Recognizing Handwritten Arabic Characters Using Deep Learning Techniques in Educational Platforms

التعرف على الحروف العربية المكتوبة بخط اليد باستخدام تقنيات التعلم العميق في المنصات التعليمية

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Abstract:

Handwriting is a fascinating aspect of human communication that embodies the complex interaction of cognitive, motor abilities, and cultural expression. Handwriting has been an enduring tribute to human inventiveness and ability, dating back to the first writings on cave walls and the exquisite calligraphy of medieval manuscripts. Handwriting, in addition to its aesthetic appeal and historical value, displays God's immense power in His creation, as seen by the exquisite design of the human hand and brain. The researchers focus their work on recognizing several linguistic handwritings. One of the languages that is still difficult for the researcher to recognize is Arabic handwriting because of a number of its characteristics, such as connectivity, the presence of dots, and diacritical marks. This paper presents the development of a system based on the recognition of Arabic handwritten characters in education platforms using three deep learning-based models. The suggested models, a pre-trained CNN (VGG-16, MobileNet) and a convolutional neural network (CNN), were trained on the AHCD dataset, which was created by 60 authors ranging in age from 19 to 40. The experiment's findings demonstrated CNN was better than the others, with 96.4% accuracy on the test set, compared to 95% accuracy for MobileNet and 90% accuracy for VGG-16.

Keywords:

Handwritten character recognition, deep learning, convolutional neural network, VGG-16, MobileNet

1. INTRODUCTION:

Writing with hands is a distinctive trait that is developed individually for each individual. Everyone has a different style of handwriting, and there is little chance that the same letters have anything in common . **(Sudana.O. , et al (2020), 1934-1941) .** The concept of recognition encompasses a wide range of topics, including face, image, fingerprint, character, and number recognition, etc **(El-Sawy, A., El-Bakry, H., & Loey, M. ,2016)**. Automatic handwriting recognition is crucial for various applications in different disciplines. It is a difficult subject that has attracted a great deal of concentration during the last three centuries. Handwriting recognition studies have been concentrated on languages from Latin; less study has been conducted for Arabic, and significant challenges remain unresolved**. Yaagoup, K. M. M., & Mus, M. ,2020,10.**

During the last several years Deep learning (DL) originated as a part of machine learning algorithms and has since become commonly used by academics. It has been used in a variety of fields, such as processing natural languages and vision in computers **(Gogate, M., Adeel, A., & Hussain, A. (2017a) , (2017b).**

DL approaches have been successfully used for handwritten recognition of Arabic and Latin text, attaining the most modern achievement in the field **(Ahmed, R., et al.. 2020) .**Many approaches have been utilized for investigating the topic of handwriting recognition, such as support vector machines (SVMs), K-nearest neighbors (KNNs), and neural networks (NNs). **(Ahmad, I., & Fink, G. A. 2016. - (Baldominos, A., Saez, Y., & Isasi, P. 2019. 3169 - (Ramzan, M. et al., (2018 9).** These algorithms enhance handwritten letters even more. These models remain constrained and cannot compete with Convolutional Neural Networks (CNNs) (**Albattah, W., & Albahli, S. 2022, 10155**).

Furthermore, handwriting recognition technology has been incorporated into various current gadgets and applications, including smartphones, tablets, electronic tablets, interactive whiteboards, and education platforms. These technologies allow people to easily migrate between analogy and digital modes of communication by digitizing handwritten notes, papers, and comments, conserving the timeless art of handwriting while using modern technology's revolutionary potential.

With the increasing trend of e-learning, we have observed the lack of comprehensive tools for recognizing handwritten Arabic alphabets. And so this proposed idea aims to develop an application for recognizing handwritten Arabic alphabets. This application will be used on educational platforms to recognize and evaluate the handwritten Arabic alphabets. By integrating handwriting recognition into educational platforms, students can practice writing Arabic letters anytime and anywhere, using their smartphones, tablets, or computers. This flexibility enables students to reinforce their Arabic handwriting skills outside of the classroom and at their own convenience.

In this work, CNN, a prominent deep learning approach, was utilized to recognize handwriting characters in Arabic on education platforms. CNN and other DL-based algorithms are capable of autonomously learning the representative characteristics of pictures without the need for human interaction. The CNN framework's functionality mirrors the functioning of the human brain. Humans discover and distinguish items with their own eyes by viewing thousands of object pictures . (**Alwaqfi, Y. M., Mohamad, M., & Al-Taani, A. T. 2022, 14(1)** CNN uses the same patterns to see and recognize things **Albahli, S., Nawaz, M., Javed, A., & Irtaza, A. 2021, 8509-8523**. Despite all of the progress made, significant problems remain, as does the need for novel approaches to overcome these constraints .**Alwaqfi, Y. M., Mohamad, M., & Al-Taani, A. T. 2022, 14.**

The paper summarizes relevant work in this area of deep learning for handwriting recognition, as well as the suggested models for deep learning. It also covers the proposed system phases, experiments, results, and debate, and concludes with future work.

2. RELATED WORKS:

This part discusses several machines and deep learning techniques for tackling the characters' handwriting recognition problems. Recently, the recognition of handwritten characters has drawn more attention from researchers.

In **2017, El-Sawy et al**. They trained and tested a CNN on the AHCD assortment of 16,800 Arabic letters typed by hand. Their approach includes normalization, dropout, and two convolutional layers. Based on the test data, the proposed CNN achieved 94.9% accuracy.

. In **2017 , Younis et al**. He introduces a deep neural network that minimizes overfitting by combining convolutional neural network models with regulation parameters such as batches of normalization for handwritten Arabic character detection. The AIA9k and Arabic Handwritten Characters Dataset (AHCD) sets were classified by him using Deep CNN, and the results showed an accuracy of classification of 94.8% and 97.6%, respectively.

.In 2018 , Latif et al.[15] created CNN for recognition of handwriting that was a combination of Persian, Devanagari, Eastern Arabic, Urdu, and Western Arabic. The entered picture is 28 x 28 pixels in size. It is then divided into two convolutional layers, each of which is subjected to a max-pooling process. The combined multilanguage database has an overall accuracy rate of 99.26%. For every language, the average accuracy is about 99%.

In **2019, Almansari & Hashim** suggested a model of a deep-learning framework employing CNN and multiple-layer (MLP) neural networks. The Arabic Handwritten Characters Dataset (AHCD), a public database, is the subject of this project's performance analysis. On the other hand, the test accuracy for this database trained with the CNN model is 95.27%, but the test accuracy for the MLP model trained with it is 72.08%.

In **2020, Shams et al** The authors suggested an approach to powerful Handwritten Arabic characters extracted and classified using a deep convolutional neural network framework. They use a dropout support vector machine to classify and find the absent characteristics that are not correctly categorized by DCNN. Furthermore, the suggested approach made an effort to determine how similar the input and stored characters were. It recognized multi-stroke characters using a clustering technique called k-means. The suggested technique has a correct classification precision of 95.07% and a minimal error classification rate of 4.93%.

In **2021, Altwaijry & Al-Turaiki** A brand-new collection of Arabic letters created solely by children in the 7–12 age range, referred to as Hajj, was presented. This data set has 47,434 letters in total, written by 591 authors. They also present an automated recognition of handwriting based on convolutional neural networks (CNNs). The model is trained using two datasets: Hijja and AHCD. The model performs better than earlier models in the research, according to the results, which show accuracy rates of 97% and 88% on the AHCD and Hijja datasets, respectively.

In **2021, Ullah & Jamjoom** proposed a model of a (CNN) for handwritten Arabic letter recognition. Techniques like batch normalization and dropout are used to regularize the model. The performance of the proposed model was assessed using a range of measures on a widely used, publicly available (AHCD). According to the experimental results, which reached 96.78%, the proposed model fits the data rather well in terms of improved accuracy results.

Many previous studies have focused on developing handwriting recognition systems that can facilitate language learning, literacy education, and personalized feedback in educational settings. This alignment with educational goals underscores the potential relevance of these technologies in education platforms. In the current study, we will build an interface similar to educational platforms through which handwritten characters can be recognized.

3. Material and Methods:

3.1.Proposed Deep Learning Models:

CNNs have proven to be extremely effective at identifying numerals and characters, while transfer learning models (such as the VGG16 model and mobilenet) have demonstrated high accuracy in recognizing Arabic characters; hence, our dataset was trained using these models.

3.1.1. Convolutional Neural Network Model

CNNs have been widely utilized to recognize handwritten characters. CNNs have shown to be the most effective model in terms of performance for many pattern categorization challenges **(Ahamed, P., et al, 2020 , 5445-5457**) CNNs are multi-layered hierarchical models made up of convolution, pooling, and fully connected layers (FCLs).

- **Convolutional Layer (conv layer):**

The convolution layer is a vital part of the CNN framework for feature extraction. It often consists of a combination of both nonlinear and linear methods, specifically the convolution operation and the activation function **(Yamashita, R., et al , 2018, 611-629)** A convolutional layer is made up of K filters (also called kernels). Every filter functions as a feature identifier., recognizing characteristics, For example, corners, edges, or ends .(**Altwaijry, N., & Al-Turaiki, I. 2021 , 7**)

- **Pooling layer:**

CNN can have local or global subsampling layers that merge the results of one layer's neurons into a single neuron in the next layer. Its principal role is to lower the dimension of space of the representation, thereby reducing the number of model parameters and calculations. It not only expedites the mathematical process but also prevents overfitting (**Dhillon, A., & Verma, G. K. , 2020, 85-112)**.This is a popular pooling approach. The max pooling is accomplished by using a 2x2 pooling window with a stride of 2 to choose the maximum element of a 2x2 area of the input feature map. This method aggressively decreases the spatial dimension of the feature maps while also condensing the derived feature information (**Qin, Z., Yu, F., Liu, C., & Chen, X. , 2018)**

- **Fully connected layers:**

The last layers of a CNN are frequently fully linked. These layers computationally add a weighted total of the preceding layer's attributes, showing an exact mixture of "ingredients" required to get a given intended final product. In the case of a completely linked layer, every component of the preceding layer's attributes is employed in the computation of each element of each output feature **(Hijazi, S., Kumar, R., & Rowen, C. 2015. 9)**

Fig. 1 depicts the proposed CNN model for feature extraction, which consists of eleven layers: five convolution layers, five max-pooling layers, and one fully connected layer. Between the convolutional and fully connected layers, there were also pooling and activation layers. To speed up the training process, the hidden layers used a non-linear function. ReLUn (**Ullah, Z., & Jamjoom, M. 2022, 8)** which is specified in Equation.

$$ReLu(z)=max(0,z).$$

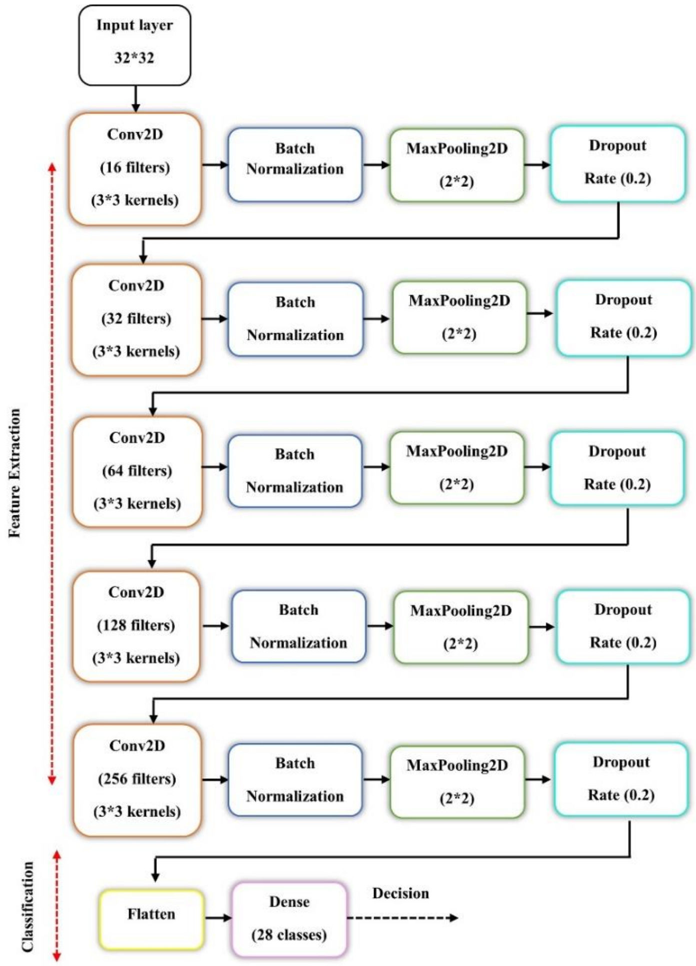


Fig1. Architecture of the CNN model

3.1.2. VGG-16 model:

Model VGG-16 is ranked inside the top five models in terms of picture categorization accuracy. VGG16 is a network that is intended to increase the volume of data and categorize the incoming picture. The network is classified as a "deep network" since it has 16 layers with different weights. Weight layers are only convolutional and fully connected because they include parameters that can be learned **(Bin Durayhim, A., et al ,2023., 1692)**

The VGG-16 pre-trained model was utilized, and a portion of it was retrained using the AHCD. The data size was processed as follows: The AHCD picture was 32×32 pixels in size, so it was scaled to 224×224 to fit the VGG-16 model, which had been trained on data of a similar size.

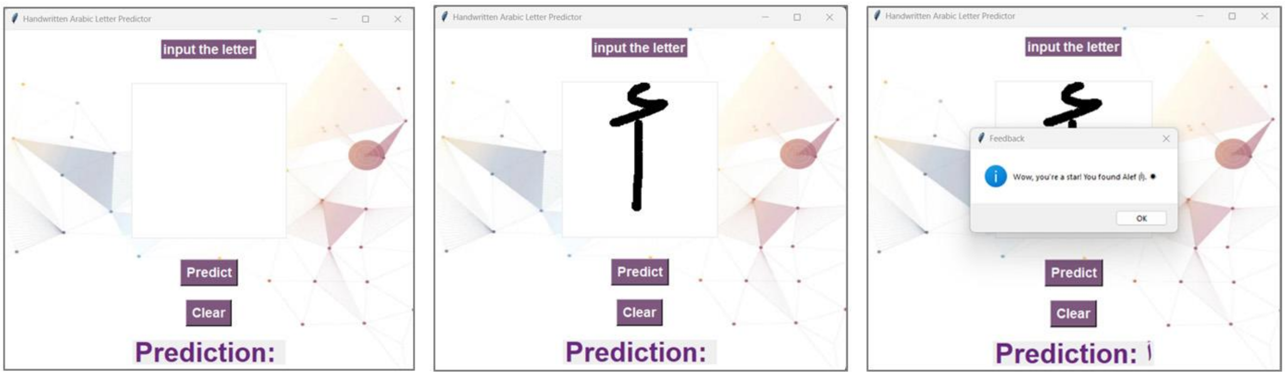
3.1.3. MobileNet model:

MobileNet is an architectural paradigm for mobile vision and image categorization that is built on CNN. While there are other models, MobileNet stands out due to its low processing resource requirements for applying or executing transfer learning. Because of this, it is perfect for low-processing-efficiency PCs, mobile devices, and embedded systems without compromising significant accuracy. Because web browsers have restrictions about computing, visual processing, and storage, it works best with them.

The MobileNet architecture was primarily utilized for feature extraction. This means that only the convolutional layers of MobileNet were used to capture the distinctive features, while the fully connected layers were modified and varied for optimal classification performance using the AHCD dataset (**Naufal, M. F., & Siswantoro, M. Z. F. N. 2023)**. The data size was processed as follows: because the AHCD picture was 32×32 pixels in size, it was scaled to 224×224 to fit the MobileNet model, which was trained on data of a similar size.

3.2. The Proposed System Stages

The purpose of this research is to design a system based on handwriting Arabic character recognition when using education platforms. Fig 2 shows the user interface. It consists of a whiteboard on which the letter is written, a prediction button that when pressed, the letter is recognized and demonstrated in its digital form, and an erase button to erase what has been written on the whiteboard. The proposed system consists of six major stages: input data, splitting data, pre-processing, feature extraction, classification, and evaluation. Fig 3 shows the outlines of the main phases of the proposed system.



(a) (b) (c)

Fig 2: the user interface.

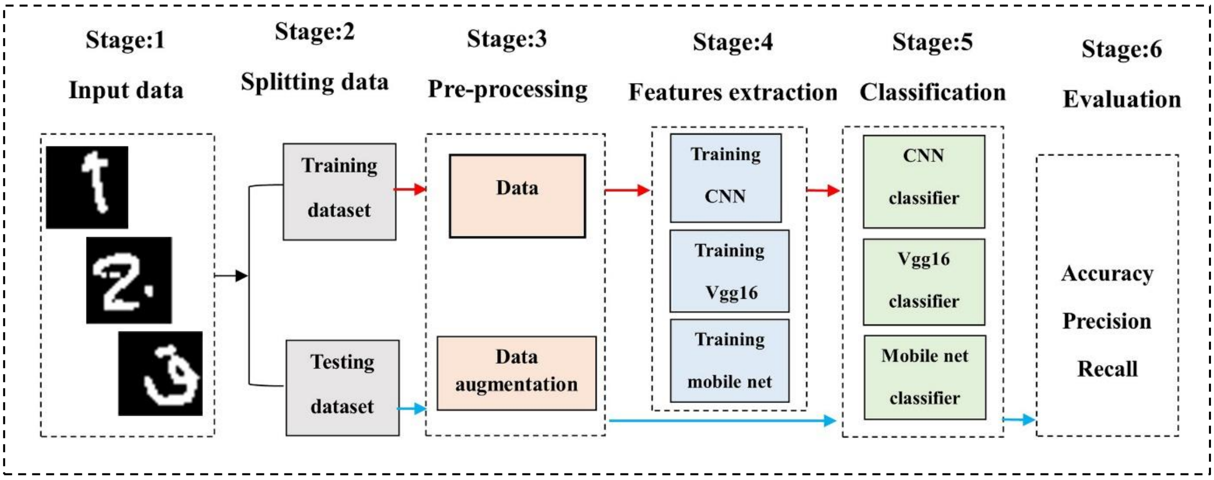


Fig 3: outlines the main phases of the proposed system.

3.2.1. Stage1: Input data:

This research makes use of a free, open-to-everyone collection of datasets of Arabic handwritten characters (AHCD). **(Alwagdani, M. S., & Jaha, E. S. 2023., 6774).** It includes 28 classes for separated (unconnected) Arabic characters and 16,800 32x32 character examples authored by 60 people aged 19 to 40. Participants wrote all 28 characters ten times, starting with "Alf" (أ) and finishing with "Yaa" (ي). Fig 4 illustrates an example of the AHCD dataset.

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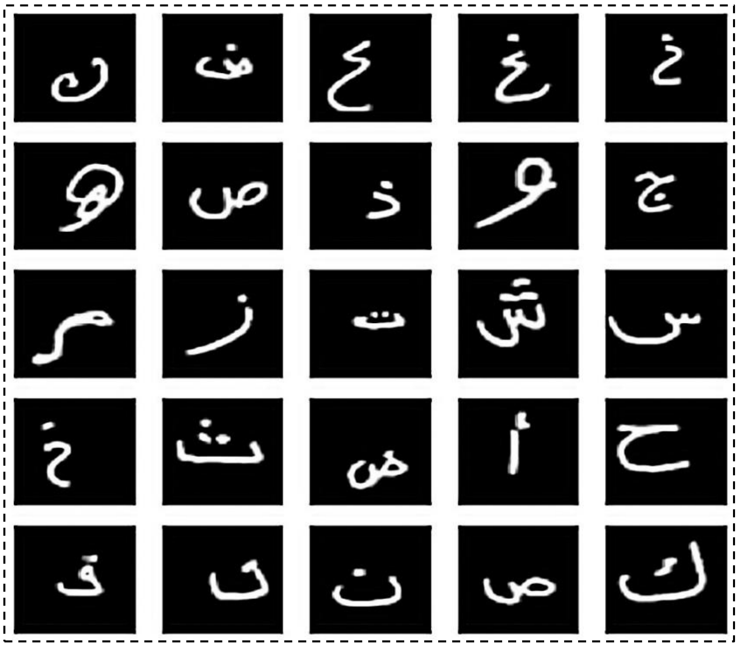

Fig 4: Sample of the AHCD.

3.2.2. Stage 2: Splitting data:

The AHCD was split into two parts: 80% to be trained with 13,440 samples (480 per class) and 20% to be tested with 3360 samples. Table 1: Overview of the Divided Datasets

Table 1: Description of the Splitting datasets

Splitting data
Our data (AHCD) creation of 28 classes where each class contains of: 80% of images for training. 20% of images for testing.

3.2.3. Stage 3: Pre-processing:

The data size of 32×32 was used with the convolutional neural network, but when using the pre-trained models, the data size was changed to 224×244, as this is the size that was used when training the models.

This study uses data augmentation to extend the dataset and increase the number of data points and variations without collecting new data. This data augmentation addresses overfitting from the start (the training phase) and enhances deep learning model generalization. As a consequence, it is anticipated that more information may be recovered from the initial data collection by easy approaches **(Alyahya, H., Ismail, M. M. B., & Al-Salman, A. 2020, 68)**

3.2.4. Stage4: Features extraction:

Feature extraction is a method that transforms raw text and picture data into a vector of features. The many feature approaches are divided into structural features, statistical features, and feature space transformations. structural elements like lines, strokes, and diacritical markings. These features are fast and low-complex, as are statistical features such as the number of branches, loops, segments, and diacritical markings. Pixel representations are transformed into more compact forms with fewer feature vector dimensionalities through feature space transformations such as principal component analysis (PCA), Walsh Hadamard transforms, Fourier transforms, wavelets, Hough transform, Gabor transform, rapid transform, and Karhunen load expression **(Ahmed, R., , et al , 2021, 340)**

In this section, the initial input scales will be preserved for each convolutional layer in this model by using the "same" padding option. The following is how the model description is given: starting with the first convolutional layer, the convolutional feature extraction procedure, which has 16 feature maps with a ReLU activation function of the neurons and a kernel size of (3 × 3) pixels for training. According to the database types utilized in the tests and CNN models., it can extract characteristics from a raw picture of 32 ×

32 or 224 × 224 dimensions in either grayscale, RGB, or RGBA format. The convolutional layers were followed by a layer of batch normalization, which is the second layer. It employed the mean and variance to constrain the output of the convolutional layers away from the area of saturation. The third layer employed for lowering the dimensionality of the feature maps was the maximum sub-sampling or pooling layer, with a pool size of 2 × 2. The following layer employed the dropout or regularization layer to lessen overfitting (**Ahmed, R., , et al , 2021, 340).**

3.2.5. Stage 5: Classification:

A classifier's performance is dependent on the quality of the extracted features. The classification stage is the recognition system's decision-making process. Its function is to identify and assign an input feature with a class label or membership scores for numbers, letters, or words to the appropriate relevant specified classes. This process transforms the texts into images in a form that is comprehensible to computers. Several classifiers are used to create the categories of various recognition methodologies found in the literature, like matching templates and the statistical, hybrid, structural, and stochastic approaches. Arabic handwriting recognition has been achieved by the use of many classifiers, including ANN, SVM, HMM, and k-nearest neighbors (kNN). This phase of recognition systems is accomplished by first choosing an appropriate recognition technique, followed by the use of two processes: the testing process which makes use of the previously created models, and the training process, which uses the retrieved characteristics to train the classifier to create the right models **(Ahmed, R., , et al , 2021, 340. Iqbal, A., & Zafar, A. 2019. Impedovo, , et al. 2019, 576-586)**

Following each of these convolutions, the model's classification layers began with a flattened layer, which turned the two-dimensional feature matrix into a single vector. This vector was then fed into the first fully connected layer, which chose 1024 neurons and the ReLU activation function. After adding the batch normalizing layer, there was a 0.2 dropout. Lastly, the highest level of the design was a second complete connection layer. The configuration was set to reflect the precise number of neurons associated with the Arabic database class labels that were being targeted. In the last layer, a list of probability-like predictions for each class label was obtained using the Softmax activation function **(Ahmed, R., , et al , 2021, 340) .**

3.2.6. Stage 6: evaluation:

The performance of our suggested CNN models was tested using the following metrics:

Recall (*R*) is the percentage of successfully categorized images relative to all images in class x.

$$\mathbf{R} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FN}}$$

Precision (*P*) is the proportion of successfully categorized images relative to all images that have been categorized.

$$\mathbf{P} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FN}}$$

***F*1** is a metric that encompasses recall and precision.

$$\mathbf{F1} = \mathbf{2} * \frac{\mathbf{Precision} * \mathbf{Recall}}{\mathbf{Precision} + \mathbf{Recall}}$$

TP (true positive) is the total number of photos that can be successfully classified as relating to class x., FP (false positive) is the total number of photos that were incorrectly categorized as relating to class X., FN (false negative) is the total number of photos that were wrongly categorized as not relating to class X. and The TN (true negative) is the total number of photos that were mistakenly categorized as relating to class x.

4. Experiments:

Three experiments are conducted to calculate and assess the performance of the proposed system for recognizing handwritten Arabic characters. All experiments have been performed using a Jupyter notebook on a Windows 11-64 machine with an Intel (R) CoreTM i7-11800H CPU, 16 GB of RAM, and NVIDIA GeForce RTX 3050 TI.

Three deep learning models are utilized to recognize Handwritten Arabic Character Data (AHCD) by training and testing them. These models are CNN, VGG-16 and MobileNet. Model performance evaluation involves the analysis of precision, recall metrics, and correlation matrices.

In all three experiments, the AHCD dataset is split into 80% for training and 20% for testing. The Adam optimizer is used to train the proposed models, with a learning rate of 0.001. The models is trained for 100 epochs. In the second and third experiments, the last layer of MobileNet and VGG-16 models is modified to output 28 classes representing Arabic characters.

5. Results and Discussion:

The experimental results showed that there is varying performance among different deep learning models. In the first experiment, the CNN model achieved the highest accuracy of 96.4%, as shown in Table 2. This table shows the CNN performance of recognizing Arabic letters using the precision, recall, and F1-score matrices for every Arabic letter. Fig.5 shows the confusion matrix of the CNN model's classification performance for handwritten Arabic letter recognition.

Table 2: The CNN performance of recognizing Arabic letters

	precision	Recall	F1-score	Support
أ	0.99	1.00	1.00	120
ب	1.00	0.99	1.00	120
ت	0.88	0.96	0.92	120
ث	0.93	0.93	0.93	120
ج	0.98	0.97	0.97	120
ح	0.93	0.98	0.96	120
خ	0.99	0.97	0.98	120
د	0.94	0.97	0.95	120
ذ	0.97	0.93	0.95	120
ر	0.94	0.99	0.96	120
ز	0.95	0.94	0.95	120
س	0.99	0.99	0.99	120
ش	0.99	0.98	0.99	120
ص	0.97	0.97	0.97	120
ض	1.00	0.92	0.96	120
ط	0.95	0.99	0.97	120
ظ	0.99	0.85	0.91	120
ع	0.98	0.98	0.98	120
غ	0.99	0.97	0.98	120
ف	0.91	0.99	0.95	120
ق	0.98	0.96	0.97	120
ك	1.00	0.97	0.99	120
ل	0.99	0.99	0.99	120
م	0.99	0.98	0.99	120
ن	0.99	0.92	0.95	120
ه	0.97	0.95	0.96	120
و	0.93	0.96	0.95	120
ي	0.91	0.99	0.95	120
Accuracy			0.96	3360
Macro avg	0.97	0.96	0.96	3360
Weighted avg	0.97	0.96	0.96	3360

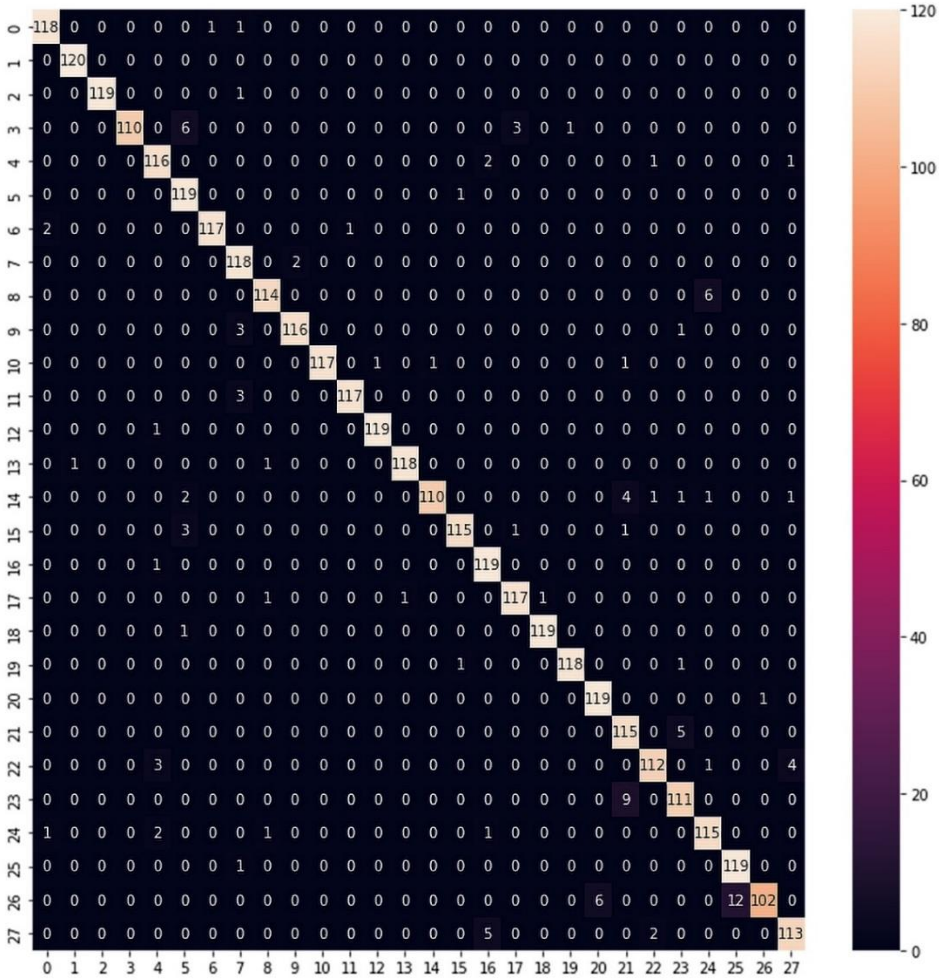

Fig 5: Confusion Matrix of CNN model

In the second experiment, the MobileNet model is achieved impressive results with a performance of 95%, as shown in Table3. The confusion matrix of the MobileNet model's classification performance for handwritten Arabic letter recognition is shown in Fig. 6.

Table 3: The Mobile Net performance of recognizing Arabic letters.

	precision	Recall	F1-score	Support
أ	0.99	1.00	1.00	120
ب	0.99	1.00	1.00	120
ت	0.90	0.93	0.92	120
ث	0.94	0.92	0.93	120
ج	0.98	0.95	0.97	120
ح	0.92	0.97	0.95	120
خ	0.97	0.97	0.97	120
د	0.93	0.93	0.93	120
ذ	0.97	0.85	0.91	120
ر	0.88	0.98	0.93	120
ز	0.91	0.92	0.91	120
س	0.94	0.93	0.94	120
ش	0.99	0.98	0.99	120
ص	0.89	0.94	0.91	120
ض	0.98	0.91	0.94	120
ط	0.91	1.00	0.95	120
ظ	0.99	0.85	0.91	120
ع	0.93	0.95	0.94	120
غ	0.99	0.96	0.97	120
ف	0.89	0.98	0.93	120
ق	0.97	0.88	0.93	120
ك	0.98	0.97	0.98	120
ل	0.98	0.98	0.98	120
م	0.99	1.00	1.00	120
ن	0.95	0.96	0.95	120
ه	0.98	0.95	0.97	120
و	0.94	0.94	0.94	120
ي	0.94	0.97	0.96	120
Accuracy			0.95	3360
Macro avg	0.95	0.95	0.95	3360
Weighted avg	0.95	0.95	0.95	3360

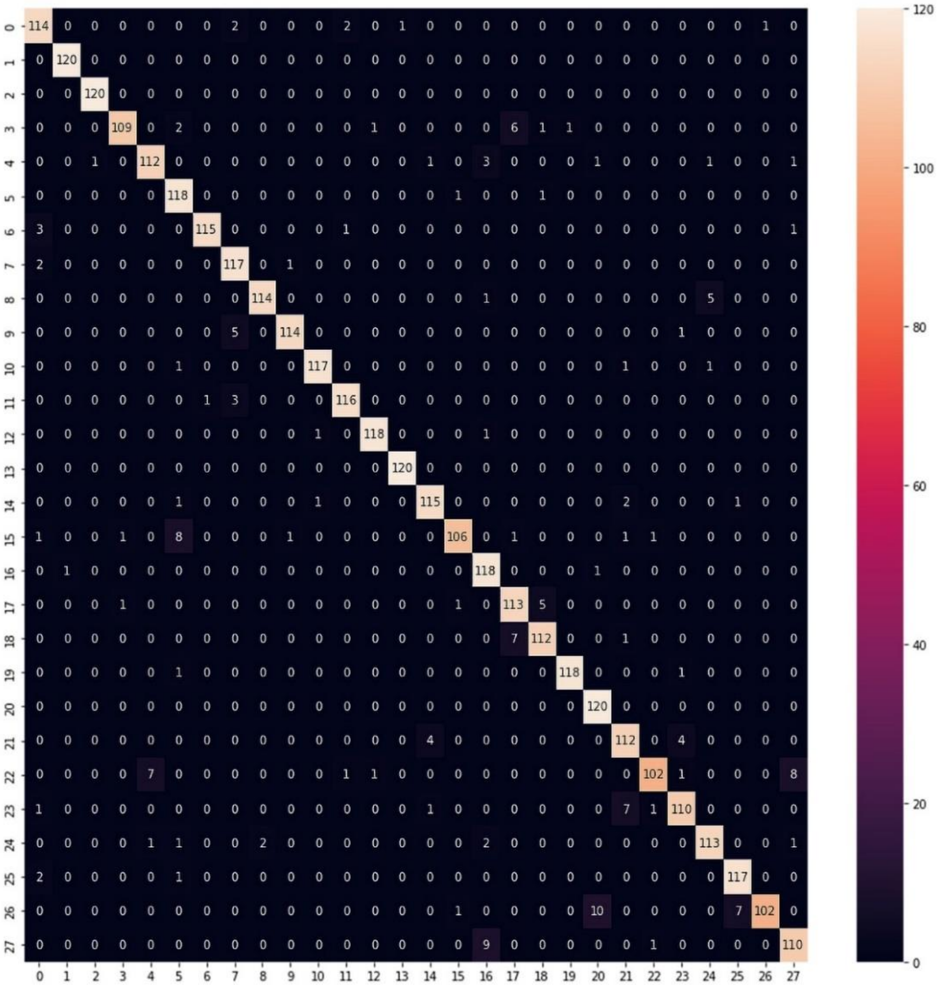

Fig 6: Confusion Matrix of MobileNet model.

In the third experiment, the VGG-16 model achieved 90% accuracy, which is slightly lower than that of both CNN and MobileNet models. Table 4 shows the VGG-16 performance of recognizing Arabic letters. The confusion matrix for handwritten Arabic letter recognition of the VGG-16 model is shown in Fig. 7

Table 4: The VGG-16 performance of recognizing Arabic letters

	precision	recall	F1-score	Support
أ	1.00	0.98	0.99	120
ب	0.99	0.88	0.93	120
ت	0.66	0.88	0.76	120
ث	0.87	0.78	0.82	120
ج	0.82	0.86	0.84	120
ح	0.81	0.87	0.84	120
خ	0.89	0.90	0.90	120
د	0.90	0.92	0.91	120
ذ	0.89	0.84	0.86	120
ر	0.91	0.97	0.94	120
ز	0.94	0.86	0.90	120
س	0.95	0.92	0.93	120
ش	0.95	0.97	0.96	120
ص	0.91	0.96	0.93	120
ض	0.87	0.91	0.89	120
ط	0.85	0.97	0.91	120
ظ	0.92	0.81	0.86	120
ع	0.86	0.88	0.87	120
غ	0.95	0.93	0.94	120
ف	0.87	0.77	0.81	120
ق	0.87	0.80	0.83	120
ك	0.98	0.93	0.96	120
ل	0.98	0.98	0.98	120
م	0.97	0.99	0.98	120
ن	0.86	0.86	0.86	120
ه	0.97	0.96	0.96	120
و	0.90	0.91	0.90	120
ي	0.90	0.88	0.89	120
Accuracy			0.90	3360
Macroavg	0.90	0.90	0.90	3360
Weightedavg	0.90	0.90	0.90	3360

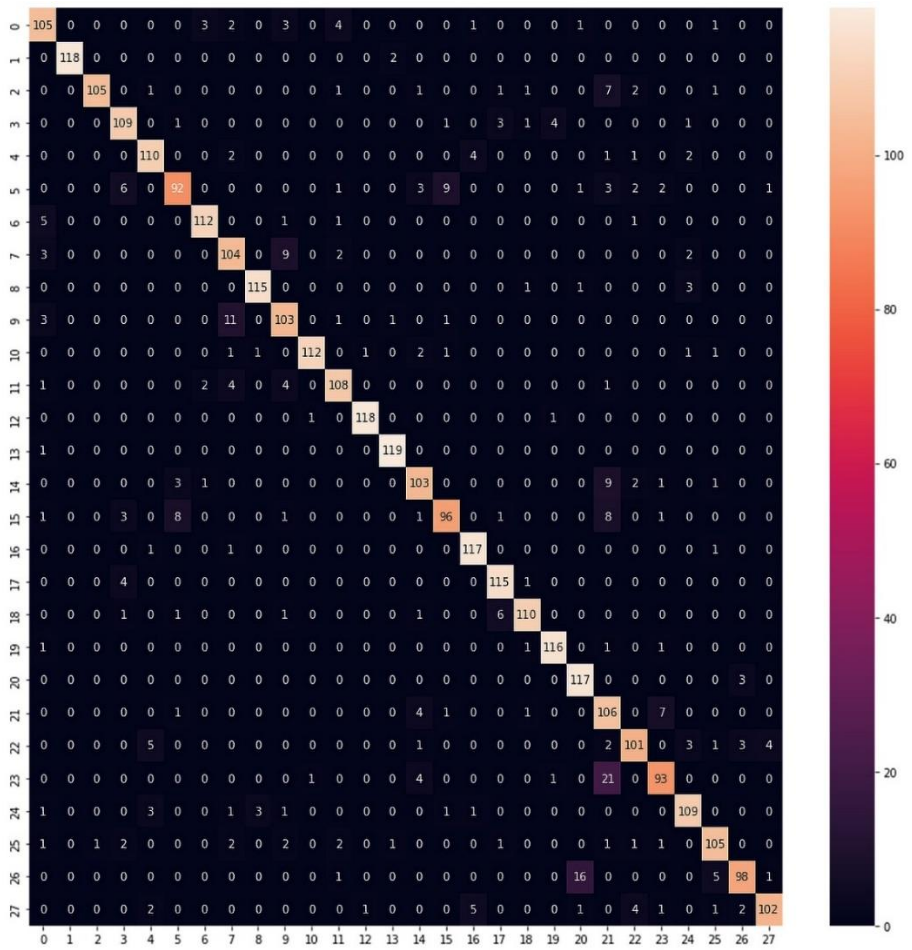

Fig 7: Confusion Matrix of VGG-16 model.

6. CONCLUSIONS:

This paper aims to propose a system for recognizing handwritten Arabic letters while learning on digital educational platforms to improve the learning process and increase interaction between teacher and student. This system aims to recognize the Arabic letters, namely 28 characters from Alef to Yaa. A CNN was designed and fine-tuned, as were a MobileNet and a VGG-16 pre-trained model for Arabic handwriting character recognition. The models were designed to classify the letters into 28 classes based on letter shape. The research was carried out using the Arabic Handwritten Character Dataset (AHCD), the best-performing model among them, namely, the CNN model, and achieved 96.4% accuracy. In the future, the system can be developed to include whole Arabic words and sentences, potentially aiding in handwriting recognition, a task considered among the most challenging in computer vision. Additionally, integrating contextual information, including linguistic rules and syntactic patterns, into the recognition process can enhance the model's understanding of handwritten text. This enhancement can result in improved accuracy, especially in situations where context plays a crucial role in interpretation.

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التعرف على الحروف العربية المكتوبة بخط اليد باستخدام تقنيات التعلم العميق في المنصات التعليمية

الملخص:

الكتابة اليدوية هي جانب رائع من التواصل البشري يجسد التفاعل المعقد للقدرات المعرفية والحركية والتعبير الثقافي. كان خط اليد تكريمًا دائمًا للإبداع والقدرة البشرية، ويعود تاريخه إلى الكتابات الأولى على جدران الكهوف والخط الرائع لمخطوطات العصور الوسطى. يُظهر خط اليد، بالإضافة إلى جاذبيته الجمالية وقيمته التاريخية، قوة الله الهائلة في خلقه، كما يتضح من التصميم الرائع لليد البشرية والدماغ. يركز الباحثون عملهم على التعرف على العديد من خطوط اليد اللغوية. إحدى اللغات التي لا يزال من الصعب على الباحث التعرف عليها هي الكتابة اليدوية العربية بسبب عدد من خصائصها، مثل الاتصال، ووجود النقاط، وعلامات التشكيل. يقدم هذا البحث تطوير نظام يعتمد على التعرف على الحروف العربية المكتوبة بخط اليد في منصات التعليم باستخدام ثلاثة نماذج قائمة على التعلم العميق. تم تدريب النماذج المقترحة، وهي (VGG-16 و MobileNet) المدربة مسبقًا وشبكة عصبية تلافيفية (CNN)، على مجموعة بيانات AHCD، والتي تم إنشاؤها بواسطة ٦٠ مؤلفًا تتراوح أعمارهم بين ١٩ و ٤٠ عامًا. أظهرت نتائج التجربة أن CNN كانت أفضل من غيرها، مع دقة ٩٦,٤٪ في مجموعة الاختبار، مقارنة بدقة ٩٥٪ لـ MobileNet ودقة ٩٠٪ لـ VGG16.

الكلمات المفتاحية:

الحروف المكتوبة بخط اليد - التعلم العميق - الشبكة العصبية التلافيفية - VGG-16- MobileNet