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Arabic Handwritten Word Recognition System Based on the Wavelet Packet Decomposition

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ABSTRACT

This paper attempts to recognize Arabic handwriting based on the Wavelet Packet Decomposition (WPD) using two different classifiers (Support Vector Machine SVM with three kernels and k-Nearest Neighbors K-NN). The proposed approach of recognizing Arabic handwriting contains three major stages including image preprocessing, extracting the features of the image, and classification. Firstly, the diacritics are removed using the opening morphological operation (i.e image preprocessing). Secondly, extracting the structure of the paragraph using the morphological method. Finally, the word image size is converted into a suitable size for the next stages. To extract features from the image, the WPD method was adopted to extract the features of Arabic handwriting as the transformation method of feature space. This extracts the Arabic global features to be classified in the last stage using the SVM with polynomial kernel and K-NN. The proposed approach of recognizing Arabic handwriting was tested on IFN/ENIT dataset by rescaling images into various sizes, 93.7% when the SVM with polynomial kernel is used, K-NN classifier achieved accuracy rate is 88.4%.

Keywords: Arabic Handwritten, Wavelet Packet Decomposition, Support Vector Machine, k-Nearest Neighbors.

1. INTRODUCTION

Recognition is an area that includes several fields such as object recognition, face recognition, fingerprint recognition, character recognition, handwritten recognition, etc. Character recognition has become significant due to the ever-demanding necessary for artificial intelligence (AI) that includes machine learning and deep learning. Handwritten recognition is a difficulty in which digits, characters, and words are written by different writers, Handwritten Recognition (HR) covers various fields, such as electronic libraries creation, mail sorting, bank check, verification checks, postal address.[1,2,3,4]

Two main techniques are used in character recognition online and offline. The online difficulty is simpler to overcome than the offline, due to the fact of a bigger data source is available for online character recognition. For instance, the way of moving a pen is used as a character feature. [5,6,7]. In offline recognition, articles, manuscripts, papers, or documents are scanned. [8,9,10]. Any recognition system contains three stages preprocessing, feature extraction, and classification.

In this paper, a handwriting recognition system proposed for Arabic word recognition using a holistic approach to avoid the additional stage include in the segmentation approach using Wavelet Packet Decomposition (WPD) based on Support Vector Machine (SVM) with tree kernels and k- Nearest Neighbors (K-NN) classifiers.

This paper has been divided into four sections. The first section deals with the introduction and related works, while section two explains the research method and describes the development of the proposed system, then section three discusses the results of the proposed system, and finally, section four introduces the conclusions.

2. RELATED WORKS

Several earlier studies have looks into offline Arabic handwritten recognition for numerals, characters and words. For example, Khalifa and Bingru [11] managed to construct a DCT/SVM classification-based approach to recognize handwriting. This attempt improved the SVM into Recursive Feature Elimination (RFE) and used the Principal Component Analysis (PCA). The reported recognizing accuracy is 91.7% using the IFN/IENIT database.

In a related study, a word-based offline approach to recognizing Arabic handwriting utilizing the DCT and SVM classifier was presented by El Qacimy [12]. The authors enhanced the classifier by using a reject option, combining a rejection condition in the classification stage, with the help of sub-words in the input word image taken from the IFN/ENIT datasets, and achieved a rate of recognition of 98.06%.

A multiclass approach to recognizing Arabic handwriting based on the classifiers K-NN and ANN has been developed by Alkhteeb [13]. The stage of extracting features is dedicated to many features like Wavelet features, overlapped blocks, Moment invariant features and Discrete Cosine Transform (DCT) features, that validated on IFN/ENIT, where the K-NN-classifier based results scored a recognition accuracy of 78.65 falling behind the ANN-classifier based results by approximately 2% (i.e., the accuracy of the ANN-classifier based results was reported as 80.75%). In [14] Fakir *et al.* developed a method that applied Line and word segmentation, for Arabic character recognition using neural network. They achieved a recognition rate between 80 % and 90%. Mohammed [15] suggested using the edge histogram descriptor (EHD), a histogram of oriented gradients (HOG), as a mechanism for word recognition using a support vector machine (SVM) classifier. By extracting the directional properties of the text, HOG and EHD provide the best features of the Arabic handwritten text; nonetheless, based on the IESK-ArDB database, the recognition accuracy was only 85%.

3. RESEARCH METHOD

The proposed system is based on the WPD and uses SVM, and K-NN classifiers developed. As presented in Figure 1 the proposed system is separated into three stages: preprocessing, feature extraction using WPD, and classification using SVM and KNN.

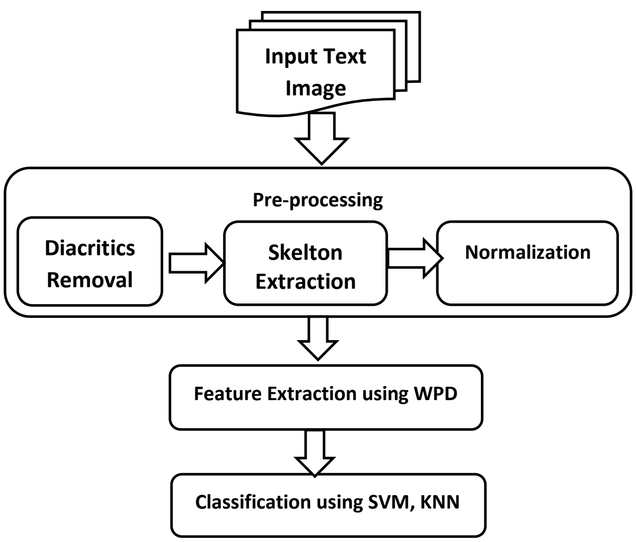


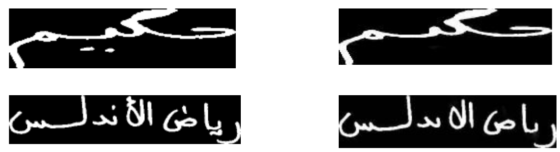
Figure 1: The proposed Arabic holistic word recognition system architecture

The purposes of image preprocessing are to decrease the noise coefficients and to improve the readability of the input. The first stage is also needed to increase the uniformity in texts which is required for any recognition system. Preprocessing is the most significant of OCR. It immediately affects the reliability and efficiency in the next stages [5]. To enhance the performance of the OCR system, usually, the preprocessing stage should include smoothing, noise removal, skew detection and correction thinning, baseline detection, and normalization. [16]

3.1 Diacritics Removal

Diacritics in the Arabic language are called Tashkeel (Fatha, Dhamma, Kasra, Sukun, Shadda, Fathatain, Kasratain, Dhammatain) also a mixture of them is possible. The diacritics in the Arabic language may change the meaning of the word, for instance: if we put Fatha on the word — حر it became حَر, which means the weather is hot, if we put dhamma on the same word, it became حُر which meaning free. [17]

The removal of diacritics as shown in Figure 2-b in the Arabic handwritten is conducted in this stage while keeping their location by using the opening morphological operation. Such operation is used because it is simplistic and it efficiently removes the diacritics. Figure 2-a shows word image with diacritics, while 2-b shows word image when diacritics removed.

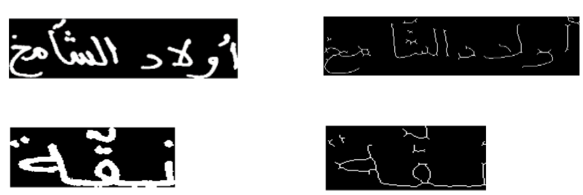


(a)With diacritic (b) Without diacritics

Figure 2: Arabic handwritten image
(a) with diacritics (b) without diacritics

3.2 Skeletonization

The outcome of this approach is a skeleton of the handwritten word. The way to reduce the size of an image to a compact size and determine the medial axis defines as a group of pixels, where those pixels have an analogous distance from the border pixels around it. [18] By using the thinning-based morphological method, the text form is made simpler and the amount of data that needs to be managed for the subsequent stages is decreased. [16]. Figure 3 presents examples of Arabic handwritten text skeletons obtained using the thinning-based morphological method.



(a) Original image (b) After thinning

Figure 3: Arabic Handwritten texts (a) before thinning and (b) after thinning

3.3 Normalization

An important phase in the text recognition system is the normalization technique. Because the writing style varies from one writer to another, size normalization is commonly used to set the sizes of letters or words to a typical size [19]. The main objective of the normalization is to produce an identical image of the text with less difference among multi-writers of the similar text either in letters or words [13]. Hence, the IFN/ENIT database has various image sizes. It is important to make all the images in the dataset of the same size to extract features.

3.4 Features Extraction Using WPD

Feature extraction is one of the dimensionality reductions categories and is a fundamental challenge in image processing. Features vector is a form of data processing, which selectively processes relevant data, and neglects redundant or irrelevant data. This technique is a convenient resort in cases, which include much data but not much information. This technique extracts relevant information from carefully chosen extracted features by reducing the full-size input into a reduced representation [20].

Wavelet transforms have become a scope of interest to replace Fourier methods in applications where signals abound due to their suitability for analyzing-stationary signals. This technique has a wide range of applications that may cover biology to telecommunications [21].

Wavelet packet analysis is a sub-category of discrete wavelet transformation (DWT) [22]. This technique is based on subdividing the whole time-frequency plane into smaller positions which allows combining decompositions from different levels [23,24]. Orthogonal wavelet decomposition is based on splitting approximation coefficients into two parts, then vectors of approximation coefficient and detail coefficients are obtained at a coarser scale. The detail coefficients capture information losses, which occur between the sequential approximations. Similarly, each detail confident is decomposed into two parts identical to the approach of approximation vector splitting.

Two-dimensional wavelet packet transform in three levels as shown in figure 4 has been performed on image samples to achieve a wavelet packet tree. This has been conducted with 84 sub-bands (namely, 4 sub-bands images, 16 sub-bands, and 64 sub-bands at levels 1,2, and 3, respectively.). The Haar (Daubechies 1) has been utilized to perform wavelet packet decomposition of the character samples. Once this has been performed, four 16×16 sub-band images, sixteen 8×8, and sixty-four sub-band images with transformation coefficients of 4×16×16, 16×8×8, and 64×4×4 at the first, second, and third levels, respectively. The mean and variance values were respectively utilized to reduce the dimensions of the feature vector for all the previously obtained sub-images and coefficients (i.e., 84 coefficients). It has been found that the variance coefficients were more efficient in comparison to the mean ones. Moreover, the experiment has been conducted to extract the feature coefficients from horizontal and vertical histograms, where forty-four coefficients have been obtained. Thirty-two of these were the vertical and the horizontal projection coefficient while 12 were directly calculated from the two histograms (i.e., mean value, median, range, variance, skewness, and kurtosis coefficients, etc).

The WPD passes the sampled signal into more filters compared to the discrete wavelet transform. This includes an additional stage to the approach, which calculates the low-pass and high-pass filters. Each level of the filter is considered as a subspace, where the results of the first filter are processed as the input to the next filter. Referring to the discrete wavelet transform, only a low-pass filter is applied here.

The WPD represents a full binary tree, where the root of the tree is the raw data, and the next level is the result of the previous step of the wavelet transform. Equations (1-3) show a numerical representation of the WPD coefficients at the jth level for the kth sample.

$$d_{j+1}^{2n}(k) = \sum_{n} h_0(m-2k)d_j^n(m) \tag{1}$$

$$d_{j+1}^{2n+1}(k) = \sum_{n} h_1(m-2k)d_j^n(m) \tag{2}$$

$$h_1(k) = (-1)^{1-k}h_0(1-k) \tag{3}$$

h_0 and h_1 represent a pair of irrelevant mirror fitters and correlated to each other by Equation (2) [20]. Figure 4 illustrates the process of WPD with three levels.

A	**h**
V	**d**

Coefficient(1 level)

LL1LL2	**LL1HL2**	**HL1LL2**	**HL1HL2**
LL1LH2	**LL1HH2**	**HL1LH2**	**HL1HH2**
LH1LL2	**LH1LH2**	**HH1LL2**	**HH1HL2**
LH1LH2	**LH1HH2**	**HH1LH2**	**HH1HH2**

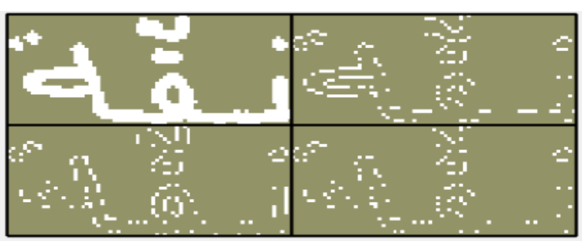
Coefficient (2 level)

LL3	HL3	LL3	HL3	LL3	HL3	LL3	HL3
LH3	HH3	LH3	HH3	LH3	HH3	LH3	HH3
LL3	HL3	LL3	HL3	LL3	HL3	LL3	HL3
LH3	HH3	LH3	HH3	LH3	HH3	LH3	HH3
LL3	HL3	LL3	HL3	LL3	HL3	LL3	HL3
LH3	HH3	LH3	HH3	LH3	HH3	LH3	HH3
LL3	HL3	LL3	HL3	LL3	HL3	LL3	HL3
LH3	HH3	LH3	HH3	LH3	HH3	LH3	HH3

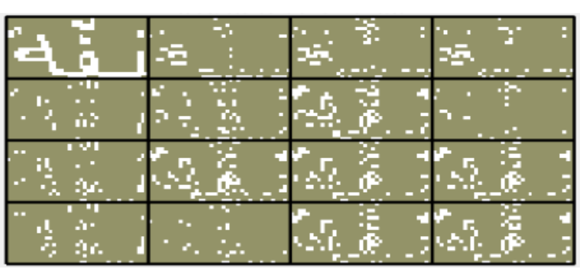
Coefficient (3 level)

Figure 4: 2D- WPD with 3- level decomposition

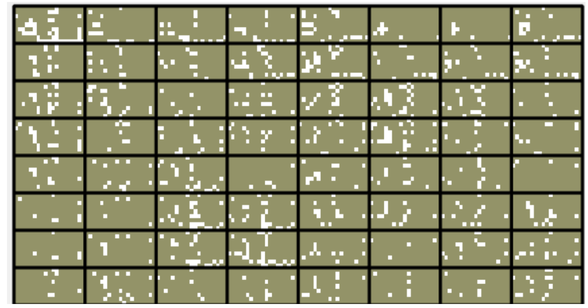
Figure 5 shows that all the sub-bands were decomposed (approximation and details) in each level, this will leads to extracting more features than DWT, DWT decomposed only the approximation sub-band. The quality and performance of the WPD are better than DWT because WPD extracts more features. Figure 5 shows the word image (نفقة) from the IFN/ENIT data set, decomposition in three levels using WPD, wavelet type (db1), and the Entropy was Shannon. The objective of the decomposition of a word image is to extract the features from it, to be used in the latest stage (classification). The Figures below (5-a, 5-b, 5-c) were implemented on Mathlab.



(a) 1 level decomposition



(b) 2 level decomposition



(c) 3 level decomposition

Figure 5: The word image (نفقة) decomposition

3.5 Classification

Classification is a general process related to categorization, the process in which the main body and objects are recognized, differentiated, and understood. This stage aims at building a prediction model on the input features vector by using a machine learning method called SVM and K-Nearest Neighbor k-NN.

3.5.1 Support Vector Machine (SVM) Classifier

The SVM method is a prediction method suggested by Vapnik in 1960 that can be utilized regardless of the linearity of the raw data (i.e., for both linear and non-linear data). The SVM method is based on dividing training records using a hyperplane. Training records from the same class are gathered on 1 side of the hyperplane while other training records (i.e., different classes) are gathered on the other side of the hyperplane.

Although SVMs can be extremely time-consuming, the results are highly accurate. This is because this approach is capable to model complex nonlinear decision boundaries. The SVM method has been numerically described by [23]. Adjusting weights can be performed as described by Equations (4) and (5) to define margin sides [23]

$$H1: W.X + b \geq 1 \; for \; y_i = 1 \qquad (4)$$

$$H2: W.X + b \leq -1 \; for \; y_i = -1 \qquad (5)$$

SVM separates classes based on kernels to find the optimal separating hyperplane utilizing a range of kernel functions that linearize a non-linear separable problem and project data into a feature space.

3.5.2 K-Nearest Neighbor Classifier (KNN)

The K-nearest neighbor (KNN) is a fast supervised machine learning algorithm popularly used in pattern recognition to categorize a pattern based on the nearest training samples inside the feature space [13,26]. K-NN classified the labeled training set with an unlabeled testing set [27]. There are several distance functions used in the K-NN algorithm the best methods are Euclidean distance of the training set samples. For instance, given a query instance for a word picture; the K-nearest instances to this query word picture form the most popular class. After determining the k nearest neighbors, the mainstream of these neighbors is taken to be the output to the class of the query word instance. The Euclidean distance (D) among two feature vectors X and Y are: [13, 28]

$$d(x,y) = [\sum_{i=0}^{m}(x_i - y_i)^2]^{1/2} \quad (6)$$

Algorithm of the suggested system:

Algorithm (1): *The proposed system for offline Arabic handwritten word recognition based on WPD method and two classifiers.*
Input: *Word image* ***Output****: Classified Word*
{Read the image of the dataset, *-Remove the diacritics* *-Extract the skeleton* *- Normalize the word image into different sizes,* *- Apply the WPD method at 3 levels to extract the features of the word image,* *- Then, use the SVM classifiers with polynomial kernel to classify the word images,* *- Classify the word images using KNN* *end}*

4.0 EXPERIMENTAL RESULTS AND DISCUSSION

In this paper, the processor used for the improvement of the proposed system and the benchmarking system is Intel (*R*) Core (TM) 5 Duo, 2.20 GHz with 8 Gigabyte DDRAM. Using Windows 10 as an operating system. The algorithms are implemented, executed, and compiled using Matlab 2016a. this study will be tested on the Tunisian database (IFN/ENIT), It contains 937 names of Tunisian town/village names, this data set contains 26459 names, approximately 115585 parts of the Arabic words (PAWs), and about 212211 characters [29,30]. The IFN/ENIT dataset is publicly available for research.

The proposed system used WPD which is recognized by SVM with polynomial kernel and KNN is verified on the IFN/ENIT database by applying various word images size to achieve the best accuracy, to verify and compare it with different systems.

The proposed system uses various word images size from the IFN/ENIT dataset, obtained accuracy results of classification are presented in Table 1 shows the performance of the proposed system based on various normalization sizes for the image word.

Table 1: The proposed system performances using KNN classifier.

Normalization size	Classification accuracy
38*38	84.5%
50*50	78.5%
80*80	83.1%
100*100	85.4%
125*125	84.4%
45*269	**88.4%**

Table 2 shows the proposed system performance in terms of classification accuracy based on different normalization sizes. SVM with different kernels (Gaussian, Linear, polynomial) accept a uniformed number of features, the normalization is a needed step for making all word images of the IFN/ENIT database in the same size, and due to its impact on the proposed system performances.

Table 2- proposed system performances based on different word normalization sizes and different kernels of SVM

Normalization size	Classification accuracy		
	Gaussian	Linear	Polynomial
38*38	92.6	80.9	91.1
50*50	90.1	82.1	86.4
80*80	91.1	86.6	91.3
100*100	**92.9**	**87.4**	**93.7**
125*125	90.8	88.1	92.4
150*150	90.4	90.8	93.2
45*269	88.2	84.7	89.5

Based on experiments related to word normalization size conducted by the researcher and the results of the tables it was found that the proposed system gives the best results when selecting 100*100-word normalization size in the SVM with the result of 93.7% when choosing polynomial kernel. On the other hand, the K-NN classifier gives the best result when the word normalization size is 45*269 (Al-Khateeb used this size in his research), Where the accuracy is equal to 88.4 when k=5.

Comparing the performances of the systems is one of the challenging tasks since the methods were developed by different authors, tested against dissimilar datasets, and in different testing environments. These environments may be different in terms of programming languages and tools used for development.

This paper compares and discusses the proposed system using WPD and applying SVM & K-NN for Arabic word recognition with [4] based on DWT and DCT.

Validating and verifying the performance for the proposed system using WPD, it has been compared with the Arabic holistic recognition system using DCT and DWT using the Tunisian dataset (IFN/ENIT), 100*100 was the best normalization size when the SVM classifier was applied. Table 3 illustrated the comparative performance results. Examined on the d set of the Tunisian dataset.

Table 3: A comparative performance in terms of classification accuracy using the benchmarking based on DCT and DWT system and the proposed based WPD recognition system using SVM and KNN classifiers on the IFN/ENIT database.

System	Future Extraction	Classifier	Accuracy
AlKhateeb 2010	DWT	KNN	50.83%
	DCT		80.0%
The proposed system	**WPD**	**KNN**	**88.4%**
		SVM	**93.7%**

From the tables above, we can notice that the proposed system produces better result compared with the DCT and DWT. It produced 93.7% when it was tested on the set d of the IFN/ENIT database. Furthermore, in the tables above, we can see that the proposed system using WPD with KNN classifier produce better result compared with the AlKateeb system using DCT and DWT, also examining the set d of the dataset. It produced 88.4% whereas AlKhateeb produced 50.83%, and 80.0% using DWT and DCT as feature extraction methods respectively. And thus, validating the efficiency of the proposed system for recognizing handwritten Arabic words in the comparison with the benchmarking system. The proposed system of Arabic holistic recognition based on SVM and KNN give a promising result compared to the other Arabic holistic word recognition system developed based on the different classifier.

5.0 CONCLUSION

In this paper, a system for Arabic handwritten text recognition using WPD is proposed and tested on the Tunisian dataset by applying various sizes for the word image. The (100*100) word image size was the most suitable size for the SVM classifier hence its reached classification accuracy was 93.7%, but when we used K-NN the system gave the best accuracy result when the normalization size (45*269) that achieved 88.4%. Finally, the proposed system results were verified and compared with other systems based on DWT and DCT, it reached accuracy rates better than others based on DWT and DCT holistic recognition systems. Furthermore, it gives a promising result when it was compared with the other Arabic holistic handwritten word recognition systems proposed based on various classifiers proposed in the literature.

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