Research Article

Character Recognition of Arabic Handwritten Characters Using Deep Learning

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Article Info	Abstract
	Optical character recognition (OCR) is used to digitize texts in printed documents and camera images. The most basic step in the OCR process is character recognition. The Arabic language is more complex than other alphabets, as the cursive is written in cursive and the characters have different spellings. Our research has improved a character recognition model for Arabic texts with 28 different characters. Character recognition was performed using Convolutional Neural Network models, which are accepted as effective in image processing and recognition. Three different CNN models have been proposed. In the study, training and testing of the models were carried out using the Hijja data set. Among the proposed models, Model C with a 99.3% accuracy rate has obtained results that can compete with the studies in the literature.

1. Introduction

Arabic handwriting recognition is so important in many parts in many applications, three decades ago handwriting recognition has been increasing in use in many applications [1]. Latin language recognition and Arabic language recognition have been researched by many researchers during the last three decades. The inputs of handwriting recognition can be from many resources such as on image handwritten, on a paper written, and many other resources.

This study aims to recognize children's handwriting recognition. The main difficulty in recognizing Arabic handwriting is that the handwriting is different from one person to another and from age to another. Recognizing children's handwriting is much more difficult than adults the only research that is done for recognizing children's handwriting is an Arabic handwriting recognition system using a convolutional neural network [2]. The accuracy of the research was 97% and the accuracy that I achieved is 99.3% on the same dataset, Hijja. Hijja dataset is written by children whose ages are between 7 to 12 years. The hijja dataset contains 47,434 characters, and this dataset was created by 591 students. The Hijja dataset is divided into training and testing. In this research, we developed 4 models for recognizing characters depending on the dataset, and the highest accuracy that we achieved from the proposed models was 99.3%.

The handwriting of the Arabic language is arranged from right to left. The Arabic letter set consists of 28 letters, each with 2-4 different structures, depending on the location of the letter in the word. For these reasons, it is more complex than languages with separate letters. This situation causes the handwritten letters to be found in very different ways and sometimes to be on top of each other. For this reason, it is necessary to parse the characters in the document before character recognition.

There are many different methods, including image processing-based methods. Machine learning is the ability to use the most appropriate algorithm to transform a dataset into a model [3] and Deep learning is a machine learning method that consists of multiple layers that portend outcomes with the available dataset. Deep learning, machine learning, and artificial intelligence have different meanings and can be abstract as a sub- substation of artificial intelligence [4]. In recent years, deep learning algorithms have been claimed as the most up-to-date method.

2. Related Works

The methods found in the literature regarding the study are summarized in this section. For Arabic handwrite recognition there are some datasets for example: Database IFN/ENIT [5] has been developed by für Nachrichtentechnik and the Ecole Nationale d'Ingénieurs de Tunis institute. The dataset was written by 411 people and it contains 26,549 images of Tunisian villages and towns.

Arabic handwriting dataset (AHDB) [6] consists of pictures of words that describe depict numbers and amounts in checks machine Intelligence and the pattern recognition center has some Arabic character's databases, such as Arabic handwrite recognition dataset [7]. Authors in addition presented a dataset that contains 16,800 Arabic characters. There have been many efforts for addressing Arabic handwriting recognition.

Ashiquzzaman et al. [8] proposed two strategies for improving the performance of Arabic numerals. Firstly, two changes they made to the MLP-based model [9] the rectified linear unit changed, and they used a trained back-propagation CNN algorithm. They get 93.8% accuracy in the first change and 97.4% in the second change.

Latif et al. [10] in 2018 designed a CNN architecture for the recognition of numerals of multi-languages: Urdu, Persian, Devanagari, Eastern, and Western Arabic. The overall accuracy he gets was 99.29% and individual language accuracy was 99.32%.

Ashiquzzaman et al. [8] recently the function of activation from ReLU to ELU they changed and augmentation data to CMARERDB 3.3.1 dataset has been used. The method they designed achieved an accuracy of 99.4%.

An Arabic dataset built by Mars and Antoniadis [11], this dataset consists of 6090 characters and 1080 words, for characters and words recognition. They used a time-delay neural network for classification their CNN architecture they achieved 96.90% for words and 98.50% for characters.

A hybrid CNN model has been designed by Maalej et all. [12] and he used it for extracting features for images raw. Then he tested the CNN on IFN/ENIT Database to achieve 92.21% accuracy. A CNN architecture was designed by El-Sawy et al. [13]. El-Sawy et all trained the model on the AHCD dataset The model has two layers' normalization and employing dropout. The CNN model achieved an accuracy of 94.9%.

Hassan et al. [14] designed a CNN architecture with two fully connected layers for recognizing historical Arabic handwrite texts. They tested their CNN model on handwriting text images historical, text image synthesized database, and text print image database and they achieved an accuracy of 85%.

Mudhsh et al. [15] designed a deep neural network (VGG net) architecture. In the mudhsh model 13 convolutional layers, 3 fully connected layers, and two max-pooling layers have been used for building the construction the model has been achieved 99.57% accuracy on the ABbase database and achieved 97.32% on the HACDB database.

Younis [16] designed a CNN architecture with three convolutional layers and one fully-connected layer. the model achieved 94.7% on AHCD and 94.8% on the AIA9K dataset. Najwa Altwaijry and Isra Al-Turaiki [17] designed a CNN for Arabic handwriting recognition on the Hijja dataset and achieved an accuracy of 97%

In this research we designed a CNN architecture with Relu and softmax activation, the structure I used is sequential with 9 hidden layers and I used Adam optimization to achieve 99.1% accuracy and I tested my model on the Hijja dataset. We also designed two more models which are model B with Gradient descent optimization and Relu + softmax activation and sequential with 3 hidden layers structure I also tested it on the Hijja dataset to achieve overall 85% accuracy.

3. Materials and methods

3.1. Hijja dataset

The important part of a computer vision system is datasets. Datasets help to compare machine learning techniques quickly. The dataset I used is the Hijja dataset, this dataset contains Arabic handwritten letters. Hijja is an open-source dataset collected in Riyadh, Saudi Arabia by students from classes 1-6. Hijja consists of 47,434 characters written by 591 students.

3.2 Methodology

The methodology of my work consists of three main phases as below:

1. Pre-process the data set.
2. Train an example model.
3. Test and evaluate different models.

    In our study, we are focusing on Arabic handwritten character recognition. This is shown in the flow chart given below:
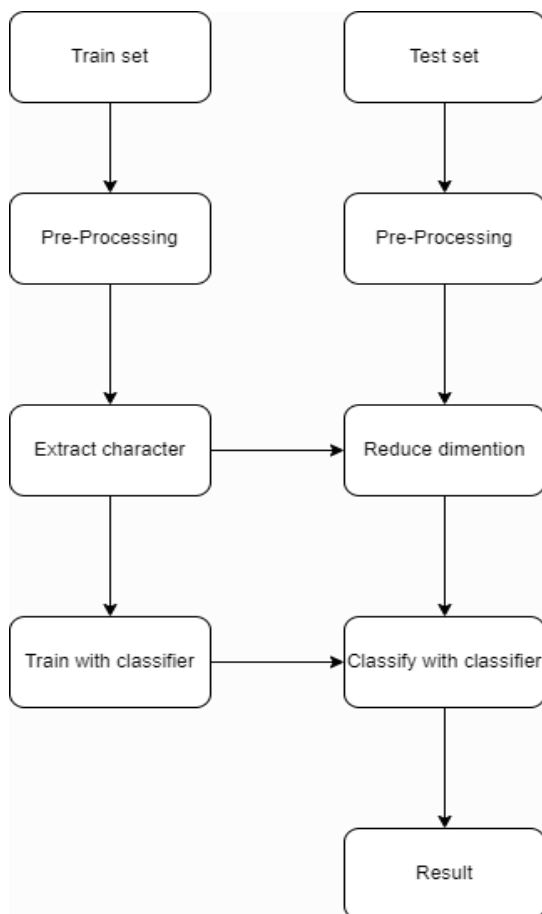

Figure 1. Preprocessing on the dataset

    Figure 1. shows the analytical process hijja data set. The dataset was split for train and test information in which 80% of data was allocated to the train data and 20% for test data.

3.2.1. Pre-Process

    In the preprocessing phase, I import my data as CSV files which are divided into two train and test files. The train consists of 13440 rows where the test has 3360 rows, each row is a sample that has a 32X32 structure of 0-255 grayscale pixel. In other words, we have a total of 16800 samples representing Arabic hand-written letters. For this matter they are labeled in 28 different classes with each class representing a letter in the Arabic language; some of the images are shown in the below illustration.

Table 1. letter image and its corresponding labels

Image	Label	Image	Label	Image	Label	Image	Label
أ	1	ب	2	ت	3	ث	4
ﻝ	5	ح	6	ح	7	د	8
د	9	ر	10	ذ	11	ز	12
ش	13	ص	14	ض	15	ط	16
ظ	17	ع	18	غ	19	ف	20
ق	21	ك	22	ل	23	م	24
ن	25	ه	26	و	27	ي	28

In the first step of our approach, the data 0-255 is normalized to 0-1 as NumPy-floats, representing the whole data as NumPy arrays. This mechanism helps the neural networks to deal with the data in a better shape.

3.2.2. Initial Model

A state of the art approach to modeling for this purpose will include a default sequential method that has the following layers:

- 2D convolution layer activated with Rectified Linear Unit (ReLU).
- A-Max pooling operation for the 2D spatial data layer.
- A Flattens layer the input which does not affect the batch size.
- Two dense layers, which are neural network layers that are connected deeply.

The model is accompanied by a Gradient descent (with momentum) optimizer; afterward, it is compiled with Adam Optimizer with categorical cross-entropy loss function. The accuracy of this basic model reaches 81%, namely known as Model A.

3.2.3. Complex Models

Our approach combines different models and observes the accuracy of each one of them, the below table represents an overview of the model developed for our problem:

Table 2. Models developed

Model	Structure	Activation	Optimization	Accuracy
Model A	Sequential with 3 Hidden Layers	Relu	Gradient descent	81%
Model B	Sequential with 3 Hidden Layers	Relu + Softmax	Gradient descent	85%
Model C	Sequential with 9 Hidden Layers	Relu + Softmax	Adam	99.3%
Model D	Sequential with 13 Hidden Layers	Relu + Softmax	Adam	93%

Model D has the most promising outcome when it is trained with 100 epochs.:

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│     Conv2D 30 X 3X3 with relu Activation      │
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┌─────────────────────────────────────────────┐
│                 MaxPool 2X2                   │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│     Conv2D 15 X 3X3 with relu Activation      │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│                 MaxPool 2X2                   │
└─────────────────────────────────────────────┘
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│                Droupout at 0.2                │
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│        Dense 128 with relu Activation         │
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┌─────────────────────────────────────────────┐
│         Dense 50 with relu Activation         │
└─────────────────────────────────────────────┘
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┌─────────────────────────────────────────────┐
│       Dense 29 with softmax Activation        │
└─────────────────────────────────────────────┘
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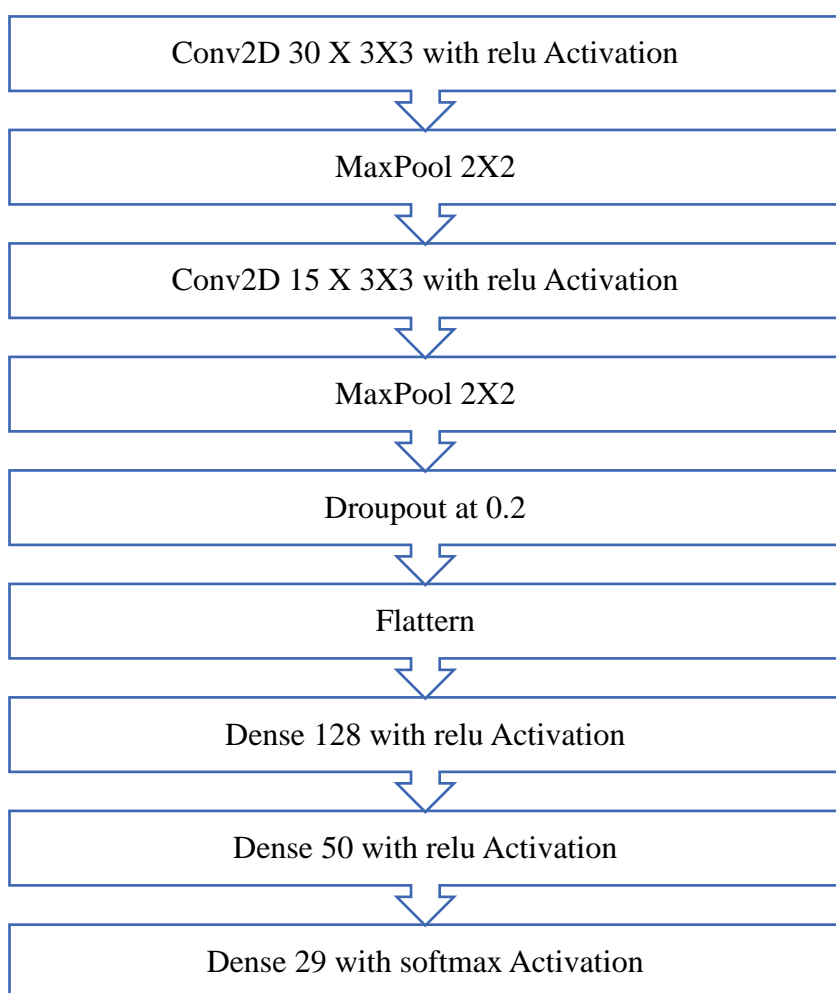
Figure 2. The model description is as follow

The model promises an acceptable accuracy when it is trained with 100 epochs on a CPU or GPU machine.

4. Results

As a result, deep learning algorithms may perform differently. Therefore, in the case of creating different combinations of optimization algorithms, activation functions, and neuron numbers while creating a model in deep learning, a more suitable architecture for the data set will be obtained. Our models were tested on the Hijja dataset and 16 core and 32 GB ram Linux server and below are the results.

Table 3. Models developed

Model	Accuracy
Model A	81%
Model B	85%
Model C	99.3%
Model D	93%

In Table 4, the results obtained in similar studies and the results obtained in the models we suggested in our study are given. As can be seen, the results obtained with our model are at a level that can compete with other studies in the literature However, in the Ashiquzzaman et al. [8] study, which was more successful than the proposed method, a different data set was used. More successful results were obtained from the study of Najwa Altwaijry using the same data set.

Table 4. Handwriting recognition models using deep learning summary

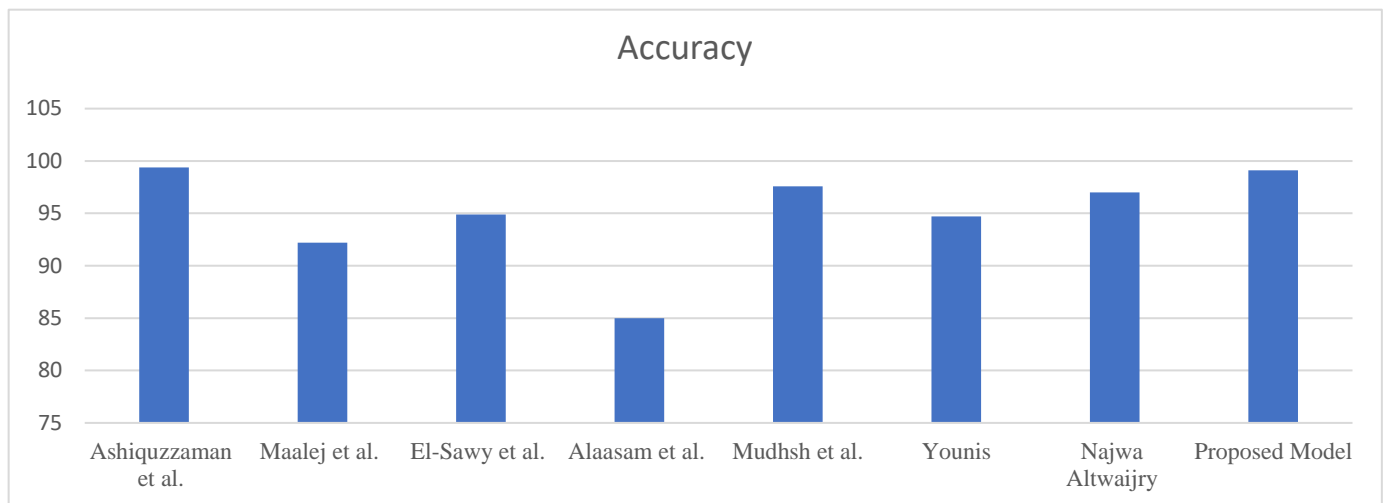| Ref	Tested on dataset	Accuracy
Ashiquzzaman et al	CMATERDB 3.3.1	99.4%
Maalej et al.	IFN/ENIT	92.21%
El-Sawy et al.	AHCD database	94.9%
Alaasam et al.	historical handwrite text images	85%
Mudhsh et al.	Abbase	97.57%
Mudhsh et al.	HACDB	97.32%
Younis	AHCD	94.7%
Younis	AIA9K	94.8%
Najwa Altwaijry	Hijja	97%
Proposed Method	Hijja	99.3%

Figure 3. Showing the Accuracy Results

4. Conclusion

In this article, new deep learning models are proposed for the recognition of Arabic characters. The models proposed with the Hijja dataset were trained and tested. Competitive results have been obtained with similar studies. It can be used for the Arabic OCR system of the proposed models. In the future, we aim to have our dataset and also, I want to include Kurdish handwrite recognition and test our model on it. However, It's beneficial to study new machine learning models and test them on the presented dataset.

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