Arabic Sign Language Hand Gesture Recognition Using the Support Vector Machine Algorithm

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Abstract: Arabic Sign Language (ArSL) plays crucial role in facilitating communication for hearing-impaired community in Arabic-speaking countries and hand gesture recognition systems can contribute to improving accessibility and enabling communication and communication with them. Hand gesture recognition (HGR) has wide range of applications, including virtual environments, intelligent monitoring, sign language interpretation, medical systems, etc. Translating Arabic Sign Language using hand gestures and machine learning (ML) algorithms is one of the most important applications we have created. To develop a system for recognizing hand gestures in Arabic Sign Language using SVM, which is one of the widely used machine learning techniques? To develop a powerful classifier for hand gesture recognition By training the model to improve the hyper-level to effectively separate different classes of hand gestures based on the extracted features and evaluating the performance of the classifier using different evaluation metrics to determine its accuracy and generalization capabilities, we need dataset of hand gesture Samples labeled with their corresponding meanings. The dataset will include features extracted from hand gestures, such as hand shape, movement, and position. It should be noted that the accuracy of the recognition system depends on the quality of dataset, feature selection, and SVM parameters. Also, pre-processing steps such as hand segmentation and normalization may be necessary to improve performance. Present paper proposes static hand gesture recognition system for ArSL. Meanwhile, it uses multi-class support vector machine (MSVM) algorithm. The current study discovered a histogram of oriented gradients (HOG) from each sample image. In addition to performing principal component analysis (PCA) on HOG image samples with 100% accuracy. Test results on ArSL showed that this method is very effective and with high accuracy. Whereas, using the Z-score normalization method, the features and sigma belonging to one class became more closely related and separated from the other class.

1 INTRODUCTION

The human body language can be understood and analyzed through the use of a technology known as gesture recognition, which then allows the system to interact with the user in the appropriate manner [1]. This, in turn, assists in the construction of a bridge between the user and the computer so that they can communicate with one another [2]. The recognition of gestures is beneficial for processing information that cannot be communicated through speech or text. Sign language translation utilizing hand gestures based on ML algorithms is one of the most important applications of gestures [3]. One of the most important tools for creating intuitive user interfaces is gesture recognition. However, gestures can usually be derived from any type of physical action or mood, the most typical sources being the face or the hand [3], [4]. Humans and machines have a natural way of communicating through hand gestures, which can be used to accomplish a wide range of activities [5], [6]. Such interaction methods are also increasingly applied in intelligent transportation systems, where gesture-based or vision-assisted controls can support driver assistance and passenger interaction, as seen in connected and intelligent vehicle frameworks like E-VANET [7].Complexity of hand motion structures, variations in hand size, hand location, and environmental illumination are just some of the variables that can throw off HGR algorithms. DL innovations of late have greatly improved the accuracy of picture identification systems [8], [9]. Hand separation methods exist. The skin color model is the most common and easiest way to get skin pixels in an image, but it has limitations because skin colors vary and the background image can contain skin pixels [10]. The type of HGR system relies on environmental factors, the person making the gesture, the efficacy of the devices used to capture it, the type of gesture – static or dynamic – and the purpose for which it is intended [11], [12]. ML is part of AI that develops data-dependent systems. Classification is a group of models or functions that distinguish class data or concepts to predict the class of an unknown entity. Classification (IF-THEN) rules, decision trees, mathematical methods, or neural networks are used to derive the model from training data [13]. SVM, PCA, HOG, and other hand detection methods are popular. The optimized kernel function and classification algorithm for hand recognition SVM method extracts all image features [9], making computation big and rapid identification of massive data tough; PCA extracts global features, but illumination affects recognition success [14], [15]. HOG is based on feature extraction, but its calculation is still big, making rapid identification difficult [16]. Features are extracted for each gesture type using various methods. The most common time domain features are mean absolute value, autoregressive coefficients of degree n, zero crossing, signal length, changes in slope sign, modified mean absolute value, simple square integral, root mean-squared value, sample mean, variance, log detector, and average capacitance change [17]. Our focus is PCA-based SVM object spotting. SVM, a descriptive traditional ML predictor, sorts classification issues linearly and non-linearly [18]. As support vectors are evaluated when separating various types of data using hyper plane, it outperforms all of its alternatives. Consider the following figure for clarification purposes. We initially employed HOG to our dataset to extract features. The extracted features were subsequently subjected to dimension reduction. As stated previously in the feature and dimensionality reduction section, extract the principal variable from the random variables. Afterwards, an SVM has been applied by the dimensionality reduction used [19]. The suggested system uses the HOG algorithm to these regions to derive HOG features once the region of interest (ROI) area in the hand gesture image is identified [10]. HOG method uses hand gesture image after pre-processing [20], [21]. The dumb and deaf have been excluded from society, and a normal person cannot learn sign language. The deaf and dumb community has not only embraced sign language but also as a form of interaction with the broader population [22]. Since there aren't any widespread ArSL communication networks, we also have to think about the linguistic diversity that exists within Arab nations [23], [24].

2 LITERATURE REVIEW

There are many domains use the ML and DL algorithm. There are various results about hand gestures by the multiple researchers.

The authors used a Leap Motion Controller and Latte Panda introduced for the first time an Arabic Sign Language (ArSL) recognition system that based on ML algorithms: k-Nearest Neighbor (KNN) and Support Vector Machine (SVM). it used an Ada-Boosting method and compared against Dynamic Time Wrapping (DTW) which is a native matching method. The proposed system was tested on 30 hand gestures, including 20 single-hand gestures and 10 double-hand gestures. Experimental results show that DTW achieved an accuracy of 88% and 86% for single-hand movement and for double-hand movements respectively. The recognition rate for single-hand and double-hand movements is achieved 92.3% and 93% respectively after the application of Ada-Boosting. The proposed model was performed on a single board (Latte Panda) [25] to improve the reliability and mobility of the system.

Using a gesture with the use of Kinect as a sensor, another authors classified some ArSL gestured dynamic words using a dynamic prototype model (DPM). This model used eleven prediction models, including SVM, RF and KNN algorithms for based on various parameter set. The outcome of experiments revealing that the SVM models had highest recognition rates for dynamic words gestured [26].

A sensory glove was developed to detect hand orientation and finger bending, with data processed and transmitted wirelessly to a computer for machine learning prediction. A dynamic dataset, including letter signals and word-like gestures, was created and used to build two machine learning models: a support vector machine (SVM) model with feature extraction (SVM-FE model) and a long short-term memory (LSTM) model. The proposed LSTM model for deep learning demonstrated superior performance with an accuracy of 99.6% [27], [28].

Other researchers [29] used the glove with flexibility, accelerometer and gyroscope sensors to understand pointing gestures for recording and collecting numerical (0 to 10), alphabetic (A to Z) and alphanumeric: (0 to 10, A to Z) datasets. Hand-collected datasets are employed to train machine learning algorithms including K-nearest neighbour (KN), discriminant analysis and support vector-based algorithms, yielding an average accuracies of 99.18%, 99.03% and 99.82% for the respective methodologies.

The opportunity of communication between the hard of hearing and the deaf Arabic people became easier by using Arabic Sign Language (ArSLR). The suggested model is implemented on Arabic signs with 20 dynamic movements and 38 static movements 28 letters, 16 static words and numbers from 1 to10. For dynamic movements, the accuracy of DTW model is achieved 97.4% for palm features set and 96.4% for bone features set. For static movements, the accuracy of KNN model is achieved 99% for palm features set and 98% bone features set. in this paper, the authors presented a method depending on tracking the palm velocity, this method with purpose that segment a string of continuous signs in actual time, this is helpful in in translating pre- segmented signals and continuous sentences. they employed Leap Motion controller, a compact and affordable device that detects and tracks the movement and position of hands and fingers in a precise way. Depending on two various features sets, many MLalgorithms were applied: K- Nearest Neighbor (KNN), Support Vector Machine (SVM), Dynamic Time Wrapping (DTW) and Artificial Neural Network (ANN) [30].

Proposed a hybrid model to extract the spatial and temporal features of sign language (i.e., letters and words). The hybrid model extracts spatial features from sign language data using a convolutional neural network (CNN) classifier, and long-short-term memory (LSTM) classifier extracts spatial and temporal features for sequential data (i.e., hand gestures). The authors produced a dataset of 20 varied words (10 static gesture words and 10 dynamic gesture words), resulting in 4,000 images of Arabic sign language (10 static gesture words and 500 videos of 10 dynamic gesture words). The CNN classifier performs better than LSTM in terms of accuracy, with an overall accuracy of 94.40% compared to 82.70% for LSTM [31].

The authors [32] utilized deep architectures for sign language and presented a signer-independent approach for sign languages using architectures of DL including hand semantic segmentation, hand shape feature extraction and deep recurrent neural network. Semantic segmentation (DeepLabv3+), trained on a set of pixel-labeled hand images, for extracting hand regions from each video frame. the detected hands and resized to a fixed size to deal with the different hand scales. Instead of commendation on transfer learned pre-trained deep convolutional neural networks, a single layer of Convolutional Self-Organizing Map (CSOM) is utilized to extract hand shape features. then bi-directional long short-term memory (Bi-LSTM) recognition process is used on the sequence of extracted feature vectors with the help of frequent neural network. The proposed approach effectiveness tested on a challenging Arabic sign language database consists of 23 words which captured by three different signers. Experimental results show that the performance of the proposed framework outperforms the state-of-the-art methods on signer-independent testing strategy with a large margin.

Another model [33] was used to create writers based on all 1400 gestures were evaluated for 28 letters of ArSL by 20 users. The sensors were utilized to collect the depth photos of the hand and derived 26 angles for every two bones and 77 angles for every joint. The Principle Component Analysis (PCA) algorithm was used to reduce of the large dataset or even delete very common, unimportant or wrong noise-based data. By this algorithm, it was reduced the 103 grabbed data to 36 for every gestured letter which is adequate to provide fluctuation of the information reached to 99%. The KSVM classifier was utilized on the leftover dataset and the recognition accuracy for the Arabic sign language letters from the test data was 86%. While the accuracy results for the training data increased to obtain 93% results with SVM algorithm.

The authors [34] used k nearest neighbor classifier to classify the 28 letter Arabic alphabet with 9240 images. It categorizes the 14 alphabets formulating the first suras of the Quranic sign language. With accuracy 99.5% has been achieved.

According to Arabic language alphabetical characters, it worked on 28 signs of Featured signs, the experiments is used dataset which consist of 1400 images: of which 50 images per each type, it divided into 80% for training and 20% for testing, the suggested model extracts hand from the captured framework for live video, Dense SIFT technique is used to extract feature of image, multi class Support Vector Machine and Logistic Regression methods were used in the classification stage, as a result, Support Vector Machine achieved up to 96% [35].

The authors [36] suggested a new convolutional neural network which employed LSTM for processing feature dependencies. This model is applied on Arabic Sign Language to recognize 7 characters of alphabetic. This model achieved a high accuracy of 97.5 %.

The authors proposed [37] various system that suit all Arabic gestures. The impaired people have used this system.it developed a deep Convolutional network to extract features from the data that collected by the sensing devices. the sensing devices played an important role in recognize 30 hand sign letters of the Arabic sign language and capture the hand movements from the dataset by using DG5-V hand wearable gloves. The CNN technique is used for categorization purposes. The proposed system takes gestures of Arabic sign language hand as an income and outcomes vocalized speech as output. The people managed to recognize 90% from the results.

The suggested online system, achieved the accuracy reached to 99.2%, can recognize the 30 Arabic alphabets correctly and in a reasonable sensible time. it supposes that the effective signer is the nearest person to the Kinect sensor, so that it isolates the person from other persons or any skin-like element that may present in the signer. then hand segmentation is done by using RGB-Ratio color model. After that, Histogram of Oriented Gradients (HOG) is taken from the image; support vector machine (SVM) classifier is trained by applying PCA (Principal Component Analysis) on HOG [38].

It is trained several model to recognize Arabic alphabets in sign language, therefore, it is outperformed VGGNet architecture on other models. The suggested model is expected to provide promising outcomes in recognizing Arabic sign language reached to accuracy of 97%. The proposed models are tested opposite a modern Arabic sign language images dataset which contains 54,049 images and considered the first big and inclusive real dataset of Arabic sign language [39].

The designed system is used to recognize ArSL alphabets automatically. In particular, trained ArSL gesture models based on 1VR by using HOG descriptors, the dataset used 210 images which are 200x200 pixels in size, the accuracy of the system reached to 63.5 % [40].

The proposed model [41] is used to detect hand signal independent by trainined 100 iterations based on CNN with cost function. it is Converted to Arabic speech by using technologies of artificial intelligence in an accuracy is 90%.

The system feature is extracting the hand gesticulations of the allocated person before the version 1 of Kinect device, the dynamic and static formation signs can be recognizing by detection the movement. The employment of Multi-class Support Vector Machines (SVMs) in coupling with the strategy of One-Against-All is utilized to locate appropriate SVMs to recognize static and dynamic hand gestures. In the recognition stage, hand gestures are first has been extracted, has been normalized, and subsequently has been filtered based on the difference in Euclidean distances between hand positions in captured frames. These filtered gestures are then processed by the respective SVMs. The identified letter or diacritic proportional to the positive label across all SVM classes. The experimental outcomes confirm that the proposed VSLRS achieves real-time recognition of Vietnamese sign language (VSL) with accuracy high level [42].

The authors [43] focus the Indian gesture recognition depending on techniques of dynamic hand recognition in the real-time. In preprocessing step, the recorded video underwent a conversion into the HSV color space, after that, in the segmentation process that based on identifying skin pixels. to enhance the precision of the result, depth information was concurrently incorporated, as the next step, features such as a motion trajectories and Hu-Moments were extracted from the image frames and Support Vector Machine (SVM) is used to classification the gestures. The system's execution and performance were tested by using both a webcam and Microsoft Kinect. Such a system holds possibility for helping in the education and communication of individuals with hearing impairments.

This system [44] proposed converting hand signs from RGB images into the HSV color space. Then, applied Gabor filters for extracting the related features of the hand signs. The high dimensionality of the features vector got from the Gabor filter, nonlinear dimensionality decrease technique is applied a known as Kernel PCA to decrease this dimensionality. Support Vector Machine (SVM) utilized classifies the extracted features. The experimental results shown that the model outperforms existing approaches in the field of Bengali hand sign recognition. This model achieves an interesting recognition rate of 97.7% for Bangla Sign Language.

In pre-processing phase, the authors [45] suggested utilized two image processing techniques:

gray scale conversion and histogram equalization. Then, they employed principal component analysis (PCA) to reduce dimensions and extract features. in classification phase, they employed the support vector machine (SVM). Results detected that merge histogram equalization significantly improves recognition accuracy. Depending on different random seeds for testing data, experiments results revealed that this model attains an accuracy of 76.8%.

3 DATA AND METHODOLOGY

3.1 Datasets

In this research, the main input data is the Arabic Alphabet Sign Language Dataset (ArASL). A new dataset includes 54,049 photos of ArSL alphabets carried out via extra than 40 people for 32 preferred Arabic signs and alphabets. The range of pictures in step with class differs from one class to some other. Sample photograph of all Arabic Language Signs is also attached. The CSV document includes the Label of every corresponding Arabic Sign Language Image based totally at the photograph file name. 's 32 ArSL images and alphabets “Mendeley Data lets you store, share, view, and cite data securely in the cloud”. The Mendley data is public library that allows researchers to use the available datasets for academic purposes. Examples of ArASL dataset are represented in Figure1.

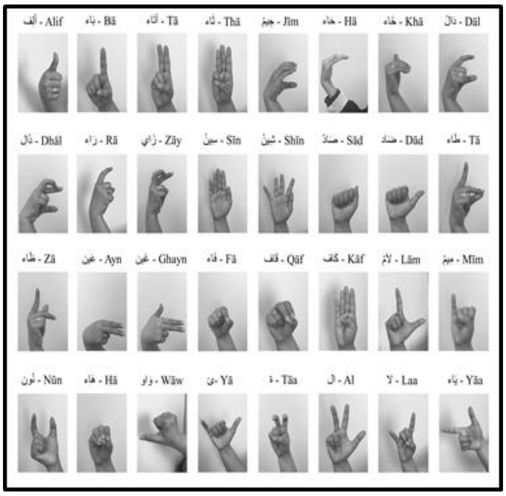


Figure 1: ArSL [46].

3.2 Datasets Architecture

Supervised ML (SVM) Methods are used to find the best hyperplane. Using an SVM, SVM maximizes the difference between two sets of data. Divide the input data into two groups using an N-dimensional hyperplane then search for the ideal number of dimensions to use for classifying. Supervised learning, which reduces overfitting even for new datasets, has grown in popularity. Other classification tasks that have used SVM include handwritten character identification and face recognition. A one-versus-all approach was added to the basic SVM design. MSVM treats multiclass labels as multiclass labels and uses classifiers to solve issues. Create a new classifier using the previous classifier's outputs. Each class has its own SVM created and trained to identify data from other classes. Unknown patterns are generally categorized using the SVMs' maximum output [3].Creating a hyperplane with the SVM, a binary typed classifier. When the data set is non-linear and multi-class, HOG with ML methods are used in this paper:

1) Convert RGB images to grayscale and resize all ArSL images to 224x224.
2) Finger boundary region is highlighted in white with the rest of the image in black using the HOG method .
3) Extract 1300 features and sigma
4) In order to eliminate overlapping feature classes and increase ArSL accuracy for 32 classes, Features and their sigma are normalized using Z-score normalization.
5) Principal component analysis (PCA) is a well-established and useful approach, but it requires understanding of data statistics.
6) The MSVM algorithm classifies the static hand gesture photos. The training results come first, followed by the test results.
7) After that the msvm approach that completion of the operations and recognition of static hand gesture images for ArSL, the training procedure for images. During the training stage for ArSL, all classes rats are (100%).
8) This stage involves testing the algorithm with unlabeled data to categorize the static hand gesture images. The accuracy for testing is also equal to (100 %).

4 EXPERIMENTAL RESULT AND DISCUSSION

The evaluation of the ArSL recognition system uses a dataset ('4800' training images), ('6400 'test images), and ('6400' validation images), all from the same 32-class dataset.

The experiments are run on a Windows 11 PC with a Core i7 processor and 16GB RAM. Python (3.8 64-bit) with Tensor Flow backend.

To identify and highlight the fingers' border region, in Figure 2 HOG algorithm is using. That highlighted in white while while the rest of the image is highlighted in black. Then, in Figure 3 using the HOG algorithm to extract 1300 features, compute sigma for 10 features for one image in each class of ArS as in Table 1

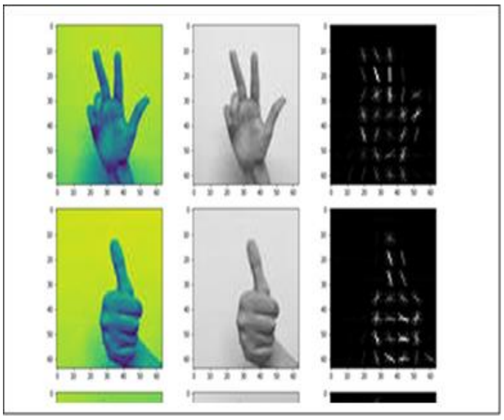


Figure 2: Randomly samples after preprocessing.

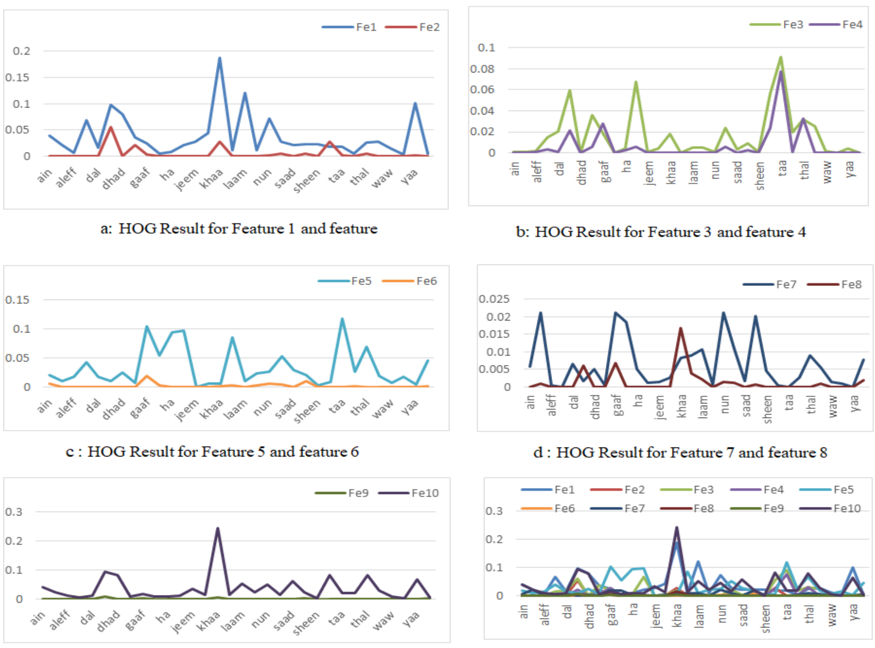
For ArSL of 32 classes, the histogram in Figure 4 shows the original features that were extracted using Z-score normalization.

PCA is a well-established and successful dimensionality reduction approach, although it requires understanding of data statistics as Figure 5 showed PCA result. For ArSL images.

After experimenting with a variety of data amounts, researchers discovered that using 80% training data and 20% test data produced the best results. The testing technique, which depends on it in the process of categorizing the data, accords a great deal of significance to this aspect. In Table 1, the accuracy and data ratios for ArSL are compared.

Post feature extraction, the system entered the classification stage. The classified stepped groups are then labeled using four features that were extracted from the pictures of hand gestures in the static phase. Then it needs two stages to finish the classification process which is the training stage and the testing stage. The recognition and classification of the hand gesture images will be done using the results of these two stages. Test Results will be printed after Training results

The ratio in our paper was not selected arbitrarily; in fact we tested the different ratios of data and the one with the best result was 80% to training and 20% of the test data set, it is critical for the testing process that is based on it in the classification task as Table 1 and Figure 3:



a: HOG Result for Feature 1 and feature

b: HOG Result for Feature 3 and feature 4

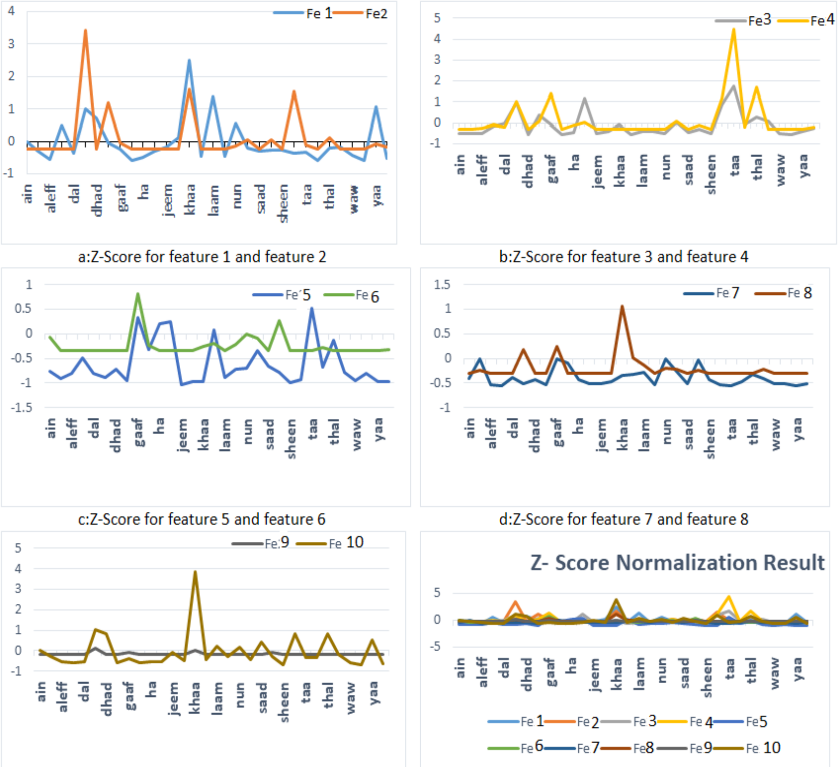
c : HOG Result for Feature 5 and feature 6

d : HOG Result for Feature 7 and feature 8

e : HOG Result for Feature 7 and feature 8

f : HOG Result for 10 features

Figure 3: HOG result.



a:Z-Score for feature 1 and feature 2

b:Z-Score for feature 3 and feature 4

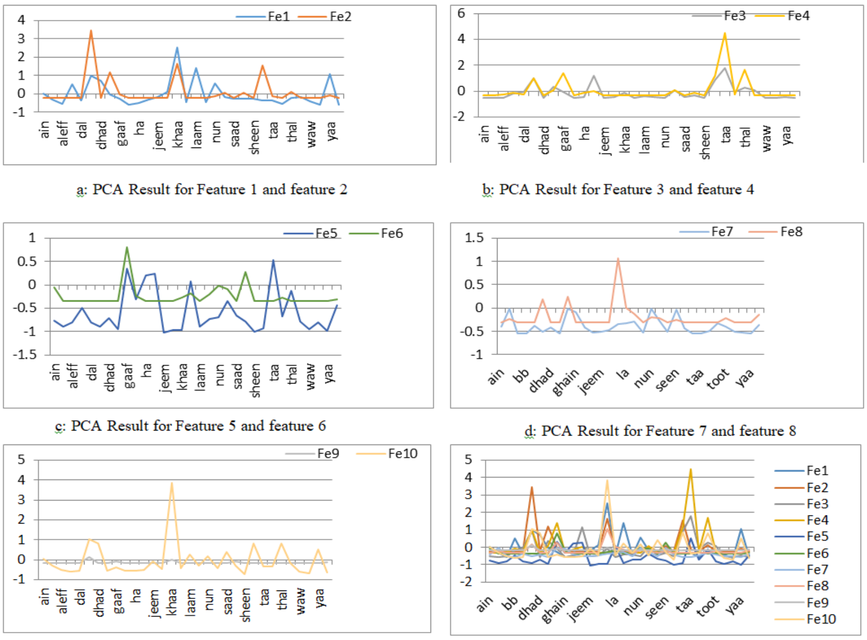
c:Z-Score for feature 5 and feature 6

d:Z-Score for feature 7 and feature 8

e:Z-Score for feature 9 and feature 10

f:Z-Score Result for 10 features

Figure 4: Z-score normalization result.



a: PCA Result for Feature 1 and feature 2

b: PCA Result for Feature 3 and feature 4

c: PCA Result for Feature 5 and feature 6

d: PCA Result for Feature 7 and feature 8

e: PCA Result for Feature 9 and feature 10

f: PCA Result for 10 features

Figure 5: PCA result.

Table 1: This caption has one line so it is centered.

Dataset (%) (training:testing)	The accuracy for training	The accuracy for testing	The total time
80:20	100%	100%	2H
70:30	99.125%	99.4%	2:30H
60:40	98%	98%	3H

5 CONCLUSIONS

This paper presents an abstract hand gesture recognition system for Arabic sign language based on SVM. The system aims to leverage the capabilities of SVM to accurately classify hand gestures and improve communication for the Arabic deaf and hard-of-hearing community. Further enhancements and optimizations can be explored to improve the system's performance and usability in real-world scenarios.The static HGR presented in this research is based on ML techniques and consists of many stages: The acquisition, preprocessing, extraction, and classification of images.

Then, hand segmentation is performed with the RGB-Ratio color model. A Histogram of Oriented Gradients (HOG) is extracted from the image and then Principal Component Analysis (PCA) is applied to HOG and HOG-PCA is used to train a support vector machine (SVM) classifier. The system can detect the 32 Arabic alphabets with 100% accuracy. The suggested offline system can recognize the Arabic alphabet almost accurately and in an acceptable time response.

Tests conducted on the ArSL Dataset confirm the efficacy and precision of this approach.
Using the HOG method and PCA in the feature extraction stage, the accuracy of the system improved as the number of features retrieved from each sample was increased, up until access was gained to 1300 features from each picture.

Z-score normalization was used to enhance the suggested system's classification precision. Using this technique, similar characteristics, and associated sigma values may be grouped together into one class while maintaining their independence from the other. This is done because having all feature classes overlap reduces the proposed system's accuracy.

6 FUTURE WORK

Suggest designing an expert system that can automatically recognize fixed hand gestures for Arabic letters of other Arabic dialects in Gulf countries and other world languages such as English, Italian, Farsi, and other languages using computer vision techniques to help deaf and hard of hearing to communicate more effectively.

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