Convolutional Neural Network Adoption for Offline Arabic Handwriting Scripts Identification

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Abstract:

Nowadays most organizations and governments have a huge amount of handwritten documents created via their daily transactions. It became necessary to utilize computer technologies to recognize and read handwritten texts. The domain of Image processing is capable of deciding difficult problems and simplifying human actions by converting handwritten documents into digital formulas. Recognition of Handwritten Arabic alphabets has been broadly studied in previous years. This paper presents a dataset containing Arabic handwriting that can be used to evaluate the performance of an offline writer identification system. Handwritten alphabets are complex to classify because of varied human handwriting techniques, the difference in shape and size of letters, and the angle of writing. A variety of recognition methodologies for handwritten Arabic are conferred here alongside their performance. In this paper, we present-day inclusive analysis for writer identification approaches and provide a taxonomy of database, and feature extraction techniques, as a conventional classification for writer identification. This scheme attained the greatest recognition accuracy of 99.36% based on some feature extraction techniques and a Convolutional Neural Network (CNN) classifier.

Keywords: Handwritten Character Recognition (HCR), Features Extraction, Features Normalization (FN), Recognition, and Convolutional Neural Network (CNN) classifier.

I. Introduction:

In people's lives, Handwriting has always played alarge role. Even afterward the creation of inventive smart devices (as per smartphones, iPads, and so on), persons motionless have a favorite aimed at writing. Consequently, numbers from hand-written documentation around us are growing daily. In a writer Identification scheme, the scheme implements a hunt in a big store data with handwriting sample (dataset) than revenues a probable applicant list from writers. This paper proposed a system for writer identification and recognition of handwritten (Arabic word characters) with segmentation to sub-letters based analysis and Convolutional Neural Network (CNN) Classification to enhance the writer identification accuracy in classification [1]. Most of the studies conducted in the handwriting classification and identification of the author offline are among the most common studies and the emphasis is on the Arabic language [2]. Off-line handwritten char recognition system mentions the manner of recognizing letters in a document that have been scanned since a surface as a sheet of paper and are kept digitalization in grayscale design. Storages of scanned documentation have to be bulky in size and several dispensation presentations as searching for content, editing, and maintenance is either impossible or hard [3] .

In our research work, we focused on character image classification and recognition. We implemented the proposed model based on improved deep learning approaches for Arabic Handwritten Character (scanned Handwritten image) segmentation, classification, and detection. A comparison of the proposed model along with other models demonstrates greater performance against similar. The main contribution of this research work is summarized as follows:

1. The proposed model is applied to classify Handwritten Characters.
2. The proposed Arabic Character Recognition transfer learning model for writer identification approaches provided a taxonomy of the database.
3. For the models, based on some feature extraction techniques and a Convolutional Neural Network (CNN) classifier.
4. The proposed model provides a good outcome compared to other models.

The following is how the paper is set up: Related work is discussed in Section 2. The approach and suggested architecture are covered in Section 3;

the dataset and experimental findings are covered in Section 4. The conclusion and further efforts are discussed in Section 5.

II. Related Works

Many studies and works have been proposed based on developments in deep learning. In [4] the author divided the lines and characters in (LBP) and (LPQ) technology by rating 1500 data and the accuracy of the system classification is 98%.

An Arabic OCR presentation was obtainable via S. Kanoun et al. [4] for the identification of Latin and Arabic texts. The style included two dissimilar analyses. The first is the morphological analysis which is executed on text_blocks levels. The second is concerned and geometrical text line levels and the associated mechanisms levels. After testing with a KNNA classifier and without the optimizing phase, it was successful with an identification ratio of 88.5%. The scheme was advanced by performing an Arabic_texts analyzing technique utilizing the affixed style [5] .

The scheme development is done [6] utilizing dissimilar methods to increase its recognition ratio via additional morphological improvement. The identification technique for ultra-low resolves Arabic words images utilizing a stochastic method was existing in [7]. It succeeded in 23% of word recognition utilizing the APTI dataset [8]. These states of the skill use recognition results were utilized as a comparison with the projected method. KHANDOKAR, I., et al. to identify the characters in a test dataset, CNN is used. The primary goal of this research is to examine CNN's capacity for character identification in the picture dataset as well as the recognition accuracy after training and testing. To distinguish between characters, CNN evaluates their differences in shapes and characteristics. With the NIST dataset, we tested our CNN implementation to determine the precision of handwritten characters. According to the test results, 200 photos using a training set of 1000 images from NIST had an accuracy of 92.91% [9].

Kamal, Minhaz, et al The proposed model achieved an accuracy of 96.93% and 99.35% when tested on the publicly accessible "Arabic Handwritten Character Dataset (AHCD)" and "Modified Arabic handwritten digits Database (MadBase)" datasets. This accuracy is comparable to the state-of-the-art and makes the proposed model an appropriate solution for practical end-level applications [10]. Mustapha, Ismail B., et al. propose the use of

Conditional Deep Convolutional Generative Adversarial Networks (CDCGAN) to assist in the development of isolated, handwritten Arabic letters. Given a mean multiscale structural similarity (MS-SSIM) score of 0.635 as opposed to 0.614 in the genuine samples, experimental findings based on qualitative and quantitative results demonstrate that CDCGAN produces synthetic handwritten Arabic characters that are equivalent to the ground truth. Comparison with the generation job for handwritten English alphabets further demonstrates CDCGAN's capacity to produce a variety of complicated handwritten Arabic character pictures that are of good quality. Additionally, the performance of the machine learning test employing CDCGAN-derived samples is outstanding, with just a 10% difference in performance between generated and genuine handwritten Arabic letters [11].

III. Image Acquisition

The first phase in an (HR) scheme is to convert the handwritten text document (Arabic) in quantities adjusted to the digital dispensation scheme with a minimum of possible losses. In an off-line method according to the obtaining tools utilized (camera or scanner), the image format used in this system is color and gray level. To grow Arabic Handwritten Texts Image Dataset (AHTID/MW) that shelters all forms and Arabic characters (beginning, middle, end, and isolated) https://www.kaggle.com/datasets/mloey1/ahcd1[12]. The suggested data (image) covers Arabic words and (text lines) written by 53 different writers. Two kinds of fixed facts grounded in content information (word image and texts-lines image) are created. These data will be completely existing for the scientific community and might be utilized as benchmark data where researchers can evaluate and compare their algorithms and results with other available workings [13]. Figure (1) illustrates the sample of Handwritten Scripts Arabic utilized in this Scheme.

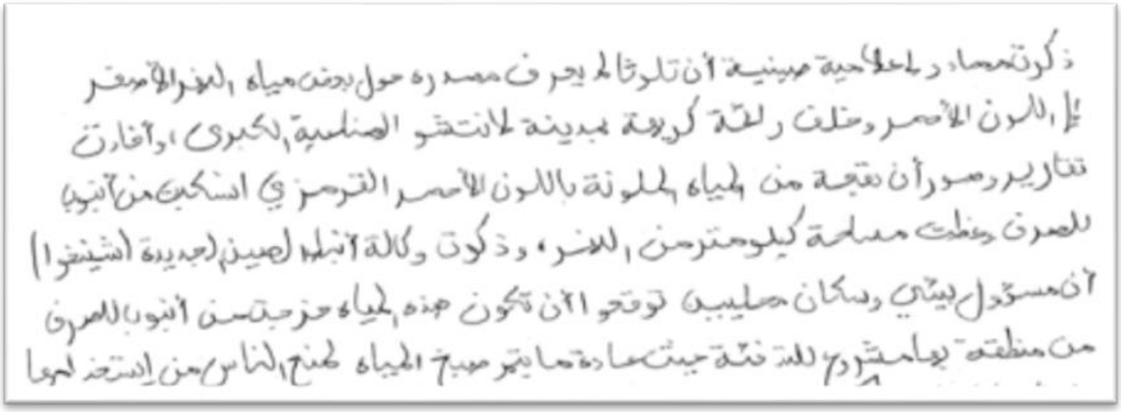


Figure (1): Sample of Handwritten Scripts Arabic utilized in this Scheme.

IV. General Structure of Handwritten Recognition System

The general structure of the HTR scheme is labeled in this part. The input to the scheme is handwritten text images and the output will be the class number that presents the wanted handwritten texts. This scheme of text recognition has numerous phases which are image acquisition, preprocessing, segmentation, feature extraction, and classification. Figure (2) illustrates the general process flow of the HTR system.

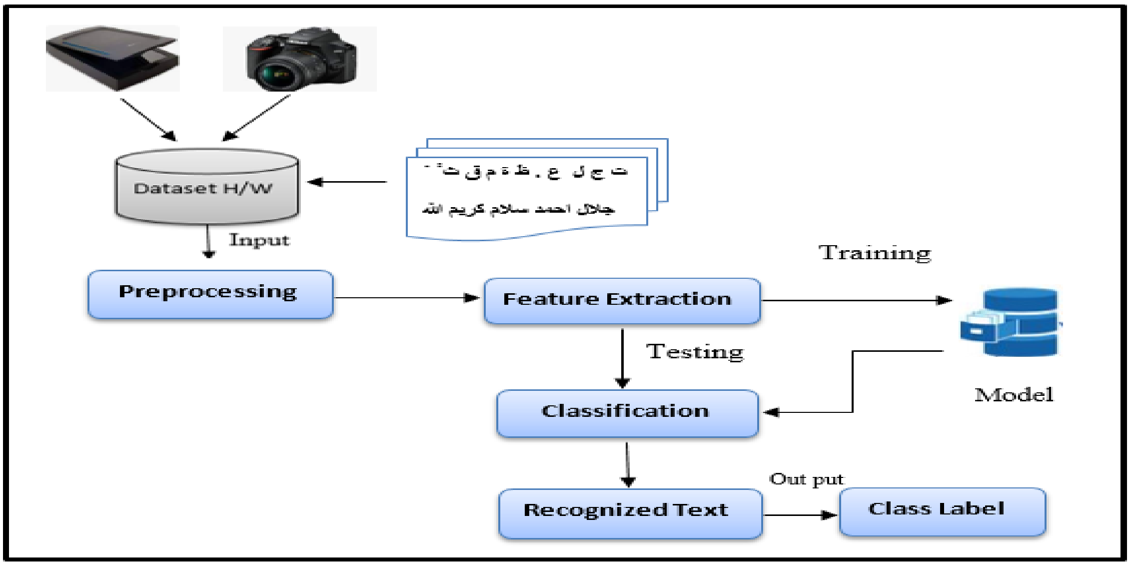


Figure (2): The General Process Flow of the HTR System.

1. Arabic language properties

The Arabic language is utilized by more than (300,000,000 persons) in more than (20) countries. The Arabic letters consist of (28) basic characters. Some of them have four figures: (initial, isolated, medial, and ending). An example is displayed in Figure (3). Arabic texts are inherently cursive both in printed and handwritten formulae and are written in a horizontal way from (right to left) [14]. The images are kept in a "JPG file" or format. Scanned images of handwritten Arabic texts are displayed in Figure (4 (a)). Then dataset is extended to contain a database of word images as in Figure (4 (b)). Each of these groups has related ground truth in the texts-line and word levels.

خ	خـ	ـخـ	ـخ
Isolated Form	**Initial Form**	**Medial Form**	**Ending Form**

Figure 3: An example of different shapes of an Arabic letter.

(a) (b)

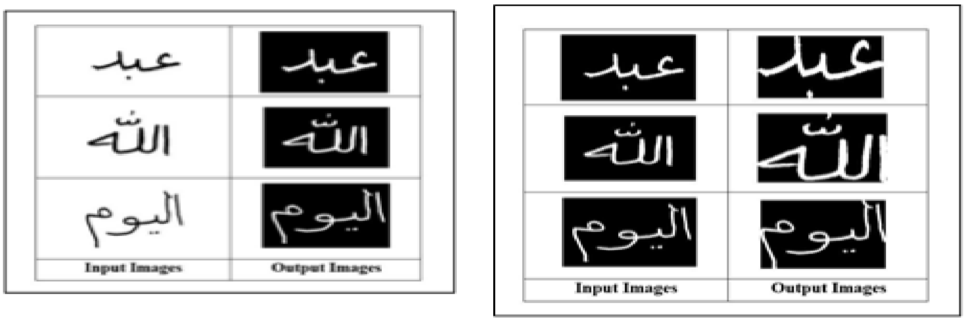
Figure 4: Example of Text-Lines and Its Agreeing Words.

2. Preprocessing

The preprocessing stage is performance significant in (pattern recognition) for matching the character and the pattern should be in distorted Character. In this technique, the data is brought into a particular arrangement for recognizing the character fatly.

2.1. Binarization and Thinning

In this section convert the pattern or image in the greyscale image and the character is converted into the binary image (0 and 1) by utilizing the global image threshold. So recognizing the character in a (black and white) color has become easy and it increases the accuracy of classification [15]. Fuzzy C-Means clustering (FCM) has been utilized for threshold purposes. Next, noise appears due to the threshold. 3*3 filter utilized to eliminate undesired information since the binary image. A black block about the written term in images doesn’t aid with any one of the recognition methods. So these unwanted spaces-blacks about the word were eliminated. To eliminate these black spaces, bounding boxes were utilized. The next step, Thinning is the method of removing unwanted pixels [16]. It performs thinning, removes the trunk of character by utilizing spurring, and brings it into standardized size. Skeletonization is obtained from the geometrical and topological properties as shown in Figure (5).



(a): Image Thresholding (b): Black space elimination

Figure (5): Preprocessing Step.

3. Feature Extraction

Feature extraction includes the conversion of an input item (object) into vectors comprised of statistical feature collections that enable them to be presented as an image. The statistics extracted from an image in a feature extraction job are called local and global features. The local feature is the integral parts of objects connected between themselves; the global feature is the entire properties that can be ascribed to the object [17]. Writer identification (WI) used for feature extraction can be clustered into two main types:

1)2D-Discrete Cosine Transform (DCT Features)

It converts all of the pixels’ values in images with spatial domains into its simple frequency modules in frequency domains. Given an image f (i, j), its 2D-DCT is definite as follows:

$$f(u,v) = a_u a_v \sum_{i=0}^{I-1} \sum_{j=0}^{j-1} \left(\mathrm{f(i.j)} \cos\frac{2i+1}{2i} \cos\frac{2j+1}{2j} \right) \quad (1)$$

Inverse transform

$$f(i,j) = a_u a_v \sum_{u=0}^{n-1} \sum_{v=0}^{n-1} \left(\mathrm{f(u.v)} \cos\frac{2i+1}{2n} \cos\frac{2j+1}{2j} \right) \quad (2)$$

And

$$a(u) = a(v) = \frac{1}{2} \qquad if\ u,v \neq 0$$
$$a(u) = a(v) = \frac{2}{2} \qquad if\ u,v \neq 0 \qquad (3)$$

Due to its robust capability to compress energy, the DCT is a beneficial implement used for pattern recognition. The 2D-DCT can add to a positive (pattern recognition scheme) by classification methods such as SVM and NNA [18].

In this proposed scheme the 2D-DCT is useful for the whole canny edge detection objects that are made as of the preceding stage. The production of the DCT is an array of DCT coefficients. The features are extracted in a vector arrangement via ordering the DCT coefficients into zigzag order, therefore the greatest of the DCT coefficients gone after the beginning are zero or small. Next testing the coefficient, creates that the greatest quantity of DCT coefficient toward the char as feature vectors is a vector is 20 [19]. The chief phases in DCT are present in the algorithm (1).

Algorithm 1: DCT Input: Binary Image Output: DCT Features
Step 1: Read the input image Step2: Convert the image into gray Step3: Compute DCT for image Step4: Convert the DCT image into 1D array in zigzag order Step5: Chose as features first 50 DCT coefficient Step6: Save features in 1D array Step7: END

2) Histogram of Oriented Gradient

It was primarily proposed by (Dalal and Triggs) [20] for human body recognition however it is now one of the positive and popular utilized descriptors in recognition and computer vision. HOG totals occurrences of incline alignment in a fragment of images henceforth it is some arrival descriptors. HOG splits the input image into minor square cells 32×32 utilized and then calculates the histogram of incline instructions or edge guidelines based on the central variances. For better-quality accuracy, the local histograms have been normalized based on difference and this is the aim that HOG is steady on lighting dissimilarity. It is a debauched descriptor in comparison to the SIFT and LBP owing to the simple calculations, it has been also exposed that HOG features are effective descriptors for discovery. The HOG was useful for the Roberts edge finding and recognized images since the preceding stage.

3) Features Normalization(FN)

A significant stage to create the mathematical calculating simple and fast FN (climbing) has been utilized to create the feature-rang [0,1] by applying the next formulation:

$$A' = \frac{A - \min A}{\max A - \min A} \qquad (4)$$

Where A’ is the normalized value, A is an original value.

4. Classification and Recognition

The CNN design is a mathematical theory that includes the group of feed-forward layers as per-convolution-layer and poo ling-layer lagged through one or other completely connected layers. The first two layers’ convolution and pooling make features extraction, and the extracted features are sketched into the last output in exchanging (2D-features)maps into 1D-vector toward classifying the dataset image via the completely connected layer. In a classification of images, the CNN algorithm can skill in the cut, or pre-training CNN features can be utilized off-the-shelf, or “unsupervised pre-training” for CNN can be implemented and fine-tuned within supervised techniques [18]. In CNN each neuron in the filter is associated with one neuron in the next layer called the “Receptive Field”. In the CNN algorithm, the area or region for input size is associated with one neuron in the next, and this area is named the reception arena and this is typically a square [19].

4.1 Convolution layer

It plays an important part in the CNN algorithm that achieves a stack with mathematical tasks as a convolution. A feature diagram is made by convolving the kernel an optimization feature extractor within the input image whose pixels are kept in 2D_array [20]. The deepness of the result feature map is contingent on the scope of the kernel (typically 3x3 or 5x5). An illustration of the convolution process is displayed in Figure (6).

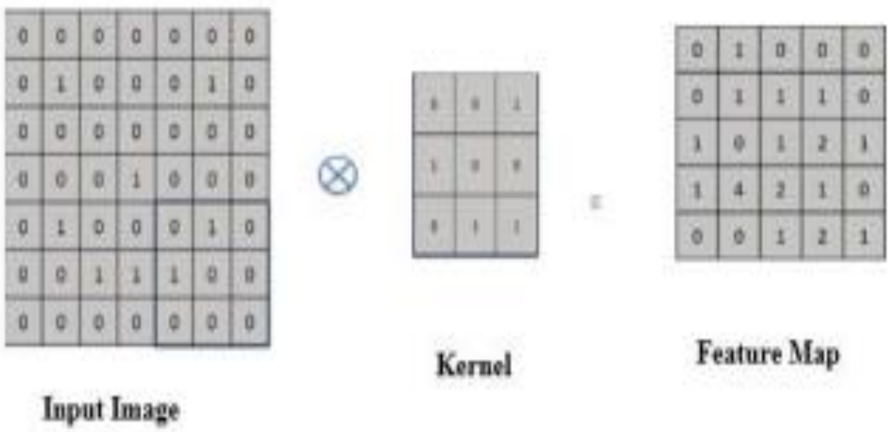


Figure (6): Example of Convolution Process for Kernel Size with 3×3.

4.2Pooling Layer or (subsampling)

It is a layer placed afterward the convolutional layer that models depressed then the chief usefulness is that in-space measurement (dimension) decreases for features charts. Fewer computational above of the approaching layers and the ability to work beside the above suitable are the two benefits for scope decrease utilizing pooling-layer [21]. The maximum frequently utilized pooling processes are average pooling and max pooling are spoken mathematically equally:

$$a_j = max\ (p,q) \qquad (5)$$

$$a_{kij} = \frac{1}{|R_{ij}|} \qquad (6)$$

where a_j is max pooling and a_{kij} is average pooling [22].

The act of the industrialized CNN typical or technique was measured utilizing the misperception matrix plot, and the metrics-accuracy, precision, recall, and f1-score were too intended as per under:

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (7)$$

$$\text{Precision}=\frac{TP}{(TP+FP)} \quad (8)$$

$$\text{Recall}=\frac{TP}{(TP+FN)} \quad (9)$$

$$\text{F1-Score}=\frac{(2*(Recall*Precision))}{(Recall+Precision)} \quad (10)$$

Where the TN, FN, FP, and TP denote the output methods as true negative, false negative, false positive, and true positive values for the training and validation images in representations. The training typical weights were saved within the /hd5-file design and utilized to expect the future via stacking the weights into the classical style [23,24].

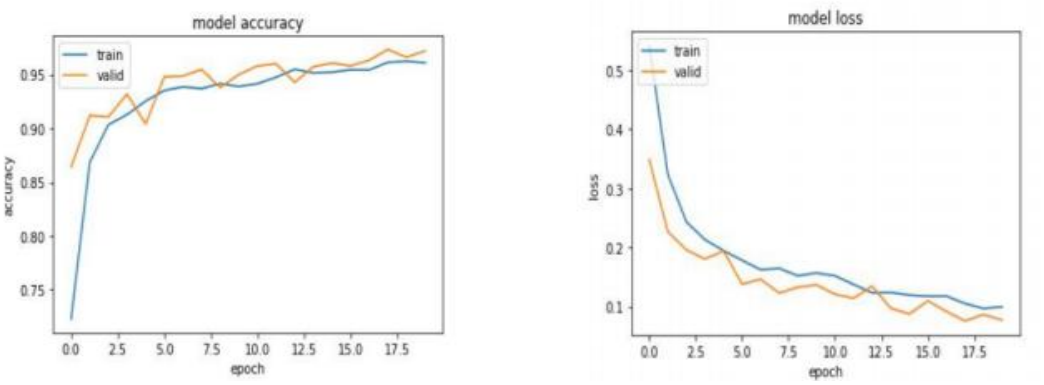
V. Experimental Results and Discussions

The proposed technique is applied to utilize Visual Basic.Net.2013, under Windows10 32-bit Operating System, with RAM 500GB, core-i7 and it succeeded in debauched and in effect results. In this system, the dataset has 360 h/w characters' images. Each character has 15 images written in, unlike different rent styles. In proposed scheme utilized 70% of the dataset for the training method and 30% for testing and it attained 99.36% accuracy in the recognition technique. In both the dataset segmented word images are provided by the author of the respective datasets Through testing all the 70% testing images, all the character images provided 100% recognition accuracy except the character (و ، م) which provided 98.72% recognition accuracy displayed in a table (1).

Table (1): Accuracy of Recognition System

Testing Data	Char.	Accuracy Rate
70%	أ ، ب ، ت ، ث ، ج ، ح ، خ ، د ، ذ ، ر ، ز ،س ، ش ، ص ، ض ، ط ، ظ ، ف ، ق ، ك ، ل ، ن ، ه ، ي	100%
70%	و ، م	98.72
Proposed System	All Char.	99.36

Figure (7 (a)) illustrates the idea of typical accuracy vs. epoch and (b) illustrates typical loss vs. epoch of training and validation image. Finally, Figure (8) illustrates the activity functions within CNN (ReLU, sigmoid, and tan). Figure (9) shows some of the training and testing samples of the dataset by the CNN classifier.



(a) (b)

Figure (7): (a) Plot for Model Accuracy vs. Epoch of Training and Validation.

(b) Plot for Model Loss vs. Epoch of Training and Validation.

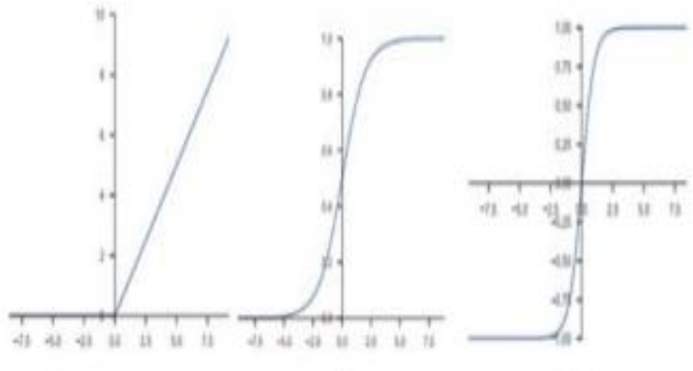
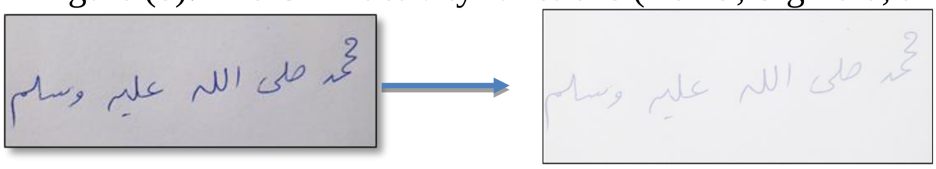
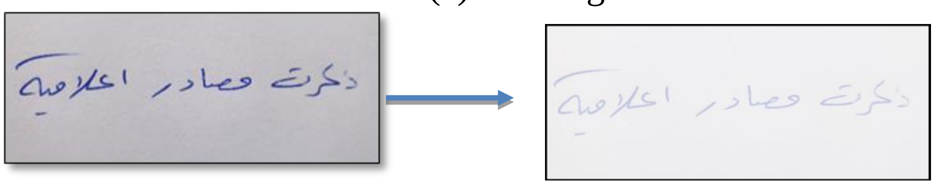


Figure (8): The CNN activity functions (ReLU, Sigmoid, and Tan).



(a) Training



(b) Testing

Figure (9): Some of the Training and Testing Samples of the Dataset by CNN Classifier.

VI. Conclusion

This work proposed a great correct HW Recognition scheme. The dataset for Arabic handwriting characters was proposed in a good way. This scheme utilizes 70% of data images in the training step and 30% in testing data and then gets high accuracy through CNN (linear kernel). The great accuracy is attained via some factors initially with the efficient pre-processing phase by the utilization of the DCT in feature-extraction ways then lastly through additional accurate recognition classifier CNN. Experimentations, our proposed method provided the maximum recognition accuracy than the existing methods.

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المؤتمر العلمي السنوي الثالث والعشرون الموسوم
(مؤتمر كلية التربية الأساسية في مجال العلوم الصرفة)
والمنعقد تحت شعار (بالبحث العلمي الرصين نرتقي ونتعلم ونتقدم)
للمدة 29ـ30 /4/ 2024

اعتماد الشبكة العصبية الالتفافية لتحديد نصوص الكتابة اليدوية العربية دون اتصال بالإنترنت

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مستخلص البحث:

في الوقت الحاضر ، يوجد في معظم المنظمات والحكومات كمية هائلة من المستندات المكتوبة بخط اليد التي تم إنشاؤها عبر معاملاتها اليومية. أصبح الان من الضروري استخدام تقنيات الحاسوب للتعرف على النصوص المكتوبة بخط اليد وقراءتها. طرق معالجة الصور قادرة على تحديد المشاكل الصعبة وتبسيط الإجراءات من خلال تحويل المستندات المكتوبة بخط اليد إلى صيغة رقمية. في السنوات السابقة قامت دراسات حول تمييز الحروف الهجائية العربية المكتوبة بخط اليد على نطاق واسع. هذه الدراسة تقدم مجموعة بيانات تحتوي على الكتابة بخط اليد العربي ويمكن استخدامها لتقييم أداء نظام تحديد هوية الكاتب غير المتصل بالإنترنت. الحروف الهجائية المكتوبة بخط اليد معقدة التصنيف لسبب أنه يوجد كثير من تقنيات الكتابة اليدوية و المتنوعة ، والفرق في شكل وحجم الحروف ، وزاوية الكتابة. يتم منح مجموعة متنوعة من طرق الكتابة باللغة العربية بخط اليد هنا إلى جانب أدائها. في هذه الورقة ، قمنا حاليا بإجراء تحليل شامل لنظام تحديد هوية الكاتب وقدمنا تصنيفا لقاعدة البيانات ، وتقنيات استخراج الميزات ، كتصنيف تقليدي لتحديد هوية الكاتب. حقق هذا المخطط أكبر دقة اعتراف بنسبة 99.36٪ استنادا إلى بعض تقنيات استخراج الميزات ومصنف الشبكة العصبية الالتفافية (CNN).

الكلمات المفتاحية : التعرف على الأحرف المكتوبة بخط اليد (HCR)، استخراج الميزات ، تطبيع الميزات، التعرف ، مصنف الشبكة العصبية الالتفافية (CNN).