Deep Learning for Arabic Handwriting Recognition System

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Abstract: Automated handwriting recognition is a crucial element in numerous applications across diverse fields. This problem has been the subject of significant investigation during the past three decades because to its complex nature. Research has mostly concentrated on the identification and interpretation of handwritten text in Latin languages. There is a scarcity of research conducted on the Arabic language. Therefore, it is crucial to build Children's Arabic handwriting recognition software and apps. In this study, we offer three models for the recognition of children's Arabic handwriting using deep learning. In this paper, an ensemble learning is employed for the Recognition Arabic handwriting, the proposed ensemble learning combined three model**,** the first with three convolution layer and the second with four convolution layer and the third model is CNN using BI LSTM. Hijja, a recent collection of handwritten Arabic by children that was gathered in Saudi Arabia, is used in training process. The most relevant work achieves less accuracy from our models for the same data sets. The three models achieve accuracies 87,88, and 89, when they work independently. The performance enhanced by use the ensemble and soft voting that increases the accuracy up to 92% which better than some works selected from the literature.

Keyword: CNN, Handwritten recognition, Arabic, Features extraction.

1. Introduction

Automatic handwriting recognition is the capacity of a system to recognize handwritten text produced by people. [1]. By converting characters into their digital counterparts, character recognition systems provide an automatic way to recognize text within images. [2]. An electronic device called optical character recognition (OCR) transforms handwriting into computer-editable and readable text. [3]. 347 million people speak Arabic, a language with many applications. [4]. However, the increasing prevalence of digital education in place of traditional schooling has made Arabic letter recognition essential for numerous applications. in recent years, particularly in light of this epidemic. As a result, children or others who need to study Arabic may need to receive their education remotely over the Internet.[5]. The biggest problem with Arabic script recognition systems is that the characters are written in a cursive style. Also, some characters can look two to four different ways based on where they are in the word. [6] It's very hard to understand Arabic because writers don't put these dots exactly where they should be. Even though Arabic writing goes from right to left, some letters crossed over to make vertical lines. [7].

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The handwriting recognition system's main goal is to convert handwritten text documents from digital picture format into legibly legible documents. encoded character format. Utilizing word processing software, read and edit.[8]. Handwritten Arabic character recognition is still a current study problem that hasn't been fully solved yet. Digitizing Arabic documents can make it possible to process (index and search) historical and Islamic papers. [9]. Arabic handwriting recognition poses many challenges because of the wide range of handwriting styles that people use, the dearth of large datasets that are freely accessible, and the features of Arabic script (cursive form, variable letter size, and morphable letter shape), depending on where it is placed) (4) Different handwriting styles [10]. In this paper, our objective is to enhance the predictive precision of the Hijja dataset by employing Convolutional Neural Networks (CNNs).

This will result in a more resilient model capable of accurately identifying Arabic script written by youngsters.[11] Due to the importance of Arabic letters for a wide range of applications and purposes, In order to recognize Arabic characters, a number of academics have recently focused on handwriting data from youngsters. However, adult handwriting has been the subject of the most studies on the recognition of Arabic characters in handwriting [12]. The field of Arabic handwritten character recognition (AHCR) has made great strides. with the use of various machine learning (ML) techniques and artificial neural networks. Additionally, convolutional neural network (CNN) based AHCR models have demonstrated impressive performance on several handwritten samples. CNNs are superior to typical machine learning algorithms in that they automatically identify and extract the distinctive and representative aspects of images, eliminating the need for manual feature definition. [13]

Systems that are based on handwriting are being used to help kids learn. Researchers have put in a lot of time and effort to create and improve handwriting learning systems for kids in schools. These systems are available in many languages and on a variety of platforms, such as websites, computer programs, and tablet apps. [13]. Another problem for experts is that the Arabic language is not always consistent. For example, some stroke characters look the same. There are also dots that help tell the difference between Arabic signs that share a stroke. Actually, the handwritten Arabic character files use images with a resolution of either 32*32 or 28*28 pixels. The dots might vanish or be removed.

because the resolution is too low or because of preprocessing. Handwriting is also different; the dots may be too small or in the wrong place. Pay more attention to the characters with dots. More research needs to be done on two-stage recognition systems. These plans are suggested for how to deal with characters that have dots. In the first step, characters are split into two groups based on whether they have dots or not. This makes it easier to sort the characters into the right groups. In the second step, the characters are put into one of the fewer groups. Researchers also must deal with problems when they try to figure out how to read handwriting on old Arabic documents. There are many different forms of the Arabic language, especially when you look at old writing and new writing. [14].

The main contributions of this research can be summarized as three CNN deep learning models Convolutional Neural Networks suggested, the first have three convolution layers, The second have four convolution layer And the third model contain from BI-LSTM. ensemble learning technique used to increases the accuracy by soft voting method. The remainder of this essay is structured as follows: CNNs' background is briefly covered in Section 2. The relevant studies in the literature on handwriting recognition methods are covered in Section 3. Section 4 displays the handwritten Arabic letter dataset from HIJJA. Our suggested work is presented in Section 5. the training environment covered in section 6 and the experiments used to identify handwritten Arabic letters. The performance of our model in comparison to other models in the literature is presented in Section 7. Section 8 concludes with some recommendations for further research.

2. Background

Machine learning techniques such as representation learning are used in the field of deep learning, where input data is expressed in several tiers of more basic representations. Put another way, simpler notions like shape or edges serve as the foundation for more complicated conceptions like "person" or "car." CNN is a unique kind of deep learning neural network that has demonstrated unheard-of effectiveness in tasks using images. CNNs have a wide range of uses, including as object recognition in photos, semantic segmentation in images, and image categorization. [1]

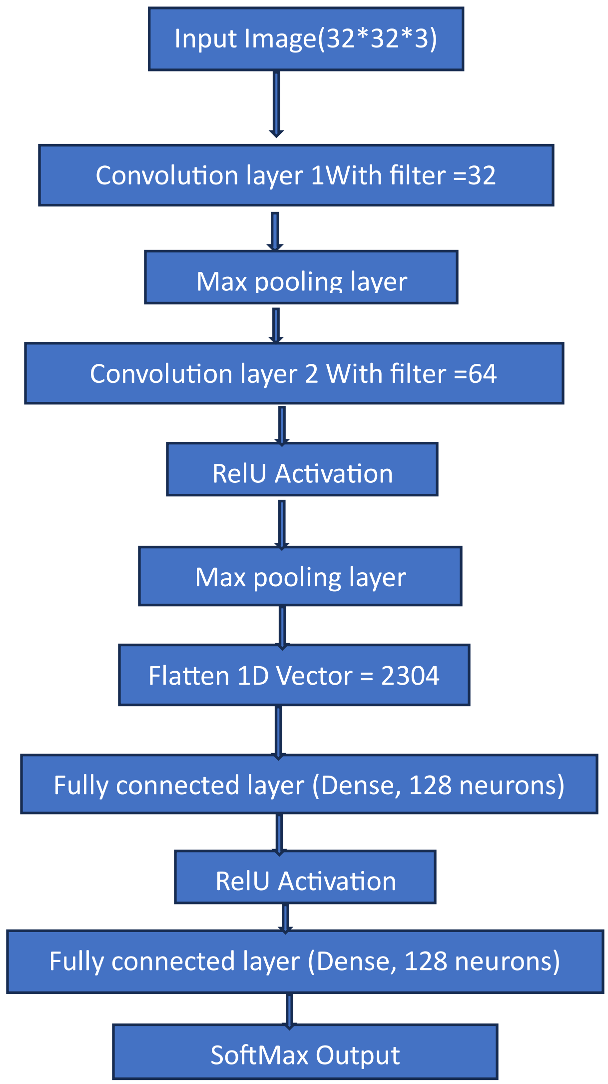

Figure 1: The Architecture of CNN

Figure1 illustrates the Standard architecture of CNN. The input layer accepts raw data, such as photos. For example, in image recognition, the input could be a two-dimensional image represented as a matrix of pixel values (width x height x channels, where channels represent RGB for colored images). Consider a 32x32x3 image (RGB). Convolutional layer This is the

fundamental component of a CNN. It takes the incoming data and applies a filter (or kernel) to extract pertinent features like edges, textures, or other basic patterns. To find various patterns, one can use multiple filters. Convolution is the process that moves the filter across the image and calculates the dot product at each point. Activation maps, or feature maps, have a depth (number of channels) equal to the number of filters as the output.
To add non-linearity, an activation function is applied element-by-element after the convolutional layer. The ReLU, or Rectified Linear Unit, is the most widely utilized activation function in CNNs. It preserves all positive values while replacing all negative values with zero. The result is that The identical feature map after applying non-linear activation.
By decreasing the feature maps' spatial dimensions (width and height), the pooling layer improves computing efficiency and lowers the possibility of overfitting. The maximum value from a narrow window (such as 2x2) is chosen via max pooling.The maximum (or average) value in the window that the pooling layer slides over the input is taken. The output is Feature maps that have been down-sampled to have less width and height.
The output is typically flattened into a 1D vector and routed through fully connected (dense) layers following numerous convolution and pooling layers. This layer completes the final classification operation and links all inputs and outputs. It applies an activation function (such as ReLU or SoftMax) and multiplies the weight matrix by the flattened input matrix. A collection of class scores (for classification tasks) is the output.
CNN SoftMax layer, which transforms the output into probability distributions across the target classes, is frequently the last layer used for classification tasks. It generates probabilities that add up to 1 by applying the SoftMax function to the output of the fully linked layer. A probability distribution among the various classes is the output.

3. Related works

Due to its rich diacritical marks, varied letter shapes, and cursive style, Arabic calligraphy is especially intricate. Numerous studies have suggested methods for recognizing Arabic handwritten text in order to enhance its recognition performance. Character image modeling and classification are accomplished by utilizing the ResNet18 architecture in a deep ensemble architecture created and developed by Alyahya [17]. To distinguish detached transcribed Arabic letters consequently, we explicitly changed ResN.et-18 by including a dropout layer after each convolutional layer and integrating it into different troupe models. The Arabic Manually written Character Dataset (AHCD) was utilized as the benchmark for preparing and evaluating each of the proposed models in the preliminaries. The creators being referred to [5] They give a technique in light of the AHCD dataset that perceives Arabic letters and characters utilizing support vector machines (SVM) and profound convolution brain organizations (DCNN). The trouble of Arabic written by hand character acknowledgment is tended to in this work by using both dropout SVM and completely associated DCNN to evaluate the likeness between the info layouts and the pre-put away formats. AL Jarrah made the idea for convolutional brain networks in [18]. to distinguish written by hand characters. To prepare the characterization model, 16,800 pictures of transcribed Arabic characters in various shapes were used. A streamlining, regularization, and dropout strategies based profound learning (DL) framework utilizes two convolutional brain organization (CNN) structures, called HMB1 and HMB2. In [19], this framework is presented. Future exploration on Arabic manually written text can involve this framework as a kind of perspective. Various execution measurements were determined, including as F1, review, exactness, and accuracy. Sixteen tests were led on the technique portrayed here utilizing HMBD and two other datasets, AIA9k and CMATER [19]. The writers in [1] offer a convolutional brain organization (CNN) based model for programmed penmanship recognizable proof. To prepare our model, we utilize Hijja and the Arabic Transcribed Character Dataset (AHCD). The outcomes show that our model's presentation seems promising. Alheraki referred to in [11]. A convolutional brain organization (CNN) model has been recommended that is equipped for perceiving youngsters' penmanship. Table 1. gives an outline of the inspected writing on programmed penmanship acknowledgment.

Past writing's models for Arabic penmanship acknowledgment have just been prepared on grown-up penmanship. Kids ought to have some work on composition the hard way. With the rising use and openness to innovation in kids' lives, penmanship acknowledgment is turning into a fundamental element of numerous applications. The first three literatures used the AHCD Dataset that is Arabic dataset for adult and CNN models that achieve high accuracy on this subject of image classification, the fourth work use the HMBD dataset this English dataset for adult too that use CNN for classification task. The fifth and sixth literature used the HIJJA dataset, it is Arabic data set for children and they use CNN model for classification but they achieve accuracy (88 - 91) %.CNN model used because it is excellent for handwritten recognition and classification image. It achieves accurate results.

Table 1: Summary of Related Work

References	Year	Model	Dataset	Type	size	Accuracy
Alyahya [17]	2020	CNN	AHCD	Chars	16,800	98.3%
Shams [5]	2020	DCNN +SVM	AHCD	Chars	16,800	95.07%
AlJarrah [18]	2021	CNN	AHCD	Chars	16,800	97.2%
Balaha [19]	2021	CNN	HMBD	Chars	54,115	98.4%
Altwaijry [1]	2021	CNN	HIJJA	Chars	47,43	88%
Alheraki [15]	2023	CNN	HIJJA	Char	47,434	91%

4. Dataset

The Hijja dataset was our major dataset that we used to train our models. Altwaijry [1]. created the Hijja, a new set of single Arabic letters that is open to everyone. Kids in Riyadh, Saudi Arabia, between the ages of 7 and 12 who speak Arabic wrote it. The dataset has 108 classes that show how to place at the start, middle, and end of a word, as well as when the letter is on its own, each Arabic letter is written in four distinct ways. There is a total of 47,434 images in the collection. There are 29 files in the dataset. Each file has pictures of one Arabic letter, plus one file with pictures of the Hamza**.** Figure 2. illustrate some images of Hijja dataset.

Figure 2: Sample of the Hijja dataset [1]

5. Proposed Deep Learning Models

The effect of several CNN models on the ensemble learning framework is consistently better than that of a single CNN model because ensemble learning can efficiently absorb the benefits of many CNN models. The proposed method suggests three CNN deep learning models. The original CNN model has three convolution layers. The third instance of the model is a CNN with BI-LSTM, and the second model included four convolution layers. In Section 5.1, the specifics of the ensemble CNNs are explained. The primary input is displayed in Figure 3.

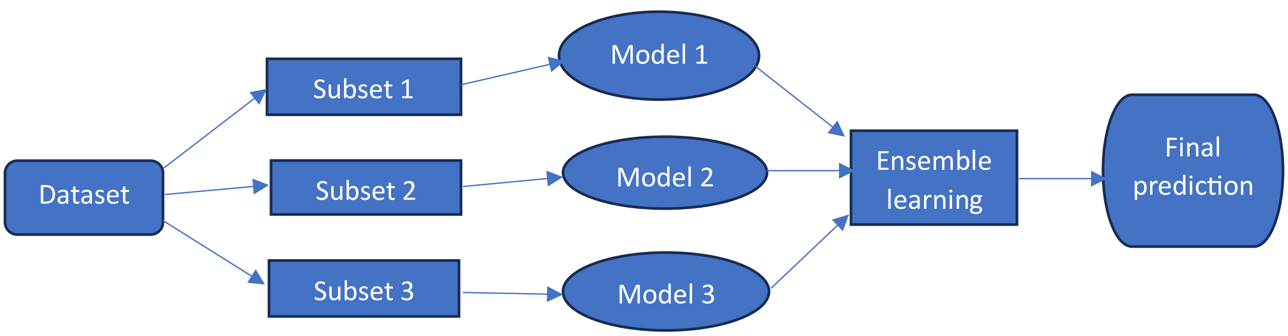

Figure3: Our proposed system

5.1 Model 1

The first model is a CNN that contain three Convolutional layers with filters (32, 64, and 128 filters), Batch Normalization is used because enhances deep learning models' training speed, stability, and generalization, enabling quicker convergence and improved performance. MaxPooling layers are used, Flattening layer, Dense layers (256, 128 neurons) and Output layer with SoftMax. compile the model and set classification cross-entropy's loss function, Train model on the training set and Apply early stopping based on validation accuracy.

The second model is a CNN with Four Convolutional layers (32, 64, and 128 filters), Batch Normalization is used. MaxPooling layers, Flattening layer, Dense layers (256, 128 neurons) and Output layer with SoftMax**.** compile the model and set the cross-entropy categorical loss function. Educate the model using the training data and apply early stopping based on testing accuracy.

The third Model is CNN contain Three Convolutional layers (32, 64, and 128 filters), Batch Normalization is used. MaxPooling layers, Flattening layer. Reshape the image to prepare data for LSTM processing. **The LSTM Layer is** Bidirectional LSTM with 128 units and dropout (0.25).

Dense layers is used (256, 128 neurons). And Output layer with SoftMax compile the model and set the loss function to categorical cross-entropy. Train model on the training set and apply early stopping based on validation accuracy.

5.2 Ensemble learning

ensemble learning is used for the three models by soft voting to increase the accuracy. Define the Architectures of three models. Train Models Independently, train Model1, Model2, and Model3 using the training dataset. Implement Ensemble Predictions, predict each model on the test set, Average the predictions to mitigate individual model biases use the ensemble predictions for final classification and Evaluate Ensemble Model using performance measurement.

6. Experimental Setup

We use the following metric to assess the performance of the proposed model:

The number of accurate predictions your model made throughout the whole test dataset is its accuracy (A): TP + TN + FN + FP equals A.

$$\text{Accuracy}= \frac{TP+TN}{TP + TN+ FP+FN} \quad (1)$$

Recall (R) is the fraction of correctly identified photos over the total number of images in the class: R equals TP + FN.

$$\text{Recall(R)} = \frac{TP}{TP + FN.} \quad (2)$$

Precision (P) is the proportion of correctly classified photos to the total number of images classified.

$$\text{Precision(P)} = \frac{TP}{TP + FP.} \quad (3)$$

F1 is a combination of recall and precision metrics.

$$\text{F1} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

7. Results for the 29Classes

In this section the performance of the suggested model is evaluated, the evaluation prosses is done to show the proposed models could recognize all the different ways. Arabic handles letters that are linked and letters that are not connected. the Hijja dataset was used to train the models. The accuracy in our model is higher than Altwaijryet.al [1] accuracy as we showed in Table 2.

Table 2. overview of the CNN models' performance and comparison using the Hijaa dataset.

	Altwaijryet model [1]			Our Model		
Char	precision	recall	f1-score	precision	recall	f1-score
أ	**0.99**	0.98	0.96	0.9	0.98	**0.98**
ب	0.92	0.97	0.94	**0.95**	0.97	**0.96**
ت	0.89	0.89	0.89	**0.92**	**0.92**	**0.92**
ث	0.90	0.87	0.88	**0.95**	**0.94**	**0.94**
ج	0.89	0.92	0.91	**0.96**	**0.94**	**0.95**
ح	0.85	0.78	0.81	**0.89**	**0.89**	**0.89**
خ	0.88	0.84	0.86	**0.94**	**0.89**	**0.92**
د	**0.82**	0.74	0.78	0.80	**0.85**	**0.83**
ذ	0.74	0.74	0.74	**0.81**	**0.78**	**0.80**
ر	0.83	0.93	0.88	**0.92**	**0.94**	**0.93**
ز	0.87	0.88	0.88	**0.93**	**0.91**	**0.92**
س	0.93	0.93	0.93	0.93	**0.96**	**0.94**
ش	0.90	0.93	0.92	**0.97**	0.93	**0.95**
ص	0.84	0.88	0.86	**0.89**	**0.93**	**0.91**
ض	0.84	0.86	0.85	**0.92**	**0.90**	**0.91**
ط	0.92	0.92	0.92	**0.93**	**0.95**	**0.94**

ظ	0.93	0.92	0.93	**0.97**	**0.93**	**0.95**
ع	0.79	0.79	0.79	**0.84**	**0.88**	**0.86**
غ	**0.90**	0.79	0.84	0.88	**0.89**	**0.88**
ف	0.74	0.83	0.78	**0.85**	**0.87**	**0.86**
ق	0.88	0.86	0.87	**0.94**	**0.91**	**0.93**
ك	0.87	0.90	0.89	**0.91**	**0.95**	**0.93**
ل	0.91	0.94	0.93	**0.93**	0.94	**0.94**
م	0.89	0.90	0.89	**0.93**	**0.93**	**0.93**
ن	**0.84**	0.82	0.83	0.84	**0.86**	**0.85**
ه	0.86	0.87	0.86	**0.91**	**0.91**	**0.91**
و	0.90	0.89	0.89	**0.94**	**0.94**	**0.94**
ي	0.95	0.92	0.93	**0.97**	**0.95**	**0.96**
ء	0.84	0.81	0.83	**0.91**	**0.87**	**0.89**
accuracy			**0.88**			**0.92**

Tabel 2. enumerate the outcomes and contrast the CNN models using the HIJJA dataset. For Altwaijryet model [1] and Our Model. our model outperforms the Altwaijryet model [1] in 25 chars except the precision in char (ن-غ-د-أ), our model achieves higher than Altwaijryet model [1] in precision, recall, f1-score and accuracy for this table on testing data is 92% in our model and 88% in Altwaijryet model [1].

8. Conclusion and future work

Deep Learning models were employed to address the issue. of feature extraction and pick the best predictor for reading handwritten Arabic characters. Most of the time, the goal of Convolutional Neural Networks is to extract the most salient characteristics from each of its several layers. The issue of selecting the optimal feature for handwritten Arabic character recognition is resolved in this way. In the future, to increase performance, many datasets may be used to train the developed deep learning models. They may also be trained to recognize associated words and letters. These models can be used in writing and dictation applications. And it would be helpful to look into the different machine learning models that work well with this dataset, like MLP, SVM, and auto-encoders. Any programmer that needs to be able to read Arabic handwriting from kids can use our model to do so. In addition, it can recognize grown-up Arabic penmanship. It very well may be utilized as a component of a framework that splits up Arabic letters that are connected to track down full words. In an exchange getting the hang of setting, the model could be utilized to peruse characters from different dialects. We want to use our neural network in a kids' app that teaches them how to spell Arabic words.

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المستخلص: استخدمنا في هذا المشروع نماذج التعلم العميق لحل مشكلة استخراج الميزات واختيار أفضل مؤشر لقراءة الأحرف العربية المكتوبة بخط اليد. في معظم الأحيان، يتم تصميم الشبكات العصبية التلافيفية للتعرف على أهم الميزات من مستوياتها المتعددة. يؤدي هذا إلى التخلص من مشكلة اختيار أفضل ميزة للتعرف على الحروف العربية المكتوبة بخط اليد
في المستقبل، لزيادة الأداء، قد يتم تدريب نماذج التعلم العميق التي تم إنشاؤها على مجموعة متنوعة من مجموعات البيانات. وقد يتم تعليمهم أيضًا كيفية التعرف على الكلمات والحروف المرتبطة. يمكن لتطبيقات الكتابة والإملاء الاستفادة من هذه النماذج .
سيكون من المفيد النظر في نماذج التعلم الآلي المختلفة التي تعمل بشكل جيد مع مجموعة البيانات هذه وأجهزة التشفير اليمكن لأي مبرمج يحتاج إلى أن يكون قادرًا على قراءة الكتابة اليدوية باللغة العربية من الأطفال استخدام نموذجنا للقيام بذلك. بالإضافة إلى ذلك، يمكنه التعرف على الكتابة اليدوية باللغة العربية للبالغين. ويمكن استخدامه كجزء من نظام يقوم بتفكيك الحروف العربية المرتبطة للعثور على الكلمات الكاملة. في بيئة تعلم النقل، يمكن استخدام النموذج لقراءة الأحرف من اللغات الأخرى. نريد استخدام شبكتنا العصبية في تطبيق للأطفال يعلمهم كيفية تهجئة الكلمات العربية

الكلمات المفتاحية: الشبكة العصبية التلافيفية, التعرف على الكتابة اليدوية, العربية, استخراج الميزات

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