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Handwritten Digits Recognition with Artificial Neural Network

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Abstract— **In a computer vision system, handwritten digits recognition is a complex task that is central to a variety of emerging applications. It has been widely used by machine learning and computer vision researchers for implementing practical applications like computerized bank check numbers reading. In this study, we implemented a multi-layer fully connected neural network with one hidden layer for handwritten digits recognition. The testing has been conducted from publicly available MNIST handwritten database. From the MNIST database, we extracted 28,000 digits images for training and 14,000 digits images for performing the test. Our multi-layer artificial neural network has an accuracy of 99.60% with test performance.**

Keywords— Computer vision, Handwritten digits, Artificial neural network, Recognition.

I. Introduction

Handwritten digits recognition becomes increasingly important in the modern world due to its practical applications in our daily life [1]. In recent years, numerous recognition systems have been introduced within many applications where high classification efficiency is required. It helps us to solve more complex problems and makes ease our tasks. An early stage handwritten digit recognition was presented for zip code recognition [2]. Automatic processing of bank checks, the postal address is widely used applications of handwritten digit recognition. A human being has been proffered a common bias to distinguish numerous objects with variations such as digits, letters, faces, voice [3]. However, executing a computerized system to do certain kinds of duties is a very complex and challenging matter. In addition, pattern identification is the fundamental ingredient of a computer vision and artificial intelligence based system [4, 5].

In this paper, we implemented an artificial neural network (ANN) and trained it to recognize handwritten digits from 0 to 9. A node in a neural network can be understood as a neuron in the brain. Each node is connected to other nodes through weights which are adjusted in the machine learning process during training. A value is calculated for each node based on values and ways of previous nodes. This process is called forward propagation [6]. The final output of the network is associated with the target output, then weights are calibrated to minimize a transgression function describing whether the network guessed correctly [7]. This process is called back propagation [8]. To add more complexity and accuracy in the neural networks, the networks have multiple layers. In between a completely connected neural network, there are some multiple layers exist, namely input, output, and hidden layers. In a fully connected neural network nodes in each layer are connected to the nodes and the layers before and after them.

II. Dataset Description

We have used MNIST dataset for our proposed handwritten digits recognition with ANN approach [9]. The dataset contains thousands of labeled images of handwritten digits written by numerous person. We extracted 42,000 samples to conduct our experiment. It is pre-divided into training, which is 28,000, and test, which is 14,000 images. These images are low resolution, just 28-by-28 pixels in grayscale, also note they are properly segmented (as shown in Fig. 1).

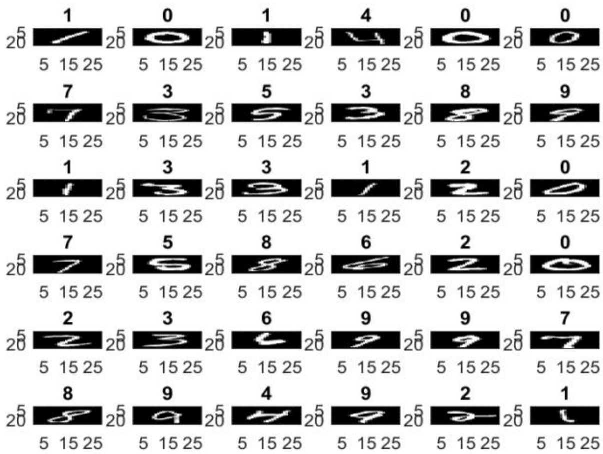

Figure 1. Example digits from MNIST dataset

That means each image contains exactly one digit. When we are working with images, we used the raw pixels as features. That is because extracting useful features from images, like texture and shapes, is hard and no feature engineering required. Now, a 28-by28 pixels image has 784 pixels, so we have 784 features. Here, we are using the flattened representation of the image. To flatten image means to convert it from a 2D array to 1D array by unstacking the rows and lining them up. That is why we had to reshape the array to display it in Fig. 1.

III. Research Methodology

A. *Initialize the Classifier*

ANN was employed as a classifier to construct a classification model. Two (2) parameters were provided to ANN. The first indicates the number of classes in the dataset (which is 10 in our dataset, one for each type of digit). The second parameter informs the classier about the number of features that have been used. ANN is designed to train the database and evaluate the test performance of the network. It is implemented by using pattern recognition toolbox in MATLAB (MathWorks, Natick, MA, USA). The basic ANN contains two layers which are a hidden layer and output layer [10]. In general, input neurons are the exact number of features vector. According to the number of training handwritten digit image samples and the extracted features per image sample, the input neurons is 784, and the input vector is 784-by-28000. Only one hidden layer with 100 neurons was taken, which found to give the best performance for the proposed application. Regarding the number of hidden layers, Hecht-Nielsen showed that neural network with one hidden layer can perform the approximation of any function [11]. The neurons of output layer are10 as the proposed system have 10 class (0-9) of handwritten image samples. A systematic method and back propagation learning algorithm are applied to train the ANN. Fig. 2 illustrated the ANN architecture.

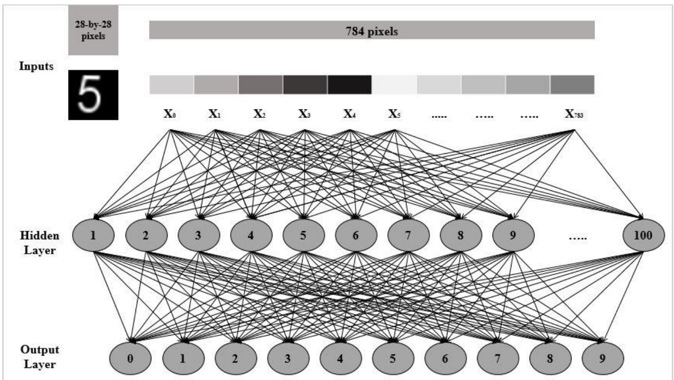

Figure 2. ANN architecture

B. *Training Performance of the ANN*

At the training stage, we distributed the percentages (%) of training, validation, and testing data to avoid the network overfitting problem. It randomly divided up the 28000 samples, in which 90% (25200) for training, 5% (1400) for validation, and 5% (1400) for testing. During the training period, the ANN is adapted according to the error of the network. To measure an ANN observation and to pause the training when observations are not improving, validation samples are used. Testing samples have no influence on training period and produce an individual measure of ANN assessment through the training and subsequent period. The output matrix format is a combination of the 28000-by-10 binary matrix as shown in Table I. From Table I, number zero's '0' corresponded output binary matrix format will be (1 0 0 0 0 0 0 0 0 0) and number nine's corresponded output binary matrix format will be (0 0 0 0 0 0 0 0 0 1).

TABLE I. Neural network output format

Rows	**Handwritten digits**									
	0	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***
0	**1**	0	0	0	0	0	0	0	0	0
1	0	**1**	0	0	0	0	0	0	0	0
2	0	0	**1**	0	0	0	0	0	0	0
3	0	0	0	**1**	0	0	0	0	0	0
4	0	0	0	0	**1**	0	0	0	0	0
5	0	0	0	0	0	**1**	0	0	0	0
6	0	0	0	0	0	0	**1**	0	0	0
7	0	0	0	0	0	0	0	**1**	0	0
8	0	0	0	0	0	0	0	0	**1**	0
9	0	0	0	0	0	0	0	0	0	**1**

Fig. 3 shows the ANN's training performance, it shows that at the initial position of the training process, the cross-entropy error is maximum. Neural network optimized the error at every iteration, at the epoch 107, the network gave the best validation performance where the cross-entropy error was 0.01331.

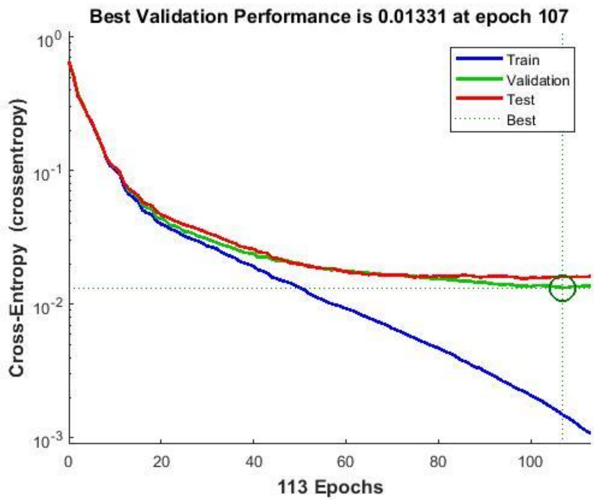

Figure 3. Training performance

ANN's training results are showing in Fig. 4. Minimum Cross-Entropy (CE) result means the classification is well performed, where CE's lower values are better and zero means there is no error exist in classification. Percent Error (%E) indicates the portion of samples which are misclassified during ANN's training. A value of 0 means there is no misclassification, 100 indicates there is full of misclassifications.

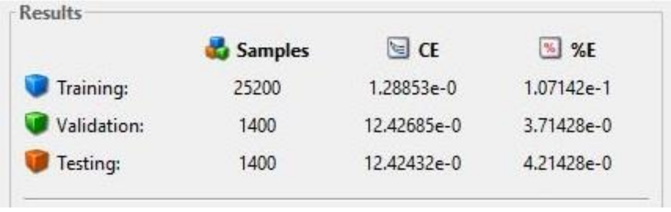

Figure 4. ANN's training results

C. Test Performance

When we are satisfied with the ANN's training results, we performed testing. Here, we have already divided 14,000 of the test sample, which is never used as training samples. Our test performance is based on the confusion matrix shows in Fig. 5.

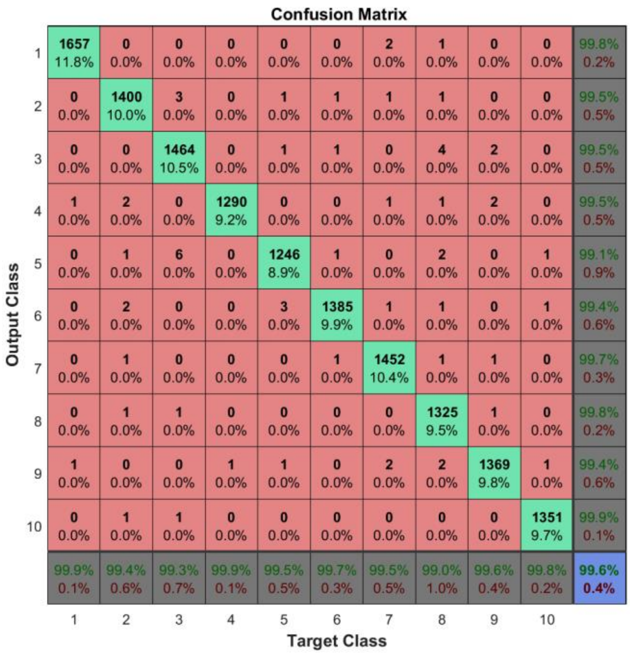

Figure 5. Test confusion matrix

From the confusion matrix, red cubes present the incorrect classification and the green cubes present the correct classification according to the output class and target class. On the right bottom corner, the blue cube shows the overall percentage of the classification. Overall, 99.60% of the predictions are correct and 0.40% are misclassifications in our experiment.

D. Result comparison

Here are the some of the similar methods which are used for digits or texts recognition purpose with different features extraction process and different classifiers. The performance is based on the features extraction method, used classifiers to classification, and the classification performance. The performance of this proposed method and other methods which are currently available are described in Table II.

TABLE II. EVALUATE THE PERFORMANCE BETWEEN PROPOSED METHOD AND OTHER EXISTING METHODS

References	Features extraction method	Classifier	Accuracy (%)
[12]	R-HOG	SVM	95.64
[13]	HOG	SVM	81.00
[14]	HOG	SVM	83.60
[15]	HOG	ANN	97.33
[16]	CCH	SVM	98.48
[17]	CNN	CNN+SVM	94.40
Proposed	Image Pixels	ANN	99.60

IV. DISCUSSION

A. Result discussion

This proposed method used the image pixels for its features extraction process. ANN carried out the classification, and the overall classification accuracy is 99.60%. P. M. Kamble and R. S. Hegadi [12] carried out the handwritten character recognition using the rectangular histogram of oriented gradients (R-HOG) features extraction. Researchers obtained 95.64% of classification accuracy with support vector machine (SVM). B. Su, S. Lu, S. Tian, J.-H. Lim, and C. L. Tan [13] also investigated the character classification task in the regular environment. Authors used convolutional co-occurrence histogram of oriented gradients (CHOG) as their features extractor and SVM as their classifier and achieved 81.00% of classification accuracy. This was also considerable because researchers used different features extraction method and different classifier. S. Tian, S. Lu, B. Su, and C. L. Tan [14] performed text recognition with CHOG and SVM as a classifier to obtain their classification accuracy of 83.60%. J. Varagul and T. Ito [15] pointed out the function object detection using computer vision. Here, the authors used the HOG as their features extraction purpose and ANN as the classifier and achieved an overall classification accuracy of 97.33%. A. Boukharouba and A. Bennia [16] found out the novel features extraction method for handwritten digits classification. Authors have used a different features extraction method called chain code histogram (CCH) with SVM as the classifier to achieve 98.48% of classification accuracy which is almost similar to this present investigation. The difference between their achievement and current investigation is only 1.12% which is consistent. Another group of researchers X.-X. Niu and C. Y. Suen [17] introduced a hybrid method for recognition of handwritten digits. Researchers used convolution neural network (CNN) to extract the image features and fed to a hybrid classifier to classification. Their hybrid classifier contained CNN and SVM and achieved 94.40% of classification accuracy and the difference from the present result is 5.20%. It has been noticed that the presents results have the higher accuracy than the previous researchers as described. From the result discussion part, it can be concluded that the performance of the ANN is more effectively better while corresponded to the classification using SVM.

B. Failure discussion

Recognition of handwriting digits is a difficult task because of the different degrees and styles of writing that can be changed between the inter-digits and between intra-digits. The most challenging part of the handwritten digits recognition is needed to address the variety of writing style. There is numerous variation exist in person to the person writing style. In a handwriting recognition system, 100% accuracy cannot be expected in practical applications. Because even trained humans are not able to recognize every handwritten digit without a doubt [18]. Maximum misclassifications are complex to be recognized for the poor contrast, image text vagueness, complicated image environment, and disrupted text stroke. One of typical vagueness in handwritten digits classification is the digits interclass and intraclass similarity. Fig. 6 shows that digit 1 and digit 7 have similarity. Furthermore, we also found out that, digit 4 and digit 9 have similarity.

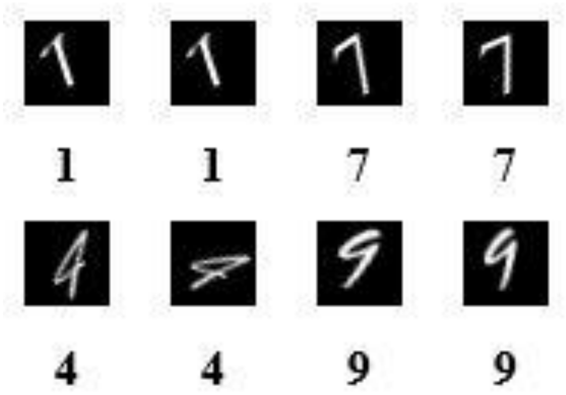

Figure 6. Digits similarity

V. CONCLUSION

Machines will power our future. We hope that this has given us a glimpse into how they learn. In this study, we have used digit images pixels as features vector and ANN as classifiers for handwritten digits recognition. We have used publicly available MNIST database for evaluating our experiments. From the results, it can see that our experiment result achieved 99.60% recognition accuracy. In future work, we plan to work on more datasets and we will further optimize the parameters of ANN to obtain higher accuracies with low implementation time. Finally, we are interested in using a combination hybrid method of feature extraction with ensemble classifier.

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