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New algorithm based on deep learning for number recognition

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Abstract

One of the problems in distinguishing numbers written in Arabic and in handwriting is the difference in the writing style for each person and the accompanying impurities with Arabic letters which requires purification in order to obtain the letters in their correct form. Through the proposed network, we reached accurate results with a very low error rate and high accuracy which distinguishes it from previous methods used to distinguish written numbers.

1 Introduction

In the convolutional wireless data transmission process, and in order to get rid of what accompanies the transmission and receiving process, a new developed

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technology has been used [1]-[9]. In the field of image processing there are many fields, including the digitization of images, which played a major role in this processing such as processing data, information and digital files at the lowest cost of processing paper files. The benefit of digitization is the presence of a handwriting recognition system that converts handwritten characters into a formatted form that the user can read automatically [10]-[16]. In the field of archeology, such as preserving old documents in libraries, banks, etc., all these applications because they deal with large data which leads to the need for high accuracy in identification. This type of application of a convolutional neural network has emerged [17]] which is concerned with the field of education such as digital dictionaries and banks. Handwritten character recognition has emerged in the field of robotics [18]-[21]. Signature also entered the field of recognizing handwritten numbers or letters to identify handwritten signatures [22]-[27]. Through the proposed network, accurate results were reached with a very low error rate and high accuracy which distinguishes it from previous methods used to distinguish written numbers.

2 Methodology

2.1 Pre-Processing

Machine and deep learning are easily implemented within the Tensor flow software framework to improve and facilitate many of the heavy mathematical expressions on which this work is based.
Handwritten digits recognition:

1. Logistic regression.

2. Neural network.

5000 training examples of handwritten digits where each training example is a 20 pixel by 20 pixel gray scale image of the digit.
Available files:

1. Display Data.m- This function maps each row to a 20 pixel by 20 pixel gray scale image and displays the images together.

2. Fmincg.m- This function optimizes the cost function fmincg, works similar to fminunc but is more efficient when dealing with a large number of parameters.

3. Sigmoid. m- Sigmoid func $\frac{1}{1+e^{-z}}$.
4. Handwrittendigits- 5,000 digit sample.

2.2 Convolutional Neural Network in MATLAB

The digit recognition in:

1. MATLAB Digit Dataset.
2. Digit Dataset Preparation.
3. Structure of a CNN.
4. Layers of a CNN and Training Parameters.
5. MATLAB Code of Training and Validation.
6. MATLAB Code of Discrete Testing.

3 The basics of building a convolutional neural network

The basic components of a convolutional network are three layers: the first is the second convolutional layer, the second is the assembly, and the last is the output layers, where the second is sometimes optional. The three layers combine to classify handwritten images as shown in Figure 1. Some neurons

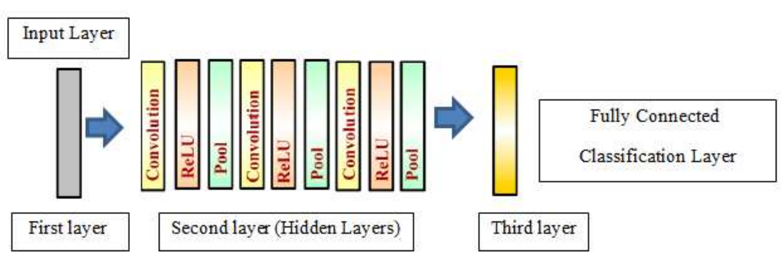

Figure 1: The three layers combine to classify handwritten images.

are connected in one layer that makes the measurement of the image with high accuracy, which is characterized by the process of aggregation to reduce the amount of data when entering the image in the form of small sub-regions that are received by applying mathematical operations in the input layer and convolution to move to the second layer, which leads to the basis of the response is Visual stimulus for a detailed description:

1. First layer: This layer is important for data entry and storage of image information such as number, height and width.

2. Second layer This layer is the basic building block of the CNN process which is responsible for highlighting the features of the task to complete the CNN process and then revealing the characteristics of handwritten numbers.

3. Third layer: This is the layer of the input image in which the convolutional operation is performed to extract the characteristics of the image, where the dimensions of the entered neuron are $(s \times s)$ by convolution with a dimension $(r \times r)$ with a filter $(s - r + 1) \times (s - r + 1)$ for output. In this layer, the padding stretch and step contribute to the function of neural activation Visible and transmitted information from the retina processed by the brain and calculating process CNN.

3.1 Mathematical aspects

To build CNN you must provide or know the padding for high accuracy, which helps to control the reduction and reduction of the results of the third layer, which is smaller than the input image also contains the output information for the pixels, which leads to the loss of angle information after adding columns and rows of zeros in the borders of the image.
To calculate the size of the feature map and the outputs are in the following two equations:

$$R_{su} = R_{s-1u} - L_{su}K_{su} + 1 \tag{3.1}$$

$$R_{sv} = R_{s-1v} - L_{sv}K_{sv} + 1, \tag{3.2}$$

where (R_{su}, R_{sv}) is the output parameters of the map size Either (K_{su}, K_{sv}) is the size of one step, and the size of the kernel is represented by (L_{su}, L_{sv}), and in equations (3.3), (3.4) are the dilations of important parameters in CNN in architecture:

$$0 - dilation = R[0] * u[0] + R[1] * u[1] + R[2] * u[2] \tag{3.3}$$

$$1 - dilation = R[0] * u[0] + R[1] * u[2] + R[2] * u[4] \tag{3.4}$$

Figures 2 and 3 show the activation processes of neurons with a filter size of 5×5 through the structure CNN.

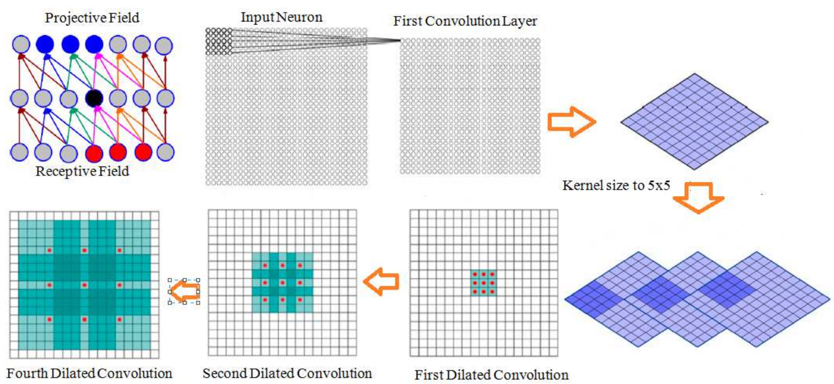

Figure 2: The activation processes of neurons with a filter size of 5×5 through the structure CNN.

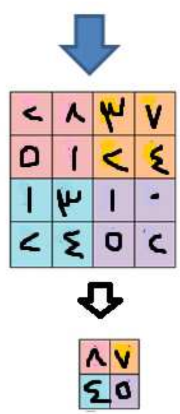

Figure 3: The result of CNN.

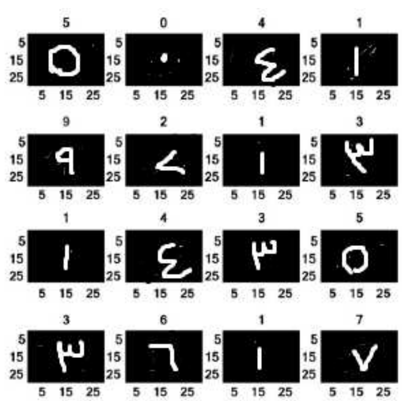

Figure 4: Arabic Numerals that represent a sample of handwritten images.

4 Discussion of the results

The numerical dataset written in Arabic and handwriting and its experimental results with the use of the different parameters of the third and fourth layers in the convolutional process of the neural network appear in the two tables 1 and 2, respectively. The sample in Figure 4 is represented by a floating value matrix between 0 denoting black and 1 denoting white (28 28) out of 784 with a dimension of 1. Let the size of the kernel be K and let the receive domain be D. Denote the expansion by E and the padding by P. Let S denote dilation which are two sizes of input and output in the feature map with the use of the three and four layers in the architecture of the convolutional neural network. The results in table 1 confirm the role of the parameters used to perform the system. The learning rate is 0.01 and the maximum is 4. The highest accuracy of 99.60% was achieved in the third stage consisting of three layers, while 99.76% was achieved in the fifth stage consisting of the 4-layer bit of the convolutional neural network, as in Table 2:

Table 1: The results achieved in a convolutional neural network with a three-layer configuration and precision.

Status	K	E	D	S	P	Input P	Output P	Recognition Accuracy (%)
1	5	2	1	2	7	4	25	98.08%
2	3	2	1	2	7	4	17	98.48%
3	5	2	1	2	7	4	29	99.60%
4	3	3	1	1	4	2	27	88.16%
5	3	3	1	1	4	2	29	93.32%
6	5	3	1	3	4	2	53	98.06%

Table 2: A four-layer convolutional neural network achieving precision and configuration.

Status	K	E	D	S	P	Input P	Output P	Recognition Accuracy (%)
1	5	2	1	2	7	4	25	98.80%
2	3	2	1	2	7	4	17	95.16%
3	5	2	1	2	7	4	29	94.04%
4	3	3	1	1	4	2	27	99.60%
5	3	3	1	1	4	2	29	99.76%

Convolutional classes include all the architectural parameters that are kernel-size 5 and step-stretch 2 with padding 2 in both tables. In cases 3 and 5,

filters extract full features for handwritten images.
We observe that the recognition accuracy is poor in Table 1 in cases 3 and 6. In Table 1 and Figure 5 the recognition accuracy is described with the reception field to capture the beginning of information such as corners and edges in the convolutional neural network to pass to the later layers and also increasing the number of filters which improved the performance of the architecture. In case 5 of Table 2, all the features of the Arabic handwritten images are extracted and this is what distinguishes this work.

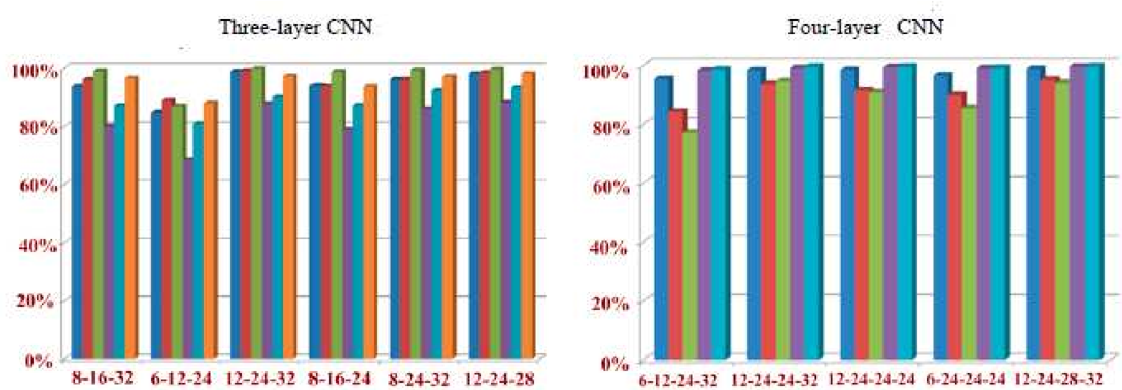

Figure 5: Convolutional Neural Network and Reception Domain with Recognition Accuracy.

5 Conclusion

The effect of increasing the number of convolutional layers in a CNN architecture on the performance of handwritten number recognition was demonstrated through experiments.
This work presented something completely different in the work of the Convolutional Neural Network which is how the network performs in recognizing handwritten numbers in Arabic. The achieved recognition rate of 99.89% is the best result compared to previous work.

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