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Handwritten English Digit Recognition: A Machine Learning Formulation

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Abstract*: Handwriting recognition is a challenging machine learning task. Handwritten Recognition (HR) systems have become commercially popular due to their potential applications. The challenges that arise due to wide range of variations in shape, structure ,size and individual writing style can be handled with the combination of a powerful feature extraction technique and an efficient classifier. In this paper, an attempt has been made to compare four different feature extraction cum classifier schemes for English handwritten numeral recognition in terms of computational time and accuracy of recognition. Observations show that single decision tree requires less computation time while SVM yields better accuracy.

***Keywords* : Numeral Recognition, HOG, SVM, single decision tree classifier.**

I. INTRODUCTION

Automatic hand writing recognition is a challenging task arising due to different individual writing styles and orientation. As the human world is increasingly digitalized, automatic information processing of bank checks, online handwriting recognition on computer tablets, zip code recognition on mail for postal mail sorting, processing numeric entries in forms filled by hand, verification of signatures is gaining importance. The research in handwriting recognition has been around two decades back. Though much work has been done in recognition of printed digits and characters, it is limited for handwritten cases. The performance in case of printed digits is high because of their minimal variations and uniformity in shape. The performance of a supervised machine learning approach entirely depends upon the underlying feature extraction and classification process. The combination of best discriminating features and a powerful classifier always yields high performance. Hence the task of handwritten digit recognition can be best solved by selecting a good feature extraction technique along with an efficient classifier.

In this paper, we have shown the performance comparison of four different classifier cum feature extractor combinations which are as follows:

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1. Support Vector Machine (SVM) classifier with Pixel intensity based features.
2. SVM classifier with HOG features.
3. Single Decision Tree classifier with pixel intensity based features.
4. Single Decision Tree classifier with HOG features.

Experimental results are obtained on the MNIST dataset containing images of English handwritten digits (0-9) through simulation results and haven been presented. The rest of the paper is organized as follows: section II provides a literature review of the work done on handwritten numeral recognition. Section III gives an overview of the handwritten English numerals. Feature extraction process and classification techniques are explained and briefed in section IV. Experimental results are produced in section V followed by conclusion in section VI.

II. LITERATURE REVIEW

Various approaches reported in the literature for handwritten numeral recognition are based on structural [1] and statistical [2] features. In [3] the authors have used the concept of fusion to merge the features based on structure, distribution and projection. [4] presents the review of the state of the art techniques for digit recognition. Karimir et al. in [5] have used ensemble classifier for Persian digit recognition and achieved 95.28% accuracy. In [6], the authors have made use of a modified quadratic classifier for recognition of six popular Indian scripts. Wang et al. in [7] have reported remarkable performance using Gabor filter based features for character recognition. [8] reports modified quadratic discriminant functions for Chinese character recognition. [9] reports Back-Propagation Neural Network (BPNN) as classifier for Kannada and Telugu digits recognition. Renate et al. in [10] have reported superior performance of SVM classifiers over multi-layer perceptron classifier for off-line handwritten digit recognition. In [12], A. Desai proposed a multi-layered feed forward neural network for identification and classification of Gujarati numerals. [13] reports a hybrid feature set obtained using different feature extraction approaches and neural network classifier for recognition of handwritten numerals.

III. ENGLISH NUMERAL DATASET

The MNIST database is a large database of handwritten numerals widely used for training and testing in machine learning applications. It contains 60,000 training images and 10,000 testing images. Each image is size normalized and centered and arranged as 28x28 matrix. Each pixel can have a value between 0-255. Sampling images from MNIST dataset is shown in fig.1.

A large variation is observed in the structural shape and individual writing style for all numerals in the dataset. The challenge is also due to the similarity noticed between digits like 1 and 7, 5 and 6, 3 and 8,etc. Similarly digits like 1 and 7 are written in many ways. We have considered the MNIST dataset for implementation purpose.

Fig.1 Sample handwritten numerals fron MNIST dataset

IV. FEATURE EXTRACTION AND CLASSIFICATION

A. Feature Extraction

The digits in the dataset are resized to (24x24). Two different sets of features are used for the implementation. The first set contains intensity information of each pixel in the digit image. Here, each numeral image is vectorized to form a column vector of size 576x1. We have selected 400 images randomly selected from the dataset for training and 200 images for testing. Hence for 10 numerals, the training set is of size 4000x1 and the testing set is of size 2000x1.

The other set is formed by extracting the Histogram of Oriented Gradients (HOG) features of each digit image [11]. To calculate the HOG features of each image, the following steps are adapted:

1. Gradient vector of each pixel is calculated along with magnitude and direction.
2. Each image is divided into cells of size 4x4.
3. In each cell, the magnitude and direction of the 16 pixels are represented by a 9- bin histogram as in which is known as HOG descriptors.
4. A block of size 8x8 is formed consisting of 4 cells which is represented by a vector of (36x1) HOG descriptors. The block is slided horizontally and vertically to cover the whole image which ultimately gives rise to 5 horizontal and 5 vertical block positions. Hence for the entire image, the final HOG vector is obtained by concatenation of HOG vectors of all blocks, i.e.,25x36x1.

B. Classification

For the classification of the handwritten numerals, Support Vector Machines (SVM) and Single Decision Tree have been used. SVMs are a class of supervised classification techniques having origin in statistical learning theory. SVMs have become popular because of their robustness, accuracy and effectiveness even in the presence of a small training set. SVMs have been effective as binary classifier as well as for multiple classification tasks. Decision tree classifiers have been used successfully used in many areas. They have the capability to capture the descriptive decision making knowledge from the training data. Decision tree classifiers are popular and easy to understand because of their simplicity.

The classifiers have been applied separately on each set of features. One set of features is obtained from the pixel intensity information whereas the other set of features is obtained from the HOG descriptors.

V. RESULTS AND DISCUSSION

For automatic recognition of numerals, we apply the classifiers on the extracted features. Two sets of features are extracted for this purpose. One set of features is based on the information of pixel intensity whereas the HOG descriptors form the other set of features. For the experimentation 400 images are randomly selected for training and 200 images for testing from the MNIST dataset for each numeral class.

SVM and Single Decision Tree classifiers are applied separately to the two different sets of features extracted. The four sets of results are presented in the form of confusion matrices. The confusion matrix reflects the number of correctly identified numerals along the diagonal . Tables 1,2,3,4 respectively show the confusion matrices for pixel intensity based single decision tree classifier, pixel intensity based SVM, HOG based single decision tree classer and HOG based SVM classifier. Table 5 shows the classification accuracy for each numeral class for four different feature extraction cum classifier schemes. Literature shows different performance measures like precision and recall which can be calculated from the confusion matrix as given by eq 1,2 .

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

where TP is true positive , FP is false positive and FN is false negative. We have used accuracy and computationaltime as performance measures for this implementation.

Table 6 presents a comparison between the computational time for the different classifier cum feature extraction techniques. The computational time is obtained by taking an average over 100 runs. Results clearly indicate that the decision tree classifier takes less computational time. Hence it is reasonable to recommend this for online applications and for applications involving large database without sacrificing the accuracy within a limit.

0	1	2	3	4	5	6	7	8	9
162	0	4	3	5	8	8	4	2	4
0	188	4	1	0	2	0	0	3	2
12	3	123	12	6	1	12	10	17	4
2	2	6	139	1	15	10	9	6	10
1	0	6	7	146	2	17	6	5	10
4	2	2	12	5	144	8	9	8	6
5	6	12	4	8	13	139	3	9	1

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3	3	13	11	6	3	2	127	4	28
4	2	11	14	9	9	21	5	109	16
3	0	2	13	17	7	3	8	7	104

Table 1. Confusion Matrix of Pixel Intensity based Single Decision Tree classifier

0	1	2	3	4	5	6	7	8	9
188	0	4	0	1	3	3	0	0	1
0	197	0	0	0	0	2	0	1	0
1	2	179	4	2	0	3	3	4	2
1	1	5	169	0	12	1	6	3	2
0	0	0	0	184	0	4	1	3	8
1	1	1	9	2	176	1	0	8	1
4	2	6	0	4	7	174	1	2	0
0	4	9	2	2	0	0	165	1	17
1	3	3	10	4	9	1	4	159	6
1	0	2	3	7	3	0	8	2	174

Table 2. Confusion Matrix of Pixel Intensity based SVM Classifier

0	1	2	3	4	5	6	7	8	9
169	0	5	7	0	3	10	0	1	5
1	192	1	0	0	0	1	4	1	0
16	2	154	9	2	1	4	6	5	1
10	0	21	137	5	11	3	4	7	2
2	8	4	4	162	0	4	7	4	5
7	4	2	7	10	158	7	2	3	0
13	2	2	1	5	11	161	0	5	0
2	5	14	7	7	1	1	146	12	5
12	5	14	8	4	9	12	0	133	3
8	1	2	2	12	2	0	14	5	154

Table 3. Confusion Matrix of HOG feature based Single Decision Tree Classifier

0	1	2	3	4	5	6	7	8	9
197	0	0	0	0	1	2	0	0	0
0	198	1	0	0	1	0	0	0	0
0	0	194	3	0	0	0	1	1	1
0	0	0	189	0	6	0	3	0	2
0	1	0	0	195	0	1	0	0	3
0	0	0	1	0	198	0	0	1	0
2	1	0	1	1	1	193	0	1	0
0	1	4	0	0	0	0	189	1	5
4	2	1	2	1	0	1	2	184	3
0	0	0	0	4	1	0	2	0	193

Table 4. Confusion Matrix of HOG feature based SVM classifier

Numeral class	Feature Extracter cum Classifier Scheme			
	Pixel Intensity + Single Decision Tree	Pixel intensity + SVM	HOG + Single Decision Tree	HOG + SVM
0	81	94	84.5	98.5
1	94	98.5	96	99
2	61.5	89.5	77	97
3	69.5	84.5	68.5	94.5
4	73	92	81	97.5
5	72	88	79	99
6	69.5	87	80.5	96.5
7	63.5	82.5	73	94.5
8	54.5	79.5	66.5	92
9	70	87	77	96.5
Overall Acuracy	70	88.25	78.3	96.5

Table 5. Recognition Accuracy of individual numerals in %

Feature extraction+classifiers	Computational Time (sec)
Pixel Intensity based Single tree classifier	0.006
Pixel Intensity based SVM	0.3444
HOG based Single tree classifier	0.0051
HOG based SVM	0.2839

Table 6. Computational time for different feature extractor cum classifier schemes.

VI. CONCLUSION

This paper highlights the performance of different feature extractor cum classifier schemes for offline handwritten numeral recognition. Remarkable results are achieved with HOG descriptor based features compared to pixel intensity based features. SVM perform better in terms of recognition accuracy . Further it is seen that Single decision tree requires less computational time compared to SVM. Further work can be carried out to improve the performance of single decision tree so as to make it more robust which will be more suitable for online tasks. Scope also exists in designing a more robust classifier that can perform well for noisy and blurred images.

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