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ORIGINAL ARTICLE

An Effective Deep Learning Approach for Improving Off-Line Arabic Handwritten Character Recognition

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ABSTRACT – Developing systems in the computer vision domain persuade researchers in many applications. The main goal in computer vision applications is to enable the computers to imitate humans in their vision system. Various systems are developed for classifying and recognizing the different types of images. This paper introduces an effective approach towards designing a system for recognizing an isolated handwritten Arabic character based on a deep learning approach. The deep learning approach is based on the convolutional neural network (CNNs). CNN plays an important role in every single application of the computer vision domain. The CNN model is developed and trained with Arabic handwritten characters in offline mode using three Arabic handwritten character recognition datasets. In order to validate the proposed system various experiments were conducted using the AHCR, AHCD, Hijja datasets. The AHCR dataset consists of 28000 images, the AHCD consists of 16800 images, and the Hijja dataset consists of 47434 images. Testing the proposed system yields excellent recognition results in both training and testing. The result shows that the performance of the proposed system achieves a superior accuracy of 89.8, 95.4%, and 92.5% using the AHCR, AHCD, and Hijja datasets respectively. .

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Arabic character recognition, AHCR dataset, convolutional neural networks (CNN), Deep learning

INTRODUCTION

Classifying and recognizing Arabic text is a hot topic for researchers due to its importance for both Muslim and Arab people. The importance of dealing with Arabic relies on the similarities among Arabic languages and other languages such as Farsi, Urdu, and Jawi. Moreover, The Holy Quran which is the holy book for all Muslims is written in Arabic. The Arabic language is written from right to left and it is used by more than 250 million all over the world [1][2]. Basically, there are different recognition systems for Arabic text based on their functions. Dealing with data acquisition, there are either online or off-line recognition systems. While dealing with the text type, there either printed or handwritten text recognition systems [3]. Using the online recognition systems, computers classify and recognize the text during its writing by a user which is done according to the movement of the pen. This means that online text recognition deals with handwritten text only. On the other hand, while using the off-line recognition systems, computers classify and recognize the text after writing it or print it which is done on the text images [4] [5] [6].

Handwritten Arabic text recognition can be classified into word, character, and digit recognition. This paper focuses on classifying and recognizing handwritten Arabic characters. Handwritten Arabic character recognition starts the last decade which means that working on Arabic text recognition is limited comparing to other recognition work that had been conducted to other languages such as English, Chinese, and Japanese. As mentioned earlier**,** Arabic writing is done from right to left and it is cursive.

Deep Learning (DL) is a new extension branch of machine learning (ML) for data learning and representation. According to its performance improvement, the algorithms of DL took the highest place in the field of pattern recognition. DL is implemented by using the convolutional neural network (CNN). Mainly, the deep neural networks consist of three main layers: the input layer, the hidden layers, and the output layer. In order to prevent overfitting, the deep neural network requires a huge set of examples. Based on the CNN architecture which is a multi-layer feed-forward neural network that extracts the main from the input images. Basically, the neural network back-propagation algorithm is used to train the CNN. The main advantage of CNN is extracting the main features from the input images [7].

The rest of this paper is organized as follows: Section 2 reviews the most related work of the handwritten Arabic character recognition. Section 3 describes and summarizes the proposed approach of the methodology and the methods used in the proposed system. Section 4 summarizes the classification phase used in the proposed system. Section 5 presents the experimental results and the performance of the proposed system which is used to evaluate the recognition rates. Section 6 reviews the conclusion of this paper.

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RELATED WORK

El-Sawy et al. [7] introduced a deep learning architecture for recognizing handwritten Arabic characters. They trained their system on the Arabic Handwritten Character Dataset (AHCD) which consists of 16800 of Arabic handwritten characters. Using the CNN model. In order to improve the performance of CNN, various optimization techniques were implemented. A 94.9% accuracy was achieved on the AHCD dataset.

Elleuch et al. [8] introduced Deep Belief Neural Networks (DBN) for recognizing the handwritten Arabic characters. No feature engineering was required in their system. Basically, the input of their system is the grey pixels of the images. Their system was evaluated on the HACDB database [9] which contains 6600 Arabic handwritten characters written by 50 writers. A 97.9% accuracy was achieved on the HACDB database.

Younis [10] introduced a deep neural network system for recognizing the Arabic handwritten characters using the convolutional neural network models. The Deep CNN was applied and tested on the AHCD dataset which consists of 16800 of Arabic handwritten characters. 97.6%, accuracy was achieved on the AHCD dataset. The AHCD dataset is available at https://www.kaggle.com/mloey1/ahcd1.

T. Khan [11] introduced a deep learning model to recognize the expiry date of an object by using and exploiting the smart expiry architecture by taking an automatic notification.

Altwaijry and Al-Turaiki [12] introduced a recognition system for the Arabic handwriting characters using the Convolutional neural network. They designed their own dataset which is known as Hijja. The Hijja dataset contains 47434 characters written by 591 writers. The performance of their systems gave an accuracy of 88% on the Hijja dataset. The Hijja dataset is available at https://github.com/israksu/Hijja2.

A. Ashiquzzaman and A. K. Tushar [13] introduced a novel algorithm using deep learning neural networks to improve and modify the recognition accuracy in recognizing Arabic number digits. Saad Bin Ahamd et al. [14] introduced Arabic scene script recognition by using the classifier of Convolutional Neural Networks (ConvNets). By exploiting the single occurrence of the Arabic character, five different orientations were employed. Also, in the classification phase training was formulated to keep the size as 3 × 3 and 5 × 5 with stride values 1 and 2. Katrina Sundus et al. [15] used the neural network of the feed-forward deep learning (DL) to recognize the Arabic script. In their model, the first layer was the frequency-inverse document (TF-IDF). Vectors were used to represent most of the frequent words. As usual, the output of the first layer is used as an input to the second layer. To reduce the classification error, Adam's optimizer was used. G. Saker et al. [16] introduced a recognition system for Arabic fonts. The deep learning concept using the convolution neural networks were employed to find the Arabic font name. They used their dataset. Maidana et al. [17] addressed several architectures of convolutional neural networks to recognize the offline handwritten chinses characters. Several and multi distinct architectural fusion methods were employed.

BACKGROUND

The main goal of this paper is to propose an effective recognition system for recognizing handwritten Arabic characters based on deep learning by using the convolutional neural networks (CNNs).

Image Acquisition

In general, all text recognition systems work on two different domains: the printed text-domain and the handwritten text-domain. In the printed domain, the printed text looks similar in its different shapes while using various devices. However, in the handwritten text-domain, there is a large variability in writing the same text by different writers. This is due to the writing style which differs from one writer to another. Using this fact, it is concluded that designing a recognition system for handwritten text is more difficult than designing a recognition system for printed text. Evaluating any recognition system needs a huge dataset for the training and testing it. In this paper, the Arabic handwritten character recognition (AHCR) dataset is used [16]. This dataset contains 28000 digital images for the Arabic alphabets. The Arabic alphabets are 28 ones, in the AHCR dataset, the data has been written by 100 different writers. Each writer wrote the whole Arabic alphabets which are 28. Each alphabet was written 10 times by each writer since a form was distributed among the writers. The writers are classified into three main categories: The computer Science academic staff members at Taibah University, Taibah University students, and high school students. The form is shown in Figure 1.

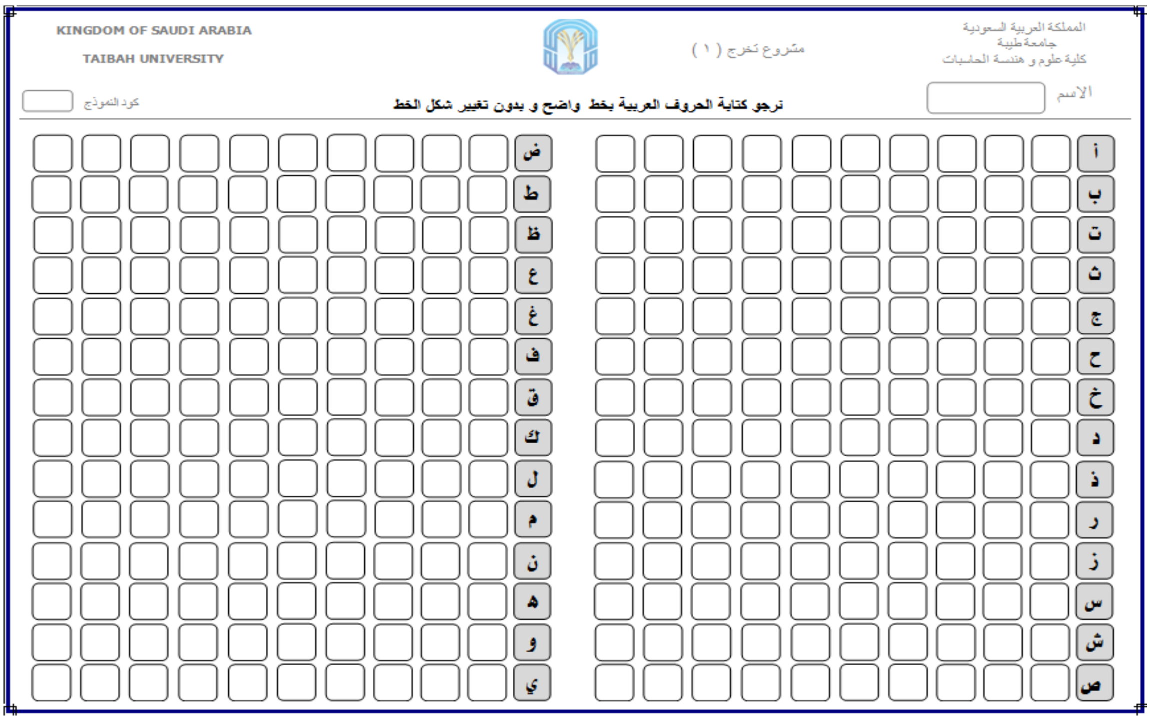


Figure 1. An Example of the form

Later on, all the forms were stored in the computer using the scanning technique. A cropping technique was applied to all the forms to obtain each alphabet separately. All the alphabets were cropped and saved with the same size 0f 50x50. There were 28 folders for the whole alphabets. After saving the alphabets in different folders, each folder was read separately and each image in the folder had been cleaned bypassing the median filter to remove all types of salt and pepper noise which comes while scanning. Furthermore, the dataset was divided into a training set and a testing set. The training set contains 80% of the data and the testing set contains the other 20% data. Finally, the dataset of the images was classified into main folders training and testing. Each folder contains 28 folders for the basic Arabic alphabets. So, the whole work is done via training and testing, the training phase is the phase which gains and obtains the knowledge to the system about the Arabic characters utilizing vector features. While the testing phase is the phase that deals with passing a query image to the system using its vector features to be recognized and classified. All the pre-processing steps were done in [18].

Convolutional Neural Network and Deep learning

In the field of computer vision and machine learning, deep learning is considered as a new area of research. Deep learning can be achieved by three different architectures. Those architectures are the Convolutional Neural Network (CNN), the Deep Belief Net (DBN), and the Stacked Auto Encoder (SAE) [19] [20]. CNN is used in this paper. CNN is a special type of multi-layer neural network (MLP). The goal of the CNN is to recognize a pattern from pixel images directly using the minimum steps of pre-processing. CNN is a deep learning algorithm [21] [22]. In CNN, computers accept the input image as a pixel array. The input images are either colored or grey images. In general, there are three main layers to any CNN network. The layers are the convolution layers, the pooling layers, and the fully connected layers [23] [24] [25].

The Convolution layer

Regarding any CNN network, the convolution layer the first layer, and it is used for extracting features from the input image. The feature map of the input image is extracted in the convolution layer by applying a filter to the input image. Striding and padding are taking in care in this layer. Striding means the number of pixels shifts across the input image at each step [23] [24].

The Pooling Layer

Spatial size reduction is performed in the pooling. Furthermore, the pooling layer is used to reduce and minimize the computation and the number of parameters in the network. The pooling layer operates on each feature map. There are several pooling algorithm approaches: the max pooling, the stochastic pooling, and the average pooling. The most common algorithm approach is the max pooling which is applied in the pooling layer in the proposed system [24].

The Fully connected layer

Mainly, the fully connected layer (FC)is the last in the CNN network architecture. In this layer, the output of the pooling layer is considered as an input of the fully connected layer. The behaviour of this layer is similar to ANN behaviour. In general, by comparing the CNN first layer with the CNN last layer it yields to a fact of there are more parameters in the fully connected layer than in the convolution layer. It is noted that the fully connected layer is connected to the output layer which acts as a classifier [24].

The Activation function

In CNN's, there are various activation functions can be employed with various architectures. There activation functions are: ReLU, LReLU, and PReLU. The use of these functions will increase the performance of the system in the training by speeding it up. The ReLU (Rectified Linear Unit) is used in this paper. Fig. 2 illustrates the architecture of CNN.

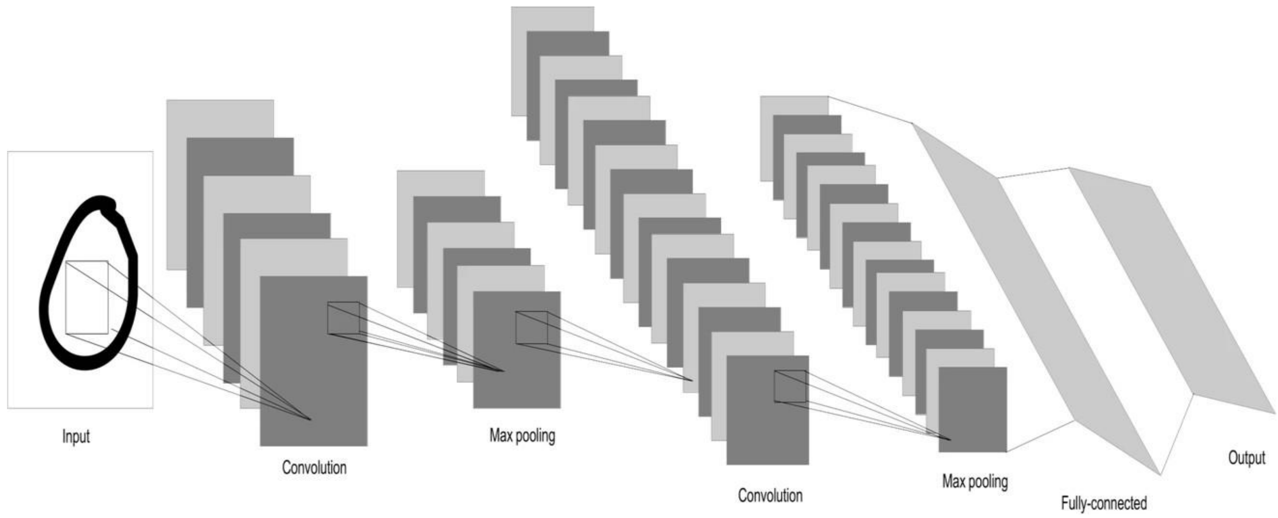


Figure 2. The convolution Neural Network architecture [12].

PROPOSED METHODOLOGY

Training and recognition are the main parts of the proposed system. Constructing, designing the architecture of the CNN network, and training the CNN network with the input image data is the main phase in the training part. However, recognizing the handwritten Arabic characters by using the training the proposed system is the main goal in the recognition part. The AHCR dataset is used in the proposed system which contains 28000 images of handwritten Arabic characters written by 100 writers. The handwritten Arabic character images were cropped and saved in gray format. During the development phase. In this paper, the images were converted to binary images and resized to 28×28 This is the only pre-processing task that was applied in this paper.

The proposed systems consist of six main layers: there are three convolutional layers; there are two max-pooling layers; finally, there is one fully connected layer.

Layer 1 is the first convolutional layer with the ReLU. This layer gets the preprocessed input image of size $n \times n = 28 \times 28$, filter (f) size is 5×5. Both hyper parameters were used as: the stride (s) is 1, and the padding (p) is 0. The number of filters is 32. By applying the convolution at this level, the feature map is obtained by using equation 1.

$$fm = \left(\frac{n+2p-f}{s}\right) + 1 \tag{1}$$

The convolution operation is applied, and the resulting feature map size is 24×24. It is noted that the ReLU activation function is done on each feature map.

$$fm = \left(\frac{28+0-5}{1}\right) + 1 = 24$$

Layer 2 is the first max-pooling layer. The output of layer 1 as the size of is 24×24 is the input of layer 2. Here, the pooling size is 2×2, the stride is 2, and the padding is 0. After max pooling is operation is performed, the resulting new feature map size is 12×12. This layer has no activation function.

$$fm = \left(\frac{24+0-2}{2}\right) + 1 = 12$$

Layer 3 is the second convolutional layer with the ReLU, where it gets its input from layer 2 as s 12×12. The filter size is 5×5. The stride is 1, padding is 0, and the number of filters is 32. By applying the convolution at this level, the resulting new feature map is obtained of size is 8×8. It is noted that the ReLU activation function is done on each feature map.

$$fm = (\frac{12 + 0 - 5}{1}) + 1 = 8$$

Layer 4 is the second max-pooling layer. The output of layer 3 as the size of 8×8is the input of layer 4. Here, the pooling size is 2×2, the stride is 2, and the padding is 0. Mainly, max pooling is performed in each feature map independently. After max pooling is operation is applied, the resulting new feature map size is 4×4. It is noted that this layer does not have an activation function.

$$fm = (\frac{8 + 0 - 2}{2}) + 1 = 4$$

Layer 5 is the third convolutional layer without ReLU, where it gets its input from the previous layer 4) as size of 4×4. The filter size is set to 4×4. The stride is 1, padding is 0, and the number of filters is 64. After the convolution operation is applied, the resulting new feature map size is 1× 1. The output of this layer is a one-dimensional vector of size 64.

$$fm = (\frac{4 + 0 - 4}{1}) + 1 = 1$$

Layer 6 is the fully connected layer which takes its input from the previous layer (layer 5). The input of this fully connected layer is the one-dimensional vector of size 64 with the ReLU activation function. The output of this layer is a one-dimensional vector of size 256.

Layer 7 is the output layer of the network. This layer computes the score of the classes resulting in a vector 0f size 28. It is a softmax classifier with 28 classes of the AHCR, AHCD, Hijja datasets. Figure 3 illustrates the proposed system architecture block diagram.

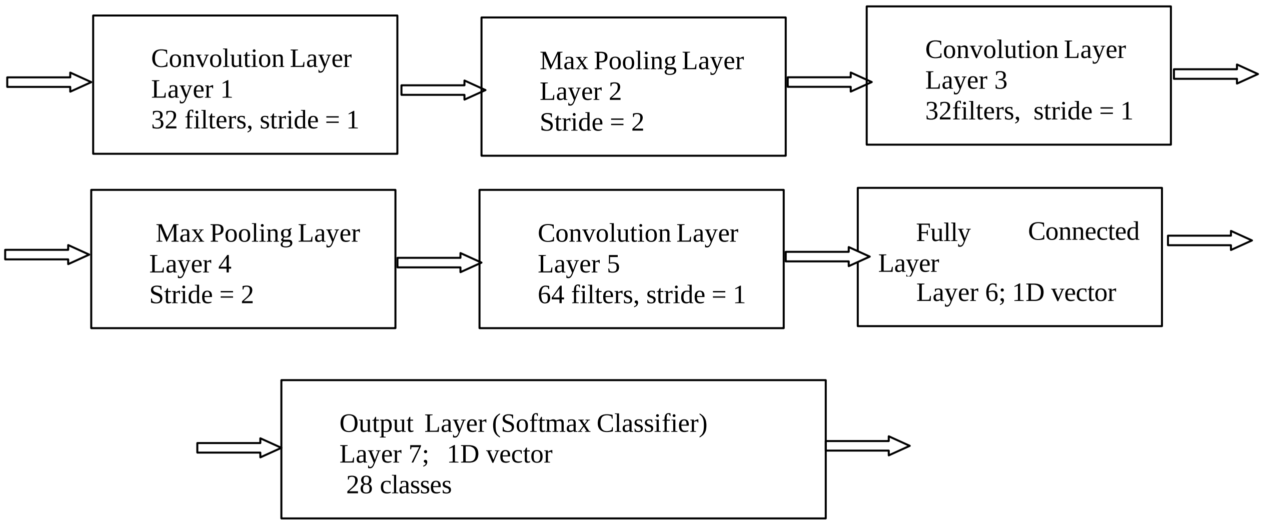


Figure 3. The proposed system architecture

RESULTS AND DISCUSSION

The proposed system was implemented on the CPU of 4Gb RAM using the MATLAB platform. In order to validate the proposed system, three different datasets were used: the AHCR, AHCD, and Hijja. The AHCR dataset contains 28000 images of handwritten Arabic characters written by 100 writers were used. The AHCR dataset is divided into two main folders training and testing. The training folder has 6000 images for each class out of 28 classes resulting in 60000 images. Also, the testing folder has 1000 images for each class resulting in 10000 images. Initially, every single image of the AHCR dataset was converted to binary images and resized to 28×28.

In addition, the AHCD dataset contains 16800 images of handwritten Arabic characters written by 60 writers. The AHCD dataset is divided into two main folders training and testing. The training folder has 480 images for each class out of 28 classes resulting in 13440 images. Also, the testing folder has 120 images for each class resulting in 3360 images. Similarly, every single image of the AHCR dataset was converted to binary images and resized to 28×28.

Furthermore, the Hijja dataset contains 47434 images of handwritten Arabic characters written by 591 writers. The dataset is set of 29 folders for 29 classes. The same 28 classes in both AHCR and AHCD with an extra class of 'hamza class'. This class is ignored in this paper.

Table 1 summarizes both training and testing accuracy of the proposed system in terms of each class.

Table 1. The proposed system accuracy.

Class No.	Class Name	Training Accuracy %	AHCR Testing Accuracy %	AHCD Testing Accuracy %	Hijja Testing Accuracy %
1	Alif أ	99.1	88.5	98.5	98.8
2	Baaب	97.1	87.9	95.9	93.3
3	Taaت	97.3	87.3	94.6	92.2
4	Thaa'aث	97.1	86.9	95.4	92.8
5	Jeemج	97.7	89.5	94.7	91.9
6	Haaح	98.1	90.3	94.9	92.2
7	Khaaخ	97.5	89.1	94.9	91.5
8	Dallد	98.2	90.6	95.3	93.3
9	Dhaalذ	98.3	89.3	95.9	93.1
10	Raaر	98.5	88.5	95.4	92.9
11	Zaayز	98.1	89.7	94.6	92.1
12	Seenس	99.1	92.1	95.2	92.1
13	Sheenش	98.2	88.7	95.4	91.6
14	Sadص	99.1	91.6	95.4	92.6
15	Dhadض	99.1	88.4	95.5	91.7
16	Ttaaط	99.3	91.3	96.2	92.9
17	Dhaaظ	99.1	89.6	96.1	91.2
18	Ayneع	98.3	92.6	95.3	92.1
19	Ghyanغ	97.1	90.3	95.7	91.3
20	Faaف	98.1	91.3	94.8	92.9
21	Qaafق	98.4	92.1	94.9	91.8
22	Kaafك	99.1	91.3	95.4	92.9
23	Laamل	99.1	92.7	95.3	92.6
24	Meemم	99.3	89.2	95.8	92.1
25	Noonن	99.5	90.4	95.2	92.7
26	Haa'ـه	97.5	88.1	95.1	91.1
27	Wawو	98.3	89.1	94.9	91.6
28	Yaaي	98.9	88.4	95.1	92.7
Average		98.4	89.8	95.4	92.5

The proposed system is compared with other systems that were tested in the same datasets. Both El-Sawy et al. [7] and Younis [10] used the AHCD dataset invalidating their systems. Figure 4 shows the comparison among the El-Sawy et al. [7] , Younis [10], and the proposed system.

Altwaijry and Al-Turaiki [12] used the Hijja dataset invalidating their system. Figure 5 shows the comparison between the Altwaijry and Al-Turaiki [12] and the proposed system.

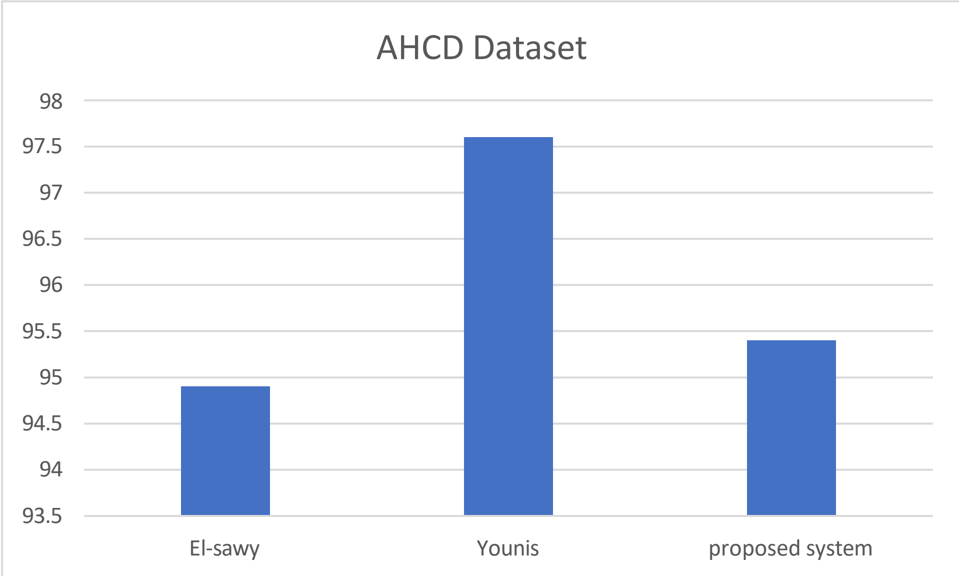


Figure 4. Results of the proposed system in comparison with other systems using the AHCD dataset.

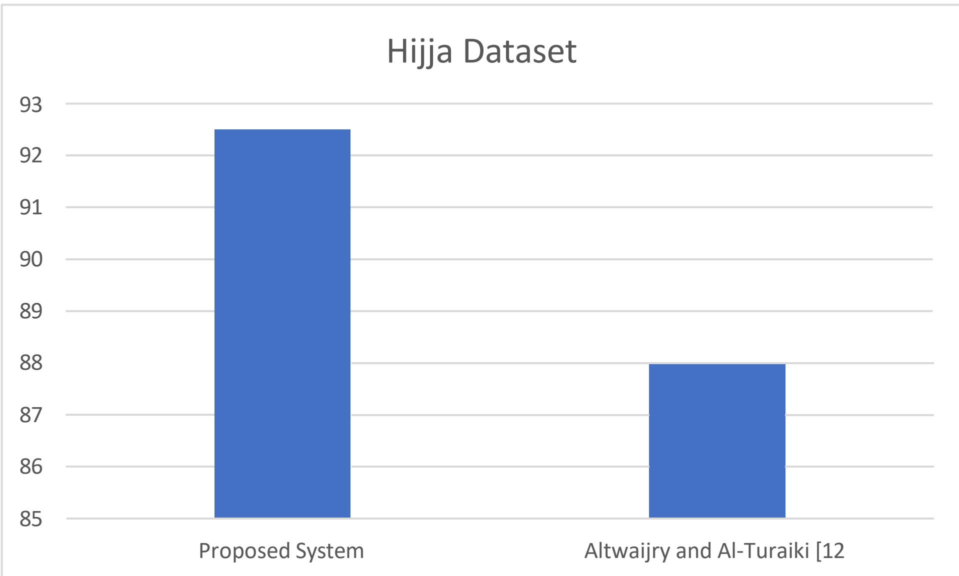
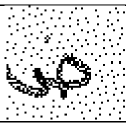
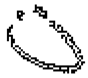
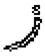
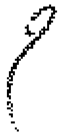
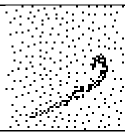


Figure 5. Results of the proposed system in comparison with other systems using the Hijja dataset.

As seen in figure 4, the proposed system performance performs better than El-Sawy [7] and less than Younis [10] in classifying and recognizing the Arabic handwritten characters. In addition, figure 5 shows that the proposed system performance performs better than Altwaijry and Al-Turaiki [12] in classifying and recognizing the Arabic handwritten characters.

It can be seen that a deep learning algorithm using the CNN model performs better in classifying the Arabic handwritten characters. The proposed system gives a testing accuracy of 89.8%, 95.4%, and 92.5% on the AHCR, AHCD, and Hijja datasets. Error in classification is due to the variation of writing and similarities in some characters. For example the letter Dhad (ض) and the letter Sad (ص (differs from the dot above the letter. In such a case, it is too difficult to tell which is which even for humans. Also, the letter Taa'a (ت) is predicted as the letter Noon (ن). Table 2 summarizes some misclassification errors where it prediction character differs from the actual character.

Table 2. Misclassification character examples

The Character	The Actual Character	The Predicted Character
	ض	ص
	ت	ن
	د	ر
	ز	ذ
	م	ح
	و	ر

CONCLUSION

In this paper, A CNN model is designed and constructed to recognize Arabic handwritten characters using the Arabic handwritten character recognition datasets: the AHCR, the AHCD, and the Hijja datasets. In this paper, it has been shown and noticed that a deep learning approach with the CNN model is effective in improving the accuracy in recognizing the handwritten Arabic characters. An accuracy of 89.9%, 95.4%, and 92.5% has been achieved while implementing the proposed system on the AHCR, AHCD, and Hijja datsets respectively. It is noted from the obtained result that CNN shows better performance. It is recommended to implement the CNN architecture to other recognition systems with a slight adaptation.

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