
5	0	1	4	12	2	447	0	0	6	0
6	7	2	1	1	6	4	246	0	3	0
7	0	0	1	14	0	1	0	266	1	4
8	3	0	11	29	3	4	2	0	247	3
9	0	2	1	4	3	0	1	10	1	313

Table 10: Digit wise recognition accuracy with k = 1 (Zoning3)

Digit	Total	Correct	Percentage
0	1251	1225	97.92
1	1089	971	89.16
2	426	408	95.77
3	496	461	92.94
4	472	465	98.52
5	472	447	94.7
6	270	246	91.11
7	287	266	92.68
8	302	247	81.79
9	335	313	93.43
Total	5400	5049	93.5

Table 11: Performance Analysis of All Zoning Techniques

kNN Classifier	ZONING TECHNIQUES			
	Zone1	Zone2	Zone3	Zone All
1	99.89%	94.96%	95.43%	93.50%
3	92.93%	89.74%	91.15%	89.24%
5	86.37%	76.08%	83.87%	84.22%

In this paper we have used Zoning Feature Extraction technique for extracting features from isolated numeric images with k-Nearest Neighbor classifier with the value of k=1. This provides the best recognition accuracy rate among all the three zoning feature extraction techniques, which are defined in this paper.

Table 12: Performance Analysis of Zoning1 Techniques

Feature Extraction Method	Classifier	k	No. of Features	Recognition Accuracy
Zoning 1	k-Nearest neighbor	1	36	99.89 %

Here in the given table as we can see that by using different zoning feature extraction methods with kNN classifier which have different values of k, different recognition rates can be achieved. But with zoning1 feature extraction method with the value of k=1 higher recognition rate is achieved, which is comparatively good than other recognition rates. So zoning1 feature extraction method with kNN classifier where value of k=1 is adopted

5. CONCLUSION

In this paper we have proposed Zone feature extraction method for the recognition of handwritten isolated numerals. Nearest neighbor classifier is used for classification and recognition. The recognition rate of 99.89% is achieved for handwritten isolated numerals. Our future work aims to improve classifier to achieve still better recognition rate and also to develop new zone based feature extractions algorithms, which provides efficient results.

6. REFERENCES

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