International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-6, March 2020

Arabic Handwritten Digit Recognition using Convolutional Neural Network

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***Abstract:** Arabic is the most widely used language in the world, especially the Arab League Country. Of course, in those countries often use Arabic numeral in banks and business applications, postal zip code and data entry application. This research has focused on handwriting recognition of Arabic numeral that has unlimited variation in human handwriting such as style and shape. The proposed method on the deep learning technique is Convolutional Neural Network. LeNet-5 architect also used in training and recognizing the handwritten image of Arabic numeral as much as 70000 images derived from MADbase dataset. The experimental result on 10000 images of database used is by comparing the number of epoch in training process yields, and the average accuracy is 97.67%.*

***Keywords:** Handwritten Digit Recognition, Arabic Numeral, Deep Learning, Convolutional Neural Network*

I. INTRODUCTION

Optical Character Recognition (OCR) provides the ability for machines to recognize various characters automatically through optical working mechanisms and has an important influence on the field of research in the development of pattern recognition. In other words, OCR is an electronic translator for handwritten images in computer format [2]**.** Of the various patterns that can be investigated and various branches of OCR, the focus of the main problem in this study is one of the OCR branches of handwriting digit recognition..

Language is the most important in communicating with one another especially in a country or culture. Every country has a language that is set and has been used as an official language.

Manuscript received on February 10, 2020.
Revised Manuscript received on February 20, 2020.
Manuscript published on March 30, 2020.
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This official language is usually used as official communication such as legislation, official correspondence and as a means of interaction related to the implementation of the position and language functions that must be learned in state education. Arabic is one of the five most used languages in the world. Evidenced by a report made by the CIA states that there are at least twenty countries that use Arabic as an official language or can be called a national language[3].

While in research conducted by [4] said that there are twenty-four countries that make it a national language. In addition, Arabic is also the liturgical language of Muslims which can be seen from the book of guidance written in Arabic. Many other languages are adapted from Arabic such as Persian, Urdu and Hindi. Nevertheless, OCR research on Arabic both letters and numbers still has not received sufficient attention [2], [4]. Sample handwritten digit in Arabic language are shown in Table 1

TABLE 1 Arabic Handwritten Digit Example

Arabic Digit	Latin Digit	Image
٠	0	
١	1	
٢	2	
٣	3	
٤	4	
٥	5	
٦	6	
٧	7	
٨	8	
٩	9	

Research on handwriting recognition in letters and numbers has been conducted in various languages. Arabic is still largely an unexplored field of study, with maximum work done previously on this language based on printed characters. In [4] conducted a study entitled Introduction to Arabic Handwriting Arabic Numerals using Multi-Layer Perceptron. This study has an accuracy of 94.93% from 3000 Arabic handwritten data obtained from three hundred participants of various ages and genders. Accuracy was obtained from experiments using fifty-four hidden networks on the Multi-Layer Perceptron. Further research was carried out by [5] in his research using Gabor Filter as a basic feature and SVM to classify Arabic numerals by using sample data of 21120 samples from 44 participants and producing an accuracy of 97.94% with a scale of 4 and orientation 6 on the application of Gabor Filter.

In the study [6] with the title A CNN-SVM novel classifier hybrid to recognize handwritten digits resulting in an accuracy of 94.40%. The SVM method is used at the output layer in the Convolutional Neural Network.
The data used in this study are MNIST data with 60000 train data and 10,000 test data. Then in [7] a study was conducted to recognize Arabic numerals using the backpropagation method. In this study, Selvi&Meyyappan produced 96% accuracy.

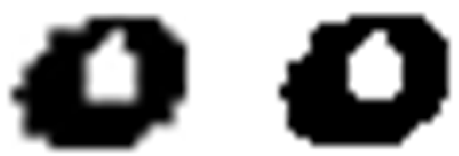
Subsequent research was carried out by [8] using HMM in classifying Latin numbers with an accuracy of 97.2% from 10,000 test data and 60000 training data sourced from MNIST data. In the same year, [9] was investigated by combining SVM, Fuzzy C-Means and Unique Pixels methods to classify Arabic numerals. They used a 3,510 samples public dataset. The accuracy is 88% from 40% of the sample data as test data. Further research was carried out by [10] using the Dynamic Bayesian Network to classify Arabic numerals totaling 10,000 test data resulting in an accuracy of 85.26%.

In this study, the proposed method is Deep Learning, which recently moved the world of machine learning that can improve accuracy in classification. In-depth learning has many architectures such as CNN. CNN is a multi-layer advanced feed neural network that extracts properties from input data and is trained with a neural network reverse propagation algorithm.

II. THE PROPOSED METHOD

A. Preprocessing

The first step in this research before images are trained and tested, the image must be shared from an RGB image to a binary image. In this pre-approval picture as agreed in figure1, using OpenCV in pythonand results of Binary Images are performed on low variant texture images to produce high-quality images[11].



(a) **(b)**

Figure 1. Preprocessing Result. (a) Original Image. (b) Binary Image.

B. Recognition

As mention in the previous subsection, to recognize Arabic handwritten digit, this research has used the convolutional neural network as an identifier.

Convolutional Neural Network (CNN) is one of the deep learning methods commonly used in processing data in the form of images. In its use, CNN allows us to detect and recognize objects in an image. CNN is not much different from ordinary neural networks. CNN consists of neurons that have weight, bias and activation functions as well as CNN trained with the backpropagation algorithm. But architecturally, CNN is different from other deep learning architectures because each layer in the CNN architecture has different goals.

CNN has a special architecture of Artificial Neural Networks, which has three additional architectural ideas consisting of local receptive fields, weight division, and sub-sampling [12]. The local receiving field extracts basic features from an insert, for example, occurs at the edge of an image. Then the feature is entered for the next layer and then extracted again so that more specific features are obtained.

The sharing parameter functions to reduce the number of usage parameters without reducing the ability of CNN itself, so that the memory usage on the computer will be more efficient. Sub-sampling functions to reduce the number of hidden units in the hidden layer and sensitivity to shifting and distortion of input features.

- Convolution Layer

The convolutional layer is the basic layer of CNN architecture. This layer usually works for convolution calculations that affect the image. This layer aims to extract the features from the image. The equation according to [13] as follows;

$$y_j^{(l)}(x,y) = \phi^{(l)}\left(\sum_{i\epsilon I}\sum_{(u,v)\epsilon K} w_{ji}^{(l)}(u,v)\,y_i^{(l-1)}(x+u,y+v) + b_j^{(l)}\right)$$

Where $w_{ji}^{(l)}$ denotes the weight on from neuron i to neuron j in layer l, $y_i^{(l-1)}$ denotes output layer on $l-1$ or input image for the first convolution layer and $b_j^{(l)}$ is the bias on neuron j on layer l. So, that formula is the activation of respective convolution maps is then simply the sum of all convolutiona result and the bias.

- Subsampling Layer

Pooling layer or subsampling is useful to change the input feature to represent the statistical results of the surrounding features, so the resulting feature size will be much smaller than the previous features [14]. The representation is also useful for reducing the sensitivity to shifting and distortion of features. For example, in the case of face detection in the image, where the face position can vary, then with pooling, convolutional neural network can detect faces in the image without the need to segment first.

The pooling method to be used is the max-pooling method because max pooling shows better results because it overlaps the two factor patches in the spatial environment and cross scaling subsampling operations.[16]. The equation according to Sugumori (2016) as follows;

$$y_{ij}^{(l)} = \max\left(a^{(k)}_{(l_1 i+s)(l_2 j+t)}\right)$$

Here, l_1 and l_2 are the size of pooling filter and $s \in [0,1]$, $t \in [0,1]$.

- Fully Connected

Fully Connected Layer is the culmination of a process on CNN that functions as a classifier. In multilayer perceptron, this layer is called hidden layer. The equation for this layer as follows:

$$y^l = \phi\,(w.y^{l-1} + b)$$

Retrieval Number: F7745038620/2020©BEIESP
DOI:10.35940/ijrte.F7745.038620
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-6, March 2020

Where, w denotes the weight, b denotes the bias and y^{l-1} denotes output from layer $l-1$.

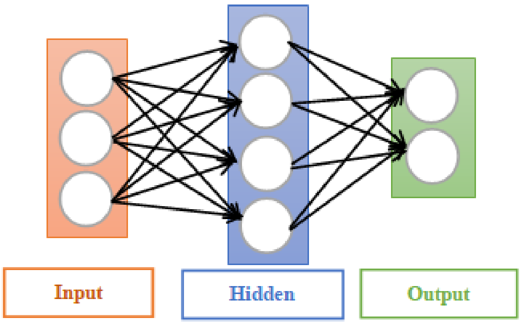


Figure 2. Fully Connected Layer

- Architecture Network

In this research, the method used is LeNet-5 architecture with 8 layers including 1 output layer, 3 convolution layers, 2 sub-sampling layers, and 2 fully connected layers. The weight and bias scale in each convolution layer is 5 x 5 and 1 x 1 which starts with a random weight and then multiplies overfitting or overlapping.

At the output layer, this study uses the softmax activation function.

$$P(o_i) = softmax(H^{out})_i = \frac{e^{H_i^{out}}}{\sum_j e^{H_j^{out}}}$$

III. DATASET

As explained in the previous section, CNN can learn the internal features of the data. To do this, the data must be entered into the input layer in the right way. Pre-processing applied in this research is to convert images into binary images. The pixel value is between 0 or 255. The dataset used from MADBase consists of 70000 digits written by 700 authors[18]. This dataset has the same format as MNIST dataset.

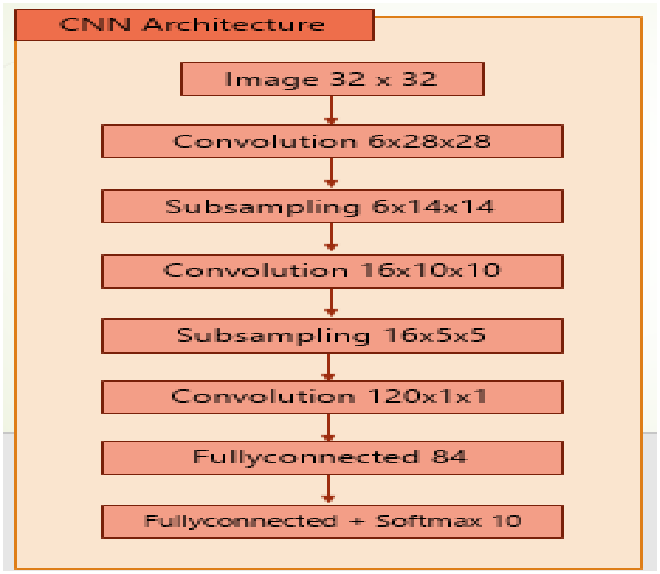


Figure 3. CNN architecture

The dataset is partitioned into two sets, 60000 digits as a training set and 10,000 digits as a test set, following Samples of MADBase 0 to 9 in Arabic writing from a dataset divided into two as exemplified in Figure 4.

Figure 4. Samples of MADBase dataset

IV. SYSTEM ARCHITECTURE

Figure 5 shows the proposed system architecture. The system incorporates two process.

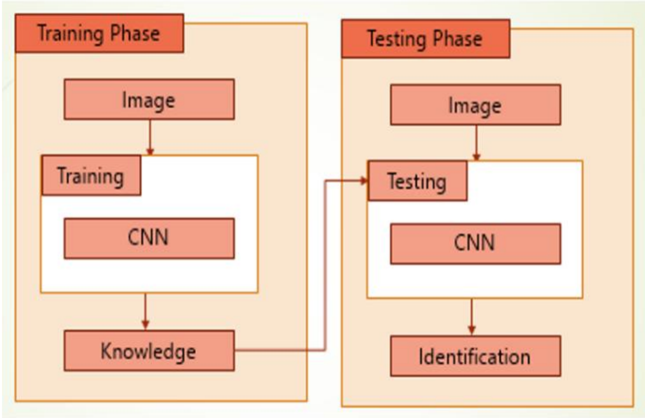


Figure 5. System Architecture

The first process trained image data that has been manipulated by pre-processing process with CNN. When training process done, the model or knowledge has been saved. The next process is identification process which is testing the knowledge that get from training process.

V. EXPERIMENT RESULT

The performance of CNN was done in training and recognition process. The propose architecture that used in training is also used in testing process.

In order to evaluate CNN method, the recognition system was trained based on 60000 images with backpropagation algorithm for 250 epochs. The test is comparing four outcomes from scenarios with differences in the number of different epochs. The result of our experiment shown in table 2and figure 6. Average recognition rates in our experiment is 97.67% from 10000 images.

TABLE 2. Testing With 100 Epoch

Epoch	Sum of Data	Unrecognized	Recognized	Percentage (%)
100	10000	275	9725	97.25
150	10000	211	9789	97.89
200	10000	219	9781	97.81
250	10000	228	9772	97.72
Average				97.6675

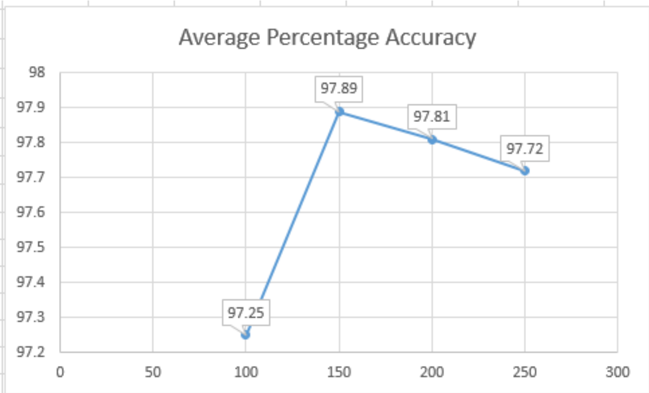


Figure 6. Comparison of Test Results

VI. CONCLUSION

In these experiments that have been carried out, it can be concluded that the system can recognize objects with an average value of 97.67%. These results indicate the proposed method is suitable for the MADBase dataset.

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