

Handwritten Digit Recognition Using Deep CNN

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ABSTRACT

This study demonstrates how the deep Convolutional Neural Network (CNN) can be effectively employed to enhance the performance of isolated digit recognition systems. The global and local features are extracted automatically by CNN from the normalized image. Classification is carried out using Convolutional Neural Network while the experimental study is conducted on the standard CVL single digit database. A series of evaluations using different configurations of CNNs realized high recognition rates which are compared with the state-of-the-art methods on this subject.

KEYWORDS

Isolated handwritten digits; Deep learning; CNN

1 Introduction

Handwriting recognition is a classical problem in the field of pattern classification and computer vision. There are wide variety of applications including OCR, postal code recognition, license plate recognition, bank checks recognition, extraction of information from forms and many more [1,2,3].

Isolated handwritten digit recognition is to classify digit into ten (10) different classes. The main challenges in recognizing handwritten digit come from variations in size, shape, inclination, and more importantly variations in the writing styles of individuals. These problems within makes the subject of our present study.

With recent advances in pattern recognition, advanced isolated handwritten digit recognition systems have been proposed [4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14], which aim to improve overall recognition performance by improving the Extraction of features and / or classification techniques.

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Some of the studies aim to improve classification performance by using a combination of several classifiers, while others aim to combine several features and to select the most relevant and optimal set of characteristics for this problem. Among well-known digit recognition systems, combination of statistical, local, global, textural and structural features [12,13,14,15,16,17] are surveys on this subject. From the view point of classification, classifiers like Support Vector Machine, Neural Networks, Hidden Markov Models (HMM) and fuzzy logic have been explored [4,5, 6,7,8,9,10,11].

The Convolutional Neural Network "CNNs" is one of the most important forms of deep learning. CNNs deals more layers of a single neural network and therefore the most important algorithm to classify images or symbols manuscripts. Although many classification algorithms based on deep learning are studied for this, the recognition rate and execution time need to be further improved. H. Zhan et al. [15] proposed a new network based on Recurrent Neural Network and Connectionist Temporal Classification (RNN-CTC) for the recognition of handwritten digits. This system uses a more efficient residual network to extract sequences of more discriminating features and to predict the results of the recognition and to modify the standard bidirectional (LSTM) by adding a fully connected layer before combining the two directions for the convergence. At the top of this network, a standard CTC is applied to calculate the loss and get the final results. Otherwise, an adaptive (Q-learning) strategy is proposed by J. Qiao et al (2016) [16] to further improve the accuracy and reduce the execution time of the recognition of handwritten digits. Combining deep learning and Q-learning to Q-Learning Deep Belief Network Q-ADBN. The authors use this strategy Q-ADBN on the one hand, to extract the main features of the original handwritten digits images by using the adaptive deep auto-encoder ADAE method. On the other hand, the Q-learning algorithm is used as a classifier and the extracted features are considered as current states of the Q-learning algorithm, generally used to reinforce the training step.

In this work, we will focus on the recognition of isolated manuscript digits using deep CNN to recognize the digits image of not normalized CVL database, we aim to classify images into ten classes of (0 to 9). Our CNNs have three layers of convolution-sized, three layers of Max-pooling and a fully connected layer that

achieve high recognition rates where realized results are compared with a number of state-of-the-art methods.

This paper is organized as follows: We first discuss the preprocessing of images and Deep Convolutional Neural Network

2.2 Deep CNN

Deep learning has been providing the outstanding performance in the field of handwritten digit recognition since the last few years. In our study on isolated digit recognition, we have chosen to

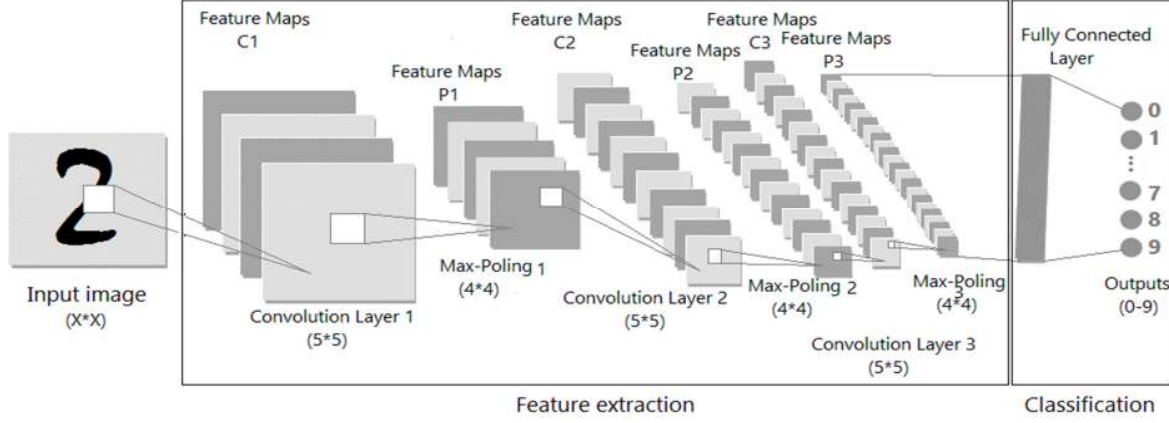


Figure 2: The "CNN" architecture proposed for the classification of handwritten digits

employed in our study in Section I. Section II details the experiment conducted along with a comparative analysis and discussion on the realized results. Finally, we conclude the paper with a discussion on future perspectives on the subject.

2 Proposed approach

Preprocessing and Deep CNN are the most critical steps in proposed approaches. The key idea is to find an effective size normalization and Deep CNN configuration of the digit patterns that minimizes the intra-class variability and which maximizes inter-class variability. So, we propose to classify handwritten digits two major steps: Preprocessing of images and Deep Convolutional Neural Network.

2.1 Reprocessing of images

The original size of images is reduced according to several size 20×20 to 40×40 pixels which are convert all RGB images to binarized images. Image interpolation is preferred method for resize image. This method works in two directions, and tries to achieve a best approximation of a pixel and intensity based on the values at surrounding pixels (see Figure 1). So, Images can keep much important information due to resizing.

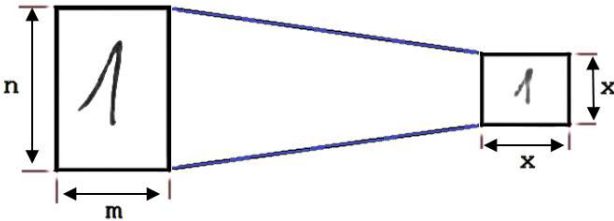


Figure 1: Example of a resized handwritten digit

employ a property CNN structure [18].

As illustrated in (Figure 2), we have designed CNN network with two convolutional layers for the classification of isolated handwritten digits from the CVL database.

The input images being of size $(x = n \times m)$ such that $n=m$, the input layer of the network contains (x) neurons and the output layer comprises 10 neurons (0-9). The three convolutional layer has filter size (5×5) and stride equal to 1. There are also three layers of Max-pooling using kernel size (4×4) and specific number of Feature Maps (FM) for each convolution layer.

Rectified Linear unit (ReLU) [20] is used as an activation function for all layers. The last activation function is a Softmax function for the classification. We use the gradient descent optimizer to update weights. Figure 2 shows the design of our proposed deep CNN architecture.

For the training step, we fixed some parameters of our architecture: 100 epochs and batch size fixed at 7 samples.

2.3 Dataset

The CVL dataset (Computer Vision Lab) is part of the CVL Handwritten Digit Database (CVL Hddb), which was collected mainly from students [19].

The CVL dataset is divided into three sets: a training set, a validation set and a test set. It consists of 10 classes (0 - 9) with 3,578 samples per class, each of these classes having the same number of images with different writing, including size variations as well as writing style (see Figure 3).

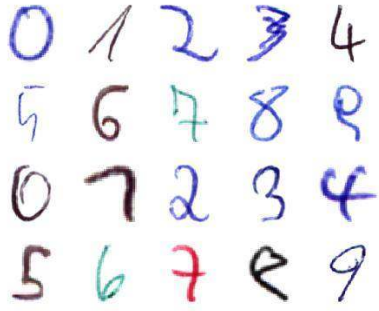


Figure 3: Examples of handwritten digits from the CVL database

The CVL dataset comprises of 7,000 isolated digits (700 digits per class) for the training set, same size for validation set (the validation database can be used for computing and validating parameters) and the test set which contains 21,780 single digits (2,178 digits per class).

In the next section, we present the experimental settings and the corresponding results.

3 Experimental results

We carried out a series of experiments to evaluate the effectiveness of the proposed system for digit recognition. The experiments are performed on the CVL database where images of isolated digits are pre-processed in two steps:

First, the size normalization of the images performs according to different size of 20×20 to 40×40 pixels. Secondly, convert RGB or gray scale image to binary image. In this experiment, we applied the above protocol to several parameters such as filters number of the first convolution layer (Feature Maps 1) as well as the second and third convolution layer (Feature Maps 2 and Feature Maps 3) with different images normalization. The results obtained in this experiment illustrate in the Table 1.

The performance of the system is quantified using the standard recall measures computed in a similar way as in the ICDAR 2013-digit recognition competition [15]. In Table 1 above, we note that the best size normalization is $[28 \times 28]$ is provided a better recognition rate of 96.63% with the Feature Maps 1= 16, Feature Maps 2 = 32, Feature Maps 3 = 64 with 85 epochs. Whilst, the lowest recognition rate achieves of 86.63% with size normalization $[40 \times 40]$ where Feature Maps1=10, Feature Maps2=20, Feature Maps3 =40 and 18 epochs. Other size normalization gives a variable recognition rate about 86.69% to 96.20%.

We also compare the performance of the proposed system with state-of-the-art digit recognition systems submitted to the Digit Recognition Competition (HDRC) held in conjunction with ICDAR 2013. A total of 7 teams submitted 9 different systems to the HDRC 2013.

Table 1: Recognition results on different parameters

Size normalization	Feature Maps 1	Feature Maps 2	Feature Maps 3	Epoch	Recall (%)
[20*20]	10	20	40	26	95.57
	12	24	48	36	95.61
	14	28	56	23	95.42
	16	32	64	44	86.69
[24*24]	10	20	40	24	95.94
	12	24	48	34	96.01
	14	28	56	41	96.03
	16	32	64	23	95.59
[28*28]	10	20	40	12	95.78
	12	24	48	87	95.85
	14	28	56	79	96.20
	16	32	64	85	96.63
[32*32]	10	20	40	41	95.44
	12	24	48	33	95.63
	14	28	56	24	95.63
	16	32	64	30	95.95
[36*36]	10	20	40	30	95.39
	12	24	48	24	95.67
	14	28	56	93	95.97
	16	32	64	47	95.95
[40*40]	10	20	40	18	86.63
	12	24	48	38	95.76
	14	28	56	46	95.68
	16	32	64	17	95.81

In addition, two systems followed the same competition protocol. The first (Gattal et al.,2016) [17] proposed an approach based on the oriented Basic Image Features (oBIFs) and the background (concavity) features and the second (Gattal et al.,2014) [5] proposed the combination of different statistical and structural features for recognition of isolated handwritten digits.

The evaluation protocol considered in our experiments is the same as that of the competition to allow a meaningful comparison as summarized in Table 2.

Table 2: Comparison of proposed method with state-of-the-art methods

Rank	Method	Precision (%)	Normalized Digits
1	Salzburg II	97.74	Yes
2	Salzburg I	96.72	Yes
3	Proposed Method	96.63	Yes
4	Gattal et al.[5]	96.62	No
5	Orand	95.44	Yes
6	Gattal et al.[17]	95.21	No
7	Jadavpur	94.75	No
8	Paris Sud	94.24	Yes
9	François Rabelais	91.66	Yes
10	Hannover	89.58	Yes
11	Tébessa II	78.43	Yes
12	Tébessa I	77.53	No

It can be seen from Table II that the proposed method realizes a precision of 96.63% which is comparable to performance of the top 3 participants of the competition. These results validate the effectiveness of Deep CNN for recognition of isolated digits.

4 Conclusions and future works

This study was aimed at enhancing the Deep CNN in isolated digit recognition systems to improve the overall recognition rates. We investigated the preprocessing of images and deep Convolutional Neural Network for this purpose. The Deep CNN are employed using different parameter settings from the CNN architecture. The system evaluated on the standard CVL single digit database using the same experimental protocol as that of the Handwritten Digit Recognition Competition (HDRC-2013) realized high precision. As a future work, we intend to address the confusing pairs into digit classes by incorporating additional features in our further study. Moreover, we plan to enhance the Deep CNN module by using advanced data augmentation technique and more advanced CNN model to arrive at the final decision about the digit class.

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