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Recognition of Arabic handwritten words using convolutional neural network

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ABSTRACT

A new method for recognizing automatically Arabic handwritten words was presented using convolutional neural network architecture. The proposed method is based on global approaches, which consists of recognizing all the words without segmenting into the characters in order to recognize them separately. Convolutional neural network (CNN) is a particular supervised type of neural network based on multilayer principle; our method needs a big dataset of word images to obtain the best result. To optimize our system, a new database was collected from the benchmarking Arabic handwriting database using the pre-processing such as rotation transformation, which is applied on the images of the database to create new images with different features. The convolutional neural network applied on our database that contains 40,320 of Arabic handwritten words (26,880 images for training set and 13,440 for test set). Thus, different configurations on a public benchmark database were evaluated and compared with previous methods. Consequently, it is demonstrated a recognition rate with a success of 96.76%.

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1. INTRODUCTION

The system of Arabic handwritten recognition makes easier the transformation of Arabic handwriting into its symbolic representation. There is several system of Arabic handwritten recognition: the recognition of handwritten text, words and characters. Our method focus on Arabic handwritten words recognition which are recognized by two approaches, the analytical approaches and the global approaches. This later addresses word recognition recognizes each letter that composes the word, but the letter segmentation is a difficult operation. Therefore, it is proposed the global approach which recognizes the words as a whole without trying to locate each of the letters that compose it. The global approach is basic of our investigation.

On the other side, neural networks are computing system allows recognizing, and contain three layers: input layer, hidden layers and output layer. The deep neural network has made it possible to make great progress in several recognition problems in scientific research, such as the detection of objects (for example, [1]-[4]), Arabic handwritten characters [5]. Deep neural networks using several hidden layers, hence it needs a large number of connection parameters and needs very large images of the database. In our work, the convolutional neural network (CNN) was used with a small number of parameters and easy for training, using the Arabic handwriting database (AHDB). Moreover, CNN has the ability to learn from very large number of complicated inputs (images or sounds), nonlinear mappings [6], [7]. The use of the same filter and weight for each input of convolutional layer is an advantage of CNN, to decrease the number of paramters and increase the performance [8].

In several investigation in the literature, researchers used several classifiers in order to recognize the Arabic handwritten words or the characters such as a methods of hidden markov models (HMM) [9]-[14], K-nearest-neighbors (KNN) [15], [16], support vector machine (SVM) [17], neural networks [18]-[20], [5], [21], [22]. Otherwise the method of classification selected still owned weak points [23]. For instance, a huge computation to compute kernels is necessary in SVM method [24], also, the extreme learning machine (ELM) performing unstably because of the random weights among the input and hidden layers [25]. Likewise, the multilayer perceptron (MLP) is based on back-propagation that is decelerate training [26]. Ghadhban *et al*. [23] proposed the incorporation of a good classifiers with easier computation and can obtain strong performance of recognition of Arabic handwriting [23]. Despite of research works in the literature made by researchers to increase the performance of Arabic handwriting recognition methods, the field still confronts problems related to computation time and result. Rabi *et al*. [27], the HMM based reference method was enhanced by the use of hybrid HMM/MLP, and hidden Markov models to extract the statistical and geometrically features. While in a recent paper, authors proposed method for recognizing Arabic handwritten word without segment them into sub letters merging the scale invariant feature transform (SIFT) as feature extractor and SVMs as classifer [28]. Likewise, in our previous work [29], we have proposed an amethod for recogning Arabic handwritten text using an integration of n-gram model.

The system of recognition of Arabic handwritten text needs the text segmentation into text lines and lines into letters or words for recognizing them, the segmentation and recognition of characters is difficult operation, since the variations in writing style, and the linking of letters between them. Therefore, the proposed method used the global approach which does not need segmentation of characters, by convolutional neural network. In related works, the algorithms presented applied on a small database of Arabic handwritten words [30]-[33] (IFN/ENIT, AHDB...), and it makes a problem in recognizing all Arabic handwritten words images. That leads us to create a new database of Arabic handwritten words by modification of pre-processing of word images (such as rotation transformation) to better the yield of the results of words handwritten Arabic recognition.

2. METHOD

2.1. Motivation

To increase the performance of Arabic handwritten words recognition, we use several knowledge of the research work. In recent years the variations styles of Arabic handwritten words, making it interested to work on and propose a new method solving the problems of Arabic handwritten recognition. The segmentation and recognition of letters is difficult operation, since the style of handwriting is varied, and the letters linked for each other, it's sufficient to recognize the whole words without characters segmentation, using convolutional neural network. To be able to obtain good decisions on a deep learning system, we need a big data (images). All databases of Arabic handwriting words in the literature didn't contain a huge number of images to obtain a good result, we proposed a method that makes images from AHDB using preprocessing of images (such as rotation). That helps our method more performance.

There are several authors used CNN for the stage of the extraction of features of the images [30], [34]. There are others which combines CNN and other classifiers (SVM and HMM) to classify the handwritten Arabic words [30], [34]. In our work, CNN used for extracting the feature and classification steps of Arabic handwritten words recognition.

2.2. Architecture

Usually, Arabic handwriting word recognition system apply a few preprocessing steps on the input images, to increase the performance of recognition. Moreover, for the system of recognition based on CNN, the pre-processing step is not necessary to apply a several operations on the input images, to reduce the variability handwriting. In our proposed system, the operations using in the pre-processing step are: binarization, normalization and transformation of rotation. The size of the input image is 100×100 after normalisation. After the pre-processing step, which prepare the input data of CNN, the input data x_1; x_2; …. x_n are word images. We use three layers type (convolutional layers (CONVL)→ pooling layers (POOLL)→fully connected layers (FCL)), M × M × H images are the input data ofCONVL (M is the height and width of the input image, H is the number of channels), the number of pixels in the each image is M×M. In our system we use gray scale images with H=1 (one channel) but for RGB image, we use three channels H=3 as shown in Figure 1.

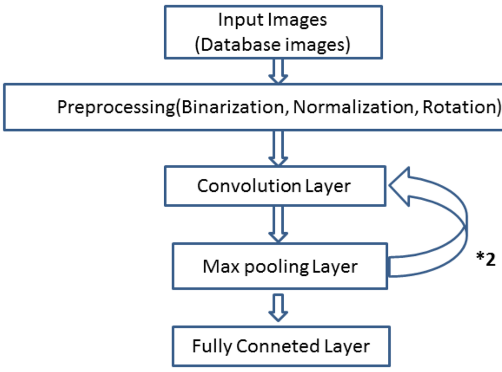


Figure 1. Architecture of proposed method

The architecture of our CNNstart by the first layer is CONVL consisting of 8 feature maps calculated by overlapping N×N kernel on the input M × M raw gray scale image. With N=5 and M=100. Then we apply the nonlinear activation function using rectified linear units (ReLU), which consist to choose the max between the pixel of the image and the value 0. For each feature map we apply POOLL using max-poolingwhich aims to extract the maximum of pixels using non-overlapping kernel 2×2. Lastly, the FCLs apply on the output of the CONVL and POOLL, as in a norm convolutional neural network system.

2.3. Preprocessing
2.3.1. Binarization
If the images of the database are in grayscale or color, the binarisation operation aims to extract the background of the word for transferring into the binary images: pixek=1 in the background, and pixel=0 in the textor reciprocal. The global thresholding used for calculating one threshold to the whole image. The pixels that are above the threshold affect 0 and others affect the value 1 [34].

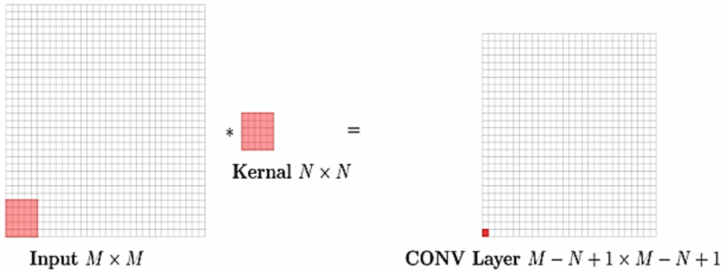
2.3.2. Normalization
In the system of CNN, the database images should be the same size. It is known, the operation of normalization make the images in the same forms related to size [29]. In the present investigation, the size 100x100 was selected and presented in the same size.

2.3.3. Rotation
Convolutional neural networks need a big training data, in the literature, there is not a database of Arabic handwritten words sufficient for our system. We proposed a method to create images from the existing database, we proposed to modify the images to change their characteristics, and the method used is a transformation of rotation. Given a point in the image, its new coordinates after the transformation of rotation of the whole image around its origin by the angle θs as shown in (1).

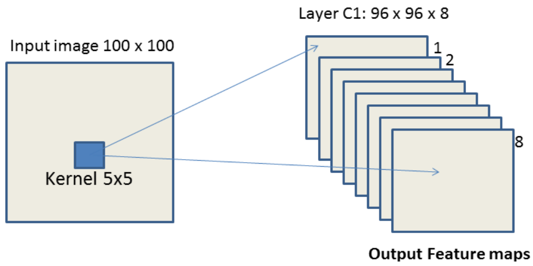
$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{1}$$

2.4. Convolutional neural network layers
2.4.1. Convolutional layer
The input of this layer is images $x_1, x_2, \ldots, x_n$. The form of the input data of CONVL is M × M × H image (M is the height and width of the input image as shown Figure 2, H is is the channels number per pixel), the number of pixels of the input image equal M × M and Hequal one channel for binary image, three channels for RGB image. N x N ×F is the size of K filters(kernels) used in the CONVL(N is the height and width of filters (kernels) and F is the same number of channels image H varied for each filter (kernel) Figure 2(a). The size ofK feature maps is M-N+1 makes when the filter convolved with the image shown in Figure 2(b). The goal of convolutional layer is extracting salient features of the inputs images.

In our proposed approach, we used the activation function rectified linear units (ReLU) that applies the output of convolutional layer. In order to affect the max with the pixel and the value 0 to replace the negative pixels by the value 0. The activation function use is ReLU non-linearity applied to each output of CONVL and FCL. The ReLU [35] aims to increase the nonlinear properties of the global network without transferring the receptive elements of the convolution layer.



(a)



(b)

Figure 2. Convolutional layer: (a) example of convolutional operation and (b) example of single convolutional layer

2.4.2. Pooling layer

After each convolutional layer, we apply pooling layer on the output data. This layer used to decrease the dimensions of the feature maps. We pooled with max or average pooling with size q × q for each feature where q comprised between 2 and 5 for large inputs. Pooling layers aims to reduce the size of the feature maps. There are several types of pooling (Max and Average), we use max-pooling in our approach with size 2×2 which consist to select the maximum pixel from the block of the feature map of the convolutional layer output. The feature map containing the most important features of the previous feature map is the output of max-pooling Figure 3.

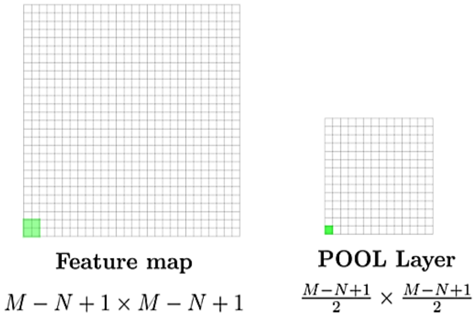


Figure 3. Pooling layer

2.4.3. Fully connected layer

We apply fully connected layer after many convolutional and max-pooling layers, which allows using the results of the convolution/pooling process to classify the image into a label. This layer aims to connect all neurons of the precedent layers with each unique neuron it has, and converts it into a single vector of values, every neuron of the output layer represents a classification label which contains a probability that a certain feature belongs to a label. Finally, we apply the softmax function on thenetwork output to compute a probability value for each class.

The architecture of our convolutional network of Arabic handwritten words recognition presented as following: INPUT→ CONVL→ ReLU → POOLL→ CONVL→ ReLU → POOLL→ CONVL→ReLU → POOLL→ FCL. The first layer is C1 convolutional layer consisting of 8 feature maps calculated by overlapping 5×5 filter on the input 100×100 raw binary image, the output size of the C1 is ((100-5)+1=96), there are 8 feature maps of 96×96. P2 is the max-pooling layer which applies on the output of the C1 layer non-overlapping 2×2 kernel, the size of the output is (96/2=48) with 8 feature maps of the same size (48×48). At layer C3 second convolutional layer, we have 16 feature maps calculatedon the output of P1by overlapping 5×5 filter, the size of output is (48-5+1=44), we obtained 16 feature maps of 44×44. At layer P4, there are 16 feature maps of 22×22(44/2=22) computing by max-pooling on the output of C3 by non-overlapping 2×2 filter. The convolutional layer C5, we obtained 32 feature maps of 20×20 calculated by overlapping 5×5 kernel with padding=1 on the output of P4, the output size is ((22-5+2×1)+1=20). The last max-pooling layer P6, we have 32 feature maps of size 10×10(20/2=10) computing on the output of the C5 by non-overlapping 2×2 filter. Finally, we obtained (10×10×32=3,200) 3,200 features are the size of the input FC7fully connected layer. The output of FC7 contains 96 classes which composed using softmax classifier to produce 96 output classes Figure 4.

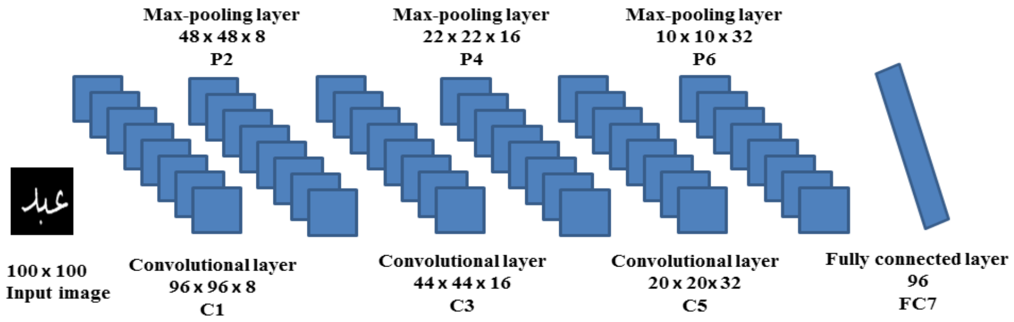


Figure 4. CNN proposed for Arabic handwritten words recognition

3. RESULTS AND DISCUSSION

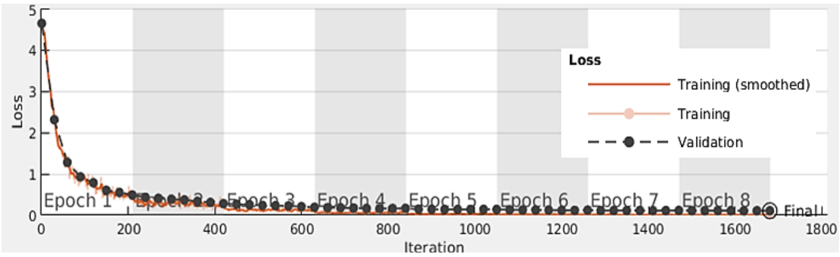
3.1. Dataset

A big training data of handwritten words images is needed from the convolutional neural network for obtaining better yield. For that, a dataset of Arabic handwritten words was collected and made using a benchmarking database, Arabic handwriting database (AHDB). This database included words images produced by writing legal amounts on Arabic checks and Arabic handwritten pages of 100 scripters [36], it's available in (http://handwriting.qu.edu.qa/dataset/), and contains 105 forms of Arabic handwritten words composed from 96 class of words, thus, the total image is 10,080 was not enough for an input of convolutional neural network to obtain a good result. Therefore, these images were used to collect other images. It was aimed to solve that problem, thanks to the pre-processing such as rotation transformation by two ways to make new images. Afterwards, we obtained a total image of words in each class 420 word images i.e. 40,320 images, and, the 96 class of database was divided into two data: a training data (26,880 words: 280 images per class) and a test data (13,440 word images: 140 images per class).

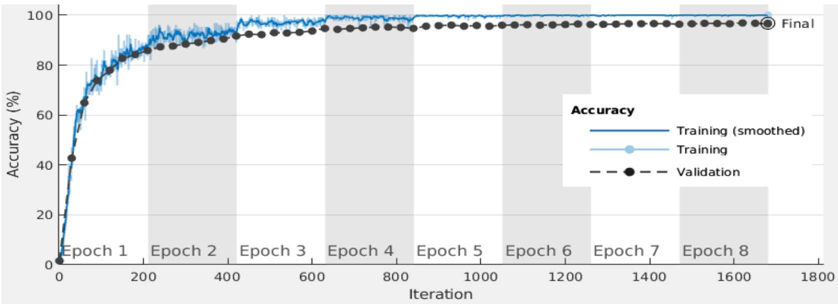
3.2. Experiments and results

As part of this work, a method of Arabic handwritten words recognition has proposedusing convolutional neural networks aiming to transform handwriting word images into their symbolic representations. The programming language used is MATLAB 2018a, the programwereimplemented in MATLAB 2018a CUDA SDK v.7.5, 1.70 GHz Core i5 PC with GPU NVIDIA GeForce GT 635M and 6G memory performed on windowsystem. We apply our method onthe 13,440 test word images (140 images for each class) to recognize the Arabic handwritten words. The result of our method was rated by computing the success rate of recognition of the obtained result, also we applied the method on 40,320 images of handdwriting Arabic words written by various scripter, divided into two sets : training sets 26,880 word images (280 for each class) and test sets 13,440 word images (140 for each class). Our algorithm is runningwith 8 epochs, but CNN start to decrease error of miss-classification from epoch 6 Figure 5(a). The result of our system is very promising, since we could achieve a successful recognition rate of 96.76% Figure 5(b).

A comparison was made between the results of our method with previously published methods of Arabic handwriting words recognition. Table 1 exhibits the successfulrecognition rates of previous work of Arabic handwritten words recognition. Clearly, our proposed method of Arabic handwritten word recognition by convolutional neural networks using AHDB database is the best one.



(a)



(b)

Figure 5. Recognition and miss-classification rate of Arabic handwritten words: (a) recognition rate and (b) miss-classification rate

Table 1. Word extraction rates

Method	Classifier	Data	Rate
Alkhoury [9]	CNN, SVM	HACDB and IFN/ENIT	94.17% for HACDB, 92.95% for INF/ENIT
Elleuch *et al.* [1]	SVM	HACDB	91.14%
Jayech *et al.* [2]	MSHMM	IFN/ENIT	91.10%(set a)
Tamen *et al.* [31]	HMM/MLP	IFN/ENIT	89.03%
Kessentini *et al.* [10]	Multilayer perceptron, SVM and ELM	IFN/ENIT	96.82%
Alkhateeb *et al.* [11]	CNN based HMM	IFN/ENIT	89.23%
Amrouch *et al.* [32]	SVM	AHDB	99.08%
Lamsaf [33]	k-nearest-neighbors (KNN)	AHDB	86.7%
AWNI [12]	deep convolution neural networks	AlexU-W and IFN/ENIT	96.11%,
Proposed method	Convolutional neural network (CNN)	AHDB Database	96.76%

4. CONCLUSION

An Arabic handwritten word Recognition is an active field in research that still needs to improve its performance. In the present paper, a method of Arabic handwritten words recognition has been proposed using convolutional neural network (CNN), in order to use new technologies in pattern recognition. The convolutional neural network is suggested for recognizing Arabic handwritten words; comparing to other system of deep learning, CNN gives the best result in big data of image proccessing field. There isn't a big database of Arabic handwritten words to use for CNN system, we proposed to collect a new database from the benchmarking Arabic handwriting database (AHDB) using the pre-processing, we apply the transformation of rotation on the images of the database to create new images with different features. The method is applied on the benchmarking databse AHDB and reachesthe best result.

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