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Recognition Impact on Rescaled Handwritten Digit Images Using Support Vector Machine Classification

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Abstract— Handwritten Digit Recognition has been proposed using different techniques that were implemented over the available datasets. Although existing systems reached high recognition accuracy, more efforts regarding speed and memory allocation is required. In this research, we experiment the impact of image resolution reduction on recognition accuracy for handwritten digits. A set of features were extracted, include histogram of pixels for horizontal, vertical, diagonal and inversed diagonal orientations. Feature vector constructed by joining these features. Then, support vector machine is applied for classification. Rescaled handwritten digit images were experimented against recognition accuracy, speed and memory. MNIST database of handwritten digits is utilized for implementation. Results showed that the reduction of the size for the features vector due to image rescaling to quarter of the original size had only about 1% accuracy degradation impact.

Keywords- Handwritten Digit Recognition; SVM; Histogram features; MNIST; Cubic Support Vector Machine and Recognition Rate.

I. Introduction

In the last decades, the increasing demand of converting massive amount of printed or handwritten documents into digital form was the driver and motivator for character recognition technology. This process was done in the past by human operators which was an error prone and time-consuming process.[1]

Handwritten Digit Recognition is known as the process of transforming images of handwritten digits into numeric values in a suitable format for the computer, for the purpose of editing, searching, processing and a minimizing memory storage size. In general, handwritten recognition systems has effectiveness and importance in many fields such as the new era of Online education due to COVID-19, processing bank check amount automatically, mail zip codes recognition for postal mail sorting purposes, electronic data indexing, handwriting recognition on mobiles, numeric entries in the form filled by hand and so on.

The handwritten recognition system can be divided into two main domains on the basis of input method; online and offline, each has its suitable processing technique. Online handwritten recognition requires writing tool trail capturing instrument (digital pen). Nowadays smart mobiles, smart boards, electronic pad (digitizers) and digital personal assistant, have imbedded online handwritten recognition system. Hence it is important to improve and optimize the performance of the recognition system, aiming for the improving the processing speed and reducing the storage space.

The static representation of a digitized document is used in the offline system of digit recognition, example of which are check form, mail or document processing. Contrary to offline, in online system depends on the information acquired during the production of the handwriting [2],[3],[4].

Offline handwritten recognition process usually passes through many phases, starting from image preprocessing and data cleaning, then feature extraction from the dataset using a suitable distinguishable feature, which usually uses histogram technique, then pattern recognition depending on one of the machines learning techniques and artificial inelegance. Such as Support vector Machines, Neural networks, K-Nearest Neighbor techniques.

Histogram as a feature extraction works mainly on converting the image into useful digital values depending on the arithmetic sum of parts of the processed image.

The rest of the paper is organized as follows: First, we give an overview of the methods and techniques used in previous literature, then we introduce the metrology followed in this research, starting from image preprocessing and SVM implementation for classification, then repeating the process after image downscaling, and calculating the recognition accuracy. The next part views results for this research, and finally in the conclusion we discuss the impact of image rescaling on the recognition accuracy, and propose focusing on other feature extraction methods.

II. Literature review

Machine learning support-vector networks or Support Vector Machines (SVMs) are part of the machine learning tools that are used in classification and regression analysis. Learning algorithms associated with SVMs are supervised learning models that recognize pattern by analyzing that data. Input vectors are mapped to a higher dimension feature space. Support vector network is a learning machine for two-group classification problems. Conceptually Support vector network implements non-linearly mapping of input vectors to a very high-dimension feature space. A linear decision surface is constructed in the mapped feature space. The data under consideration, the Support Vector Machines are modelled to categorize [3]. SVMs can implement a non-linear classification using what is called the kernels, implicitly mapping their inputs into high-dimensional feature spaces. The following steps are generalization of modelling of hand written digit recognition. Starting from modeling the SVM and then selecting the data set to train this model. From the training of the SVM model the hyperplane is generated. This hyperplane categorizes data into set classes. After configuration of the hyperplane, testing dataset is given as an input to the SVM model and calculating the accuracy output compared with the proposed values.

In [5] feature extraction technique proposed was radial histogram, and Euclidean distance for classification, the research was implemented for Gujarati handwritten Characters. Simple Normalization & Binarization pre-processing step was also implemented. A 72 feature vectors of a 5-degree interval was generated to build the radial histogram.

Another research presented handwritten recognition algorithm based on histograms, structural features, and profiles. Vertical and horizontal histograms were used, in combination with the radial histogram, a 280-features vector was built from the representation of 32x32 image matrices for the characters using out-in radial and in-out radial profiles. The recognition process has been supported by a lexical component based on dynamic acyclic FSAs (Finite-State-Automata). [6]

Using combination of multiple feature extraction methods and an ensemble classifier system is can increase the model accuracy. In [7] research paper Six feature set using different approaches were extracted depending on zoning, projections, edges, concavities and gradient to increase diversity to the feature extraction phase of the model. The importance of diversity in the methods enhanced the ability to recognize certain types of images. The research shows that using a combination of six features enhanced the recognition rate. Therefore, these six methods are sufficient to achieve a very high recognition rate. But on the other hand, that raised a problem of finding the best scheme to combine those features.

III. Methodology

In this research we will find the impact of rescaling (down scaling) handwritten digit images on recognition accuracy. MNIST database [10] will be used as, this dataset contains 60000 training images and 10000 testing images, each image is 28x28 pixel 256 gray level. The images will be preprocessed and converted into Monochrome 1bit depth images depended on an experimented threshold as a Binarization stage, which was implemented by experimentally selecting a threshold for the gray value of the pixel color and convert it into binary value. The next step is implementing histograms for four proposed features to build features vector. The features vector is processed using different SVM kernel models and recognition of the system is evaluated, Fig.1 shows the flowchart for the recognition process.

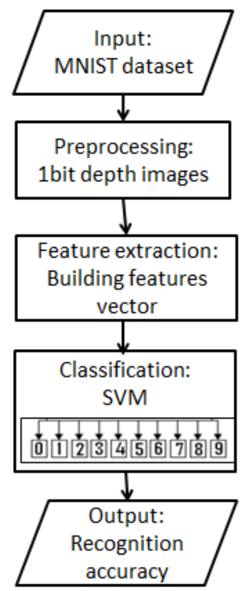

Figure 1. Recognition Process

The second phase in this paper will reduce the resolution of the dataset images to be (14x14), this will reduce the size of the data to be processed to one forth the original size, then repeat the steps of the first phase.

In this research for four features were selected (Vertical, Horizontal, Diagonals and Inverse-diagonals Histograms) for the feature extraction stage. Vertical histogram as in (1) generates 28 element, horizontal histogram as in (2) generates also 28 elements, while Diagonal (3), (4) generates 55 element, and Inverse-diagonal (5), (6) generates 55 elements too. All these elements were joined in one feature vector of 155 elements.

$$V[i] = \sum_{j=1}^{28} pixel\ (i,j) \tag{1}$$

$$H[j] = \sum_{i=1}^{28} pixel\ (i,j) \tag{2}$$

$$D[x] = \sum_{i=1,\ j=29-x}^{i=x,\ j=28} pixel\ (i,j) \tag{3}$$

$$where\ x = 1\ to\ 28, \quad D[1]\ to\ D[28]$$

$$D[28+x] = \sum_{i=x+1\ ,j=1}^{i=28\ ,j=28-x} pixel\ (i,j) \tag{4}$$

$$where\ x = 1\ to\ 27, \quad D[29]\ to\ D[55]$$

$$ID[x] = \sum_{i=x,\ j=1}^{i=1,\ j=x} pixel\ (i,j) \quad ,i--,j++ \tag{5}$$

$$where\ x = 1\ to\ 28, \quad ID[1]\ to\ ID[28]$$

$$ID[28+x] = \sum_{i=x+1\ ,j=28}^{i=28\ ,j=x+1} pixel\ (i,j) \quad ,i++,j-- \tag{6}$$

$$where\ x = 1\ to\ 27, \quad ID[29]\ to\ ID[55]$$

The next stage is applying the features vector to 3 different SVM model types (Quadratic, Cubic and Medium Gaussian) and calculating the recognition accuracy. This part was implemented using MATLAB learner classification confusion matrix.

The second phase of this research, worked on reducing the resolution of the digit images to be 14x14 instead of 28x28. This reduced the storage size of the dataset, and should reduce the processing time for the SVM stage as a result.

The reduction was implemented depending on a voting value for adjacent pixels vertically and horizontally to generate one value for the new pixel, we use 1bit depth also for this stage. This size of the new images was 196 pixels.

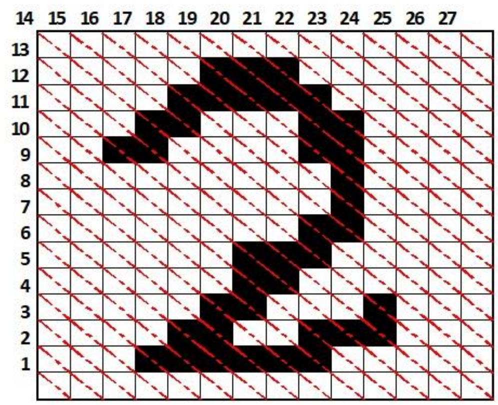

Figure 2. Inverse diagonal features maping 14x14 image

Implementing the proposed feature extraction method mentioned before generated feature vector of 82 elements, divided as follows, vertically and horizontally 14 feature each, diagonal and inverse-diagonal 27 feature each.

IV. Results

Through the experimentation stage, we initially implement SVM on each feature separated, it was found that diagonal, and inverse-diagonal histograms generated higher recognition accuracy than vertical and horizontal histogram, but even with a low recognition accuracy value (less than 75% for the inverse-diagonal). While using a feature vector combined from two histograms (diagonal and inverse-diagonal) gives noticeable enhancement in recognition accuracy of 92.3%.

By implementing the SVM on all features as one feature vector, on the original images that had 155 features, the recognition accuracy reached up to 97.2% using Cubic SVM model, 96.9% using Quadratic SVM model, and 96% using Medium Gaussian SVM model. Total processing time for all stages was 7700 second, and memory size of 89 Mbytes. Fig. 3 shows the confusion matrix for resulting from implementing Cubic SVM model on the 155-features vector.

By implementing the SVM on all features as one feature vector, on the reduced resolution images that had 82 features, the recognition accuracy reached up to 96.2% using Cubic SVM model, 95.8 using Quadratic SVM model, and 95% using Medium Gaussian SVM model. Total Processing time for all stages was 6299 second, and memory size of 46 Mbytes.

From the results, it was noticed that reducing the image resolution from 28x28 pixels to quarter size the original 14x14 pixels, had only a small negative impact on the recognition accuracy of about 1% only (from 97.2 to 96.2) while it had a positive impact on the reduction of the processing time of 18.2% (from 7700 sec. to 6299 sec.).

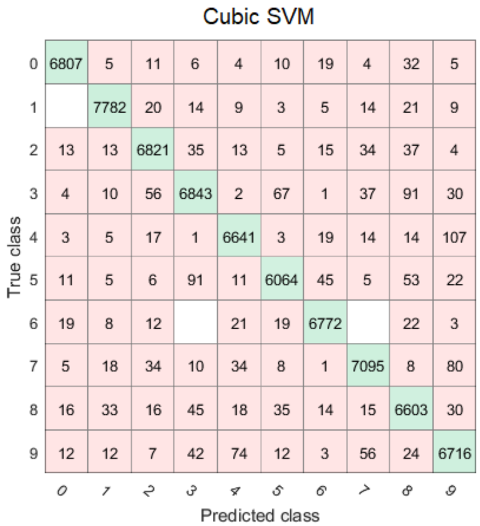

Figure 3: Confusion matrix for Cubic SVM model of 155 features.

From comparing the three different SVM models applied inn this research we noticed that cubic SVM model gives the highest recognition accuracy 97.2% on the original images, and 96.2% on the downscaled images.

From feature extraction process it was noticed that Diagonal and inverse-diagonal histogram features have higher effect over vertical and horizontal.

V. Conclusion

Existing handwritten recognition systems reached high recognition accuracy. In this research, we aim to reduce the processing time and memory size by rescaling the digit images, and find the impact of image resolution reduction on recognition accuracy on handwritten digits. The selected set of features depended on the evaluating histograms for Horizontal, vertical, diagonal and inversed diagonal orientations of the digit images. A features vector of 155 elements for the original images was constructed, and another feature vector of 82 elements for the rescaled images was constructed. Classification was implemented by applying SVM on each feature vector. Results showed that the reduction of the size for the features vector due to image rescaling to quarter of the original size had only about 1% accuracy degradation impact.

The size of features-vector is still high, this will enhance the SVM processing time. More studies are needed on enhancing the feature extraction stage, looking for more suitable features can enhance the recognition accuracy, and can minimize the size of features-vector without impacting on the recognition accuracy.

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