Volume 9, No.1, January – February 2020 International Journal of Advanced Trends in Computer Science and Engineering

Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse117912020.pdf https://doi.org/10.30534/ijatcse/2020/117912020

A hybrid Feature Selection Approach for Arabic Handwritten Text Based on Genetic Algorithm and Support Vector Machine



Atallah AL-Shatnawi¹, Faisal Al-Saqqar², Hamza Al-Smadi²

¹Department of Information Systems, Al al-Bayt University, Mafraq, Jordan, atallah@aabu.edu.jo ²Department of Computer Science, Al al-Bayt University, Mafraq, Jordan, faisalss@aabu.edu.jo

ABSTRACT

Reducing features dimensionality in Arabic handwritten text recognition is a crucial issue, due to its impact on the overall recognition performance. In this paper, an Arabic handwritten text recognition model based on a hybrid feature-selection approach and Artificial Neural Network (ANN) classifier is proposed. The proposed feature selection approach mainly based on Genetic Algorithm (GA) and Support Vector Machine (SVM). By doing so, we aim to reduce the dimensionality of Arabic handwritten text features and optimize the recognition overall performances. The proposed based on GA-SVM approach was tested using the IFN/ENIT dataset. The results proposed of the features-selection are promising; since they reduce the number of tested features up to 78% by removing the irrelevant and redundant features. Using the ANN classifier, the proposed model reaches a 96.5% recognition rate, which supports its effectiveness in recognizing Arabic handwritten texts.

Key words: Arabic handwritten text; Artificial Neural Network; Feature selection; Genetic algorithm; Support vector machine.

1. INTRODUCTION

The supreme goal of any Arabic Text Recognition (ATR) System is to mimic the human understanding abilities in order for the computer to read and understand text and perform text processing in a similar way to that of the human mind [15], [10]. In the domain of pattern recognition using Artificial Intelligence (AI) methods, handwritten text recognition is one of the most sophisticated problems [4]. The ATR system can be implemented using any one of two methods: offline recognition and online recognition. In the offline recognition method, the image of text is handled after being input to the recognition system by, for example, scanning. Online recognition, on the other hand, has different input ways as the writer writes to the system directly, e.g., using light pen as the input tool. Usually, offline recognition is harder to handle than online recognition because more information is often available in the latter than in the former

case. As an example, the pen movement can be employed as feature of the character [6], [4], [9], [7], [27].

The Arabic language is a universal language and the formal language of 25 countries and more than 300 million persons worldwide. Furthermore, Arabic characters are used in several languages like Jawi, and Urdu languages [5], [1], [8]. Review of the literature reveals that there are two main offline Arabic systems for text recognition; segmentation-based systems and segmentation-free systems (holistic recognition approaches [12], [16]. The offline holistic Arabic text recognition system typically consists of four processes: image acquisition, image preprocessing, feature classification (i.e., recognition), and feature extraction. Sequential implementation of these processes leads to achievement of the goal of the recognition process and to improved performance of text recognition [2], [3], [4], [6].

The eventual goal of feature extraction is to provide an efficient representation of the text image using a set of distinct features [6], [15]. Review of the literature reveals that there are three main feature extraction techniques were used for Arabic handwritten text recognition: (i) statistical techniques such as Mean, Standard Deviation and PCA, (ii) Geometrical or structural techniques for extracting lines, dots, holes and many others, (iii) space transform techniques such as Discreet Cosine Transform (DCT) method [6], [12], [18].

Arabic handwritten texts suffer from the features high dimensionality problem [17]. Arabic handwritten text recognition features dimensionality reduction is a crucial issue, due to its impact on the overall recognition performance. Therefore, the irrelevant or the redundant features need to be removed and ignored prior of the recognition process due to its insignificant meaning.

In this paper, an Arabic handwritten text recognition model based on a hybrid-feature selection approach and Artificial Neural Network (ANN) classifier is proposed. The proposed model consists of three main stages: features extraction, feature selection using GA, and classification using ANN classifier. The proposed model aims at reducing the dimensionality of Arabic handwritten text features and optimizing the overall recognition performances. The main contributions of this paper can be summarized as follows: (i) extracting the Arabic handwritten text features using the Mean, Standard Deviation, Local Binary Pattern (LBP) features, and Geometric feature extraction techniques, (ii) proposing a hybrid feature selection approach for Arabic handwritten text based on Genetic Algorithm (GA) assisted by Support Vector Machine (SVM) algorithm, (iii) comparing the proposed feature selection method with two benchmark methods based on the Principle Component Analysis (PCA) and GA assisted by (k Nearest Neighbors) kNN method, and (iv) testing and evaluating the proposed model on the IFN/ENIT dataset of Arabic handwritten text using ANN classifier.

The reset of this paper is organized as follows. Section 2 reviews the offline holistic approaches to recognition of the handwritten Arabic text. Section 3 presents the proposed Arabic handwritten text recognition model architecture. It also describes the proposed hybrid-feature selection approach. Section 4, illustrates the experimental results. The discussion is presented in Section 5. Finally, section 6 provides conclusion and future suggestions.

2. RELATED WORKS

Many past researchers examined offline holistic approaches to recognition of the handwritten Arabic text. For instance, El-Hajj et al. [25] suggested a HMM-based scheme for offline recognition of handwritten Arabic text. In the suggested system, the text features are derived from the sliding windows and extracted based on the densities of the foreground pixels and their concavities. When evaluated on the IFN/ENIT database using the HMM classifier, this system produced recognition accuracy of about 87.20%. In another related work. Pechwitz et al. [23] compared efficiencies of extraction of features of handwritten Arabic words based on two measures, namely, pixel values and skeleton directions, in offline text recognition using the HMMs. Recognition accuracies were assessed on the IFN/ENIT database and classification accuracies up to 89.1% were obtained.

Elbaati et al. [20] developed an offline Arabic handwritten text recognition based on the temporal order restoration of the text trajectory and HMM model. In this work, the text strokes sequences were optimized using the GA. Many text characteristics such as the curvilinear velocity signal were calculated using the beta-elliptical modeling. The developed system was validated and tested on the IFN/ENIT dataset. The best recognition rate was achieved 83.71%, when the developed system was tested on set (d) of the IFN/ENIT dataset using 21 extracted features.

Alalshekmubarak et al. [11] presented offline holistic system for recognition of the handwritten Arabic words based on grid feature extraction and the normalized poly kernel SVM classifier. This system extracts the features by means of the uniform grid feature approach, which divides the word image into a number of regions. Thereafter, the black pixels in every split region are summed. Performance of this system was investigated on the IFN/ENIT database and recognition accuracies of 92.34% and 95.27%, respectively, were obtained with subsets of 56 and 24 classes.

Nemmour and Chibani [18] suggested a system for recognition of the handwritten Arabic words that is based on the Artificial Immune Recognition System (AIRS) to solve the medium vocabulary recognition problem. In this system, the relevant features are extracted by combining the Ridgelet transform with the topological grid features. Performance of this system was assessed on vocabulary of 24 words that were extracted from the IFN/ENIT dataset. The results showed that feature combination enhances the accuracy of Arabic word recognition by more than 1.0%.

Al-Smadi [17] developed an offline Arabic handwritten text recognition model based on ANN classifier. In this proposed model, the statistical extracted features were combined with geometric extracted features that were extracted from the text skeleton. In this work, 21 efficient features were selected using GA assisted by kNN method. The selected features were tested on the IFN/ENIT dataset, it achieved 94.2% recognition rate using ANN classifier.

Al-Saqqar et al. [15] introduced an offline system for holistic recognition of the handwritten Arabic text based on PCA and SVM classifiers. This system was evaluated on version 2 of the IFN/ENIT database of handwritten Arabic text using the linear, Gaussian, and polynomial SVM classifiers. Performance of this system was promising and the highest classification accuracies (89.96% and 77.80%) it produced were obtained using the Gaussian SVM classifier and the 125x125 image normalization size when the system was assessed on the (d) and (e) sub-sets of the IFN/ENIT database, respectively.

3. THE PROPOSED MODEL

In this paper, an Arabic handwritten text recognition model depending on a hybrid-feature selection approach and ANN classifier is proposed. The hybrid-feature selection approach is developed based on the GA assisted by SVM algorithm. The proposed model aims at reducing the dimensionality of Arabic handwritten text features and optimizing the overall recognition performances. The proposed model consists of three main stages including features extraction, feature selection, and classification. The proposed Arabic handwritten text recognition model architecture is presented in Figure 1. The proposed model stages are explained in the following sub-sections.

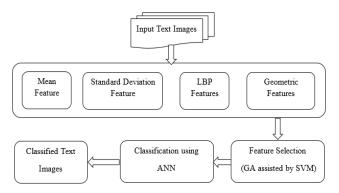


Figure 1: The proposed Arabic handwritten text recognition model architecture.

3.1 Features Extraction Stage

In this stage, 116 features are extracted using four different statistical and structural feature extraction techniques. The statistical features are extracted using the mean, standard deviation, and the LBP feature extraction methods; whereas the structural features (Geometric) are extracted from different text images zones. The four feature extraction methods are described as follows:

1- Mean Feature

The mean is the number of the black pixels divided on the overall total number of pixels [26]. The mean feature is calculated using (1) [17].

$$\mu = \frac{\sum_{l=1}^{N} \sum_{j=1}^{M} A(i,j)}{M * N}$$
(1)

Where μ denotes the average of all values in the image, M (i) represents rows and N (j) represents columns.

2- Standard Deviation Feature

In addition to the mean feature, the standard deviation feature is computed using (2) [17], [28].

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} \sum_{j=1}^{M} (A(i,j) - \mu)^2}{(M * N) - 1}}$$
(2)

Where σ denotes the standard deviation average of the all pixel values in the image, M(i) denotes rows and N(j) denotes columns.

3- Local Binary Pattern (LBP) Features

In this stage, the LBP feature extraction method that originally developed by Ojala et al. [21] (2002) is applied, as well as, to extract the Arabic handwritten texture features. The basic LBP method considers a small circularly neighborhood and rotation invariant texture that has symmetric points (*P*) equally spaced pixels on a circle of radius (*R*) for the entire text image by using the global threshold [13]. To implement the LBP technique, the text images are firstly normalized, then the (16 * 16) LBP is applied to yields a feature vector of (32) features named hereafter by LBP1 to LBP32.

4- Geometric Features

In this stage, 82 geometric features are extracted from the text skeleton based on dividing the text image into 9 different zones. Gaurav and Ramesh [14] extracted such features from the isolated English letter based on the text contour. In this paper, the structural features are extracted using the following steps [17]:

Step 1: extract the Arabic handwritten text skeleton using the thinning based morphological operation method that have been described by AL-Shatnawi [2].

Step 2: Divide the text skeleton image into 9 equal zones (3 equal columns and 3 equal rows), the divided zones are ordered from 1 to 9 as shown in Figure (2).

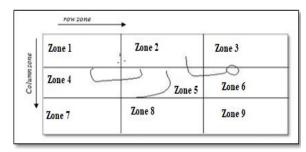


Figure 2: Example of Arabic handwritten text skeleton divided into 9 equal zones.

Step 3: For each zone, find a vector of 9 features extracted based on the localizations of various line segments in the skeleton of the word using the following criteria [17], [14]:

- 1. Number of horizontal lines.
- 2. Number of vertical lines.
- 3. Number of right diagonal lines.
- 4. Number of left diagonal lines.
- 5. Normalized length of all horizontal lines.
- 6. Normalized length of all vertical lines.
- 7. Normalized length of all right diagonal lines.
- 8. Normalized length of all left diagonal lines.
- 9. Normalized area of the skeleton.

Step 4: In addition to the previous extracted geometric features, extract the Euler Number, which represents the difference between number of objects and number of holes in the input text images.

3.2 Feature Selection Stage

In this stage, a hybrid feature-selection approach based on GA assisted by SVM is proposed, in order to select the best features out of the previously 116 extracted features of the Arabic handwritten text images for optimizing the overall recognition performances. In the hybrid feature-selection approach, GA is used to obtain the best feature sets, while SVM is used for estimating the GA fitness function values of the generated subset features during the evolutionary process. In the context of the evolutionary, each subset feature is firstly represented in a chromosome. GA population is generated randomly of different binary chromosomes. For each individual chromosome the fitness function is computed and assisted using the SVM algorithm. GA iteratively searching about the best chromosomes according to their lowest error rates. It will stop searching when the value of the generation size is reached. Table 1 shows the GA setting parameters [17]. Table 1 GA setting parameters with its values

Parameters	Values
Chromosome size	116
Population Size	50
Maximum no. of Generation	100
Selection Method	Selection Tournament
Tournament Size (Selection)	2
Crossover Method	Crossover Arithmetic
Crossover Probability	0.8
Mutation Method	Mutation Uniform
Mutation Probability	0.1

3.3 Classification using ANN Stage

To mimic the neuron of the human brain, ANNs as a machine learning approach in artificial intelligence [24]. In this approach, each neuron is linked to another using a connection link. Each link is given special weight. Typically, conventional ANNs built using the model of neurons. To model an ANN, we firstly start by designing the network. After that, we move towards training the network. During the design phase, we need to figure out the following: number of layers, number of neurons inside each layer, the activation function of each neuron and how layers and neurons are connected [19].In this stage, an ANN prediction model is developed based on the input features vector. In the ANN prediction model, the input features are divided into: (i) 70% for training (ii) 15% for validation, and (iii) 15% for testing. In this stage, 200 hidden layers are used depending on the classification accuracy, while neurons numbers equal number of the best selected features.

4. EXPERIMENTAL RESULTS

In this paper, 116 features of the Arabic handwritten text images are extracted using the Mean, Standard Deviation, LBP features, and Geometric features methods. In order to select the best features out of the previously 116 extracted features, a hybrid feature-selection approach based on GA assisted by a SVM is proposed. The best-selected features are then classified using the ANN classifier. The proposed system is tested and evaluated on the well-known IFN/ENIT Arabic handwritten text dataset. The IFN/ENIT dataset composed of five sets of 26,459 Arabic handwritten Tunisian town/villages names texts [22].

The 116 extracted features are tested using the GA- SVM feature selection approach in order to select the best set of features for enhancing the overall Arabic handwritten text recognition performance. Figure 3 presents, the feature selection process implemented in this paper. Furthermore, it shows the overall fitness values that have been computed by SVM for each of the GA generation associated with its error rate. It is clear that, the best features are those having the lowest error rates. The proposed hybrid feature-selection approach selects 26 features which are the best out of the extracted 116 features. Those selected best features are shown in Table 2.

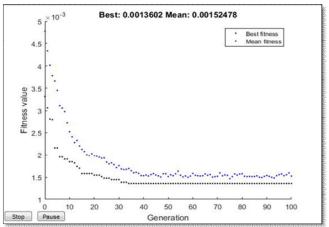


Figure 3. The proposed hybrid feature selection approach results.

Table 2. The best features are selected using the proposed			
hybrid feature-selection approach			
#	Features		
1	Number of Horizontal Lines (Zone 4)		
2	Number of Vertical Lines (Zone 4)		
3	Number of Right Diagonal Lines (Zone 4)		
4	Number of Left Diagonal Lines (Zone 4)		
5	Normalized Length of All Left Diagonal Lines		
	(Zone 4)		
6	Number of Horizontal Lines (Zone 6)		
7	Number of Vertical Lines (Zone 6)		
8	Number of Left Diagonal Lines (Zone 6)		
9	Normalized Length of All Horizontal Lines (Zone		
	6)		
10	Normalized Length of All Vertical Lines (Zone 6)		
11	Number of Horizontal Lines (Zone 5)		
12	Number of Vertical Lines (Zone 5)		
13	Number of Right Diagonal Lines (Zone 5)		

 Number of Left Diagonal Lines (Zone 5) Normalized Length of All Horizontal Lines (Zone 5) Normalized Length of All Vertical Lines (Zone 5) Normalized Length of All Left Diagonal Lines (Zone 5) Number of Horizontal Lines (Zone 1) Normalized Length of All Left Diagonal Lines (Zone 1) Normalized Length of All Left Diagonal Lines (Zone 1) Number of Vertical Lines (Zone 2) Number of Right Diagonal Lines (Zone 2) Number of Horizontal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) Euler Number 		
 5) 16 Normalized Length of All Vertical Lines (Zone 5) 17 Normalized Length of All Left Diagonal Lines (Zone 5) 18 Number of Horizontal Lines (Zone 1) 19 Normalized Length of All Left Diagonal Lines (Zone 1) 20 Number of Vertical Lines (Zone 2) 21 Number of Right Diagonal Lines (Zone 2) 22 Number of Left Diagonal Lines (Zone 2) 23 Number of Horizontal Lines (Zone 3) 24 Number of Right Diagonal Lines (Zone 3) 25 Number of Left Diagonal Lines (Zone 3) 	14	Number of Left Diagonal Lines (Zone 5)
 Normalized Length of All Vertical Lines (Zone 5) Normalized Length of All Left Diagonal Lines (Zone 5) Number of Horizontal Lines (Zone 1) Normalized Length of All Left Diagonal Lines (Zone 1) Number of Vertical Lines (Zone 2) Number of Right Diagonal Lines (Zone 2) Number of Left Diagonal Lines (Zone 2) Number of Horizontal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 	15	Normalized Length of All Horizontal Lines (Zone
 Normalized Length of All Left Diagonal Lines (Zone 5) Number of Horizontal Lines (Zone 1) Normalized Length of All Left Diagonal Lines (Zone 1) Number of Vertical Lines (Zone 2) Number of Right Diagonal Lines (Zone 2) Number of Left Diagonal Lines (Zone 2) Number of Horizontal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 		5)
 (Zone 5) 18 Number of Horizontal Lines (Zone 1) 19 Normalized Length of All Left Diagonal Lines (Zone 1) 20 Number of Vertical Lines (Zone 2) 21 Number of Right Diagonal Lines (Zone 2) 22 Number of Left Diagonal Lines (Zone 2) 23 Number of Horizontal Lines (Zone 3) 24 Number of Right Diagonal Lines (Zone 3) 25 Number of Left Diagonal Lines (Zone 3) 	16	Normalized Length of All Vertical Lines (Zone 5)
 18 Number of Horizontal Lines (Zone 1) 19 Normalized Length of All Left Diagonal Lines (Zone 1) 20 Number of Vertical Lines (Zone 2) 21 Number of Right Diagonal Lines (Zone 2) 22 Number of Left Diagonal Lines (Zone 2) 23 Number of Horizontal Lines (Zone 3) 24 Number of Right Diagonal Lines (Zone 3) 25 Number of Left Diagonal Lines (Zone 3) 	17	Normalized Length of All Left Diagonal Lines
 Normalized Length of All Left Diagonal Lines (Zone 1) Number of Vertical Lines (Zone 2) Number of Right Diagonal Lines (Zone 2) Number of Left Diagonal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 		(Zone 5)
 (Zone 1) 20 Number of Vertical Lines (Zone 2) 21 Number of Right Diagonal Lines (Zone 2) 22 Number of Left Diagonal Lines (Zone 2) 23 Number of Horizontal Lines (Zone 3) 24 Number of Right Diagonal Lines (Zone 3) 25 Number of Left Diagonal Lines (Zone 3) 	18	Number of Horizontal Lines (Zone 1)
 20 Number of Vertical Lines (Zone 2) 21 Number of Right Diagonal Lines (Zone 2) 22 Number of Left Diagonal Lines (Zone 2) 23 Number of Horizontal Lines (Zone 3) 24 Number of Right Diagonal Lines (Zone 3) 25 Number of Left Diagonal Lines (Zone 3) 	19	Normalized Length of All Left Diagonal Lines
 Number of Right Diagonal Lines (Zone 2) Number of Left Diagonal Lines (Zone 2) Number of Horizontal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 		(Zone 1)
 Number of Left Diagonal Lines (Zone 2) Number of Horizontal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 	20	Number of Vertical Lines (Zone 2)
 Number of Horizontal Lines (Zone 3) Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 	21	Number of Right Diagonal Lines (Zone 2)
 Number of Right Diagonal Lines (Zone 3) Number of Left Diagonal Lines (Zone 3) 	22	Number of Left Diagonal Lines (Zone 2)
25 Number of Left Diagonal Lines (Zone 3)	23	Number of Horizontal Lines (Zone 3)
C	24	Number of Right Diagonal Lines (Zone 3)
26 Euler Number	25	Number of Left Diagonal Lines (Zone 3)
	26	Euler Number

It is clear that, the proposed hybrid feature selection approach based on GA assisted by SVM reduces the dimensionality of Arabic handwritten text features by ignoring the undesirable and redundant features (i,e. the insignificant features such as the features are equal to zeros). It reduces the number of tested features up to 78%, which speeds up the system performance. The selected 26 features are tested using the ANN on the IFN/ENIT Arabic handwritten text dataset. The classification accuracy achieved is 96.5%. This result is promising, and supporting the effectiveness of the proposed model when the irrelevant features are removed and ignored.

5. DISCUSSIONS

In this paper, an Arabic handwritten text recognition model based on a hybrid feature-selection approach and ANN classifier was proposed. The hybrid feature-selection approach was developed based on the GA assisted by SVM algorithm. The proposed based on GA-SVM model performance results have been compared with two benchmark feature selection methods including PCA and GA assisted by kNN algorithm. Both benchmark methods were used for selecting Arabic handwritten text best features by Al-Smadi [17].

The proposed feature selection and the two benchmarks methods are applied on the 116 extracted features that have been previously extracted using the mean, Standard Deviation, LBP and Geometric features methods. The number of best selected features out of the 116 extracted features are presented in Table 3. The best features extracted by the three methods are tested on the IFN/ENIT dataset using the ANN classifier. The performances results are presented in Table 4.

Table 3. Numbers of Selected features using the proposed and the two benchmark methods.

Feature Selection Approach	Numbers of the Selected Features
PCA	30
GA-KNN	21
Proposed (GA-SVM)	26

Reducing features dimensionality in Arabic handwritten text recognition is a crucial issue, due to its impact on the recognition performance and speed. The proposed hybrid feature selection approach based on the GA assisted by SVM algorithm reducing the number of tested features up to 78%. On the other hand, the two benchmark methods based on PCA and GA-kNN methods were reducing the number of tested features up to 75% and 82% respectively. Figure 4 shows the features reductions ratio produced by the three methods. Based on the above reduction ratios, we can noticed that, there are many irrelevant features need to be removed prior of recognition process due to its insignificant meaning.

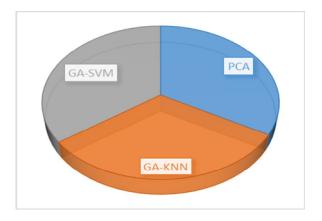


Figure 4: Features reductions produced by the proposed feature selection method based on GA-SVM and the two benchmark methods based on PCA and GA-kNN.

Table 4. Performance results based on the three feature		
selection method when tested on the IFN/ENIT datasets		
using ANN classifier		

Future selection approach	Recognition rate	
PCA	92.7%	
GA-kNN	94.2%	
Proposed (GA-SVM)	96.5%	

The proposed method produced the best classification results among the other two benchmark methods tested on the IFN/ENIT dataset using ANN classifier. Hence, it achieved (96.5%) recognition rate, while the benchmark systems based on the PCA and the GA-kNN achieved 92.7% and 94.2 recognition rates respectively. Thus, support the proposed model effectiveness in recognizing the Arabic handwritten texts.

6. CONCLUSIONS AND FUTURE WORKS

In this paper, an Arabic handwritten text recognition system based on the hybrid feature selection approach and ANN classifier was proposed. The hybrid feature-selection approach was developed based on the GA and SVM algorithm. The proposed model composed of three main stages: (i) features extraction (ii) feature selection using GA, and (ii) classification using ANN technique. In the feature extraction process, 116 features were extracted using four different statistical and structural feature extraction techniques. The statistical features were extracted using the mean, standard deviation, and the LBP feature extraction methods; whereas the structural features (Geometric) were extracted from 9 different text images zones. The extracted features were reduced by choosing the best features for Arabic handwritten text using the proposed hybrid feature selection approach based on the GA assisted by SVM algorithm. It reduced the number of tested features to 78%. This paper concluded that, there many redundant and irrelevant features need to be ignored and removed prior of recognition process due to its insignificant performance.

The proposed based on the GA-SVM feature selection approach was tested on the IFN/ENIT dataset using the ANN classifier. As well as it was compared with two benchmark models based on the PCA and GA-ANN feature selection methods. It was produced the best classification results among the other two benchmark methods. Hence, it achieved (96.5%) recognition rate, while the benchmark systems based on the PCA and the GA-kNN were achieved 92.7% and 94.2 recognition rates respectively. Based on the achieved results, this paper can conclude that, removing the redundant and the irrelevant features could be supporting the proposed model effectiveness in recognizing the Arabic handwritten texts. It will be interesting in the future to testing the proposed method on different datasets. As well as to testing it using different well-known machine learning approaches such as kNN and SVM classifiers.

REFERENCES

- 1. A. Al-Shatnawi and K. Omar, "Methods of Arabic language baseline detection -the state of art". IJCSNS, 8 (10), 2008.
- A. Al-Shatnawi, "A Non-Iterative Thinning Method Based on Exploited Vertices of Voronoi Diagrams", PhD Thesis, University Kebangsaan Malaysia, Malaysia, 2010.
- 3. A. Al-Shatnawi, "A Novel Baseline Estimation Method for Arabic Handwritten Text Based on Exploited Components of Voronoi Diagrams", International Arab Journal of Information Technology (IAJIT), 13(3), 2016.
- 4. A. Al-Shatnawi, "A Preprocessing Model for Hand-Written Arabic Texts Based on Voronoi Diagrams", International Journal of Computer Science

and Information Technology (IJCSIT), 7(6), (p.p 1-18) December 2015.

https://doi.org/10.5121/ijcsit.2015.7601

- 5. A. Al-Shatnawi, "A skew detection and correction technique for Arabic script text-line based on subwords bounding", In Computational Intelligence and Computing Research (ICCIC), IEEE International Conference on, (pp. 1-5), IEEE, 2014.
- A. Al-Shatnawi, A. S. Safwan, F. AL-Zawaideh, and K. Omar, "Offline Arabic Text Recognition–An Overview". World of Computer Science and Information Technology Journal (WCSIT), 1(5), (pp.184-192), 2011.
- 7. A. Al-Shatnawi, and K. Omar, "The Thinning Problem in Arabic Text Recognition-A Comprehensive Review", International Journal of Computer Applications, 103(3), (pp. 0975-8887), 2014.
- A. Al-Shatnawi, and K. Omar," "Detecting arabic handwritten word baseline using voronoi diagram." In 2009 International Conference on Electrical Engineering and Informatics, vol. 1, pp. 18-22. IEEE, 2009.
- A. Al-Shatnawi, and K. Omar,"A comparative study between methods of Arabic baseline detection." In 2009 International Conference on Electrical Engineering and Informatics, vol. 1, pp. 73-77. IEEE, 2009. https://doi.org/10.1109/ICEEI.2009.5254814
- A. Al-Shatnawi, and K. Omar, "Skew detection and correction technique for arabic document images based on centre of gravity." Journal of Computer Science 5, no. 5 (2009): 363.
- 11. A. Alshekmubarak, Q. Hussain, and F. Wang, "Off-line handwritten arabic word recognition using SVMs with normalized poly kernel" in Neural Information Processing, Springer Berlin Heidelberg, pp. 85-91, 2012.
- 12. B. El Qacimy, A. Hammouch, M.A. Kerroum, "A review of feature extraction techniques for handwritten Arabic text recognition" in Book A review of feature extraction techniques for handwritten Arabic text recognition, IEEE, pp. 241-245, 2015.
- C. Huang, M. Shan, Y. Ardabilian, L. Wang, and Chen, "Local binary patterns and its application to facial image analysis: A survey", IEEE Trans. Syst. Man Cybern. C Appl. Rev., vol. 41, no. 6, pp. 765-781, Nov. 2011.
- 14. D. Gaurav and R. Ramesh, "A feature extraction technique based on character geometry for character recognition," CoRR, vol. abs/1202.3884, 2012.
- F. Al-Saqqar, A. M. AL-Shatnawi, M. Al-Diabat and M. Aloun, "Handwritten Arabic Text Recognition using Principal Component Analysis and Support Vector Machines" International Journal of Advanced Computer Science and Applications(IJACSA), 10(12), 2019.
- F. Nashwan, M. A. Rashwan, H. M Al-Barhamtoshy, S. M. Abdou, and A. M. Moussa, "A holistic technique for an Arabic OCR system", Journal of Imaging, 4(1), 6, 2018.

https://doi.org/10.3390/jimaging4010006

- 17. H. Al-Smadi, "Arabic Handwritten Text Recognition Using Genetic Algorithm and Artificial Neural Network", Master thesis, AL-alByte university, Jordan, 2019.
- H. Nemmour, and Y. Chibani. "Artificial immune algorithm for handwritten arabic word recognition." Int. Arab J. Inf. Technol. 14, no. 2 (2017): 186-194.
- J. K. Basul, D. Bhattacharyya, and T. Kim, "Use of Artificial Neural Network in Pattern Recognition", International Journal of Software Engineering and its Applications, vol. 4, no. 2, 2010.
- M. Elbaati, H. Boubaker, M. Kherallah, A. M. Alimi, A. Ennaji, and H. El Abed. "Arabic Handwriting Recognition Using Restored Stroke Chronology". In 2009 10th International Conference on Document Analysis and Recognition. (pp. 411-415). IEEE, 2009.
- M. Ojala, T. Pietikainen, and T Mäenpää "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971-987, July 2002.
- 22. M. Pechwitz, S. S. Maddouri, V. Märgner, N. Ellouze, and H. Amiri. IFN/ENIT- database of handwritten Arabic words. In CIFED, pages 127-136, 2002.
- 23. M. Pechwitz, V. Märgner, H. El Abed, "Comparison of Two Different Feature Sets for Offline Recognition of Handwritten Arabic Words", 10th International Workshop on Frontiers in Handwriting Recognition (IWFHR), 2006.
- 24. P. A. Schrodt, "Prediction of interstate conflict outcomes using a neural network." Social Science Computer Review 9, no. 3 (1991): 359-380.
- 25. R. El-Hajj, L. Likforman-Sulem, and C. Mokbel. "Arabic handwriting recognition using baseline dependant features and hidden markov modeling." In Eighth International Conference on Document Analysis and Recognition (ICDAR'05), pp. 893-897. IEEE, 2005.
- S. S. El-Dabi, R. Ramsis, A. Kamel, "Arabic Character Recognition System: A Statistical Approach for Recognizing Cursive Typewritten Text", Pattern Recognition, vol. 23, pp. 485-495, 1990.
- 27. T. Parvez, and S. A Mahmoud, "Offline Arabic handwritten text recognition: a survey", ACM Computing Surveys (CSUR), 45(2), 23, 2013. https://doi.org/10.1145/2431211.2431222
- X. Patel, G. Hong, and Zhao, "Selective deep features for micro-expression", Proc. 23rd Int. Conf. Pattern Recog., pp. 2259-2264, 2016.