Smart Glove for Bi-lingual Sign Language Recognition using Machine Learning

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***Abstract*—The deaf community in our society has a right to live a comfortable and respectable life by having communication with normal people without any hurdles or impediments. To address this objective, several research attempts have been made to develop smart gloves to provide a means of converting sign language to speech or text. This paper carries these efforts to a next level, where we propose to design, implement and test non-visual-based smart glove. More specifically, we have used five flex sensors and an accelerometer to provide sign language recognition and its further conversion into speech and textual information. We have used prominent Machine Learning (ML) classifiers (LR, SVM, MLP and RF) for recognising both American Sign Language (ASL) and Arabic Sign Language (ArSL). We have achieved a classification accuracy of 99.7% for ASL and 99.8% for ArSL with Random Forests (RF). Further, we have also found through Feature Importance that the accelerometer features are dominant features in recognizing the sign language as compared to the flex sensor features. In order to further advance this research work, we plan to compare the implementation and performance aspects of non-vision and vision-based sign language recognition.**

***Index Terms*—Smart Glove, Machine Learning, Arabic Sign Language, American Sign Language, Flex sensors**

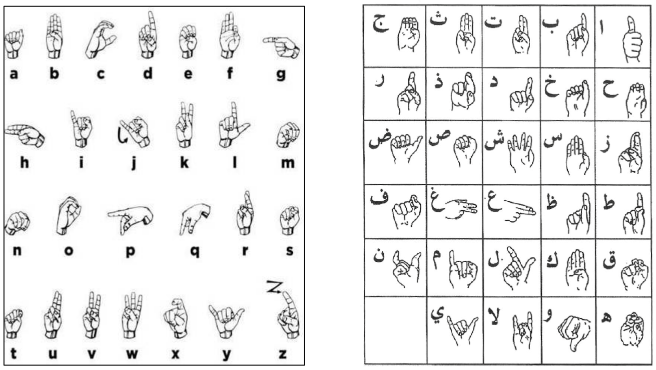
I. Introduction

Living in a modern era has made it critical to be in line with the latest technology in the market. Technology has provided us with great innovations that assist several sectors and as it evolves it makes human life much easier. Particularly for people with disabilities, technology will work towards normalizing the life of these special people and addressing the challenges that they encounter in their day to day lives. Deaf-Mute is a term that refers to a person who has disabilities in hearing and speech, but this term was historically used and considered offensive. Nowadays, since the majority of deaf people can speak, thus the appropriate term to use in such cases is deaf. The deaf community has certain institutions where they can meet with their peers and get to study and communicate with each other using sign language in a stress-free comfortable environment [7].

However, the deaf community often experiences difficulties in the real world while meeting other people (non-signers) because they can't speak the spoken language of the place they are in, and perhaps the people find it difficult to learn sign language. Deaf people often feel uneasy interacting and communicating with the rest of the society, which results in creating barriers and feeling disconnected. The disconnection in terms of cultural, religious, or technical domains among various sections of the society results in frustration [19]. Hence, the approach proposed in this paper aims to facilitate the process of communication between speakers of sign language and other people who can speak and listen.

Achieving quality communication among all segments of society is the aim of this research, with a special focus on the deaf community. This is to help them integrate into society, work, and study environments, and so that they become self-reliant without depending on a caregiver or translator. At the same time, we would like the people who are blessed with hearing and speaking abilities to understand the situation of the deaf. We are aware, that deaf people can communicate among themselves with the aid of Sign Language ([17] [15]) and the normal people can communicate within themselves with spoken words. In order to bridge the gap between the deaf and normal community, a smart glove is a excellent resort. This can help the deaf person's sign language to be translated to spoken words which the normal people can understand.

Smart gloves can be implemented in either a vision-based or non-vision-based manner [10]. In a vision-based approach a camera reads the sign and uses deep learning algorithms to identify the sign and convert to speech. However, this approach can be computationally complex and slower in converting the signs to speech. Therefore, we propose to apply non-vision-based approach where sensors (usually, Flex sensors and Accelerometer) are used to gather the information about the



American Sign Language (ASL) Arabic Sign Language (ArSL)

Fig. 1. The standard ASL and ArSL [17] [15]

signs and use traditional Machine Learning (ML) algorithms to estimate the sign and convert to speech. Hence our research objective is to design a smart glove using flex sensors and accelerometer to recognise sign language for two languages, namely, American Sign Language (ASL) and Arabic Sign Language (ArSL) (see Fig. 1).

The rest of the paper is organised as follows. In section II we present a comparative review of existing research in the domain of sign language recognition. Section III describes the details of the proposed methodology. Results and their discussions are presented in Section IV. Finally, Section V concludes the paper with salient conclusions and possible pointers to future work.

II. Related Work

There are various research attempts in the domain of ML-based smart gloves, which are presented concisely in this section. In order to make a fair comparison we are presenting only the non-vision-based approaches which are utilising ML and non-ML techniques.

One of the approaches in this area [13], utilizes flex sensors, Arduino, accelerometer, text-to-Speech module and MATLAB to translate ASL, as well as some of the words (that can be signalled using one hand) into speech and text. In order to differentiate between some similar values coming from the sensors, a contact sensor circuit was added to indicate whether there is a contact between fingers or not. In addition, the contact sensor was used to switch between alphabets mode and sentences mode by only touching the index and middle finger. The data was sent to another Arduino via Bluetooth module to display on a LCD screen and also to translate it into speech.

In order to make communication between deaf people and normal people accessible and simple, the authors in [20], used an Arduino and sensor-based method to translate sign language to text and speech and speech back to sign language. Flex sensors, accelerometer, and Arduino were the main hardware components of the research along with a touch sensor to detect whether or not the fingers are in contact with each other. In addition, an Android phone and Android application were used to display the translation. Thus, a Bluetooth module was needed to send data from Arduino to the phone. For voice translation and text, Google text-to-speech was utilized and a speech recognizer was utilised to transform the speech to text.

In another solution [14], Hall Effect sensors were used at the tip of each finger (with exception of the thumb), along with flex sensors and accelerometer to recognise ASL numerals. The reason for adding Hall effect sensors was to increase the accuracy of the smart glove. The approach achieved an accuracy of 96% with a low cost implementation. Another approach which is very similar to our proposed methodology in terms of design, components, and experimentation is presented in [16]. They used flex sensors, a LCD screen, and a voice module, however they used Arduino Mega as opposed to Raspberry Pi. The uniqueness of this work is the ability to operate household appliances by using a sign for operating a switch key from on to off position and vice versa.

Deaf people have a major communication problem since they can’t absorb new information from their daily conversations and speech. In order to engage deaf people in the normal life like others, the approach in [18], utilises five flex sensors, a PC interface, and an Arduino Uno microcontroller. The deaf person signals alphabet and other gestures that are initialized in the system, such as ”call me”, ”good job”, ”check please”, etc. The output data of the sensor determines the bending degree that is fed to the microcontroller and if the combination of inputs are already recognized by the model, it will respond with the appropriate answer, if not it will show that it is not available with an option of creating more patterns in the database.

Speech-impaired people need to communicate with the normal people in an easier manner and for this purpose a system was designed to produce proper sign outputs regardless of factors like the size and shape of the hand. The glove uses the SVM ML algorithm to translate sign language to speech. The system makes use of five flex sensors, MPU-6050 accelerometer, contact sensors, and ATmega1284p microcontroller. Flex sensors were used to determine the bending angle of signs, accelerometer for the position/orientation of the sign, and a contact sensor was added to differentiate between very similar gestures such as U, V and R. The data was read and then sent to the microcontroller, by the user’s PC to run a python script to figure out the corresponding output [5].

More recently authors in [12], have worked on ASL through the application KNN, SVM, NB and RF classifiers to achieve a maximum recognition accuracy of 94% with RF. The hardware implementation was simple with use of flex sensors and they could translate the signs to text. However, the drawback was that they did not implement the ArSL in their work. In another work [11], NB, KNN, DT and LR were utilised on the Arabic words rather than ArSL alphabets. They too achieved very high accuracy of 98.2% with DT, but their hardware implementation was complex.

Based on the observations from the related work (Table I), we now propose the design methodology of our approach for providing bi-lingual sign language translation.

TABLE I
SUMMARY OF RELATED WORK IN ML-BASED SMART GLOVES FOR SIGN RECOGNITION

Paper	Year	Approach	Dataset	Accuracy	Hardware	Features	Pros	Cons
[14]	2014	Logistic Regression	ASL numerals only	Accuracy of 96%	Flex sensors, accelerometer and Hall effect sensors	Translate sign language to text	Lower costs	Only 10 signs included
[5]	2014	SVM	ASL	Accuracy of 98%	Flex sensors, accelerometer	Signs to text and speech	High accuracy	Requires PC support for functioning
[18]	2017	Non-standard pre-trained gestures	Uses certain specific words	Not reported	Flex sensors	Signs to text and speech	Less implementation complexity	Does not use ASL or ArSL
[16]	2018	Encoder-based solution	Non-standard, self-generated	Not applicable	Only flex sensors	Sign language to text and speech	Low complexity	Only pre-defined gestures used instead of ASL or ArSL
[13]	2018	SVM and DNN	ASL alphabets and numerals	SVM accuracy 80.3% and DNN accuracy of 93.81%	Leap motion controller	Conversion to text and speech	Works for both alphabets and numerals	Expensive hardware and complex implementation
[20]	2018	Encoder-based using pre-set gestures	ASL	Not reported	Flex sensors and accelerometer	Text and audio output	Bi-directional system	Does not report accuracy results
[12]	2022	KNN, SVM, NB, RF	ASL	Accuracy of 94% with RF	Flex sensors	Signs to text	Simple implementation with high accuracy	Does not implement ArSL
[11]	2022	NB, KNN, DT, LR	ArSL (words)	Accuracy of 98.2% with DT	Flex sensors	Signs to text	Variety of ML classifiers with high accuracy	Complex hardware and works on Arabic words

III. PROPOSED METHODOLOGY

This section details the methodology used in our smart glove system design which includes both the hardware and software components. Fig. 2 shows the process which is utilised in our proposed smart glove based on ML. One of the unique features of our approach is that the smart glove can convert both the ASL (which consists of 26 English alphabets, shown in Fig. 1) and the ArSL (which consists of 28 Arabic alphabets, shown in Fig. 1) to text and speech by using an LCD screen and a speaker.

A. Hardware Design & Implementation

The proposed smart glove includes five flex sensors in total, each placed on a finger of the glove, that measure the bending angle value along with the accelerometer readings. Further, the Raspberry Pi recognises the sign using ML models and outputs the estimated equivalent alphabet to the speaker (as speech) as well as on the LCD (as text). We now briefly provide the specifications of these hardware components.

- *Raspberry Pi 3 Model B* is a powerful microcontroller, which has a 64-bit quad-core ARM Cortex-A53 processor with 1GB RAM, 40 general-purpose input/output (GPIO) ports, LAN, Bluetooth and Ethernet connectivity [4]. It uses the Raspbian OS and we have used the Python programming functionality to train our ML models.

- *Flex sensor* is a thin strip torsion sensor that comes in different lengths (2.2 or 4.5 in), has a tolerance of ±30%, power rate of 0.5W and operates at low voltage levels (3.3V-5V) [2]. They measure the twisting angle in one direction in which the resistance changes according to

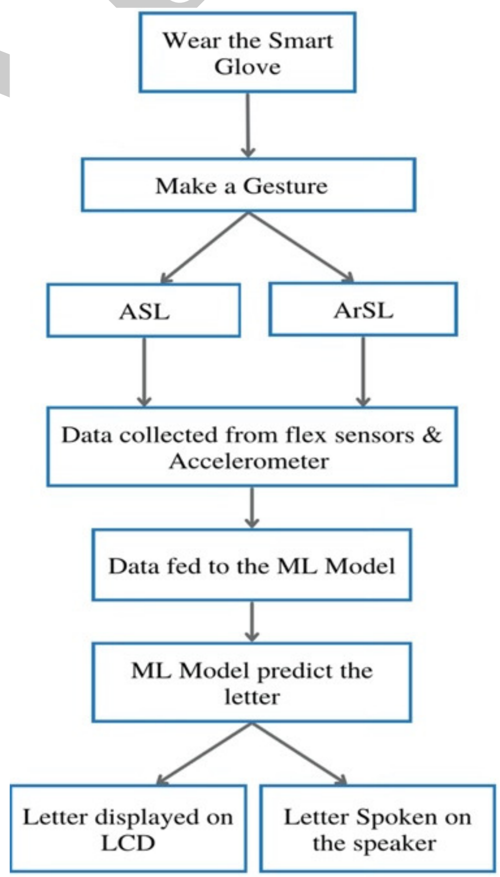


Fig. 2. Proposed smart glove approach for ASL and ArSL using ML

Flex0	Flex1	Flex2	Flex3	Flex4	X_axis	Y_axis	Z_axis
1013	1022	1022	1013	1005	169	-210	35
1012	1022	1023	1014	1006	35	-209	34
1015	1022	1023	1012	1006	34	-205	34
1015	1022	1023	1012	1005	34	-205	30
1012	1022	1023	1013	1005	30	-206	30
1014	1023	1023	1014	1006	30	-214	32
1013	1022	1023	1012	1006	32	-210	34
1012	1021	1023	1012	1005	34	-208	35
1013	1021	1023	1012	1006	35	-211	33
1013	1022	1023	1014	1005	33	-210	37
1014	1022	1023	1012	1005	37	-206	38
1014	1022	1023	1013	1005	38	-205	37
1013	1021	1023	1012	1006	37	-207	37
1007	1022	1023	1012	1007	37	-211	40
1012	1021	1023	1012	1004	40	-211	39
1013	1021	1023	1014	1005	39	-208	39
1013	1023	1023	1013	1005	39	-207	34
1014	1020	1023	1013	1005	34	-209	37
1014	1022	1023	1011	1005	37	-206	31
1013	1021	1023	1013	1006	31	-209	33
1012	1023	1023	1013	1006	33	-208	33
1013	1022	1023	1012	1006	33	-208	35
1010	1023	1023	1013	1005	35	-210	37
1013	1023	1023	1012	1006	37	-208	34
1013	1020	1023	1012	1006	34	-209	35
1013	1021	1023	1012	1006	35	-209	38
1013	1023	1023	1012	1006	38	-209	38
1013	1022	1023	1009	1008	38	-205	31
1022	1022	1023	1020	1018	31	-204	32
1020	1022	1023	1020	1017	32	-207	33
1020	1023	1023	1019	1018	33	-210	33
1020	1023	1023	1019	1017	33	-212	32
1021	1016	1023	1020	1017	32	-214	33
1021	1023	1023	1021	1016	33	-209	35
1020	1023	1023	1020	1018	35	-206	35

Fig. 3. Sample of ASL feature readings for letter H

the bend of the sensor. We plan to use five flex sensors which are positioned on each finger of the glove in order to read the signs.

- *Triple-axis Accelerometer (ADXL345)* is a 3-axis accelerometer, which provides acceleration readings along the X, Y and Z axes. The sensor operates at a voltage of 3V - 5V DC and provides several sensitivity ranges [1]. In our approach the accelerometer is used to calculate the rotation and position of the palm (where it is attached to).

- *Other hardware components* which support us in implementing a complete system are the Analog to Digital Converter (MCP 3008 ADC chip), LCD screen (QA-PASS LCD-1602A) and a speaker (Genius SP-Q160). The ADC is used for converting the analog resistance values obtained from the flex sensors to digital form. The LCD screen displays the textual information, while the speakers output the speech information, pertaining to the ASL and ArSL.

B. Dataset Description

The process of data collection, pre-processing, training and testing process are described next.

- *Data Collection:* Since ML relies heavily on the amount and quality of data, thus collecting the data is a crucial step in our approach. It is important to ensure that the data is a true representation of the system variables and has a fairly large quantity, since the classification accuracy of the ML algorithms will heavily depend on it. The dataset which we collected in were, consisted of 200 instances for each alphabet in the ASL (except J and Z which involved movements) and ArSL. Further, each instance had a total of 8 features which came from the flex sensors and accelerometer. The 5 features fom the flex sensors were termed as $Flex0$, $Flex1$, $Flex2$, $Flex3$, $Flex4$. The 3 features from the accelerometer were termed as X_axis, Y_axis and Z_axis. A sample of the data collected for the alphabet H of the ASL is shown in Fig. 3

- *Data Pre-processing:* In this step we converted the raw data that was collected, into understandable information as well as cleaning the data. This is another critical stage in ML as it guarantees that the data has the least amount of errors in its representation and also to account for the missing data. Here we also perform, data labeling and identifying the predicted feature (which are the ASL and ArSL alphabets).

- *Training and Testing sets:* After collection and labeling of the data is done, the next step is to train the model which is teaching the model how to predict an output based on a set of inputs. For this purpose the entire dataset was split into two parts, one for training which is 80% of the data (160 instance for training set) and the remaining 20% for testing (40 instance for testing set).

C. ML Algorithms

Below is the brief description of ML classifiers used in predicting the ASL and ArSL alphabets. We have identified Logistic Regression (LR), Support Vector Machines (SVM), Multi-Layer Perceptron (MLP) and Random Forests (RF) as the popular ones.

- *Logistic Regression (LR)* performs a classification for discrete data types. LR can be of three types, namely, Binary Logistic Regression which that provide binary outcome of two class values for instance, A or B, yes or no. Also, Multinomial and Ordinal Logistic Regression are available for providing predictions of multi class values of different categories [9].

- *Support Vector Machines (SVM)* is considered one of the most accurate performing ML algorithms and also most memory efficient. SVM is a supervised classification method and can be used for both regression as well as for outlier detection [6]. This model learns from previous data therefore, the larger the data the better the results are going to be.

- *Multi-layer Perceptron (MLP)* is a complex supervised ML algorithm that relies on neural networks connections to map the data and make a prediction. MLP is used when data belong to a specific label or class [3]. In

TABLE II
CLASSIFICATION RESULTS FOR ASL AND ARSL USING FLEX SENSORS (5 FEATURES)

	ASL				**ArSL**			
Classifier	*Accuracy*	*Precision*	*Recall*	*F1-score*	*Accuracy*	*Precision*	*Recall*	*F1-score*
LR	0.922	0.920	0.920	0.920	0.896	0.900	0.900	0.900
SVM	0.941	0.940	0.940	0.940	0.917	0.920	0.920	0.920
MLP	0.939	0.940	0.940	0.940	0.917	0.920	0.920	0.920
RF	0.945	0.950	0.940	0.940	0.918	0.920	0.920	0.920

TABLE III
CLASSIFICATION RESULTS FOR ASL AND ARSL USING ACCELEROMETER (3 FEATURES)

	ASL				**ArSL**			
Classifier	*Accuracy*	*Precision*	*Recall*	*F1-score*	*Accuracy*	*Precision*	*Recall*	*F1-score*
LR	0.858	0.840	0.860	0.840	0.969	0.970	0.970	0.970
SVM	0.909	0.920	0.910	0.900	0.979	0.980	0.980	0.980
MLP	0.924	0.930	0.920	0.920	0.984	0.980	0.980	0.980
RF	0.909	0.910	0.910	0.910	0.981	0.980	0.980	0.980

TABLE IV
CLASSIFICATION RESULTS FOR ASL AND ARSL USING FLEX SENSORS AND ACCELEROMETER (8 FEATURES)

	ASL				**ArSL**			
Classifier	*Accuracy*	*Precision*	*Recall*	*F1-score*	*Accuracy*	*Precision*	*Recall*	*F1-score*
LR	0.977	0.980	0.980	0.980	0.970	0.970	0.970	0.970
SVM	0.992	0.990	0.990	0.990	0.991	0.990	0.990	0.990
MLP	0.993	0.990	0.990	0.990	0.990	0.990	0.990	0.990
RF	0.997	1.000	1.000	1.000	0.998	1.000	1.000	1.000

MLP all the nodes in the hidden layers are functioning as neurons to model a nonlinear activation function.

- *Random Forests (RF)* is an ensemble of multiple decision trees which are initially constructed and combined in a random fashion to build a forest of trees. Further, the trees in the forest are trained using a sample of data chosen randomly from the training dataset. The advantage of RF is that it minimizes the overfitting problems in the trained model, by incorporating a Bagging step which uses bootstrap aggregation. [8].

IV. RESULTS AND DISCUSSION

Based on the proposed methodology in the previous sections, we conducted various experiments to verify the validity of the system design. We split the experiments into three types for each ASL and ArSL, namely, with flex sensors, with accelerometer and with both flex sensors and accelerometer. Also, we studied how important the features are in contributing to the performance of the ML classifiers by doing a Feature Importance test. Finally, we compared the performance of theoretical ML predictions and the real-time testing of the actual implemented system. We now present and discuss these results in detail.

A. Flex Sensors Results

Initially we started implementing the system with only 5 flex sensors and collected the 5 features, namely, $Flex0$, $Flex1$, $Flex2$, $Flex3$, $Flex4$. The accuracy, precision, recall and F1-score results of the 4 ML classifiers for both ASL and ArSL are presented in Table II. From the accuracy comparisons it is found that RF classifier performs best in the ASL with 94.5% and in ArSL with 91.8%. Also, it is noticed that ASL recognition is better than the ArSL and the reason for this is that the ArSl has more signs than ASL and also the signs have more similarity so it is easier to make errors.

B. Accelerometer Results

Further we planned to incorporate into the system one accelerometer and collected the 3 features, namely, X_axis, Y_axis and Z_axis. The accuracy, precision, recall and F1-score results of the 4 ML classifiers for both ASL and ArSL are presented in Table III. From the accuracy comparisons it is found that now MLP classifier performs best in the ASL with 92.4% and in ArSL with 98.4%. Also, it is noticed that here ArSL recognition is better than the ASL and the reason for this is that the ArSl involves rotation and movement of palms more than the ASL which are captured better by the accelerometer as compared to flex sensors.

C. Flex Sensors and Accelerometer Results

Finally, we combined the features of 5 flex sensors and one accelerometer and collected 8 features, namely, $Flex0$, $Flex1$, $Flex2$, $Flex3$, $Flex4$, X_axis, Y_axis and Z_axis. The accuracy, precision, recall and F1-score results of the 4 ML classifiers for both ASL and ArSL are presented in Table IV. From the accuracy comparisons it is found that again RF classifier performs best in the ASL with 99.7% and in ArSL with 99.8%. Also, it is noticed that here ArSL recognition and ASL recognition are comparable. The reason is that now we

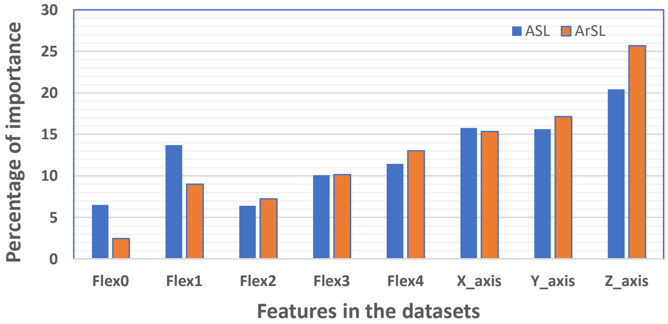


Fig. 4. Importance of features in the ASL and ArSL datasets

have more features and it makes the RF combine the benefits of both types of features. Further we see an increase in the classifier performance by at least 4% when we have taken more features to train the ML models.

D. Feature Importance

Fig. 4 presents the comparative study of the importance of features in making the ML classifier predictions. It is observed that the flex sensors have lower importance as compared to the accelerometer features. That is why we see that the accuracy of accelerometer results were better than flex sensors by at least 5%. Further, it is observed that in the ArSL case the accelerometer features play more important than the flex sensors. But, it is opposite in the case of flex sensors while comparing the ASL and ArSL cases.

E. Real-time Testing

In order to see the difference between the theoretical predictions and the real-time performance, we now present this as our final result. It was found that for the ASL case, the model gave a theoretical accuracy of 97.71% and in real-time it gave only an accuracy of 76.22%. Also, in the case of ArSl these values were 97% and and 79% respectively. This clearly shows that the errors are natural to happen during the practical implementation as compared to the theoretical model predictions, due to improper readings, calibration issues and noise during the operation phase. Finally, in Fig. 5 we show the final developed prototype of our proposed approach. This can be further improved based on the recommendations mentioned in the conclusions.

V. Conclusions

This paper has proposed, designed and implemented a bi-lingual sign language non-visual-based smart glove using ML classifiers. The motivation behind this solution to assist the deaf community to have a respectable and comfortable life similar to normal people in our society. The hardware involved five flex sensors and an accelerometer to provide sign language recognition and conversion of ASL and ArSL signs to speech and text. Among the 4 ML classifiers (LR, SVM, MLP and RF), the RF classifier performed the best with a classification accuracy of 99.7% in ASL and 99.8% in the ArSL case. Also, with Feature Importance we found that accelerometer feature contribute more to the ML performance as compared to the flex sensors. Since the real-time performance was not as expected, we plan to further improve this research work, by comparing the implementation and performance issues of non-vision and vision-based sign language recognition.

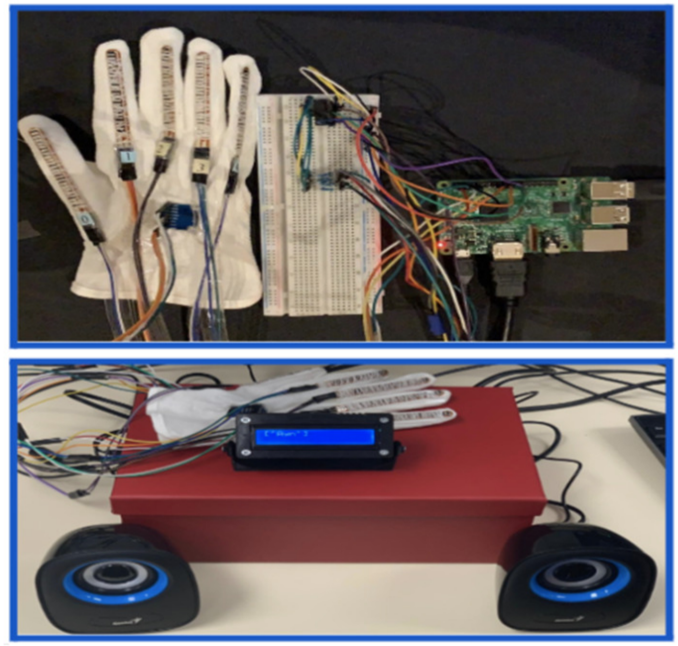


Fig. 5. Prototype implementation with Flex sensors, Accelerometer, LCD and Speakers

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