AUTOMATIC TRANSLATION OF ARABIC SIGN TO ARABIC TEXT (ATASAT) SYSTEM

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ABSTRACT

Sign language continues to be the preferred tool of communication between the deaf and the hearing-impaired. It is a well-structured code by hand gesture, where every gesture has a specific meaning, In this paper has goal to develop a system for automatic translation of Arabic Sign Language. To Arabic Text (ATASAT) System this system is acts as a translator among deaf and dumb with normal people to enhance their communication, the proposed System consists of five main stages Video and Images capture, Video and images processing, Hand Signs Construction, Classification finally Text transformation and interpretation, this system depends on building a two datasets image features for Arabic sign language gestures alphabets from two resources: Arabic Sign Language dictionary and gestures from different signer's human, also using gesture recognition techniques, which allows the user to interact with the outside world. This system offers a novel technique of hand detection is proposed which detect and extract hand gestures of Arabic Sign from Image or video, 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, C4.5, VFI and SMO and compare these results to get better classifier.

KEYWORDS

Sign language, Hand Gesture, Hand Signs Construction, gesture recognition, hand detection

1. INTRODUCTION

Sign language is the prominent means of communication among the deaf and the hearing-disabled. Two approaches are mainly followed in sign language; they are vision-based and bio mechanical (Gloves sensor). The advantage of vision-based systems over the counterpart is that users do not need to use complex equipments but in the pre-processing stage requires sufficient computations in place of cameras which are used in vision based systems , sensor-based systems use sensor enabled instrumented gloves this paper presents computer vision-based gesture interface that is part of a sign language recognition system, and also explains computerized sign language recognition system for the vocally disabled (deaf and dumb) that uses sign language for communication.

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Generally there are three levels of image based ATASAT, they are continuous recognition, alphabet recognition and isolated-word recognition. The input of the vision based methods is a set of images or video sequence of the signs. The signers are asked to have pause between the signs to isolate the signs which is done manually This paper will present research progress and findings on techniques and algorithms for hand detection as it will be used as an input for gesture recognition process.

The ATASAT system using image and pattern recognition technology is presented in Section I. Related works are described in section 2. Overview of the proposed system is discussed in Section 3. In Section 4, the computer simulation results of the system are presented, finally Conclusions and Future Directions are summarized in Section 6.

2. RELATED WORKS

Deaf and dumb or Hearing impairment people cannot talk and hear like normal people; so they have to depend on some types of visual communications in most of the time. [1]

The communication between hearing impairment and normal people depends only on the sign language, while the vast majority of normal people don't know this language. Sign language is not universal; it varies according to the country or regions, class of people [2].

A finger spelling recognition method by using distinctive features of hand shape was proposed by Tabata et al [3]. An Arabic sign language translation system on mobile devices was introduced by Halawani [4]. To use input device of wearable computer, a new glove-based input device was proposed by Tsukada et al [5]. Statistical template matching was used to recognize Pakistan sign language based on data glove by Khalid Alvi et al [6]. Arabic sign language recognition system was developed using an instrumented glove proposed by AI-Buraiky et al [7] Arabic sign language (ArSL) has recently been recognized and documented. Many efforts have been made to establish the sign language used in Arabic countries. are trying to standardize the sign language and spread it among members of the deaf community and those concerned. However, Arabic speaking countries deal with the same sign alphabets [8], [9].

Feris et al [10] proposed an approach to exploit depth discontinuities for finger spelling recognition to differentiate between similarities of some signs by using multi flash camera. On the other hand, Tanibata et al. [11] provided a prototype approach based on feature extraction to solve hand occlusion problem for Chinese sign language recognition. Mohandes [12], [13] introduced a prototype system to recognize the Arabic sign language based on Support Vector Machine (SVM) and also an automatic Translation system to translate Arabic Text to Arabic Sign Language. Foong et al [14] proposed A Sign to Voice system prototype which is capable of recognizing hand gestures by transforming digitized images of hand sign language to voice using Neural Network approach.

3. OVERVIEW OF THE PROPOSED SYSTEM

In this section an overview of the proposed Automatic Translation Arabic Sign to Arabic Text (ATASAT) System consists of five main stages Video and Images capture, Video and images processing, Hand Signs Construction, Classification and Text transformation and interpretation, cycle of proposed system is given in Figure 1.

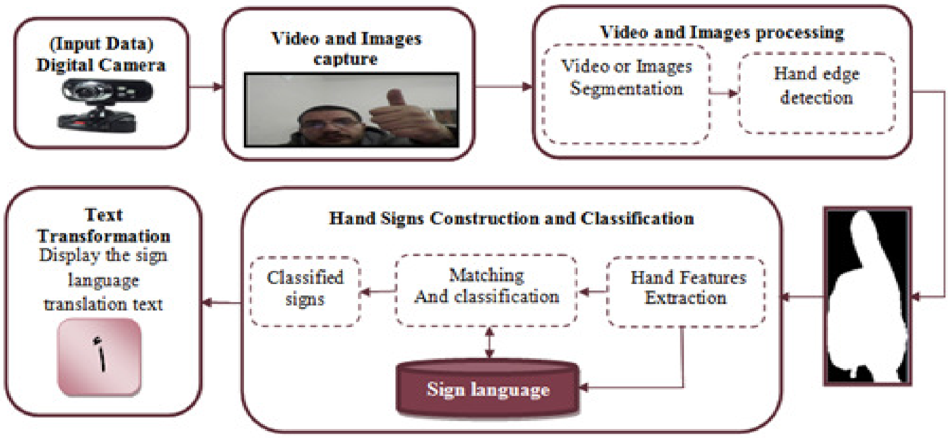

Figure. 1 The cycle of proposed system ATASAT System

The ATASAT system goes throw many steps which are illustrated in the following flow chart shown in Figure. 2, the next sections explain in details every step.

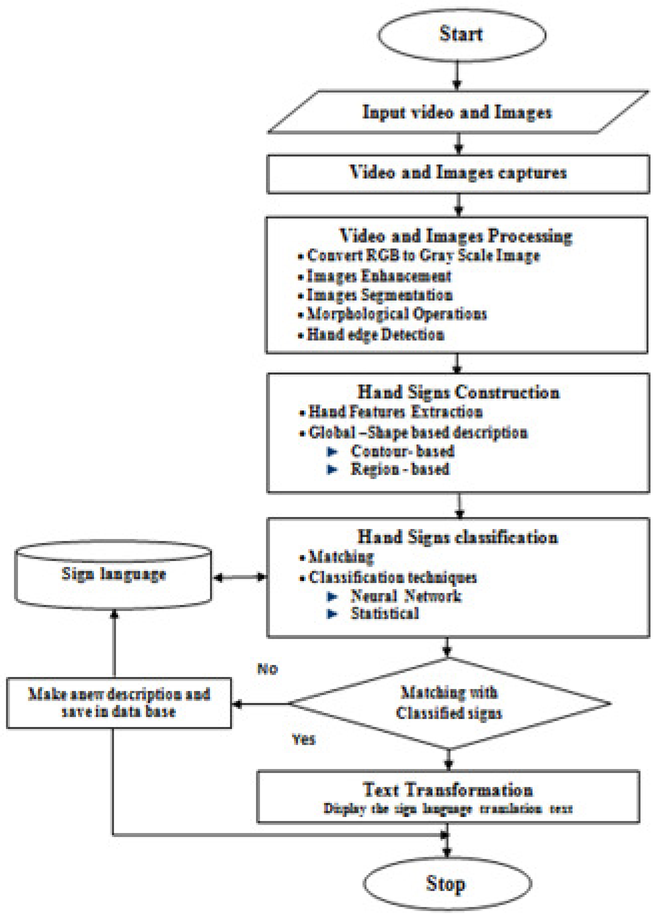

Figure.2 The ATASAT System flow chart

3.1 Video and Images capture

In first step in ATASAT system, the visual data is captured from the environment using input device like camera, Data entered for this stage give rise for gestures carried out by a number of indicators by wearing the glove dark color in different lighting environments with a light background(first data set) or without wearing a glove (natural color of the skin) with a dark background (second data set) so that it output of this stage is a set of colored image (RGB) representing the hand gestures corresponding to each one letter of the Arabic sign language the Figure 3 describes the image capture process.

Figure.3 The main screen of the proposed ATArSArT System

3.2 Video and images pre-processing

In the second step was 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, it has been using a number of algorithms to discover it and choose the appropriate adjectives to describe and distinguish the form of a gesture hand and draw these qualities for use in computer training to get to know the letters, and the corresponding characters in the Arabic language.

Once the frame image is captured, it requires RGB to Gray conversion as our taken image is in RGB form. After the conversion, we are having Gray scale image and now use some different techniques to perform operations in order to enhance image, image segmentation and conduct morphological image processing to remove noise, and revealing important areas (hand shape) in the image.

To complete image processing operation, we designed a new algorithm is called Arabic Sign Hand Detection (ArSHD) this algorithm has been proven effective in the process of image processing and distinguish easily understanding and implementation, the implementation of this algorithm proposed several methods to detect a hand such as Sobel ,canny edge, threesholding and Adjust the contrast method ,these are similar in technologies used to convert the image to gray, extract hand after detection of the image and these are different in technologies to enhance image, image segmentation and morphological image.

Use a combination of Captured images in the first stage around 700 pictures at the rate of 25 images for each letter an indicative of letters Arabic alphabet 28 and the type of images extracted is black and white Each image in the form of a gesture hand after the isolation, detection and the following figure is represents an example for each letter an indicative before the primary image processing process.[15]

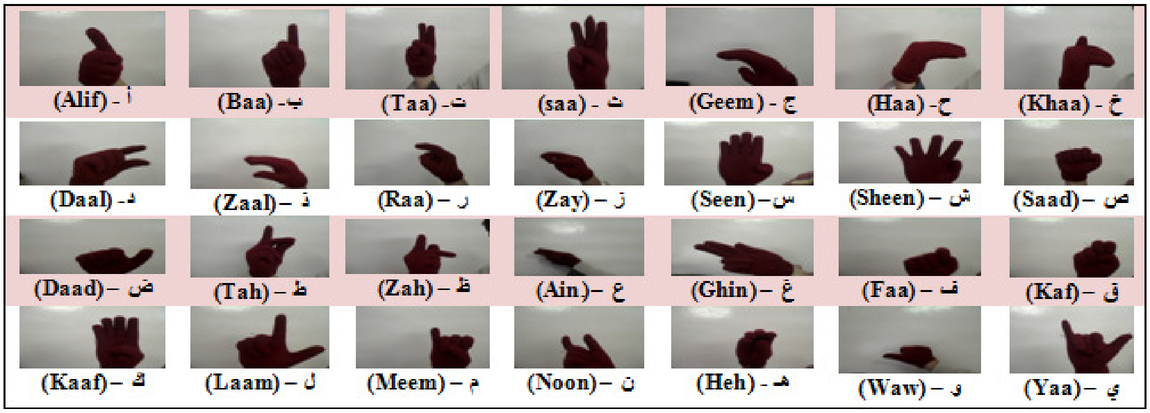

Figure 3 the ATASAT system dataset of alphabets letters before pre-processing

The following figure shows some images of characters indicative, and explains how to extract shape of the hand from the background in images indicative characters after the processing, which has to one of the previous methods such as Sobel, Canny, Threshold and adjust the contrast.

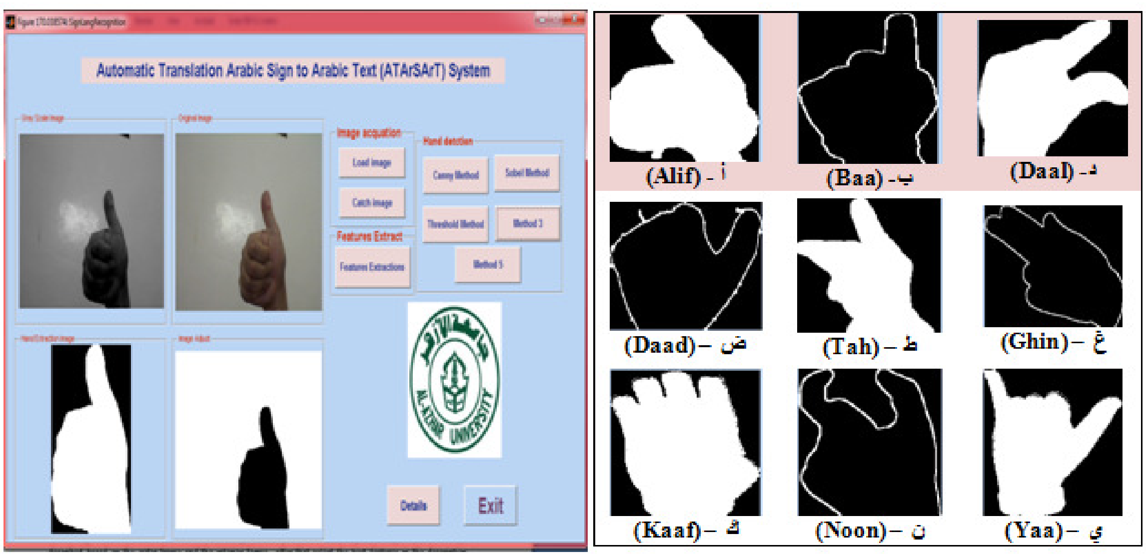

Figure.5 (a) the result of image processing (b) Examples of hand detectction by different methods

3.3 Hand Signs Construction

In this step conducted Hand is described in the image caused by hand detection step according to one of the methods described based on the outer frame and the interior forms,, after that select the best features in the description gesture and distinguish them from other gestures, then, feature extraction, which have been selected for the processing of income data, which are then used in the training or testing processes.

Feature extraction stage depends on the success of hand gesture recognition in the previous stage; this is achieved through five basic steps data collection, features selection, select model of classification, classifiers training and evaluation. These steps can be summarized in two steps:

a. Choose a good description of shape to be recognizable through analysis of data in this method and it collects data and choose the features of object must take into account the features of shape learned several things as follows[16]

   - The many small differences between the features of same classifier that is convergent.
   - Choose a smaller number of features for class to get a high percentage of accuracy
   - Discrimination varieties from each other by choosing the big differences between the features of each class and other.
   - Identify potential feature points for each class.
   - Identify attributes and features that are helpful for distinguish each class even if change his place, his change any factor of its factors, such as displacement, rotation, size, its coordinates and area.

b. Choose the method for effective classification and there are several well-known to identify the patterns and the following table illustrates these methods and how to represent the patterns, recognition function, typical criterion that use with each method [17] , [18]

Table1. The important characteristics of the pattern recognition methods.

Classification methods	**Statistical**	**structural**	**Template matching**	**Artificial neural network**
Representation	Features	Primitives	Sample, pixel, curves	Samples, pixels, features
Recognition function	Discriminate function	Rules, grammar	Correlation, distance measures	Network function
Typical Criterion	Classification Error	Classification Error	Classification Error	Mean square Error

A lot of shape description and similarity measurement techniques have been developed in the past. A number of new techniques have been proposed in recent years. There are 3 main different classification methods [19]

1. Contour-based methods and region-based methods [20]. This is the most common and general classification and also is based on the use of shape boundary points as opposed to shape interior points.

2. Space domain and transform domain. Methods in space domain match shapes on point (or point feature) basis, while feature domain techniques match shapes on feature (vector) basis.

3. Information preserving (IP) and non-information preserving (NIP). IP methods allow an accurate reconstruction of a shape from its descriptor, while NIP methods are only capable of partial ambiguous reconstruction.

We have adopted in this paper on the first method to describe a shape that called Contour-based and region-based method, in order to get easy features account and fixed for rotation, displacement and change the size of the order to the same gesture.

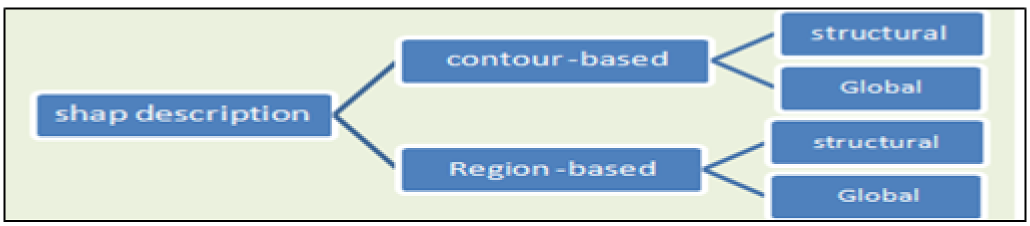

Figure.6 The representation and description of shapes techniques

3.3.1 Hand Features Extraction Implementing

The proposed system success is heavily dependent on the choice of a good description of the gestures of the hand so that it becomes It can be distinguished from other gestures of hand.

As we mentioned in section 3.4 we use shape-based description in the present research Depending on the global method that calculate features through Contour –based or Region -based We have chosen a set of features for describing hand gesture.

a) Object area (The number of pixels that compose the object (hand gesture))
b) Object Perimeter (Minimum bounding rectangle and corresponding parameters)
c) The center of gravity is also called centroid.
d) Object Major Axis Length
e) Object Minor Axis Length
f) Bounding box
g) Eight terminal points of the object coordinates (Extrema)

The following figure shows the illustration description features of hand shape that has been study [21]

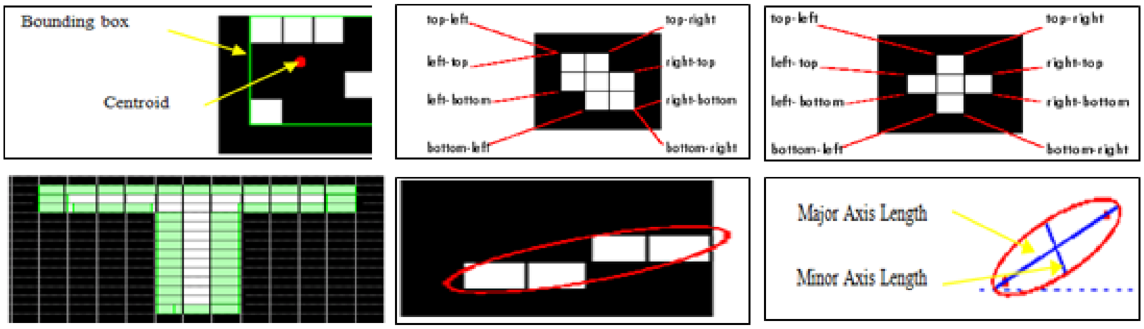

Figure.7 The Illustration of hand shape features

The calculation the studied features hand in a gesture of characters indicative table below illustrates some of the values of the features of these gestures.

Table 2 the calculated values for some features characters indicative gestures

The features		**(Alif) - أ**		**(Seen) – س**	
Object area		20195		30945	
Object Perimeter		904.4579		1.1479e+003	
Object centroid		CX=69.3843 CY=136.4365		CX=76.7294 CY=130.7228	
Object Major Axis Length		222.6721		254.5715	
Object Minor Axis Length		129.8120		165.1430	
Bounding box		x.width =136 , y.length =232		x.width=165 , y.length =236	
Extrema	Top –Left	54.5000	0.5000	76.5000	0.5000
	Top –Right	69.5000	0.5000	165.5000	0.5000
	Right-Top	136.5000	165.5000	165.5000	0.5000
	Right-Bottom	136.5000	232.5000	165.5000	236.5000
	Bottom-Right	136.5000	232.5000	165.5000	236.5000
	Bottom-Left	0.5000	232.5000	0.5000	236.5000
	Left- Bottom	0.5000	232.5000	0.5000	236.5000
	Left- Top	0.5000	167.5000	0.5000	55.5000

By study and calculate the features of all the gestures and the examples of it b we have noted that the traits important to distinguish the hand gesture, however, the group captured images are real image, and result in a significant difference to the values of features examples of one class per gesture, the interference with the values of the features between two classes of hand gestures for many reasons.:-

a) Resize the image as a result of changing the distance from the camera.
b) Change angle image capture for the same type of gesture.
c) Rotation and displacement of the image, or one of its parts as a result of moving the hand.
d) Distortions of some captured images gestures.
e) The similarity of some of the characters gestures.
f) Human differences in some methods of represent gestures per class.

Due to these reasons, we have the work of modifying the values of these features to improve the description of shaped gesture for the characters in order to obtain the highest accuracy in the classification stage.

For example, it can be modified a number of selected features by deleting endpoints (Bottom-right, Bottom-Left) because it is useless values to distinguish hand shape because it reflects where to place the palm of the hand.

The following table describes the modified features and methods of calculating the value of each it.

Table 3 The modified features to characters indicative gestures

Features	feature description	feature equation
F1	The ratio coordinates of the hand center of mass on the x-axis, to the width of around box by hand	F1=CX/ x.width
F2	The ratio coordinates of the hand centre of mass on the y-axis, to the length of around box by hand	F2=CY/ y.length
F3	The ratio between the width of around box by hand to the length of around box by hand	F3= x.width / y.length
F4	The ratio pixels of between the object(Hand) area to the area of around box by hand	F4= area (object)/ area of bounding box
F5	The ratio between object(Hand) Perimeter to object (Hand) area	F5= Perimeter (object) / area (object)
F6	The ratio between Object Major Axis Length to area of bounding box	F6= Object Major Axis Length / area of bounding box
F7	The ratio between Object Minor Axis Length to area of bounding box	F7= Object Minor Axis Length / area of bounding box
F8-F15	Extrema (Endpoints of hand shape)	F8= X Top –Left
		F9= X Top –Right
		F10= X Right-Top
		F11=Y Right-Top
		F12=X Right-Bottom
		F13=Y Right-Bottom
		F14= Y Left- Bottom
		F15= Y Left- Top

3.4 Hand Signs classification

In the classification process we will use two methods statistical classification and classification through neural networks in order to know the alphabet indicative fingers in the translation system into Arabic.

In the stage classification, choose one of the statistical classification algorithms or neural networks to design a classifier, and his teaching under the supervision of the training data (database formed in the previous phase of the system),to classify a new gesture (hand shape) is not represented in the training set to one of the existing categories.

The main objective of the ATASAT System is to create a matching between the indicative letters played by dumb people, and the signs of letters were stored in database signs that generated in the previous step.

This process will be designed classifiers uses one of the Education algorithms supervised, to do the task of classification a new character indicative to the corresponding product was his depending on digital data base resulting from the application extracting hand shape features (which was exposed when applying hand detection of the resulting images of the stage capture images database), which represent training data set for the classifiers and sometimes test data set.

In the implementation of the classification process based on statistical classification algorithms (C4.5, Naïve-Bayesian, K-NN), Multilayer perceptron (MLP) network algorithm Sequential Minimal Optimization (SMO) and Voting Feature Intervals (VFI) algorithm and compare the results in order to choose the best seed in terms of accuracy and speed.

Classification algorithms were applied using a WEKA program to compare the results with the results of classification using the ATASAT system to the same data base the results are presented in the fourth section of this paper.

3.5 Text transformation and interpretation

Text transformation stage, to display the Arabic letter that corresponding and matching with the image of the character stored in the given data base.

According to the built-in database which contains a image signs features describing a pattern, the obtained matching pattern is presented through its text. Repeating this step for each input image and video frame allows integration between their descriptions, and leads to formulating the text representing the translation of the input image or video. The features obtained from the gesture sign language database for every key frame are concatenated to transform the image gestures into a text.

4. RESULT EVALUATION AND DISCUSSION

Results of Implementing Classification in Weka Software has been conducting a number of experiments are described as follows:

4.1 Role of the methods of estimate error classification

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

The following tables presents the results of comparing the performance of the six classifiers studied in the research about the number of letters gestures classified correctly according to the group for the first dataset features images.

Table 4 Recognizing gestures letters accuracy by Holdout in dataset-1

Classifiers	Holdout Percentage				
	50%	66%	75%	80%	90%
C4.5	94	97.0588	97.7143	99.2857	98.5714
SMO	96.8571	98.3193	97.7143	99.2857	98.5714
VFI	95.7143	95.3782	98.2857	98.5714	98.5714
MLP	100	100	100	100	100
K-NN	100	100	100	100	100
Naïve-Bayesian	100	100	100	100	100

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	97.1429	98.1429	97.5714	98.1429
SMO	99.1429	99.1429	99.1429	99.1429
VFI	97.4286	97.2857	97.4286	97.4286
MLP	100	100	100	100
K-NN	99.8571	99.8571	99.8571	99.8571
Naïve-Bayesian	99.7143	99.7143	99.8571	99.8571

The following tables presents the results of comparing the performance of the six classifiers studied in the research about the number of letters gestures classified correctly according to the group for the second dataset features images of characters signs by using two these methods.

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

Classifiers	Holdout Percentage				
	50%	66%	75%	80%	90%
C4.5	76.2857	80.6723	85.7143	86.4286	85.7143
SMO	70.5714	70.1681	78.2857	77.8571	82.8571
VFI	68.5714	69.3277	73.1429	73.5714	67.1429
MLP	86.8571	88.6555	88.00	92.1429	92.8571
K-NN	88.5714	91.1765	93.1429	95.7143	94.2857
Naïve-Bayesian	86.8571	84.4538	86.2857	83.5714	84.2857

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

Classifiers	Cross-Validation value			
	Fold=5	Fold=10	Fold=15	Fold=20
C4.5	81.00	83.857	84.8571	84.143
SMO	83.00	82.1429	83.00	81.8571
VFI	72.4286	70.2857	71.7143	70.7143
MLP	90.143	91.000	92.00	90.429
K-NN	92.286	93.000	93.00	93.286
Naïve-Bayesian	87.286	88.000	87.00	88.286

4.2 Role value of the neighbouring K in the performance of the k-NN algorithm

In this section presents the results performance of classifier K-NN according to the value of neighbour by choose values has been increasingly for a neighbour from 1 to 10, the following table describe this results.

Table 8 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 –data set -1	99.8571	99.7143	99.143	98.5714
The proportion of correct classified examples –data set -2	93.00	88.5714	86.8571	81.00

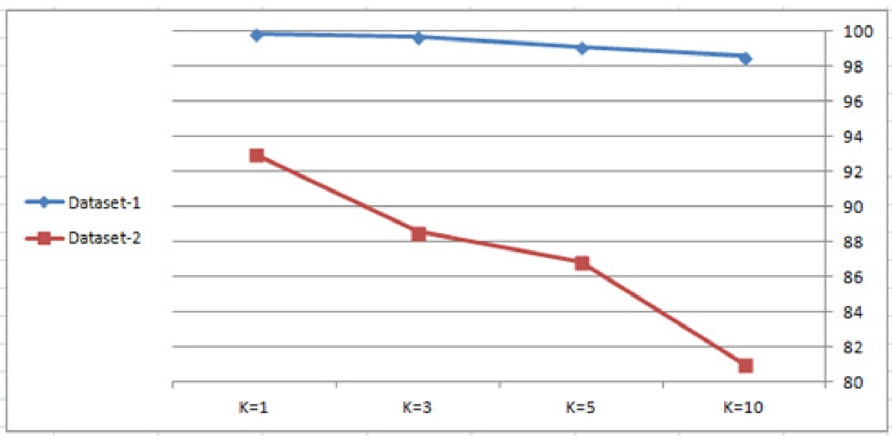

Figure.8 A graph describe role of K value in the performance of the K-NN algorithm

5. CONCLUSIONS AND FUTURE DIRECTIONS

5.1 Conclusions

The results obtained after performing the cross validation method (fold=10) shows much better performance compared to all other existing algorithms taken for the comparison. The value of k used in our approach (KNN) is very important and it has a significant role in the classification process. Its highly recommend to use the value of k=1 which gives the best performance results.
When holdout percentage values for the image features which is included in dataset2 is performed, our algorithm (K-NN) is giving better results than the other approaches (C4.5, SMO, VFI, MLP and Naïve-Bayesian).

Same as the other approaches like MLP and Naïve-Bayesian, K-NN also use images contains glove weared gestures with white background and one-signer. When the holdout percentage values for different percentages (50%,66%,75%,80% and 90%) are calculated for the featured images of dataset-1, our algorithm along with MLP and Naïve-Bayesian shows far better performance compared to other classifiers. Results are shown in Table 4.

Two data sets are introduced for the analysis, containing the image features for gesture recognition. Six classifiers based on statistical and neural network approaches are used for the comparison. MLP, K-NN and Naïve-Bayesian are based on neural topology, C4.5, SMO, VFI are based on statistical approach. We used to estimate the error classification is holdout for the selection of samples for testing and training data sets and second method is cross validation used to measure performance evaluation. In cross validation method the experimental results shows that the MLP classifier gives better accuracy results using two datasets (dataset-1 and dataset-2). In Estimation error classification method, K-NN classifier has remarkable holdout value when compared with all other classifiers.

5.2 Future works and directions

The researcher hopes to use an initial model in educational programs for the deaf by Computer, As well as a means to communicate with the deaf and understand their language. So far in this area single signer means of gesture recognition is taken into account. High researches scopes are there if double hand gesture recognition approaches are put forwarded. Sign language to voice recognizer methods can also be implemented; even mobile phone platforms can also be used for this. Social networking like instant messaging services for the hearing disabled people can also be possible, more researches need to be carried out in this regard, so that it can make a revolutionary change in the lives of people who all are deaf and dump.

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