مجلة كلية الآداب بقنا (دورية أكاديمية علمية محكمة)

Recognize the Alphabet of Fingerspelling Using Statistical Classifiers to Facilitate Communication Between Hearing-Impaired Persons and Others

Dr. Amr Mohmed Soliman
Special Education Dept, College of Education, King Khalid University, Abha, Saudi Arabia

Dr. Mahmoud M. Khattab
Dr. Abdelmoty M.Ahmed
College of Computer Science, King Khalid University, Abha, Saudi Arabia

DOI: 10.21608/qarts.2023.192742.1617

مجلة كلية الآداب بقنا – جامعة جنوب الوادي – العدد 57– أكتوبر 2022

الترقيم الدولي الموحد للنسخة المطبوعة **ISSN: 1110-614X**

الترقيم الدولي الموحد للنسخة الإلكترونية **ISSN: 1110-709X**

موقع المجلة الإلكتروني: **https://qarts.journals.ekb.eg**

Recognize The Alphabet of Fingerspelling Using Statistical Classifiers to Facilitate Communication Between Hearing-Impaired Persons and Others

ABSTRACT

The predominant method of communication for hearing-impaired and deaf people is still sign language. It is a carefully constructed hand gesture language, and each motion denotes a certain meaning. The purpose of this paper is to create a system for Arabic Sign Language automatic translation. The proposed Arabic sign to Text System consists of five primary stages and serves as a translator for deaf and dumb persons and normal people to improve communication. This system depends on building a two datasets image features for Arabic sign language gestures alphabets from two resources: the Arabic Sign Language dictionary and gestures from different signers' humans. It also uses gesture recognition techniques, which lets the user interact with the outside world. Video and images capture, Video and images processing, Hand Signs construction, classification, and finally text transformation and interpretation. In this paper, we use a set of appropriate features in step hand sign construction and classification of based on different classification algorithms such as (KNN, MLP and C4.5) and compare these results to get better classifier. This system offers a novel technique of hand detection that detects and extracts hand gestures of Arabic Sign from Image or Video..

KEYWORDS: ARABIC SIGN LANGUAGE, HAND GESTURE, FEATURES EXTRACTION, HAND DETECTION.

1. INTRODUCTION

The predominant method of communication for hearing-impaired and deaf people is still sign language. It is a carefully constructed hand gesture language, and each motion denotes a certain meaning. The purpose of this paper is to create a system for Arabic Sign Language automatic translation. The suggested Arabic Text (PROPOSED) System consists of five primary stages and serves as a translator for deaf and dumb persons and normal people to improve communication. capturing images and video, The primary form of communication for deaf and hearing-impaired people is sign language. The two basic methodologies used in sign language are vision-based and biomechanical (Gloves sensor). Users of vision-based systems do not need to employ expensive equipment, but the pre-processing stage does require significant computations. Sensor-based systems, in contrast, use sensor-enabled instrumented gloves in place of the cameras used in vision-based systems. This paper outlines a computerized sign language recognition system for the vocally impaired (deaf and dumb) who use sign language for communication, as well as a computer vision-based gesture interface that is a component of the system.

A typical image-based PROPOSED system has three levels: continuous recognition, alphabet recognition, and isolated-word recognition. A collection of images or a video sequence of the indicators serves as the input for vision-based approaches. To manually separate the signs, the signers are requested to halt in between each sign. The methodologies and algorithms for hand detection, which will be used as an input for the gesture recognition process, will be presented in this paper along with research findings in progress.

Section I introduces the proposed system, which employs image and pattern recognition technologies. Section 2 provides a description of related works. The proposed system's overview is covered in Section 3. The system's computer simulation findings are reported in Section 4 before a summary of the conclusions and next steps is provided in Section 5.

2. RELATED WORKS

People who are deaf, dumb, or have hearing impairments are unable to speak and hear like regular people; as a result, they must frequently rely on visual means of communication. [1], The only form of communication between those with hearing loss and those without it is sign language, yet the vast majority of people without hearing loss are not familiar with it. The use of sign language varies by country, geography, and socioeconomic status [2], Tabata et al. [3] suggested a method for recognizing finger spelling that makes use of distinguishing characteristics of hand form. Halawani [4] unveiled a mobile device translation app for Arabic sign language. Tsukada et al. [5] presented a new glove-based input device to be used as a wearable computer's input device. Based on data glove, Khalid Alvi et al. [6] recognized Pakistani sign language using statistical template matching. A glove with sensors was used to create an Arabic sign language recognition system, according to AI-Buraiky et al. [7] Recently, the Arabic sign language (ArSL) has been acknowledged and documented. To establish the sign language used in Arabic-speaking countries, numerous initiatives have been made. are working to standardize sign language and promote it among the deaf community and other interested parties. The same sign alphabets are used in Arabic-speaking nations, but [8], [9], Feris et al. [10] presented a method to use depth discontinuities to distinguish between some signs' similarities by employing a multi-flash camera for finger spelling recognition. However, Tanibata et al. [11] offered a prototype method based on feature extraction to address the hand occlusion issue for the recognition of Chinese sign language. Support vector machine (SVM)-based prototype systems for Arabic sign language recognition and an automatic translation system for Arabic text to Arabic sign language were both introduced by Mohandes [12, 13]. A Sign to Voice system prototype that can recognize hand motions by converting digitized images of hand sign language to voice using a Neural Network technique was proposed by Foong et al. [14].

3. THE PROPOSED SYSTEM

This section provides an overview of the five key steps of the proposed Automatic Translation Arabic Sign to Arabic Text System. Figure 1 depicts the proposed system's cycle for video and image acquisition, video and image processing, hand sign construction, classification, and text transformation and interpretation.

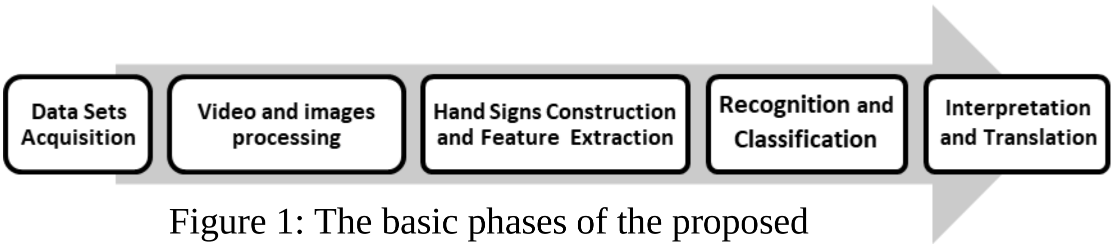


Figure 1: The basic phases of the proposed PROPOSED System

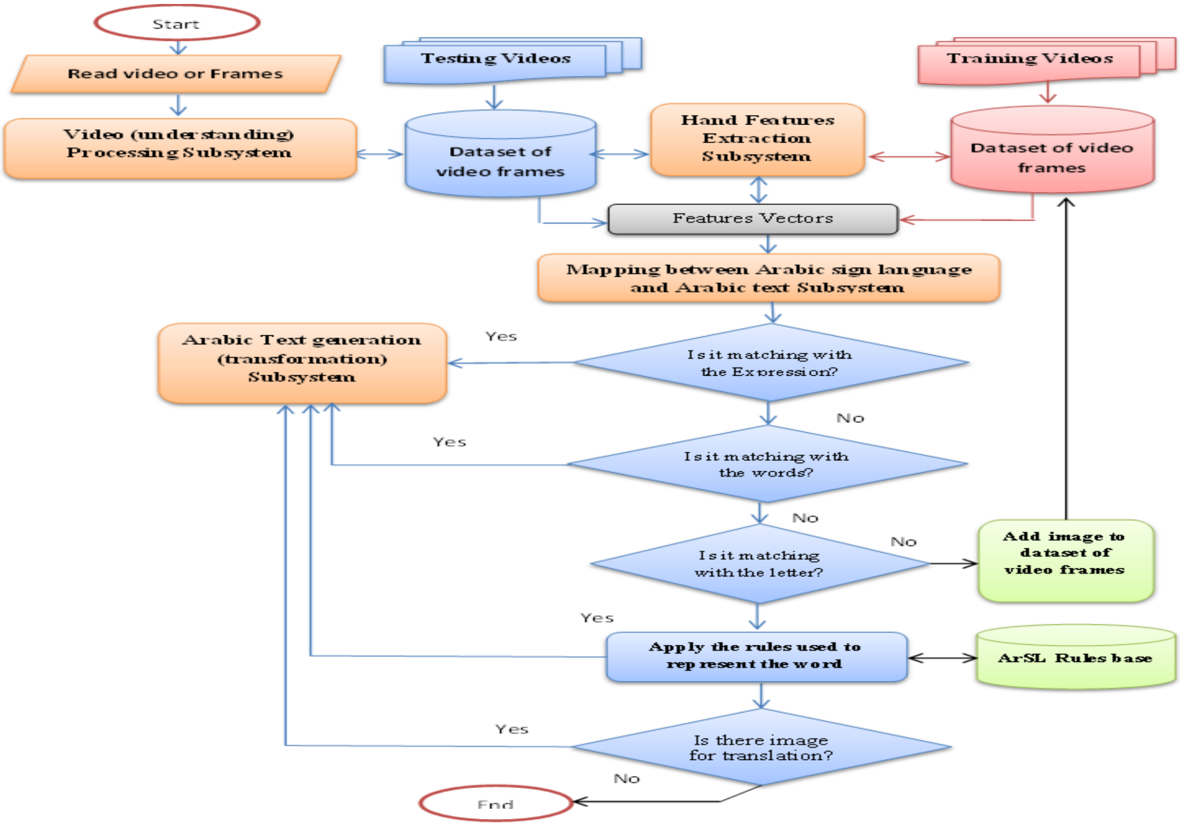


Figure 2:Flow chart of the proposed system to translate ArSL into Arabic language

The following flow chart, displayed in Figure 2, shows the various processes the proposed system must go through. The following sections go into greater depth about each step

3.1.Video and Images capture phase

The proposed system's initial stage involves capturing visual data from the environment using an input device like a camera, This stage's output is a set of colored images (RGB) representing the hand gestures that correspond to each individual letter of the Arabic sign language, as shown in the Figure 3. The data entered for this stage give rise to gestures performed by a number of indicators while wearing gloves of a dark color in various lighting environments with a light background (first data set) or without gloves (natural color of the skin) with a dark background (second data set).

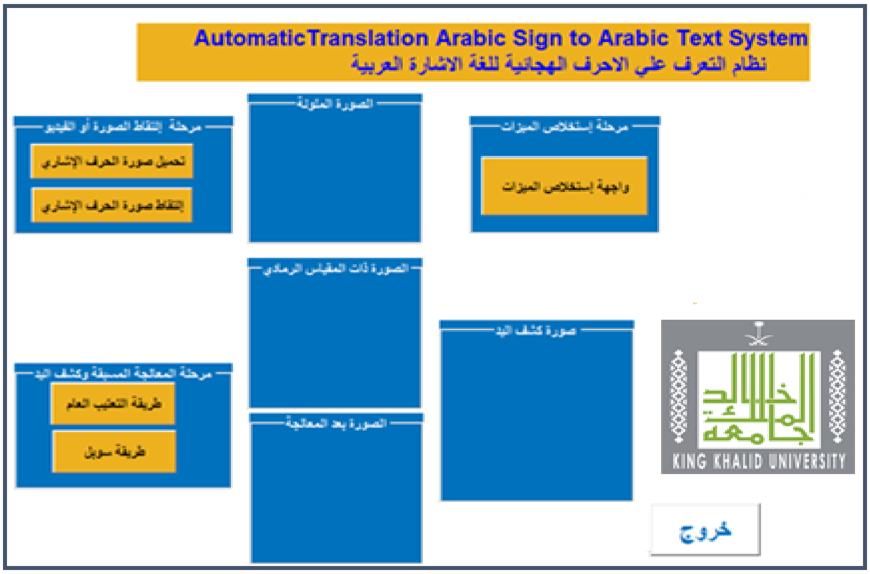


Figure.3 The main screen of the proposed System

3.2.Video and images pre-processing phase

It has been using a number of algorithms to discover it and select the appropriate adjectives to describe and distinguish the form of a gesture hand and draw these qualities for use in computer training to learn the letters, and the corresponding characters in the Arabic language. The second step involved the use of image processing techniques for initial processing of images captured gestures in order to hand detection of the image and isolate it from the background.The RGB to Gray conversion is necessary after the frame image is taken because it is in RGB format. After the conversion, we are left with a grayscale image, which we may now enhance using a variety of approaches. These include image segmentation, morphological image processing, noise removal, and highlighting key areas (such as the hand shape) in the image.The implementation of this algorithm proposed several methods to detect a hand, such as Sobel, Canny Edge, Thresholding and Adjust the contrast method, which are similar in technologies used to convert the image to gray, extrapolation, and other operations. This algorithm has been proven effective in the process of image processing and distinguish easily understanding and implementation. Utilize a mixture of 700 photographs that were initially captured, with 25 images being used for each letter of the Arabic alphabet. The images that were extracted were all black and white. Following isolation, detection, and the subsequent figure, each image in the shape of a hand gesture serves as an example for each letter of the alphabet before the main image processing procedure. [15]

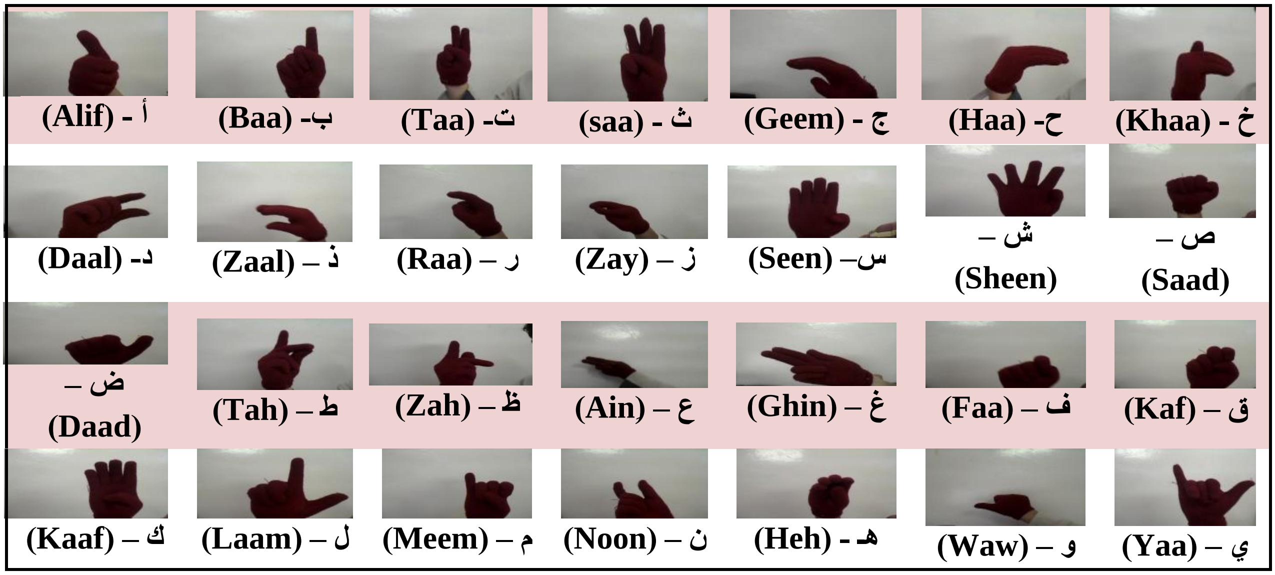


Figure.4 the proposed system dataset of alphabets letters before pre-processing

The second stage in our system is the pre-processing is the data preparation process. The data sets have been made robust as separate images were taken of more signers with different manual sizes and complex backgrounds and contain round samples and variable angles between 60 and -60 degrees to make the system robust. Color images are processed to improve image quality. The color image is converted to a gray scale image of 256 density levels and resizes to a 640 x 480 pixel image. Some filtering methods can be applied to remove unwanted noise.

The pre-processing stage aims to convert data into a format that can be processed more easily and effectively as this stage consists of several methods of, optimization and enhancement Image, segmentation, and morphological filtering.

The pre- processing image stage depends on the steps of hand detection, where techniques optimization and enhancement Image, segmentation, and morphological filtering are applied to the color image in several ways to obtain the best sample to help us later extract the best features and then get the best accuracy.

At this phase, several steps for pre-processing ArSL's alphabet gesture images are represented, these steps are shown in Figure.5

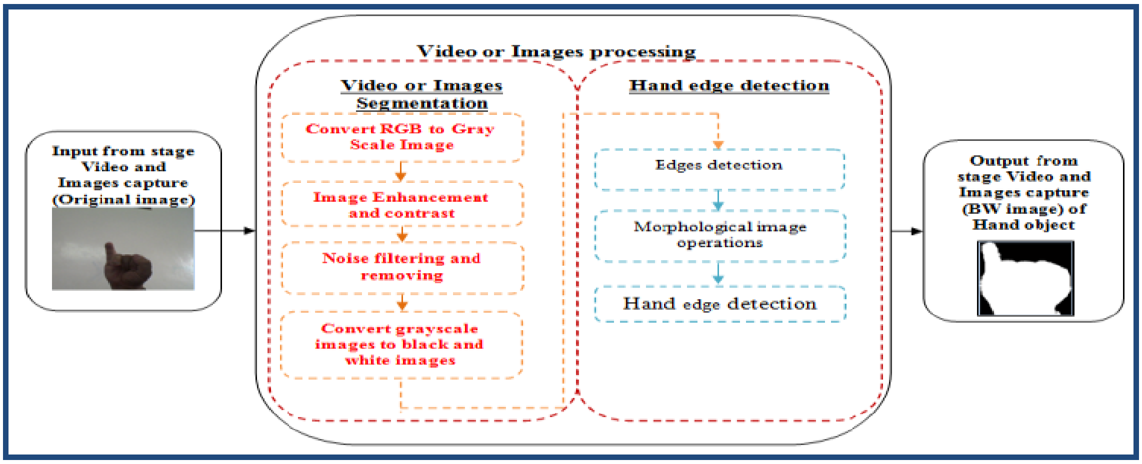


Figure 5: Cycle of second stage in proposed system

3.3.hand sign construction and detection Stage

In this section, the results of implementing the hand detection stage and extracting it from each alphabet gesture for each of the three data sets mentioned previously in the image acquisition phase used in this system will be presented and depending on the two methods used in this step. The table.2. shows some of the letters of the alphabet, and the shape of the hand after extracting it from the background in the pictures of the alphabet gestures after processing.

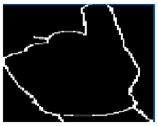
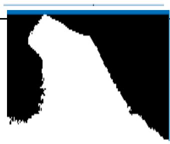
Hand Detection Case	Sobel Method		Threshold Method	
Hand Detection				
				
Hand Detection with noise				
				
No Hand Detection				
				

Table 2: The hand detection in proposed system by two methods

In the previous table, models for hand extraction and detection using the two selected methods are shown. Figures 6, 7 and 8 show results of comparison between the two methods for hand extracting and detection in each of the three dataset.

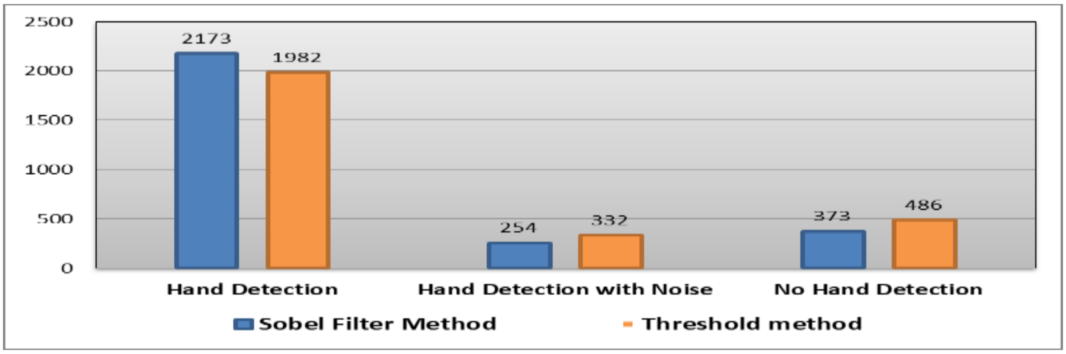


Figure 6: Hand detection ratio by two methods for dataset No. 1

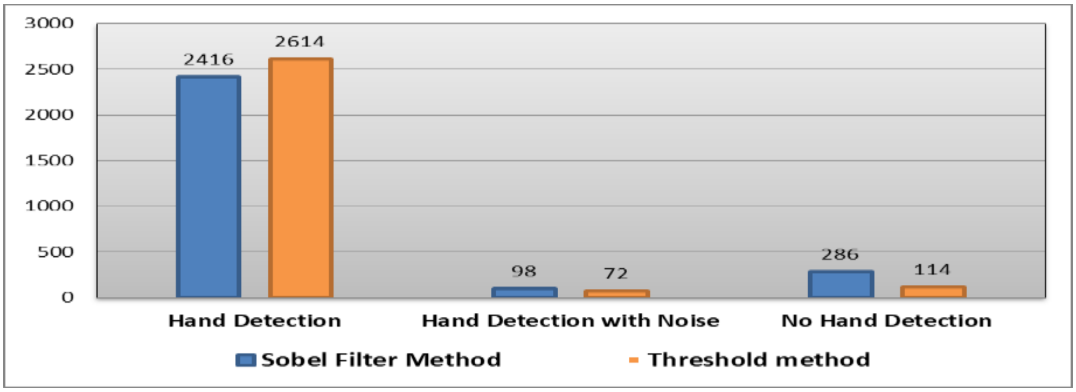


Figure 7: Hand detection ratio by two methods for dataset No. 2

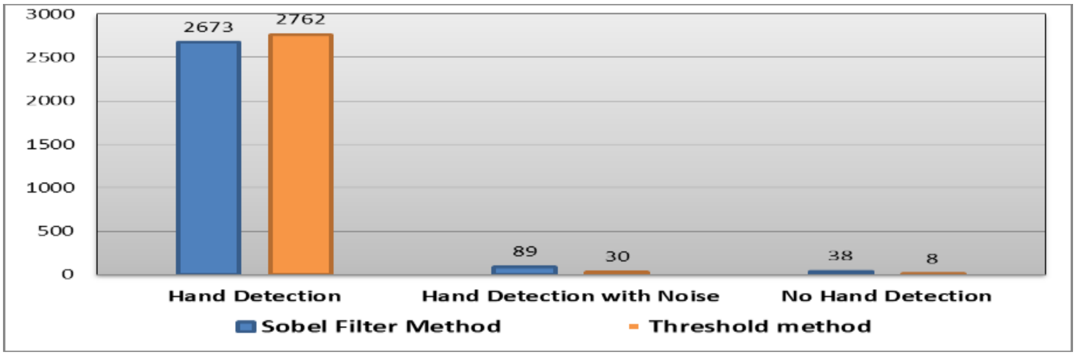


Figure 8: Hand detection ratio by two methods for dataset No. 3

The accuracy of hand detection was evaluated in each method by calculating the number of examples in which the hand was successfully detected and isolated relative to the total number of examples according to equation 1 and ignoring the examples in which the hand was detected with the presence of noise, and considering them unacceptable because the noise affects negatively significantly when calculating the properties of a shape the hand gives wrong results in the classification phase. The table 3, below illustrates the proportion of the hand detection in each set according to each method.

$$\text{Hand Detection Rate} = \frac{\text{Correct Samples without Noise}}{\text{Total Samples}} * 100 \qquad \textbf{(Eq. 1)}$$

Table 3: The ratio of the hand detection in each dataset

No. Of Dataset	Hand edges detection method	
	Sobel method	Threshold method
Dataset 1	77.61%	70.79%
Dataset 2	86.29%	93.36%

4. Experimental Results of classification stage

In this section, we will display the results of the recognition of alphabets Arabic sign language by using one of the supervised learning algorithms as mentioned above, relying on one of the three data sets resulting from the stage of extracting hand shape features which represent training data for the selected classifiers.
The implementation results of the classification and recognition phase using the WEKA software tool are discussed, where a number of experiments are conducted as follows:

A. Results using estimate error classification

Two methods were used to estimate the error classification, the first method is holdout for the selection or vote of samples for testing and training data sets and second method is cross validation used to measure performance evaluation.

The WEKA software Tool was used to apply classification based on statistical classification algorithms (C4.5,NaiveBayes,KNN) and a Multi-Layer Perceptron (MLP) network learning algorithm and a comparison of results in order to choose the best classification in terms of accuracy and speed.

The following tables 4,and 5 are present the results of comparing the performance of the four classifiers studied in the research about the number of letters gestures classified correctly (according to the group for the first dataset features images, using the Holdout method rates experimental ranging from 66% to 90%.

The method Holdout for the selection or vote of samples were used to estimate the error classification, for make testing or training for data sets used to measure performance evaluation.

Table 4: Recognizing gestures letters accuracy by Holdout in Dataset1

Classifiers	Holdout Percentage				
	66%	75%	80%	85%	90%
C4.5(J48)	80.6723	85.7143	86.4286	88.5174	85.7143
MLP	88.6555	86.8571	90.00	94.2857	91.4286
K-NN(IBK)	90.7563	92.5714	95.00	93.3333	92.8571
Naïve-Bayesian	84.4538	86.2857	83.5714	83.8095	84.2857

Table 5: Recognizing gestures letters accuracy by Cross-Validation in dataset-1

Classifiers	Cross-Validation value			
	Fold=5	Fold=10	Fold=15	Fold=20
C4.5(J48)	82.2857	84.2857	84.00	82.8571
MLP	90.1429	91.5714	91.5714	91.1429
K-NN(IBK)	91.1429	92.2857	91.5714	92.5714
Naïve-Bayesian	85.5714	85.8571	86.4286	86.7143

The results of comparing the performance of the four classifiers studied in the study regarding the number of letters gestures correctly categorized according to category for the second dataset features images of characters signs by using two of these methods are shown in the tables 6 and 7 below.

Table 6: Recognizing gestures letters accuracy by Holdout in dataset-2

Classifiers	Cross-Validation value			
	Fold=5	Fold=10	Flod=15	Fold=20
C4.5(J48)	90.4286	90.7143	92.5714	91.00
MLP	97.8571	98.2857	97.5714	97.2857
K-NN(IBK)	97.5714	97.8571	97.8571	98.00
Naïve-Bayesian	96.00	96.5714	96.5714	96.4286

Table 7: Recognizing gestures letters accuracy by Cross-Validation in dataset-2

Classifiers	Holdout Percentage				
	66%	75%	80%	85%	90%
C4.5(J48)	89.4958	90.8571	91.4286	89.5238	90%
MLP	94.1176	96.5714	97.1429	94.2857	98.5714
K-NN(IBK)	97.479	97.1429	98.5714	98.0952	98.5714
Naïve-Bayesian	96.6387	97.7143	97.1429	96.1905	97.1429

According to the previous table, we noticed that the K-NN classifier is the highest in the classification accuracy, Table.8 illustrate the rate of recognition of each letter from these letters using KNN classifier and the number of samples that were recognized correctly.

Table 1: The alphabets Matrix of Single Handed ArSL Recognition Using KNN

a b c d e f g h i j k l m n o p q r s t u v w x y z aa ab <-- classified as	Arabic Alphabets
60 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | a = alef	أ
0 61 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | b = ba	ب
0 0 60 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | c = ta	ت
0 0 0 65 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | d = th	ث
0 0 0 0 63 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | e = gem	ج
0 0 0 0 0 62 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | f = haa	ح
0 0 0 0 0 0 59 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | g = kha	خ
0 0 0 0 0 0 0 61 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | h = dal	د
0 0 0 0 0 0 0 0 58 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | i = zal	ذ
0 0 0 0 0 0 0 0 0 62 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | j = ra	ر
0 0 0 0 0 0 0 0 0 0 50 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | k = za	ز
0 0 0 0 0 0 0 0 0 0 0 60 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | l = sen	س
0 0 0 0 0 0 0 0 0 0 0 0 62 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | m = shin	ش
0 0 0 0 0 0 0 0 0 0 0 0 0 63 0 0 0 0 0 0 0 0 0 0 0 2 0 0 | n = sad	ص
0 0 0 0 0 0 0 0 0 0 0 0 0 0 61 0 0 0 0 0 0 0 0 0 0 0 0 0 | o = dad	ض
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 63 1 0 0 0 0 0 0 0 0 0 0 0 | p = tah	ط
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 59 0 0 0 0 0 0 0 0 0 0 0 | q = thah	ظ
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 60 0 0 0 0 0 0 0 0 0 0 | r = ayn	ع
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 61 0 0 0 0 0 0 0 0 0 | s = ghayn	غ
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 62 1 0 0 0 0 0 0 0 | t = fa	ف
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 60 0 0 0 0 0 0 0 | u = ka	ق
0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 60 0 0 0 3 0 0 | v = kaf	ك
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 63 1 0 0 0 0 | w = la	ل
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 64 0 0 0 0 | x = mem	م
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 59 0 0 0 | y = non	ن
0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 1 0 0 0 58 0 0 | z = he	هـ
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 63 0 | aa = wa	و
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 62 | ab = ya	ي

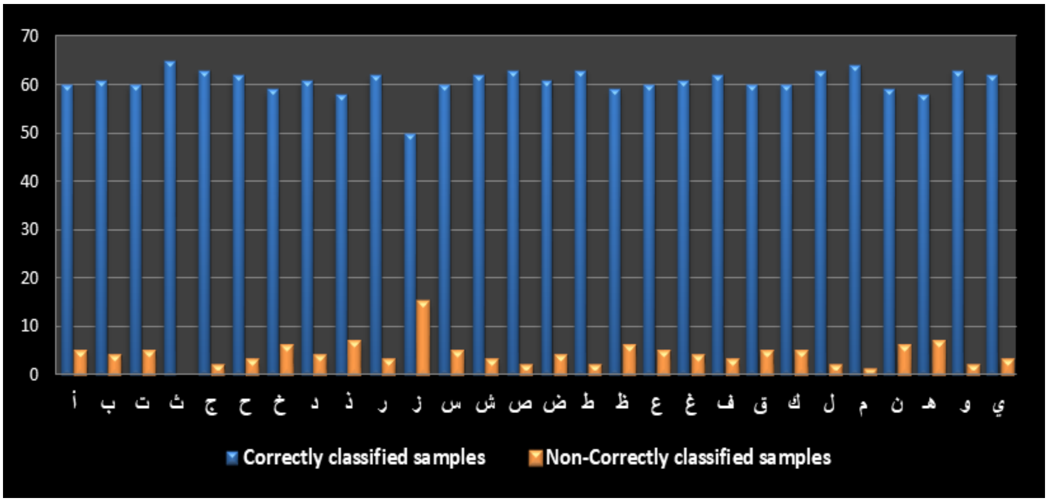


Figure 9: The total number of samples correctly identified in the alphabets.

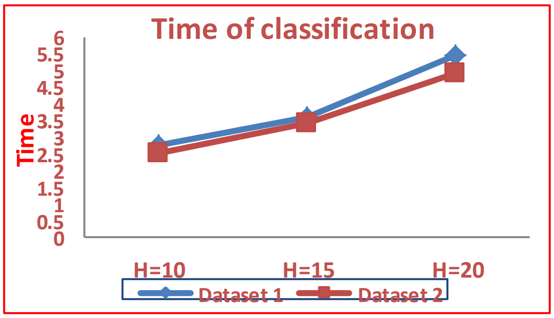
B. **The effect of the number of hidden neurons on the accuracy rate using MLP**

The number of hidden neurons in the structure of neural networks plays an important role in the recognition and classification process. Table.9 shows the Results of the performance of MLP network classifier according the numbers of correctly classified instances, and the classification time for several experimental values for the number of neurons in the hidden layer.

Table 9: The effect of neurons number in MLP network on the accuracy and time of classification

No. of neurons	H=10	H=15	H=20
Time of classification (Dataset 1)	2.59	3.51	5.13
Performance of classification(Dataset 1)	83.6134	89.4958	89.4958
Time of classification(Dataset 2)	2.55	3.42	5.04
Performance of classification(Dataset 2)	92.8571	92.8571	94.1176

We note from the results that the performance of the neural network increases with the increase in the number of neurons in the hidden layer as shown in Figure 9, but the classification time increases significantly.



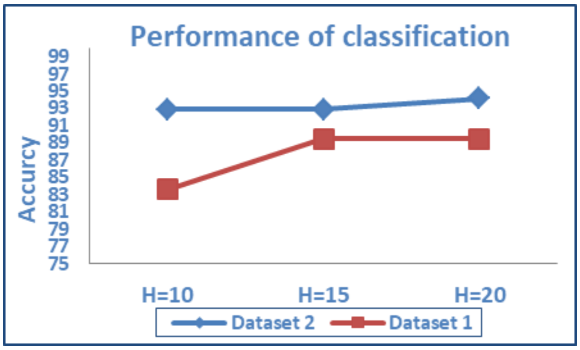


Figure 9: A graph describe Role of number of hidden neurons, in the performance of MLP

C. The role of value of K in the performance of KNN classifier

In this section, the output of the classifier K-NN is presented according to the value of the neighbor by choosing values that have been increasing for a neighbor values 1,3,5 and 10, as seen in the table 10.

Table 10: The role of K value in the performance of the K-NN algorithm

K- Neighbour value	K- value			
	K=1	K=3	K=5	K=10
The proportion of correct classified examples –Dataset1	92.2857	89.0756	86.1429	80.8571
The proportion of correct classified examples –Dataset2	97.8571	96.2857	95.7143	91.8571

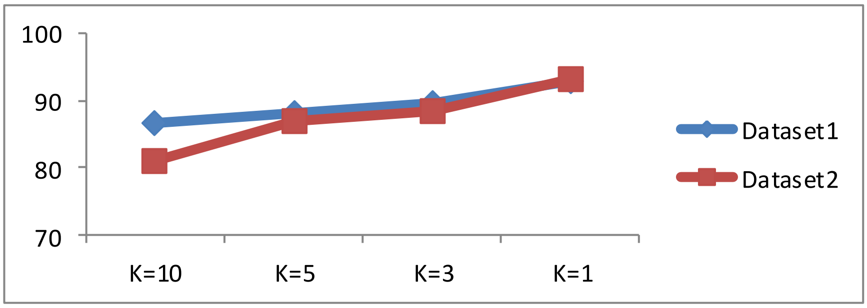


Figure 10: A graph describe role of K values in the performance of the K-NN algorithm

We note from the results that the lower the value of neighborhood K in the KNN algorithm, the more accurate the recognition of the alphabet

D. **Performance of the classifiers used in proposed system**

The classification was performed; the performance of the classifiers used in the proposed was compared in terms of the number of Correctly Classified Instances and the number of Incorrectly Classified Instances for dataset 2

Table 2: Comparing the performance of the classifiers used in proposed system.

Classifier Name	Cross-Validation with Flod=10				No. of Repetition =100	
	Correctly Classified Instances		Incorrectly Classified Instances		Root Mean Squared Error	Kappa Statistic
	number	percentage	number	percentage		
C4.5	2736	97.7143 %	64	2.2857 %	0.0372	0.9763
MLP	2647	94.5357 %	153	5.4643 %	0.0556	0.9433
K-NN	2792	99.7143 %	08	0.2857 %	0.0143	0.997
Naïve-Bayesian	2418	86.3571 %	382	13.6429 %	0.0931	0.8585

The percentage of Correctly Classified Instances is as high as possible with a KNN classifier and as little as possible with a classifier Naïve-Bayesian as shown in the diagram in Figure 11, describe the correctly and non-correctly classes for each classifier.

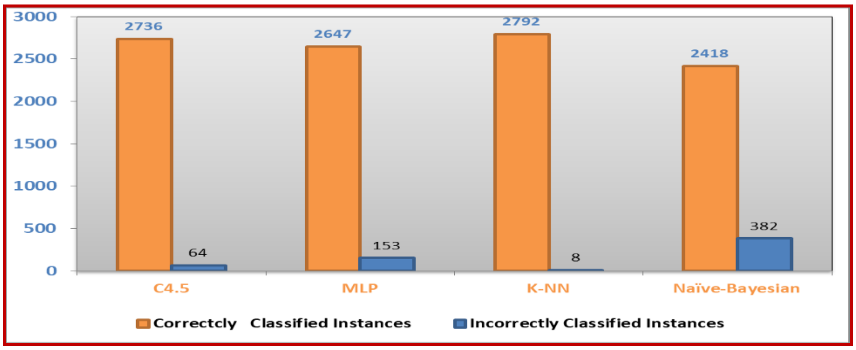


Figure 11: The correctly and non-correctly classes for each classifier using in PROPOSED System.

The prediction scale (Kappa Statistic) is successfully linked to the classification of the correct examples, which is the largest scale possible in a KNN classifier , and the least possible in Naïve-Bayesian classifier, also, the Root Mean Squared Error (RMSE)is inversely proportional to the rudder of the classification, so it is the largest possible in a classifier Naïve-Bayesian , It is the lowest possible in the KNN classifier, and the Figure 12 shows the relationship of both the prediction scale (Kappa Statistic) and the RMSE for each of the four classifiers.

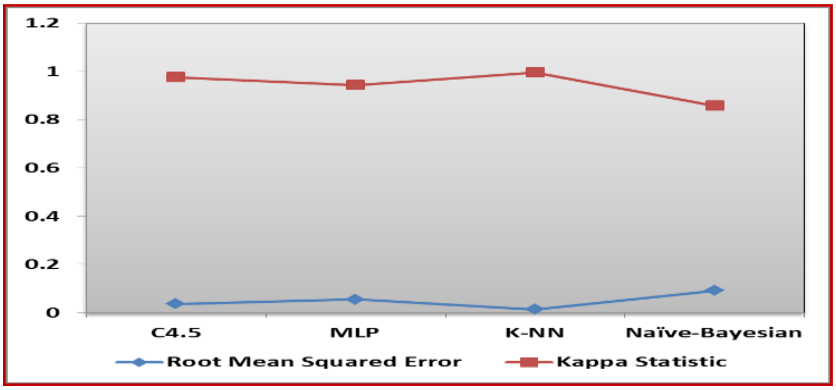


Figure 12: The relationship of Kappa Statistic and the RMSE for each classifier using in proposed System.

E. **Result of Classification in PROPOSED System**

The two most accurate classifiers were chosen among the four studied classifiers in order to test them within the PROPOSED system using MATLAB software as in the Figures 12 and 13.

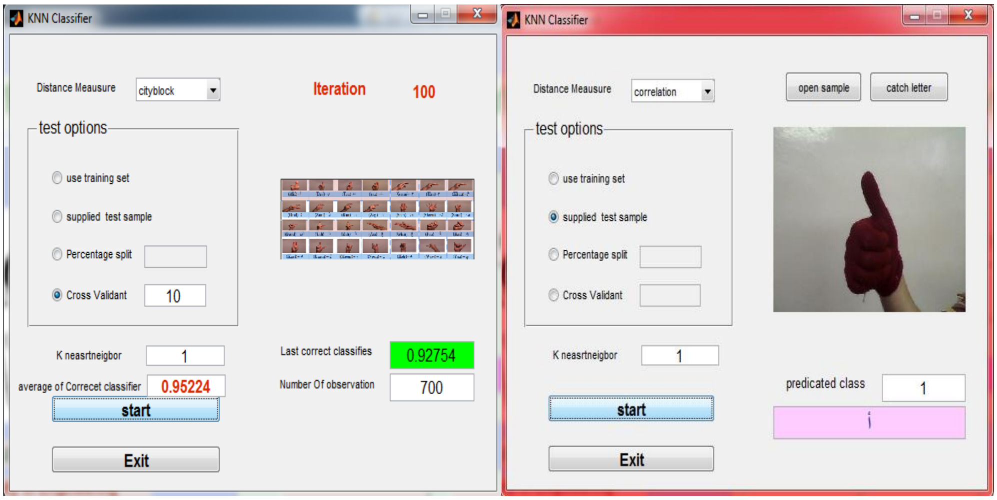


Figure 12: KNN classifier screen in PROPOSED System

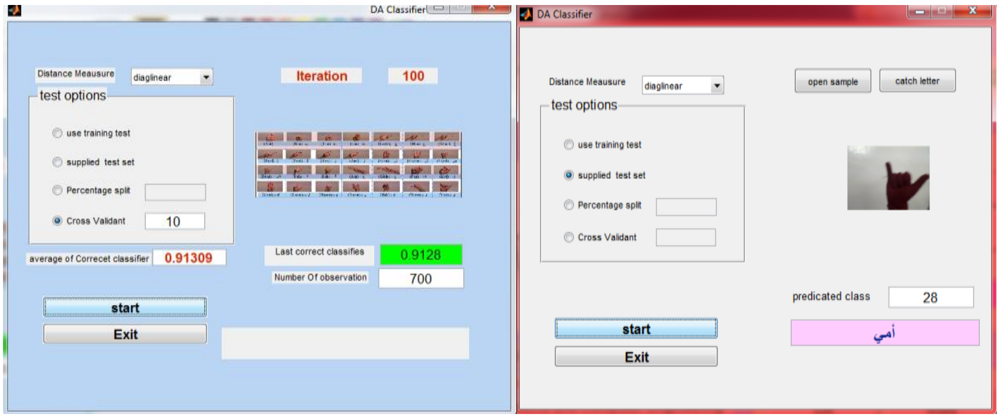


Figure 13: Decision Tree (C4.5) classifier screen in PROPOSED System.

The table.12 shows the results of a classification by KNN algorithm for k = 1 in the PROPOSED system using several options for calculating the distance, repeating the classification 100 times, and calculating the arithmetic mean of the accuracy by cross validation method by Flod=10

Table 3: Recognizing gestures letters accuracy by PROPOSED using MATLAB software

K- Neighbour value	K=1 and Flod=10			
	correlation	cosine	Euclidean	cityblock
The proportion of correct classified examples	0.91844	0.92019	0.97681	0.98249

It is clear from the above table that the PROPOSED system achieves higher classification accuracy when using cityblock distance measurement while ready-made software such as WEKA is used Euclidean distance measurement only. The possibility of changing the distance used in the proposed system can be considered an important feature not available in ready-made software.

5. Conclusions and Future Directions

The findings of the cross validation method (fold=10) demonstrate much superior performance when compared to all other existing algorithms used in the comparison. The importance of the k value in our technique (KNN) and its significance to the classification process cannot be overstated. The value of k=1 is strongly advised because it provides the best performance outcomes.

When holdout percentage values for the image features included in dataset 2 are calculated, our technique (K-NN) outperforms the other methods (C4.5, MLP, and Naive-Bayesian) in terms of performance.

Similar to MLP and Naive-Bayesian, K-NN uses photos of a single signer making glove-wearing movements over a white background. When the holdout percentage values are produced for the featured images of dataset-1 at various percentages (50%,66%,75%,80%, and 90%), our approach, along with MLP and Naive-Bayesian, performs significantly better than other classifiers. In Table 4, results are displayed.

Two data sets with the visual attributes needed for gesture recognition are presented for examination. For the comparison, six classifiers based on statistics and neural network techniques are utilized. While C4.5, SMO, and VFI are based on statistical methods, MLP, K-NN, and Naive Bayesian are based on neural topology. We used holdout for the selection of samples for the testing and training data sets and cross validation as a second method to estimate the error classification. The experimental data demonstrates that the MLP classifier provides superior accuracy results when employing two datasets in the cross validation procedure (dataset-1 and dataset-2). When compared to the other classifiers in the Estimation error classification method, the K-NN classifier has an exceptional holdout value.

The researcher wants to employ a preliminary model in computer-based deaf education programs as well as a way to interact with the deaf and learn their language. Until now, only single signer gesture recognition methods have been considered in this field. If double hand gesture recognition techniques are advanced, there are significant research opportunities. Methods for translating sign language into voice can also be used, and mobile phone platforms can be used for this. More study must be done in this area before social networking services like instant messaging are made available to the hearing impaired. If successful, this would revolutionize the life of everyone who is deaf and hard of hearing.

REFERENCES

[1] Ravikiran J; Kavi Mahesh, "Finger Detection for Sign Language Recognition", Proceedings of the International Multi Conference of Engineers and Computer Scientists, vol.1, 2009.

[2] Joyeeta Singha, Karen Das, " Indian Sign Language Recognition Using Eigen Value Weighted Euclidean Distance Based Classification Technique", (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 4, No. 2,2013

[3] Tabata Y, Kuroda T. Finger spelling recognition using distinctive features of hand shape. In: 7th ICDVRAT with Art Abilitation. Maia, Portugal: 2008:287-292.

[4] Halawani S. Arabic sign language translation system on mobile devices. IJCSNS. 2008; 8(1):251.

[5] Tsukada K, Yasumura M. Ubi-Finger: a Simple Gesture Input Device for Mobile and Ubiquitous Environment. Journal of Asian Information, Science and Life (AISL). 2004; 2(2): 111-120.

[6] Khalid Alvi A, Azhar M, Usman M, Mumtaz S, Rafiq S, Rehman R, et al. Pakistan Sign Language Recognition Using Statistical Template Matching. In: Proceedings of world academy of science, engineering and technology. Rome, Italy: 2005;3:52-55.

[7] AI-Buraiky S. Arabic sign language recognition using an instrumented glove. Master Thesis, King Fahd University of Petroleum & Minerals, Saudi Arabia. 2004.

[8] Nashwa El-Bendary, Hossam M. Zawbaa, Mahmoud S. Daoud,Aboul Ella Hassanien: "ArSLAT: Arabic Sign

Language AlphabetsTranslator", International Journal of Computer Information Systems and Industrial Management Applications, Vol.3, 2011,

[9] Samaa M. Shohieb, Hamdy K. Elminir, A.M. Riad "Signs World Atlas; a benchmark Arabic Sign Language database" Journal of King Saud University - Computer and Information Sciences Volume 27, Issue 1, January 2015, Pages 68–76

[10] Feris R, Turk M, Raskar R, Tan K, Ohashi G. Exploiting depth discontinuities for vision-based finger spelling recognition. In: Proceedings of the 2004 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'04) Vol 10. IEEE Computer Society; 2004.

[11] Tanibata N, Shimada N, Shirai Y. Extraction of hand features for recognition of sign language words. In: The 15th International Conference on Vision Interface. 2002:391-398.

[12] Mohandes M. Arabic sign language recognition. In Proceedings of the Int. Conf. on Imaging Science. 2001. Las Vegas, Nevada, USA: CSREA PRESS; 2001 ;(1):25-28.

[13] Mohandes M. Automatic Translation of Arabic Text to Arabic Sign Language. ICGST International Journal on Artificial Intelligence and Machine Learning, AIML. 1996; 6(4):15-19.

[14] Foong OM, Low TJ, Wibowo S. Hand Gesture Recognition: Sign to Voice System. International Journal of Electrical, Computer and Systems Engineering (IJECSE). 2009; 3(4):198-202.

[15] Abdelmoty M. Ahmed, Reda Abo Alez , Muhammad Taha , Gamal Tharwat. Propose a New Method for Extracting Hand using in the Arabic Sign Language Recognition (Arslr) System. International Journal of Engineering Research & Technology (IJERT). Volume. 4 - Issue. 11 , November – 2015 e-ISSN: 2278-0181

[16] Priyanka Sharma, Manavjeet Kaur. Classification in Pattern Recognition: A Review. International Journal of Advanced Research in computer Science and Software Engineering (IJCARCSSE). Volume 3, Issue 4, April 2013- ISSN: 2277 128X

[17] Mingqiang Yang, Kidiyo Kpalma, Joseph Ronsin. A Survey of Shape Feature Extraction Techniques. Peng-Yeng Yin. Pattern Recognition, IN-TECH, pp.43-90, 2008.

[18] Jie Liu, Jigui sun Pattern recognition: An overview, 1st edn. Wang. College of computer science & technology, china. IJCSNS, International Journal of Computer Science & Network Security. VOL.6. NO.6. June 2006.

[19] Navdeep Kaur, Usvir Kaur, Survey of Pattern Recognition Methods, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 3, Issue 2, February 2013.

[20] Kidiyo Kpalma and Joseph Ronsin, An Overview of Advances of Pattern Recognition Systems in Computer Vision Source: Vision Systems: Segmentation and Pattern Recognition, ISBN 987-3-902613-05-9, IETR, UMRCNRS 6164.

[21] http://ch.mathworks.com/help/images/ref/regionprops.html?requestedDomain=www.mathworks.com

التعرف علي أبجدية الأصابع الإشارية باستخدام المصنفات الإحصائية لتحسين التواصل بين ذوي الاعاقة السمعية وفئات المجتمع الأخرى

د. عمرو محمد سليمان عبدالرحمن

أستاذ مشارك الصحة النفسية جامعة الملك خالد

د. محمود مصطفي خطاب

أستاذ مساعد علوم الحاسب جامعة الملك خالد

د. عبد المعطي محمود محمد أحمد

أستاذ مساعد علوم الحاسب جامعة الملك خالد

الملخص:

تسعي هذه الدراسة الي تقديم تقنية جديدة للكشف واستخراج إيماءات أبجدية الأصابع الإشارية الخاصة بلغة الإشارة العربية (للصم) من الصورة أو الفيديو، حيث لا تزال لغة الإشارة هي طريقة الاتصال السائدة للأشخاص ضعاف السمع والصم؛ إنها لغة إيماءات يدوية، وكل حركة تشير إلى معنى معين، فالغرض من هذه الدراسة هو إنشاء نظام للترجمة الآلية للغة الإشارة العربية، يتكون نظام الترجمة الألية للغة الإشارة للنص العربي المقترح من خمس مراحل أساسية ويعمل كمترجم للصم والبكم والأشخاص العاديين لتحسين التواصل، يعتمد هذا النظام على بناء مجموعتين من ميزات الصورة البيانات الإيماءات الأبجدية من مصدرين: قاموس لغة الإشارة العربية الموحد والإيماءات (إشارات اليد) من خبراء بلغة الاشارة؛ كما تستخدم تقنيات التعرف على الإيماءات، والتي تتيح للمستخدم التفاعل مع العالم الخارجي، من خلال التقاط الفيديو والصور، ومعالجة الفيديو والصور، وإنشاء واستخراج ميزات الإشارات اليدوية،

والتصنيف، وأخيراً تحويل النص وتفسيره؛ في هذا البحث ، نستخدم مجموعة من الميزات المناسبة في بناء علامة اليد خطوة وتصنيفها بناءً على خوارزميات تصنيف مختلفة مثل KNN و MLP و C4.5 و VFI و SMO ومقارنة هذه النتائج للحصول على تصنيف أفضل.

الكلمات المفتاحية : المعاقين سمعيًا، لغة الإشارة؛ معالجة الصور ؛ معالجة الفيديو .