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Recognition of Handwritten Digits using Proximal Support Vector Machine

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Abstract

Handwritten Digit Recognition System involves reception and interpretation of handwritten digits by a machine. Due to variation in shape and orientation of handwritten digits, it is difficult for a machine to interpret handwritten digits. Handwritten digit Recognition has a wide area of research due to its vast applications like automatic bank cheques processing, billing and automatic postal service. In this paper, an Offline Handwritten Digit Recognition System is presented. The recognition system is broadly divided into 2 parts, first part is feature extraction from handwritten images and the second one isclassification of feature vector into digits. We propose descriptorsfor handwritten digit recognition based on Histogram of OrientedGradient (HOG) feature .It is one of the widely used feature vector for object detection in computer vision. For classification of features, linear Proximal Support Vector Machine (PSVM)Classifier is proposed. This is a binary class classifier which is further converted to a 10 class classifier by means of One against all algorithm. Due to small training time, PSVM classifier is preferable over standard Support Vector Machine (SVM) Classifier. The handwritten images both for training and testing are taken from MNIST database. The performance of the system is measured in terms of Sensitivity, Accuracy, Positive Predictivity and Specificity. The performance of PSVM classifier is better compared to Artificial Neural Network(ANN).

***Index Terms*— Histogram of Oriented Gradient (HOG) feature, Proximal Support Vector Machine (PSVM) Classifier**

I INTRODUCTION

Handwritten Digit Recognition System involves reception and interpretation of handwritten digits by a machine. Handwritten Recognition System can be divided into Offline and Online Recognition System. In case of Offline Recognition System the image of the handwritten text is scanned off- line from document by optical scanning known as optical character recognition (O.C.R.) .Where as in case of Online Recognition the text as it is written on a special digitizer or Personal DigitalAssistant (PDA).

Writing styles differs in shape and orientation from person to person that makes handwriting digit recognition a challenging task. For the development of reliable handwritten digit recognition, two steps are important. The first step isextraction of discriminating feature from handwritten images and the second method is the classification of new digit images. The dimension of feature should be small. The feature to be extracted should have minimum variance within a class and maximum variance between classes. The Classifier to be used should able to classify digit with high accuracy and should take less training time during classification.

This thesis focuses on Offline Recognition System. The handwritten images are taken from MNIST (Mixed National Institute of Standards and Technology) database. The handwritten digits from 0 to 9 are trained and then tested usingsupervised machine learning model. Histogram of Oriented Gradient (HOG) based features are extracted from handwritten digits. Proximal Support Vector Machine (PSVM) classifier is used .The performance of classification is measured in terms four parameters derived from confusion matrix and training delay. The performance of Proximal Support Vector Machine (PSVM) Classifier is compared with Artificial Neural Network (ANN).

Handwritten digit Recognition has a wide area of research due to its vast applications. Recognition system can be divided into two major steps. First step is feature extraction from handwritten images and the second one is classification.

Researchers suggested different methodologies for feature extraction [4-7]. Fourier and wavelet based features are some of them [1-2]. The coefficients of Discrete Wavelet Transform DWT are shift variant, and the directional selectivity of subband images are poor. Complex Wavelet Transform (CWT) has been developed in order to overcome the drawbacks of DWT's but the problem is high dimension of feature vector i.e. 180 and 148 features for feature set 1 and feature set 2 respectively [3]. Histograms of Oriented Gradient Features is used for object detection like Human Detection [8- 9], Pedestrian Detection [10], Large Scale Sign Detection [11] [13], Real-Time Detection and Recognition of Road Traffic Signs [12] . The popularity of HOG feature is due to invariance to local geometric and photometric transformations within local spatial or orientation bin size. In order to implement such property, it is used as a feature descriptor for handwritten digits.

For classification of features of handwritten digits, classifiers like ANN [16-18], k-nearest neighbours (k-NN) [19] and Support Vector Machine (SVM) [20-21] are used. Out of these classifiers SVM is widely applicable. The main advantage of SVM classifier is high accuracy, but the classifier takes long training time. The computational time taken by Proximal SVM (PSVM) classifier is very less as compared to SVM. Considering reduced training delay during classification,PSVM classifier is used in this wok.

Machine learning deals with the study and the construction of machine or system that can learn from data. It can also be defined as learning from experience .For example, a machine learning system can able to distinguish between spam and non-spam messages by learning on email messages. After training, it can differentiate new email messages into spam and non- spam folders. The need of machine learning is to make system automated. System automation reduces operation time and manual labour. In supervised learning model along with input data, desirable response are also provided to the system [14]. The process is divided into two phases, first the training phase and second the testing phase. During the training phase the weights of the network are updated on the basis of training input and desirable response. Weight updating is done on the basis of specific optimization algorithm. On completion of training phase the weight of the network is considered to be optimum. This model is called as predictive model .The supervised learning model is shown in Fig.1. A test dataset is applied to the network for validation after then the model is made generalized. Generalization refers to the ability to produce reasonable outputs for inputs not encountered during the training.

The learning model implemented for handwritten digit recognition is supervised. As discussed earlier, supervised machine learning has two phases- training and testing. First, from images of handwritten digits(i.e. training set images), features are extracted using HOG feature extraction .These feature vectors along with desirable response are given to PSVM networks so that the weights of the network get optimized and fixed. This completes the training phase.

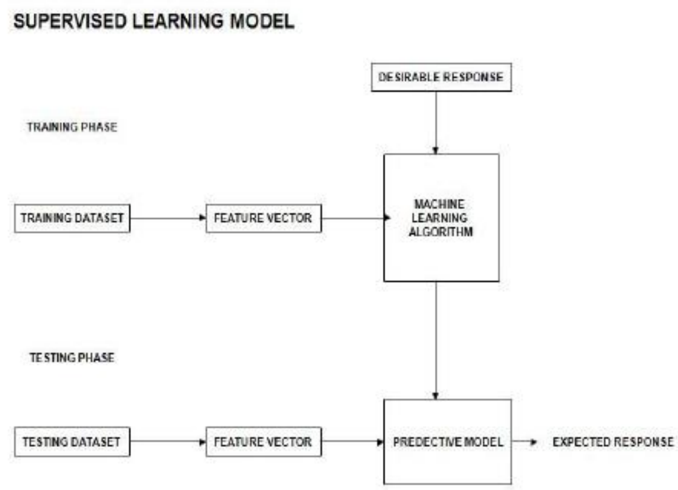

Fig.1: Supervised Learning Model

The entire training process is represented by black arrow as shown in Fig.2During testing phase; the features of unknownhandwritten digits are extracted using the same feature extraction method. After then the feature vector for the test image is given to the weighted PSVM network and then the response is noted and then given to the decision unit. The decision unit makes decision and recognize the handwritten digit. In the above figure, the testing process is represented by red arrow.

II DATASET DESCRIPTION

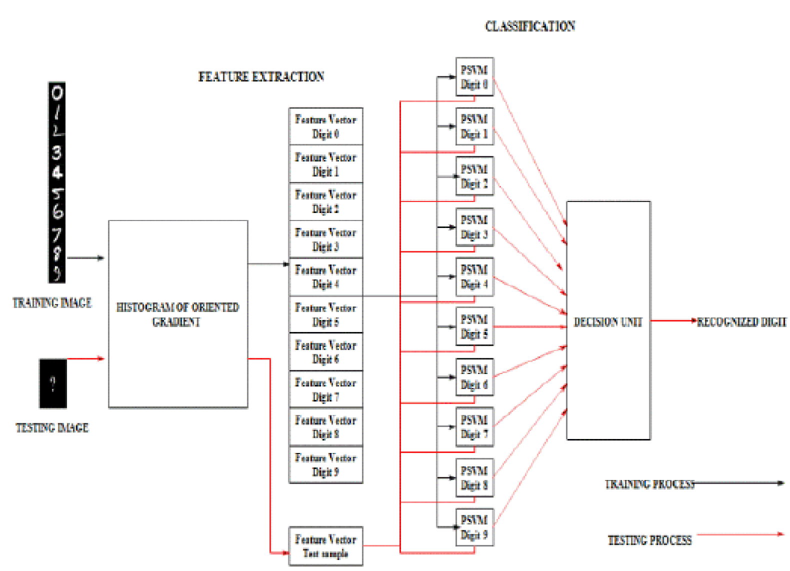

Fig .2: Handwritten Digit Recognition System

We consider the recognition system to be offline. The images of handwritten digits are taken from MNIST database and the algorithms are implemented in MATLAB codes. The training and the testing handwritten images

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are shown in Fig.3. The MNIST database contains 60000 training set and 10000 testing set handwritten digits ranging from 0 to 9 [34].Each digit is normalized and centred in a gray-level image with size 28 X28. Table.1 shows the distribution of training and testing dataset for handwritten digit 0-9 that are used in this experiment. A total of 10000 samples are taken both for training and testing set respectively.

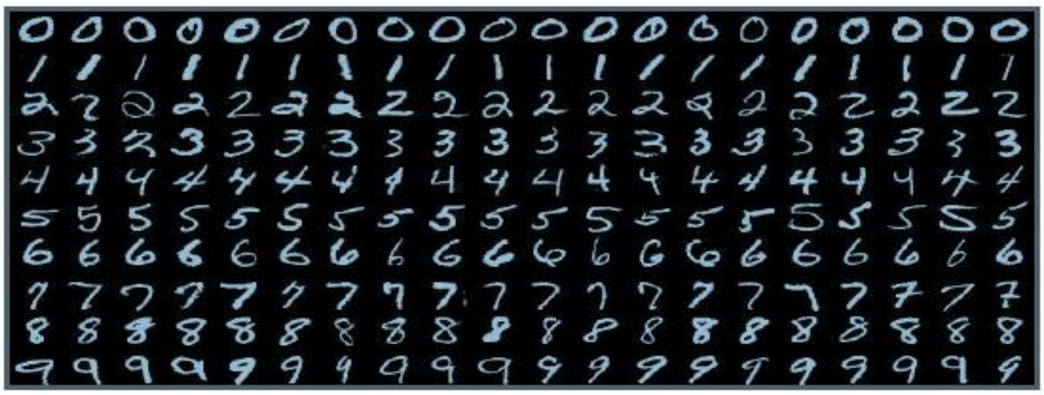

Fig.3: MNIST dataset

Table 1: Dataset Distribution

Digits	Training Set	Testing Set
0	1000	980
1	1000	1135
2	1000	1032
3	1000	1010
4	1000	982
5	1000	892
6	1000	958
7	1000	1028
8	1000	974
9	1000	1009
Total	10000	10000

FEATURE EXTRACTION

The representation and description of images in terms of feature vector is done by means of feature extraction. The widely used feature vector for object detection in computer vision is Histogram of Oriented Gradient (HOG) .Some applications of the object detection where HOG feature descriptor is used are human detection for surveillance, detection and recognition of traffic sign [8-12].The aim of feature extraction is to obtain a feature vector that describes digit local shape as well as the spatial layout. The HOG feature descriptor measures the frequency of gradient orientation within local portions of a digit. Local shape and appearance of handwritten digits of an image can be represented in terms of edge directions. The local portion of the image can be obtained by dividing the image into small block .For each block histogram of gradient directions for the pixels are calculated. The combination of histograms then represents the feature vector for handwritten digits. The HOG feature vector hasmany advantages.

As the HOG feature vector operates on localized block, it upholds invariance to geometric and photometric transformations makes small difference if they are much smaller that the local spatial or orientation bin size [8].

The feature extraction procedure from images of handwritten digit is given in Fig.4.

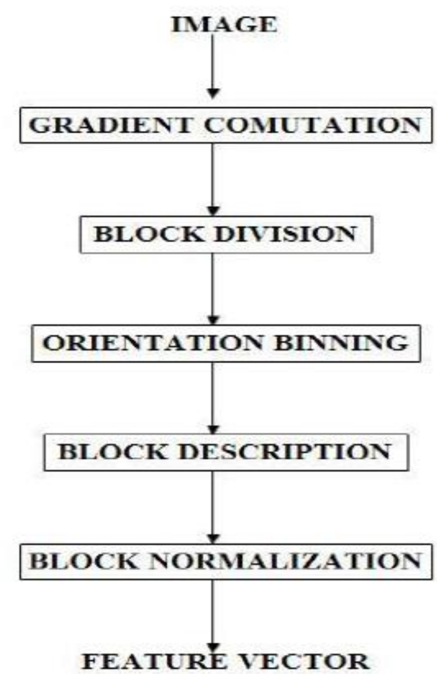

Fig.4. Flowchart for HOG feature extraction

IV MULTICLASS- LINEAR PROXIMAL SUPPORTVECTOR MACHINE (PSVM)

A Proximal Support Vector Machine (PSVM) Binary Classifier classifies features depending on the proximity to oneof the two parallel plane in such a way that the distance between 2 features is maximum i.e. error of misclassification is minimum **.**The objective function defined for PSVM is strongly convex as a result of which the training times require for such classifier is lesser as compared of standard Support Vector Machine (SVM) Classifier[15] [32].Due to this reason a Linear PSVM Classifier is preferable over Linear SVM classifier for handwritten digit recognition.

Consider two classes A+ and A-. Objective is to classify m features in the n-dimensional real space R^n. The feature vector is represented by an m x n matrix A. D is m x m diagonal matrix with + 1s representing class A+ and -1s representing class A-, along its diagonal. The quadratic programming parameter and the bias are represented by $\mu > 0$ & γ respectively. y is the slack/error variable and the column vector e of values 1 of size mx1.

The separating surface for SVM is given in equation 1

$$x^T w - \gamma \begin{cases} > 0 \, , x \epsilon A^+ \\ < 0 \, , x \epsilon A^- \\ = 0 \, , x \epsilon A^+ \text{ or } x \epsilon A^- \end{cases} \qquad (1)$$

Let T = {(x_i, d_i)} $_{i=1}^{m}$, $x_i \epsilon R^n$ be the training sample, the objective is to find the optimum values of the weight vector w_o and bias b_o such that they satisfy the constraints

$$D(Aw - e\gamma) + y \geq e_i \ \text{ for } i = 1,2,3,\ldots,m \qquad (2)$$
$$y_i \quad \geq 0 \text{ for all i.}$$

the weight vector w ,bias γ and slack variable y minimizes thecost function:

$$\Phi(w,\gamma,y) = \frac{1}{2}(w^T w + \gamma^2) + \mu\frac{1}{2}||y||^2 \qquad (3)$$

In above equation the square norm of y is minimized. Whereasin case of SVM only the norm of slack variable is minimized. In PSVM, the square norm of y leads to strong convexity ofthe objective function. The inequality constraint is convertedto equality as follows

$$D(Aw - e\gamma) + y = e_i \ \text{ for } i = 1,2,3,\ldots,m \qquad (4)$$
$$y_i \quad \geq 0 \text{ for all i.}$$

The PSVM is shown in figure 3.1.

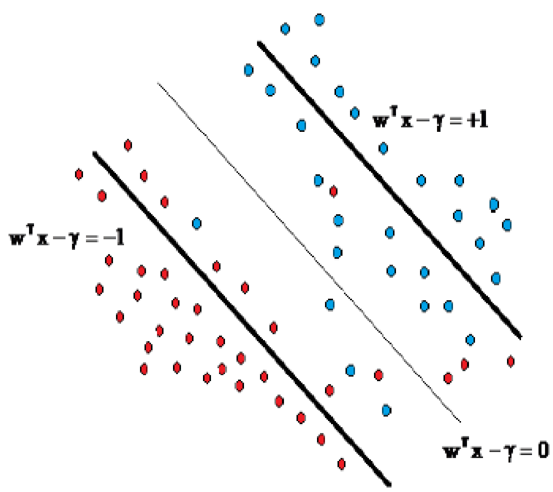

Fig 5: Proximal Support Vector Machine

The objective function is defined as L, where u is LagrangianMultiplier in equation 6

$$L(w,\gamma,y,u) = \frac{\mu}{2}||y||^2 + \frac{1}{2}||\begin{bmatrix} w \\ \gamma \end{bmatrix}||^2 - u^T(D(Aw - e\gamma) + y - e) \qquad (6)$$

By taking derivative of L with respect to (w, γ, y, u), the Karush-Kuhn-Tucker (KKT) necessary and sufficient optimality conditions are obtained.

V. IMPLEMENTATION OF MULTICLASSPSVM

The algorithm mention above is for 2 class classification. But for handwritten digit recognition system, we need a classifier that can classify handwritten digits in 10 classes i.e. from 0 to 9.One way to implement a multiclass classifier by converting a multiclass problem to many binary class problems and using many binary classifiers.

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Several methods are proposed for conversion of multi-class problem into several binary problems using Support Vector Machines as binary classifiers [24-27] .Such methods are listed below

(i) One-against-all
(ii) One-against-one

For handwritten digit classification One-against-all method is applied to binary linear PSVM classifier as the one against all significantly more accurate for digit recognition using SVM classifier .

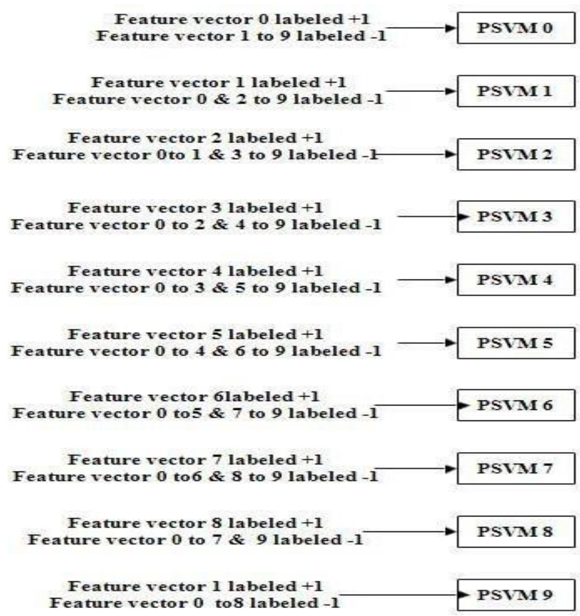

Figure 6: Training PSVM using One-against-all Method

In One-against-all method for the 10-class problem, 10 binary linear PSVM classifiers are constructed. The i^{th} class PSVM istrained while labeling the feature descriptor in the i^{th} class as +1 and all the rest as -1as shown in Fig 6
In the recognition phase, a test feature descriptor is presentedto all 10 PSVMs and is labeled according to the output whichis proximal or nearest to the label +1 among the 10 classifiersin decision unit as shown in figure 7.

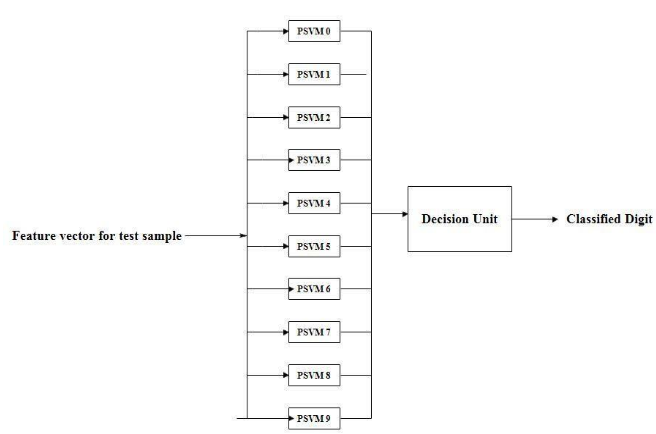

Fig 7: Recognition Phase of handwritten digit

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VI. EXPERIMENTAL RESULT ANDDISCUSSION

In this thesis first HOG based features are extracted fromhandwritten digits after than 10- class PSVM Classifier is used. Many handwritten digit classification system uses Support Vector Machine as a classifier .In this paper we are taking Proximal SVM as a classifier, as it requires lesser computation time than SVM for classification [32]. The binaryPSVM classifier is implemented using toolbox [33], which is further converted to a 10-class classifier. Some misclassification errors are shown in. The number on left hand side of the equality represents correct digit and on the right hand side represents misclassified digit.

Horizontal row represents the handwritten digits that is input or given to the recognition system and vertical column represents the classified response of the recognition system. The number belonging to 6th row and 0th column represents, 10number of handwritten digits belonging to digit 6 butmisclassified as digit 0.The number of correct classification are along the diagonal of the confusion matrix i.e. 7th row and 7th column represents the correct classification of digit 7.So total 886 out of 1028 digit are correctly classified for digit 7.

The overall performance of the recognition system is

Sensitivity = 93.22%

Positive Predictivity =93.27%

Specificity =99.25%

Accuracy =98.65%

The recognition rate for individual digits are shown in Fig.8

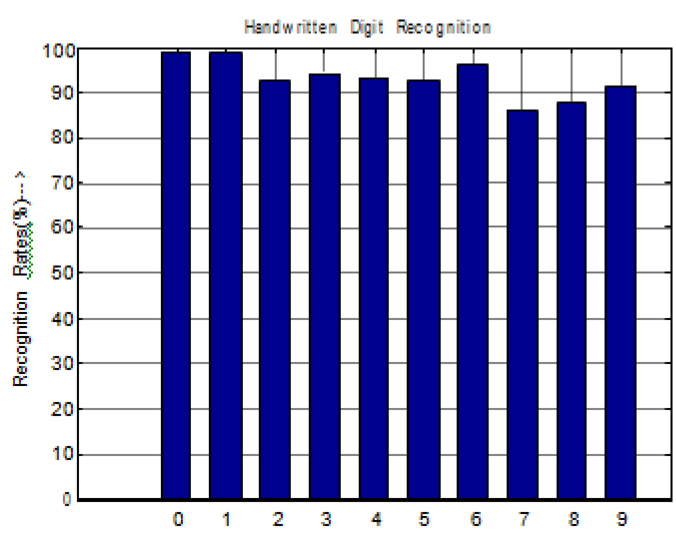

Figure 8: Individual Digit Recognition Rate

In the above figure, recognition rate for digit 0 is maximum and for digit 7 it is minimum. From the confusion matrix from table 3.2, it is found that most of the handwritten digits 7 are misclassified as digit 2 and digit 9. The system shows a poor recognition for digits 7 and 8 but showing a very good response for digits 0, 1, 2, 3, 4, 5, 6 and

9.The digit recognitionsystem is also implemented using ANN classifier. The feature extraction method is same as in PSVM network. The design of 3-layer Artificial Neural Network is shown in table 2.

Table 2: Design of ANN

Training Method	Gradient Descent Backpropagation with Adaptive learning Rate
Number of Input Nodes	81
Number of Output Nodes	10
Number of Hidden Nodes	60
Activation Function	Hyperbolic tangent sigmoid
Learning Rate	0.5

Table 3: Comparison between Classifiers

parameters	ANN(1000 epoch)	PSVM
Sensitivity %	91.84	93.22
Positive Predictivity %	91.87	93.27
Specificity %	99.09	99.25
Accuracy %	98.37	98.65
Training Time(classifier) in second	109	0.059

The performance of Proximal Support Vector Machine (PSVM) Classifier is compared with Artificial Neural Network(ANN) in table 3.4.The overall Sensitivity, PositivePredictivity, Specificity, Accuracy for 1000 epoch ANN is91.84, 91.87, 99.09, 98.37 respectively and by using PSVM
classifier increases to 93.22, 93.27, 99.25, 98.65 respectively. The training time for ANN is 109 second which reduces to 59 milliseconds for PSVM classifier.

CONCLUSIONS

In this thesis HOG-PSVM handwritten digit recognition system is presented. The images of handwritten digits are described in terms of 81 dimensions HOG feature descriptor. The HOG feature vector holds invariance to geometric and photometric transformations that are smaller than the localregion of size 7X7 or orientation bin size 40 degrees. For recognition of HOG patterns of handwritten digits, a 10-class linear PSVM classifier is used. The overall accuracy of PSVM classifier is 98.65% with a training time of 59 milliseconds. PSVM classifier in less training time shows better performance as compared to ANN. Along with achieving a good recognition rate of 98.65 %, the system has also maintained small dimension for feature vector (i.e. 81dimension HOG feature) without using an additionaldimension reduction technique and small training time required by PSVM classifier.

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