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SENSOR-EQUIPPED GLOVES FOR RECOGNIZING ARABIC SIGN LANGUAGE.

Ahmed Ayad Saleh, Dr. Hardik Joshi

[1]Department of computer science Gujarat University

Ahmadabad, Gujarat, India

Email: ahmedayadsaleh@gmail.com

[2]Associate Professor Department of computer science

Gujarat UniversityAhmadabad, Gujarat, India

Email: hardikjjoshi@gmail.com

Abstract

This study aims to propose a low-cost, smart glove-based sensory recognition system. This involves designing a glove containing multiple sensors to record data on static signs in Arabic Sign Language. The research was divided into several successive phases. The first phase included an analysis of the hand structure and movement in Arabic Sign Language to extract essential features that would help define the requirements of the recognition system. The study examined the language from several morphological and kinetic perspectives. The second phase focused on the design and development of the DataGlove through iterative refinement processes based on the requirements of the first phase, with the goal of improving its efficiency and performance. In the third phase, a sensory dataset was created based on the proposed glove, adopting a clear methodology for data collection and processing. The subsequent phase involved building a recognition system using machine learning algorithms, with a thorough evaluation of the effectiveness of the proposed methodology. The glove enabled the production of new, large-scale datasets for Arabic Sign Language (ARSL) using a sensory approach. The results demonstrated a number of significant benefits. The experiments demonstrated that the data glove design is an effective means of identifying similarities in hand postures and recording a wide variety of movements. The experiments achieved high accuracy, reaching 100%, in recognizing words, letters, and numbers using the Extra Trees algorithm. These results confirm that the proposed system achieves high recognition rates, and that the ARSL dataset will provide a supportive foundation for future research in Arabic sign language recognition systems. The results are encouraging, contributing to bridging the communication gap between the deaf and hard-of-hearing community and society.

Key Words: Arabic Sign Language (ArSL), DataGlove, Sensory Recognition System, Machine Learning, Sensory Dataset, Static Sign Recognition.

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1- Introduction

According to the World Health Organization and the World Federation of the Deaf, approximately 70 million people worldwide are deaf and mute. Most individuals with speech and hearing impairments are unable to read or write in normal language. The natural language that deaf and mute people use to communicate with others is sign language (SL). Sign language uses gestures instead of speech to convey meaning, it involves the use of hand gestures figure 1 , and shapes, fingers, facial expressions [1], a large number of individuals with special needs experience severe deprivation and neglect [2]. According to the study [3], students with hearing impairments find it difficult to get along with their hearing peers. Due to their loss of a sense of belonging, they are admitted to special education facilities, and one of the factors that contributes to student dissatisfaction is the absence of sign language interpreters in the classroom.

Figure 1. Arabic Sign Language Alphabets (ArSLA).

There are a number of problems with sign language, deaf groups find it difficult to learn or translate sign language (SL), including Arab deaf communities, due to the lack of a standardized linguistic format [4], it lacks a standardized form, making teaching sign languages difficult for deaf individuals [5]. Furthermore, although it is the primary means of communication for people with disabilities, sign language is not a widely used means of communication for people with disabilities. Sign language has differences across countries and dialects. For example, Arab deaf communities often speak a variety of sign languages, including Egyptian, Jordanian, Tunisian, and Gulf, and there is a gap in this language due to the lack of knowledge and communication gap between deaf and hearing individuals. Such difficulties with Arabic sign language and the distinction between Arabic sign language and spoken language make machine translation between them more necessary than Arabic sign language recognition systems alone. These technologies can facilitate the integration of deaf individuals into different educational levels and provide them with the ability to access scientific information through their native language [1][5]. Sensor-based gloves that can translate movements into words seem to be a more viable option for people with disabilities.

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In terms of reducing the complexity of data processing [6] and not having restrictions on movements (such as sitting behind a desk or chair). In addition, they are adaptable to many environments. [7][8] Lightweight (i.e. a wearable, easy-to-move, and comfortable sensor-based glove device) [9][10] Apart from that, both normal and disabled people can learn the source language using this recognition system [11]. The sensor-based glove was adopted in building the system.

2- Literature Review

A large number of scholars have recently been interested in the problem of sign language recognition. Numerous survey studies have been created expressly to highlight the issues with sign language recognition [12][13][14][15]. A many scholars have concentrated on the recognition of sign language based on glove . For instance, a two of data gloves have been developed in this study [16] offered a smart glove that can recognize motions used in Arabic sign language. The identification system based on two gloves was implanted with five flexible sensors and a tilt sensor unit apiece. Words and phrases were intended to be recognized by the system. Thirty words and fifteen phrases were used in the system's testing, and 90% of the words were recognized on average. This study [17] created and constructed a wearable sign language interpreter. Six IMUs were placed on the back of the palm and each fingertip of the glove in order to capture hand and finger motions and orientations. Using a long-term memory (LSTM) method, the system was able to recognize the movements and, when tested with 28 ASL phrases, obtain up to 99.89%. Reference [18] employed a wearable IMU device to detect Indian sign language motions using a one-dimensional convolutional neural network. Three-axis gyroscope and accelerometer data were generated by the IMU. The recorded signals were classified using two different CNNs: one was used to categorize the general sentences, while the other was used to categorize the interrogative sentence. The suggested method's performance shown an average accuracy of 93.50%. To identify American Sign Language (ASL) static postures and dynamic motions, a wearable autonomous device was developed and put into use[19]. The idea behind the glove is to use conductor to create strain sensors that span all of the hand's joints. To do this, around 2 centimeters of stripped wire are woven into a rough loop via knitting. Because the knitting response is strain-sensitive and the wires are coupled to the microcontroller, the resistance measurement functions as a strain sensor, the neural network was utilized, and it has long short-term memory (LSTM). Using cross-validation methods, 12 ASL words and 12 letters were categorized in real time. 96.3% accuracy was achieved with the segmented instances, while 92.8% of the live-stream produced accurate rolling forecasts. A wearable sensor glove with an accelerometer and five sensors was designed and presented in another study [20]. An Arduino Nano microcontroller receives the produced data and processes it into words. After processing, the data is sent over Bluetooth to the Sign Language Translator (SLT) app, which runs on Android. The system was tested for thirteen American Sign Language gestures, with thirty repetitions for each gesture, in order to display the corresponding texts and perform the speech associated with the gesture. The text and speech were displayed at the designated time

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based on the number of correct and incorrect detection times for these repetitions, which varied depending on the gesture's shape and the likelihood that the application would interpret it. Even though there were only a few of these gestures, some of them had repeated mistake rates, while other gestures in the suggested system had error rates of one for every 29 right instances. An Arduino Uno board, an LCD display, an MP3 player, and five flexible sensors were all employed in this study's wearable glove [21]. Upon activating the operating mode, the sensors provide values to the Arduino, which then verified using a matching mechanism that compares the digital data with the trained model using algorithms such as KNN, SVM, LDA, HMM, and ANN. If the matching is successful, the speaker receives the generated alphanumeric-based data, which is shown on the LCD display. Additionally, 98% of the results were accurate when using the 26 alphabetic letters that make up the American Sign Language alphabet. In this study[22], hand motions in American Sign Language were recognized and accurately interpreted using a glove. A series of sensors is mounted on the glove by the system to record various hand movements. The glove has five flex sensors and contact sensors positioned in between the fingers. Arduino records the sensor readings of these signals, which it then processes using the K-nearest kbor machine learning technique. The value of K was adjusted to provide the greatest results while sending data via USB to a screen for display. With 93% accuracy, the algorithm was able to classify 21 common letters and phrases. The researchers[23] created a glove with an accelerometer to aid in hand movement detection and a set of flexion sensors on the metacarpal and interphalangeal joints to detect finger flexion. For the thumb and little finger, one flexion sensor is utilized, and for the remaining fingers, two. The flexion sensor variable length is 2.2 inches. The microcontroller board receives the sensor values, processes them, and uses a custom machine learning algorithm to find a match. The alphabet is then wirelessly transmitted, and an Android application called "Dastaana" allows the user to view and hear the alphabet or word on an Android smartphone. The average success rate for this method was 94.23%. This study [24],suggested creating a customized sensory glove utilizing an Arduino Nano controller, one accelerometer, and five flex sensors. Along with the creation of an Android application, through the use of sensors, the glove records Arabic sign language hand gestures. Then these are transmitted to the controller via Bluetooth, where they are recognized by the program and shown on a screen with accompanying audio. Good results that are compatible with the job, its cheap cost, and its prompt response were obtained after attempting five Arabic letters and other numerals.

3- Proposed Framework

The proposed framework describes the methodology of the Arabic Sign Language recognition framework. The research methodology cycle is divided into four stages. The first stage describes the analysis of Arabic sign language and the extent of the impact of each of the available elements on the gesture and examining ArSL from different points of view to extract useful features that help in drawing the requirements of the recognition system.

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The second stage describes the design and development of the data glove and proposes several stages for optimal development. While the third stage describes the data set and the proposed data collection methodology to create the sensory data set based on the data glove. The fourth phase includes the recognition system by using machine learning algorithms and, finally, evaluating the performance of the proposed methodology. Figure 2 below.

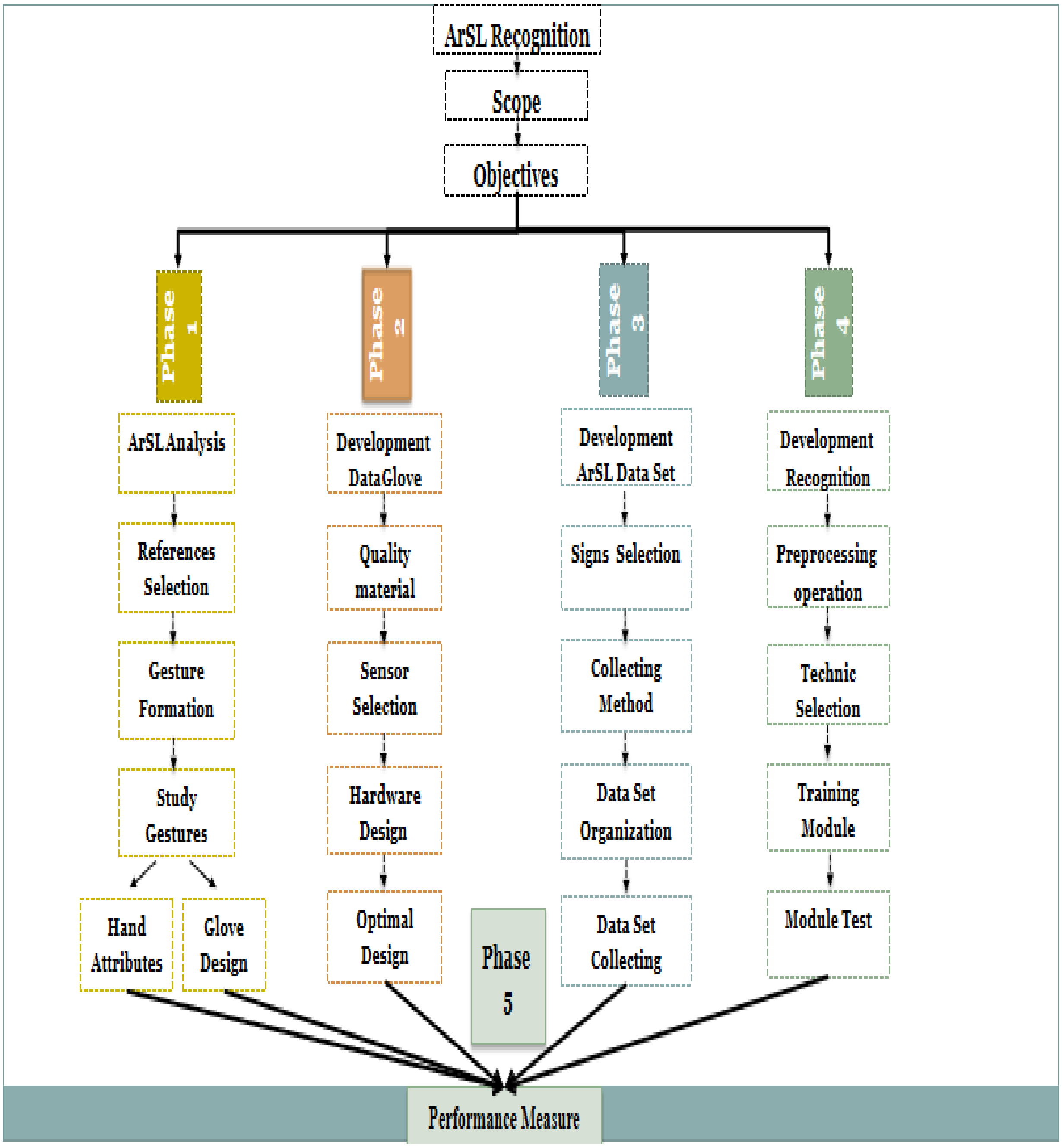

Figure 2. Arabic Sign Language Recognition Framework.

3.1 Sign Language Analysis

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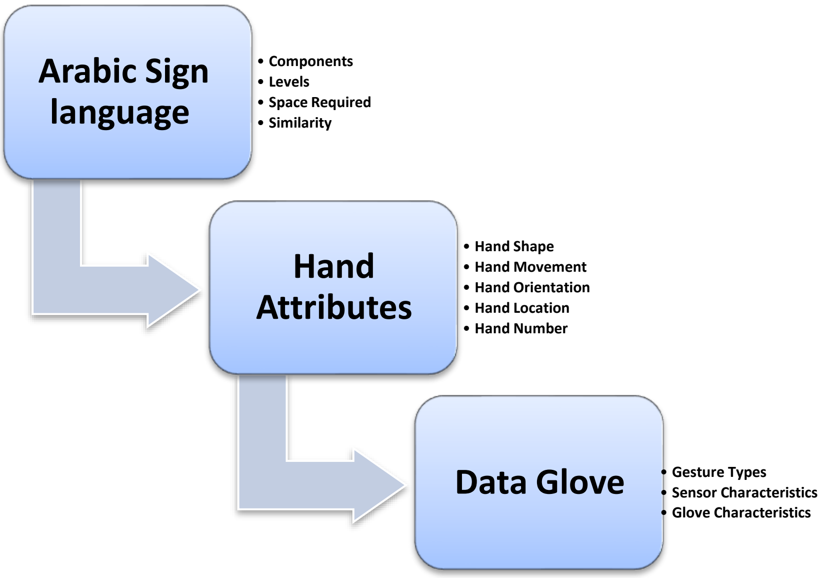
Sign language in general and Arabic sign language in particular have many aspects and ways of understanding. Sometimes Arabic sign language differs from one Arab country to another. This leads us to expand the scope of thinking and find constants that enable people to understand sign language in an easy and understandable way. The gesture is built on the basis of several factors, some of which are related to the structures of sign language itself, such as characteristics, size, and the space required to build the sign in this language, and some of which are related to the characteristics of the hand performing the gesture in terms of the size of the hand performing the gesture, in addition to the direction of the hand movement, its location, and the number of stages required by the gesture to obtain the final form of this gesture. Sign language gestures consist of a complex combination of key components, namely hand direction, hand movement, direction of movement, finger movement, direction of movement, hand position, etc. figure 3 below.

Figure 3. Sign Language Analysis.



After examining 1350 signs from the textbook of educational materials, we noticed that there are several important phenomena that interfere with the meaning of the signs. When the hand direction changes, many cases of the same hand shape are produced with different meanings, so the hand direction is an effective element in the meaning of the sign, and the position of the "height" of the hand relative to the body gives a different meaning. The above points emphasize the fact that similar hand shapes do not necessarily give the same meaning. Therefore, similar shapes can be distinguished either by the direction of the hand shape or the position of the hand or both.

3.2 Data Glove Design and Development

Hardware design is critical to the development of a Sign Language Recognition (SLR) device to ensure accurate data recording. This development includes:First, "defining the glove specifications." It must be capable of connecting wirelessly to a mobile phone or computer,

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be portable, battery-powered or USB-powered, easy to calibrate, and capable of tracking the required number of degrees of freedom to effectively record and classify Arabic Sign Language . Furthermore, the device must be safe. Regarding glove quality, gloves must be made of good, durable, breathable materials, easy to put on and take off, and the sensors used in the glove must provide clear and repeatable readings. The glove must also be as cost-effective as possible.

Second, "defining the data range." Signal sources must be identified, as there are many available for sign language learning. The number of hands compiling the data must be known and determined, which affects the number of target signals. The signal type must also be identified. Next, signal samples are identified, which will be the result of applying all the previous points. Finally, the participants who will execute the pre-defined gestures must be identified. Third, "Design Specifications". There are several constraints that must be considered to obtain a high-quality data glove, including the necessity of recording finger curvature and hand movements by equipping the glove with capture modules, specifying a sufficient number and type of sensors to reliably capture static movements, and developing the data glove to capture continuous expressions and dynamic gestures. The sensors, microcontrollers, and output units are the most important processing tools responsible for the glove design. Five 2.2-inch flexibility sensors were used to detect the curvature of each of the five fingers. Four FSR 402 sensors were used as pressure sensors, positioned between the fingers, to measure finger movement. An MPU9250 motion sensor inertial measurement unit (IMU) was used to detect hand movement or direction, which provides nine degrees of freedom (9DOF). Figure 4. In order to process the data collected from the sensors provided by the data glove in order to recognize the signal, an ESP-WROOM-32 microcontroller was used, which has some interface ports that make it easier to connect analog sensors to the ESP. Then this data is transferred to the output device so that it can be viewed. In the final stage, an Arduino serial monitor was used to display the captured signal as data on the computer screen , figure 4.

Figure 4. Building a Glove Design.

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3.3 The Data Set

Based on the literature, there is a severe lack of availability of sensor-based datasets for SLR in general which is inherent in ArSL datasets, so it is important to develop a large-scale dataset and make it publicly available to other researchers.

Data collection requires users to physically wear a glove on their hands and connect it to computer input devices, the gloves with devices provide data values for finger and hand movement, and the recorded data values are based on the sensors equipped with the data glove which is a valuable resource for researchers in the field of sign recognition and human activity analysis. The selected signals were identified in the study, and 94 static signals met the inclusion criteria. After investigating approximately 1350 signals included in both textbooks for teaching Arabic Sign Language. These signs are commonly used in daily life and are divided into three groups, numbers which contain nineteen fixed numbers (0-9)-(10 - 20 - 30... 90) and letters which include the Arabic Sign Language alphabet which has 28 letters, and words which include 47 isolated signs representing different words in Arabic Sign Language. Data is collected from six volunteers who know ARSL well. Each of them performs all 94 gestures one hundred times to increase the recognition of the sign, volunteers were selected at different ages ranging from 20 to 35 years to achieve sign independence. The recording program was created and developed in Python programming language using Arduino IDE to create a large-scale ArSL dataset. All these gestures are fixed and are performed using only one hand. The recorded input data for each sign is saved in a comma separated value (.csv) format where each .csv file is a data record containing either literal, numeric or word gestures. Each gesture repeated 100 times represents one gesture. Each column in the .csv file contains a channel attribute for a particular sensor. The last column represents the gesture attribute, see table 1.

Table 1. Description of Selected Sample .

Type of Gesture	Description	Samples Numbers
Letters	All alphabet in ASL from "أ" to "ي"	**28**
Numbers	Number from 0 to 9 and from 10 , 20 , 30 to 90	**19**
Words	Static signs generated with right hand.	**47**
Total Gesture		**94**

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3.4 Recognition Stage

The Arabic Sign Language Recognition stage comes after the completion of data analysis, glove building, and dataset building. This stage involves building machine learning models to efficiently analyze the data, recognize patterns in the data, and extract useful features that lead to the results. Data-driven machine learning algorithms are used in the training process. The dataset is entered for reprocessing which helps to make the dataset smoother and suitable for the machine learning model, which also increases the accuracy and efficiency of the machine learning model. This is done by applying different techniques such as labeling, scaling, resampling, and removing unnecessary data points. The data is divided in specific proportions into an 80% training set and a 20% test set. In training mode, the SLR software receives the values provided by the elastic sensors, FSR sensors, and IMUs through the ESP-WROOM-32 microcontroller board. The labeled dataset is read to learn the input values and their corresponding labels to gain experience for learning future patterns, the resulting labeled data with ten features and their corresponding labels are saved in new comma separated value (CSV) files for further processing. Several classifiers were used for the classification process based on what has been done in many previous studies. three classifiers, namely Support Vector Machine (SVM), Decision Tree, Random Forest, Gradient Boosting, Extra Trees, and Multilayer Perceptron (MLP) algorithm were used in this work.

3.5 Performance Measure

According to the Cambridge Dictionary, “the process of measuring performance is the process of judging the quality, importance, or value of something” (Cambridge, 2018a). In the field of artificial intelligence, a validation dataset is a dataset used to test expert systems with the aim of confirming and generalizing the module. Evaluation is a need whenever systems are developed to determine the accuracy of the model. Therefore, the validity of the results of the work was determined by precision, accuracy, recall and F-score. The accuracy is calculated using the following formula:

$$\textbf{Accuracy} = \frac{\boldsymbol{Right\ Detected}}{\boldsymbol{Num.of\ Iteration}} \text{ [25]}$$

The Precision is calculated using the following formula:

$$\textbf{Precision} = \frac{\boldsymbol{True\ positives}}{\boldsymbol{True\ positives + False\ positives}} \text{ [25]}$$

The recall is calculated using the following formula:

$$\textbf{recall} = \frac{\boldsymbol{True\ positives}}{\boldsymbol{True\ positives + False\ negatives}} \text{ [25]}$$

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F-score (also known as the F-measure) can be calculated using the following equation:

$$\textbf{F-Score} = \frac{2(\boldsymbol{Sensitivity})(\boldsymbol{Precision})}{(\boldsymbol{Sensitivity})+(\boldsymbol{Precision})} \quad [25]$$

Where the Sensitivity equation is

$$\textbf{Sensitivity} = \frac{\boldsymbol{True\ Positive}}{\boldsymbol{Fuls\ Negitive}+\boldsymbol{Ture\ Positive}} \quad [25]$$

4- The Results

The results of the gesture recognition process do not stop at one specific aspect, but are the result of an interconnected series of analyses, operations and correct choices. The process of analyzing Arabic sign language revealed the extent of the influence of specific elements on gestures. The design of the glove in shape and data alone gave high reliability and accuracy in collecting data, in addition to the method of collecting data and selecting the required vocabulary and adult participants and determining a mechanism for collecting fixed data for each participant with repetitions, provided us with a huge data set with high accuracy and in a smooth and understandable manner. Through pre-processing, features are measured to prune the data and extract representative information from the rules to obtain all variables with similar value ranges and make them suitable for building and training machine learning models. The data set was divided into 80% training set and 20% test set to be the input elements for the algorithms according to the programming code in Python in the Arduino environment. After meeting all the requirements for accurate recognition of sign language according to our study and selecting the required algorithms, three algorithms were chosen: Extra trees, SVM algorithm, and Decision tree. Satisfactory recognition results were obtained for each algorithm, and the results for each algorithm are as follows.

The following tables show the results of the three algorithms we obtained for the proposed glove module. The first column in the table represents the class ID from 0 to 93 for the selected gestures for the study, which consist of 94 gestures, each repeated 100 times. The remaining three columns represent the precision, recall, and F1 score, respectively. The table is divided into two parts from 0 to 46 and from 47 to 93 to show the results of the selected 94 gestures. Thus, the performance of the proposed system can be measured by calculating the recognition accuracy of each gesture followed by the overall accuracy of the entire system. By creating a data set for each tree with unique samples, the first algorithm in this work, the Extra trees algorithm, gave a distinct degree of accuracy, as the Extra trees algorithm achieved an accuracy result of 100%. Table 2 below shows the results of this algorithm.

Table 2. The Results of Extra Trees Algorithm.

Class ID	precision	recall	f1-score	Class ID	precision	Recall	f1-score
0	99	100	100	47	99	100	99
1	100	99	100	48	100	99	100
2	100	100	100	49	99	100	100

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3	100	100	100	50	99	100	99
4	100	100	100	51	98	99	99
5	100	100	100	52	100	100	100
6	100	100	100	53	100	99	100
7	100	100	100	54	99	99	99
8	100	99	100	55	98	98	98
9	100	100	100	56	97	100	99
10	100	97	99	57	99	99	99
11	100	100	100	58	98	100	99
12	100	100	100	59	100	100	100
13	100	100	100	60	100	99	100
14	100	100	100	61	100	100	100
15	100	100	100	62	100	99	100
16	100	99	100	63	100	99	100
17	99	100	100	64	100	100	100
18	100	100	100	65	100	100	100
19	100	100	100	66	100	100	100
20	98	100	99	67	100	100	100
21	100	100	100	68	99	100	100
22	100	100	100	69	100	100	100
23	99	100	100	70	100	100	100
24	100	99	100	71	100	100	100
25	99	100	100	72	100	98	99
26	98	97	98	73	100	100	100
27	100	98	99	74	98	98	98
28	98	99	99	75	100	100	100
29	100	100	100	76	97	99	98
30	100	99	100	77	100	100	100
31	100	100	100	78	100	100	100
32	97	98	98	79	100	100	100
33	100	99	100	80	100	100	100
34	99	98	99	81	100	100	100
35	100	99	100	82	100	100	100

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36	100	100	100	83	100	100	100
37	100	100	100	84	100	100	100
38	97	97	97	85	100	99	100
39	100	100	100	86	100	100	100
40	98	99	99	87	100	100	100
41	98	100	99	88	100	99	100
42	100	100	100	89	100	100	100
43	99	96	98	90	100	100	100
44	98	99	99	91	100	99	100
45	97	98	98	92	99	99	99
46	99	100	100	93	100	99	100

Support Vector Machine (SVM) that divides data into several separate parts, so that each part represents a specific class or classification of the data by finding a hyperlevel. The results of accuracy for this algorithm were 86% as shown in Table 3.

Table 3. The Results of SVM (Support Vector Machine) Algorithm.

Class ID	precision	recall	f1-score	Class ID	precision	recall	f1-score
0	85	95	90	47	68	88	77
1	75	91	82	48	90	72	80
2	96	94	95	49	79	92	85
3	100	96	98	50	98	96	97
4	97	94	96	51	89	48	62
5	88	93	90	52	90	93	91
6	92	83	87	53	79	59	68
7	80	83	81	54	72	76	74
8	86	86	86	55	85	100	92
9	97	98	97	56	56	53	55
10	61	79	69	57	68	49	57
11	91	96	93	58	65	72	68
12	96	100	98	59	53	54	53
13	93	97	95	60	66	70	68
14	85	89	87	61	88	93	90
15	72	92	81	62	92	94	93

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16	75	77	76	63	98	85	91
17	88	81	84	64	96	92	94
18	97	97	97	65	96	85	90
19	79	93	85	66	92	95	94
20	60	83	70	67	90	58	70
21	79	89	84	68	97	100	99
22	100	100	100	69	90	97	93
23	91	93	92	70	94	95	94
24	94	99	96	71	98	100	99
25	98	98	98	72	95	86	90
26	73	64	69	73	95	96	96
27	96	96	96	74	73	82	77
28	88	88	88	75	65	75	70
29	90	86	88	76	70	80	74
30	98	96	97	77	99	100	100
31	100	100	100	78	79	86	82
32	87	85	86	79	82	91	86
33	78	57	66	80	100	100	100
34	96	88	91	81	97	99	98
35	91	97	94	82	100	100	100
36	87	74	80	83	99	90	94
37	100	100	100	84	92	85	88
38	79	90	84	85	67	63	65
39	98	98	98	86	95	96	96
40	98	98	98	87	94	82	87
41	73	73	73	88	99	98	98
42	94	92	93	89	98	97	97
43	60	58	59	90	74	79	76
44	91	95	93	91	71	59	65
45	84	77	80	92	84	78	81
46	89	90	89	93	96	98	97

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The last table 4 shows the results of the decision tree algorithm, the results of this algorithm were 94%.

Table 4. The Results of Decision Tree Algorithm.

Class ID	precision	recall	f1-score	Class ID	precision	recall	f1-score
0	97	97	97	47	86	89	87
1	94	97	96	48	92	97	94
2	97	97	97	49	96	94	95
3	100	96	98	50	98	96	97
4	97	99	98	51	84	80	82
5	97	98	98	52	92	93	93
6	98	95	97	53	92	88	90
7	95	95	95	54	94	93	94
8	96	98	97	55	94	91	93
9	99	97	98	56	87	90	88
10	84	94	89	57	88	91	89
11	97	95	96	58	92	93	92
12	98	99	99	59	90	92	91
13	98	95	96	60	95	94	95
14	95	96	96	61	96	99	97
15	96	97	96	62	98	98	98
16	93	86	89	63	86	91	88
17	99	97	98	64	92	96	94
18	98	99	99	65	97	92	94
19	98	96	97	66	99	100	100
20	94	92	93	67	91	89	90
21	96	95	96	68	98	99	99
22	99	100	100	69	90	91	91
23	94	93	94	70	97	99	98
24	96	97	96	71	97	98	98
25	96	97	97	72	93	97	95
26	89	87	88	73	99	96	98
27	99	95	97	74	90	94	92
28	90	94	92	75	98	88	93

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31	100	100	100	78	89	94	91
32	89	90	89	79	99	100	100
33	91	95	93	80	100	97	99
34	97	93	95	81	97	98	98
35	94	96	95	82	100	100	100
36	92	93	92	83	98	96	97
37	100	100	100	84	99	98	98
38	90	81	85	85	88	95	91
39	97	98	97	86	94	97	95
40	94	96	95	87	89	96	92
41	91	84	87	88	100	99	100
42	98	91	95	89	100	98	99
43	77	76	76	90	93	97	95
44	93	87	90	91	88	90	89
45	91	88	90	92	92	92	92
46	93	97	95	93	97	97	97

5- Results Discussion

This section shows a discussion of the algorithms results, where the results of the three classifiers used in this work showed a not large variation in the accuracy of distinguishing Arabic sign language gestures. The highest results were obtained from the Extra Trees algorithm with 100% accuracy. This algorithm creating a dataset for each tree with unique samples, because the samples are taken for each tree randomly, without replacement. With 94% accuracy, we obtained the results of the Decision Tree algorithm, and compared to the previous results, it is considered a high result, but it is not the best, as this algorithm explains all the possible outcomes of a decision using the branching approach. The results obtained from the most famous algorithms used in this field, which is the support vector machine algorithm (SVM). Despite the popularity of this algorithm and the large number of people working with it, compared to the rest of the algorithms that gave higher results than the support vector machine algorithm, the accuracy was 86%, because the data set that was dealt with was large and the support vector machine algorithm gives better results with data that is small in size. The chart in the figure 5 bellow shows the results of accuracy for these three algorithms used in the work, which shows that the highest accuracy

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is 100% for Extra Tress algorithm and that the lowest accuracy obtained is 86% for the support vector machine algorithm.

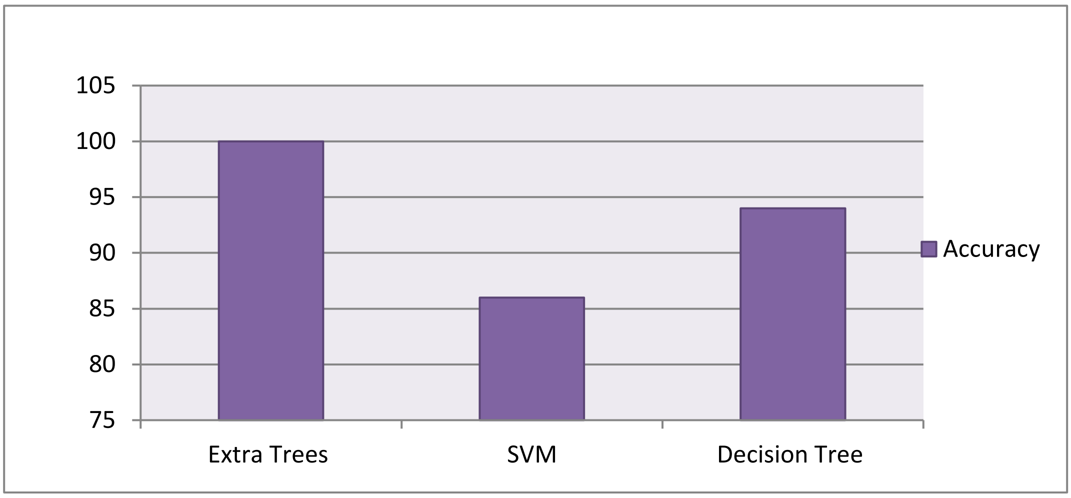

Figure 5. Results Chart For All Algorithms in The Accuracy Field.

It can be said that all the results obtained are reliable and dependable results despite the slight difference between the results of the classifiers. This is due to several reasons that may be related to the way the algorithm works, the size of the data and the arrangement of this data. The highest results were for the additional tree classifier, from which we obtained an ideal result with 100% accuracy. It is one of the algorithms approved in the field of data classification that can be trusted in work and classification of Arabic sign language gestures.

6- Comparative Analysis With Academic Literature

There are many studies that used the sensory approach of gloves to recognize sign language, but not many of them included Arabic Sign Language. These studies provided many results in different directions trying to address the gaps in these systems, as a number of studies focused on a small subset of these positions, such as several letters of the alphabet only [24] [26]. Other studies used only numbers in the range from 0 to 9 [27]. Also, some studies used only the most common words in the source language. [16]. While a few studies used a comprehensive system of a combination of words, numbers and alphabets [28] [29] to conduct their research and create an SLR system. Our current study was broader and more comprehensive and included a set of numbers and the alphabets of Arabic sign language. Our study also included many static words in Arabic sign language, so the majority of static gestures in Arabic sign language were within the scope of our study. This opens up horizons for further progress and development to support the deaf group interested in this field.

The issue of similarity of signs is one of the problems related to accuracy [30] Similarity of signs may lead to error [31]. Therefore, analyzing sign language was one of the main factors for developing a sign language recognition system in a large-scale project with high results that can be trusted despite the presence of many similar gestures in our dataset. For example, the word "father" and the word "mother" are gestures that are similar in hand shape, we achieved an accuracy of 100% for Extra Tree algorithm whose results mentioned in the

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previous section. This indicates that the system is able to distinguish between similar signs, which researchers have diagnosed as one of the main problems in recognizing sign language. Sign language analysis was important for knowing the factors that reduce the performance of the system by knowing the characteristics of language gestures and analyzing them and knowing the characteristics of the human hand in order to accurately choose useful sensors and the places to benefit from the locations of sensors on the fingers and hand in general, including reducing sensors and reducing the cost of the system and choosing the appropriate material for the glove to prevent the sensors from slipping, as the cost of the system was around 185$. To ensure the validity of the system according to standards researches , our current study is compared with previous studies in a table that includes a number of previous studies in Arabic sign language that used the sensory approach of the glove, table 5. The table started with the selected studies, then the number of sensors used in the study, the range of gestures in the study (numbers, letters, words, sentences), the size of the data set in the study. In addition to the accuracy of the proposed system for the study, which shows the effectiveness of the system in distinguishing Arabic sign language gestures in those studies.

Table 5. Comparative Our Study With Previous Studies.

Authors	**No. of sensors**	**Gestures**			**Size of data**	**Accuracy**
		Numbers	**Letters**	**Words**		
[29]2024	5 Flex sensors Accelerometer Gyroscope MAX30102		•	•	20 Samples	85%
[32]2023	Accelerometer Gyroscope 5 potentiometer			•	400 Samples	98%
[33]2021	5 flex sensors accelerometer		•		1100 Sample	98%
[16]2020	Two Glove each have 5 flex 1 MPU6050			•	45 Test	90%
Our study	5 flex sensors 4 FSR sensors 1accelerometer 1gyroscope	•	•	•	56400 Sample	100%

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1magnetometer

As shown in the table 5 already a number of studies used the sensory approach of the glove to distinguish Arabic sign language. In a recent study [29] the researcher presented a glove-based system to test only 12 Arabic letters and 8 words in Arabic sign language. The glove contains five flexible sensors, the MPU6050 which gives only six degrees of freedom (6DOF), a MAX30102 Oximeter sensor to measure blood oxygen saturation through the finger and to measure heart rate, called the SPO2 sensor. The test was conducted on a data set consisting of 20 samples and the system achieved an accuracy rate of 85%.

In this study [32], the researcher built an electronic glove that uses an MPU6050 accelerometer/gyroscope with 6 degrees of freedom, in addition to a strain gauge for each finger, to monitor changes in the position of the fingers of the hand. While performing a set of 40 words in Arabic sign language, the researcher obtained 400 samples in the dataset for this study. The highest accuracy achieved by the system from the decision tree learning algorithm was 98%. In this study.

This study [33] in the table used a system consisting of five flex sensors and a 3axies accelerometer sensor, this study included Arabic alphabetic letters without words or numbers. The data set obtained by the researcher was 1100 samples of Arabic alphabetic letters and the system achieved an accuracy of recognizing Arabic sign language alphabets by 98%.

This study [16] presented the construction of two gloves to recognize Arabic sign language for 30 words and 15 expressions, each glove contains 5 elastic sensors and one MPU6050, tests were conducted, a total of 30 words and 15 expressions were programmed to be tested, by conducting several experiments for both users, the average recognition rate was 90%.

It is necessary to know the characteristics of our proposed study to distinguish Arabic sign language gestures (words, letters, numbers). The glove contains five flex sensors to read the curvature of the fingers, four (FSR) pressure sensors to know the contact of the fingers in addition to the MPU9250 9 degrees of freedom (9DOF) 3 axis accelerometer, magnetometer, gyroscope. We have a large data set consisting of 56400 samples in a reliable work format. The system was tested for a group of classifiers and the highest percentage of the system was the Extra Trees algorithm with 100% accuracy.

Previous studies showed a lack of data volume and availability of data sets, which creates a large gap in research on sign language classification, especially in Arabic sign language and we intend in our study to make this huge data available to the researchers for further progress as it can be relied upon to develop research in this field and motivate researchers as well as reduce their effort and time

7- Conclusion and Future Work:

There was a thorough review of sign language gesture recognition technology with regard to the sensory approach, specifically in Arabic sign language, which was the least interesting to researchers based on the available research in this field. The goal of this study

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was to remove the communication barrier between people with hearing impairments and regular people. This highlighted the significant problems and presented gaps in the field.

While creating data gloves based on ArSL analysis has been shown to be an effective method for recording a variety of gestures, groups in ArSL can improve the recognition rate of ArSL. In this study, 94 static signs are examined with varying accuracy rates of 100%, 97%, 94%, and 86% for words, characters, and numerals. The ArSL dataset can aid in creating a more thorough analysis for a future ArSL recognition system. The results are encouraging, and this breakthrough may help close the gap between the deaf and the general public in the near future.

The second argument is that picture-perfect recognition requires a comprehension of the characteristics of sign language. Furthermore, there are recurring informational patterns in certain ArSL motions. Thus, 56,400 ArSL signs are first categorized according to hand shape, which allows one to differentiate between gestures with similar shapes but distinct meanings. It is crucial to investigate sensor sites and select the appropriate sensor for the job, a topic that hasn't received enough thorough discussion in research. Lastly, currently there is not an available big dataset for Arabic Sign Language captured by sensory gloves.

Researchers now have access to a novel and extensive dataset for ArSL based on the sensory method thanks to this study. This dataset is highly helpful for creating new methods for ArSL recognition using machine learning. The combination of findings and recommendations highlights the importance of this research in promoting Arabic sign language and encourages more investigation and use of its findings. This study adds to the body of knowledge in Arabic sign language. Further analysis of the conversation's syntax rules, which are important in identifying continuous signs of problems, and the development of dynamic gesture recognition technology to enhance translation system performance are some ideas for future work that could enhance this work.

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