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Glove based wearable devices for sign language-GloSign

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ABSTRACT

Loss of the capability to talk or hear has psychological and social effects on the affected individuals due to the absence of appropriate interaction. Sign Language is used by such individuals to assist them in communicating with each other. This paper proposes a glove called GloSign that can convert American sign language to characters. This glove consists of flex and inertial measurement unit (IMU) sensors to identify gestures. The data from glove is uploaded on IoT platform, which makes the glove portable and wireless. The data from gloves is passed through a k-nearest neighbors (KNN) Algorithm machine learning algorithm to improve the accuracy of the system. The system was able to achieve an accuracy of 96.8%. The glove can also be used to form sentences. The output is displayed on the screen or is converted to speech. This glove can be used in communicating with people who don't know sign language.

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1. INTRODUCTION

Loss of the ability to communicate with others can have devastating effects. Sign language is a way for communication to overcome this problem. Sign language involves gestures made by hands and facial expressions. It is a very effective and interactive way of communicating [1]. The problem that arises from sign language is that not everyone is familiar with the gestures. It would be challenging for people with disability to communicate with people who don't know this language. Furthermore, it can't be used to communicate digitally. Another issue with the sign language is that there is no universal sign language. Every country has their own sign language with gestures that have different meaning than the sign language of other countries.

To overcome the issue of communication, a glove has been proposed in this study called GloSign. The major focus is to translate the sign language into English language. This paper focuses on American sign language, as it is the most common sign language. American sign language is mostly used in America and some parts of Canada. American sign language was devised in the 19th century by the American school of deaf. Like any other language, sign language has formal and informal parts. This paper covers the formal part of the communication. The formal part of the American sign language consists of 26 alphabets. These alphabets can be used to form words and sentences. The gestures associated with these letters are defined by four components. These are the shape of the hand, position in relation to the body, hand movements and alignment of the palm. Few of the gestures are dynamic. These gestures require the movement of the hand. Figure 1 shows the basic gestures for the English alphabets in American sign language.

This glove consists of flex sensor, accelerometer, and gyroscope to aid in recognizing gestures made. This wireless glove uses an IoT platform for uploading the data. This data is analyzed to understand the gesture made using the glove. Then it will be used to form words and sentences. The sentences will then be displayed on the screen running the gesture recognition software, along with conversion of the sentence to speech.

Figure 1. American sign language

This paper is divided into four sections. The first section is the literature review followed by methodology followed by results and the last section is the discussion. The fourth section concludes the paper.

2. LITERATURE REVIEW

The literature reviewed here is divided by the types of sensors, communication, algorithms that is used and how the gestures are outputted. In [2]–[6], the authors use a glove consisting of flex sensors. The gestures recorded by these sensors were displayed on the LCD. This glove was able to predict all the alphabets with a decent accuracy. The focus of this project was to develop a cheap glove to assist disabled people in communicating. The authors of [7], [8] developed a wireless gesture decoder that used flex sensors and accelerometer to determine the gestures. These gestures were sent to the mobile application using Bluetooth. The glove was able to determine all the alphabets and 15 words with an accuracy of 95%. In [8], a wireless glove was developed that consisted of the flex sensors and inertial unit. The glove was able to communicate using an Andriod application through Bluetooth. The glove achieved an accuracy of 98.2% when pressure sensors were added to the system. Similar glove was designed using flex sensors. This system achieved an accuracy of 83%. The system was able to determine the gestures using the voltage levels from flex sensors. After determining the gesture, it was displayed on a phone or laptop using Bluetooth communication.

The authors in [9]–[12] used flex sensors and accelerometer to identify the gestures made by the glove. It took around 0.74s to convert the gesture to sound and text. The glove was able to convert basic words to text and speech. The speech was stored in the card and played when the sign was made.

Tanyawiwat and Thiemjarus [13] made a cheap portable glove for gesture recognition known as GesTALK. It would convert the static gestures to speech. The system was able to work with American sign language (ASL) and Pakistan sign language (PSL). The glove was able to achieve an accuracy of 90%. Another glove in [14] had contact sensors placed along with flex sensors. This glove was able to convert gestures from 8 sign languages to text. It achieved an accuracy of 93.16%. El-Din and El-Ghany [15] used a glove with flex sensors and inertial sensor to determine the gestures made by the glove. The system was able to achieve an accuracy of 88% with dynamic gestures. It was able to convert gestures from 2 sign languages, American sign language (ASL) and Arabic sign language (ArSL) using a python graphical user interface (GUI) program.

Tanyawiwat and Thiemjarus [13] added extra sensors such as Touch sensors to the glove. To improve the accuracy, the glove data was passed through multivariable Gaussian distribution and multi-objective Bayesian framework for feature selection. The major problem was the ambiguity of the gestures that caused error in determining the letters. Another paper [16], also used contact sensors to aid in determination of gestures. It utilized a k-nearest neighbors (KNN) algorithm to increase the efficiency of the system to 91.54%. Ahmed *et al.* [17] and Arif *et al.* [18] designed a glove with contact sensors, flex sensors and inertial sensor. This framework achieved an accuracy of 92% using a gesture recognition algorithm. This gesture recognition algorithm used the readings from the contact sensor to determine the gesture. After the algorithm generated the possible alphabets, it would corroborate them with the flex sensor readings to make the decision more precise. At the end, values from inertial unit were used to finalize the alphabets.

Wu *et al.* [19] used surface Electromyography (EMG) sensors along with accelerometer to determine the gestures made. After getting the readings, the data was passed through multiple classifiers to get more accurate responses. The system was able to achieve an accuracy of 96% on 80 gestures. Abhishek *et al.* [20], the authors used capacitive touch sensors to help in determination of the gestures. The system was able to determine gestures in 0.7s with an accuracy of 92% using a python code. Mehdi and Khan [21] used a 7-sensor glove from 5DT company. It consists of a tilt sensor to determine the rotation of the glove. The data from the glove was passed through three-layer algorithm. The three-layer neural network used to assist in finding the alphabets. The first layer consisted of raw sensor values which are passed to a hidden layer with 52 nodes. The third layer consisted of 26 nodes, each associated with an alphabet character. This algorithm achieved an accuracy of 88% in determining the gestures. The paper [22], [23] uses immersion's 18 sensor CyberGlove which consists of resistive bend, abduction and flexion measuring sensors. This framework gets the raw data from the sensors and passes it to a neural network. This system was able to achieve an accuracy of 90%, but the major drawback of this framework was that it was not real-time.

In this paper, we propose a glove that can translate gestures into alphabets. This glove is:
- Wireless and portable [24]
- Real-time
- Able to form words and sentences [25]
- Accessible anywhere using IoT platform

The technological developments of the present era have paved the way for state-of-the-art and competent solutions to developing problems. The literature review on medical gloves emphasizes the features and limitations of the several gloves available in the market. However, the glove under consideration stands out as it is designed to cover the gaps left by earlier gloves. This glove offers real-time results, which is a significant benefit in situations where prompt action is obligatory. These results have been demonstrated in the result section. Its convenience and ease of access are other features that make it a convenient option for healthcare experts. The ability to address the failings of earlier gloves makes this glove an advanced solution that can contribute to enhancing the quality of patient treatment.

3. METHOD

The transformation of sign language into English language using the GloSign glove involves multiple stages that require careful attention to detail. Firstly, the sensors on the glove must be selected and placed correctly to capture the movements of the wearer's hands accurately. This is crucial for the accurate interpretation of sign language gestures. Secondly, an internet of things (IoT) platform must be connected with the GloSign glove to transmit data to a computer or mobile device. This allows for real-time interpretation of sign language gestures and makes communication between deaf or hard-of-hearing individuals and hearing individuals possible.

Finally, the data collected from the GloSign glove is interpreted using machine learning algorithms, which have been trained on sign language datasets. These algorithms can recognize patterns in the movements of the hands and translate them into English language sentences or phrases. Through this process, GloSign is able to bridge the communication gap between deaf and hearing individuals, providing a more inclusive and accessible world.

3.1. Selection and placement of the sensors o

This subsection defines the method used in selection and placement of the sensors. The sensors used are flex sensors, contact sensor and and inertial measurement unit (IMU) sensor. The IMU sensors consist of an accelerometer and a gyroscope.

The flex sensors will be used to measure the angle at which fingers are bent. Depending on the angle the values of the flex's resistance change. The ideal place would be to place them on top of the glove. The flex sensors will be connected to the Arduino using the diagram shown in Figure 2. The first pin of the flex sensor (red) is connected to 3.3v of Arduino NANO IoT, while the other pin (blue) is connected to a resistor. The connection before resistor is connected to the analog input of the Arduino, while the other connection (black) is grounded.

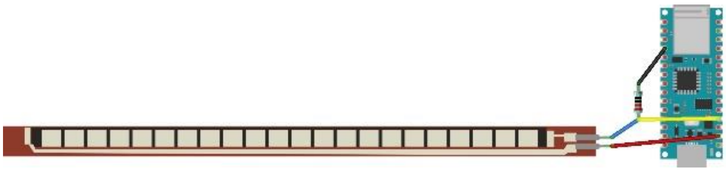

Figure 2. Flex sensor connection

American sign language has multiple gestures that look very similar and is very hard to distinguish. The contact sensor will be used to differentiate similar gestures. The contact sensor will have similar connection to the Arduino as shown in Figure 2. The contact sensors are placed on the index and middle finger. This positioning of the sensor will help in differentiating among many of the signs.

The IMU sensor will be used to detect the dynamic gestures. The IMU sensor is a part of the Arduino, so it will be placed on the top of the hand. Figure 3 shows the placement of all the sensors on the glove. The glove is connected to an IoT platform using the Wi-Fi on Arduino. The IoT platform used in this project is international business machines (IBM) Watson IoT platform. The Arduino sends the raw values to the IoT platform. These values consist of accelerometer, gyroscope, and flex sensor data. The platform can be used to track the changes when the gestures are changed with the help of scatter plot in the platform. Later these values will be extracted from the platform to the PC using IBM Watson IoT software development kit (SDK). Figure 3 shows the flow of data from the glove to the PC for further processing.

Figure 3. Sensor placement and flow of data

3.2. Data from glove

The data from the glove is uploaded on the IBM Watson IoT platform. This data needs to be extracted and used to determine the gestures. The data is extracted through the python SDK for IBM Watson IoT platform. The data consists of flex sensor data, contact sensor data, accelerometer data, gyroscope data and movement data. These sensor data are then mapped and calibrated onto various letters. The training of the system is offline. Therefore, a data set is generated and used for training a Machine-learning model.

To improve the accuracy of the detection, a KNN algorithm is used. This machine learning algorithm helps in classification of the alphabets. In order to find the most optimal value of K for prediction of the signs, various values of K have been tested. K values ranging from 1 to 25 have been tested for every 1,000 iterations and the accuracy was recorded. At the end, the K values with the best accuracy and the least K value were chosen. The best value provides the best accuracy and the lowest K provides the best speed of the system.

The model with the best K value could be deployed. This model can receive the data from the IBM Watson IoT platform and predict the closest letters. Because of similarity of the some of the gestures to each other, it is possible that duplicate or incorrect letters are predicted. However, this issue would be dealt with after the sentence formation process.

The letters predicted at this stage will then be used to form words and sentence. Spaces can be added to a sentence using an additional gesture. At the end of the sentence generation stage, the sentence is passed through a filter that will correct any erroneous words that have been generated during this process. If a word is identified as incorrect, then the filter will examine the letters with similar gestures to the letters used in the word to fix the word. This is done for every word in the sentence. After every word in the sentence is deemed correct, the whole sentence is passed through a grammar checker to verify if the sentence grammatically is correct. This process takes around 2-8 seconds to process, depending on the length of the sentence and is done by a process that is called the gesture fix algorithm. This process is responsible for fixing the words in the sentence and making sure the sentence is grammatically intelligible. The gesture fix algorithm processes the sentence as a whole. The advantage of this is that there is no delay in processing. If the system processes it word by word, it could cause delay and loose some letters when the previous word is being processed.

After the sentence is generated, it will be displayed on the screen running the gesture recognition software and then the sentence will be converted to speech using the IBM Watson text to speech SDK. This program can be installed on any PC that has a stable internet connection and has the ability to run python software. However, there could be differences in the performance depending on the specification of the system.

4. RESULTS AND DISCUSSION

This section discusses the findings from the experiments conducted with the glove. The system is divided into three parts, the first part is uploading data on the IoT platform. The second part consists of analyzing and decoding the data. The final part is outputting the data.

4.1. IoT platform and sensors

The IoT platform used in this experiment is IBM Watson IoT platform. Arduino NANO IoT on the glove is connected to this platform, using Wi-Fi communication. The data from the glove is divided into two parts, the data from flex sensors and the data from contact sensor and IMU. The IMU and contact sensors outputs are Boolean. If the contact sensors are touching each other, the Arduino will register a reading of 1, else its 0. The IMU sensor built-in the Arduino NANO IoT is used to determine if the glove is being moved or not. If the glove is being moved it would register a reading of 1, else 0 would be sent.

Table 1 shows the average readings of around 5,000 gestures. The contact and movement values range between 0 and 1. The contact value is 1 if contact is registered in the gesture. The movement value is 1 when a dynamic gesture is registered. The flex sensors have a range between 0 and 90°. The flex sensors F1, F2, F3, F4 and F5 represent fourth, third, second, first fingers and the Thumb respectively. The data depicted in the Table 1 shows that most of the gestures have very similar sensor values. For example, the gestures like “i” and “j” have very similar sensor values except for the value of the movement sensor.

Table 1. Average sensor values for each gesture

Alphabet	F1	F2	F3	F4	F5	C	M
a	43.03	25.94	39.80	51.28	0.27	1	0
b	0.55	-4.49	-3.45	-0.05	30.30	1	0
c	19.27	30.81	52.50	33.57	2.92	1	0
d	32.01	42.04	51.73	0.13	-1.50	0	0
e	66.83	71.89	73.64	58.29	35.41	1	0
f	5.98	0.80	1.22	69.99	5.40	0	0
g	76.21	66.59	83.98	-0.50	4.54	0	0
h	59.45	56.08	-4.44	-0.03	12.33	0	0
i	3.45	79.17	65.58	79.62	17.40	1	0
j	2.78	71.62	60.66	74.46	15.61	1	1
k	70.55	62.95	-6.81	-0.66	-0.64	0	0
l	83.53	73.88	77.67	-1.13	-0.82	0	0
m	77.58	57.87	53.03	54.70	10.29	1	0
n	90.52	71.54	58.45	61.96	-2.11	1	0
o	44.81	43.63	51.74	42.93	7.46	1	0
p	57.93	49.62	2.35	-0.80	-3.45	0	0
q	74.20	69.96	68.03	-0.21	-2.14	0	0
r	60.91	47.69	-5.54	-1.10	6.88	0	0
s	95.83	78.83	71.81	75.64	35.59	1	0
t	76.92	34.22	40.41	52.19	-68	0	0
u	82.84	31.52	-6.82	-1.11	13.97	1	0
v	77.50	38.18	-7.07	-0.76	14.15	0	0
w	53.30	-4.28	-7.13	-0.47	12.56	0	0
x	76.99	75.49	70.31	58.34	41.50	0	0
y	1.06	74.33	68.31	80.23	-1.50	1	0
z	64.54	62.94	73.39	-0.73	7.17	0	1

Figure 4 shows how the data is visualized in the platform to aid in understanding different gestures. The C (contact sensor) and M (dynamic gesture) part shows the contact sensors and movement readings. The value C which in in turquoise color goes high when the contact sensors are touching each other. The value M, which is in light turquoise color, goes high when there is any movement in the glove.

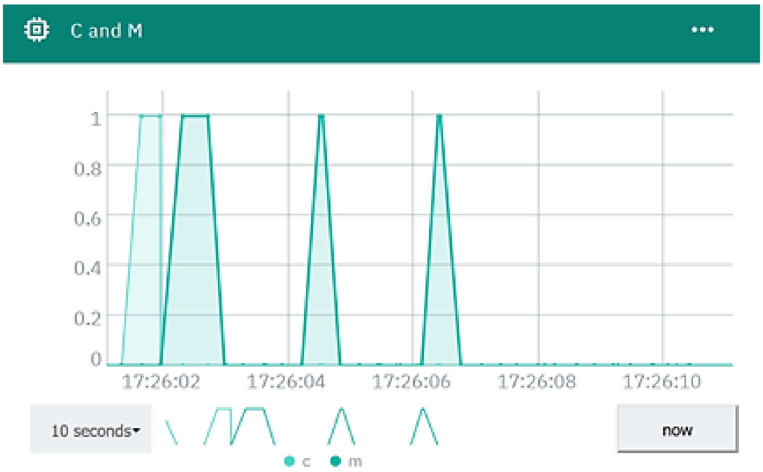

Figure 4. Visualization of C and M from glove on IBM Watson IoT platform

Figure 5 shows the flex sensor readings. The chart shows five sensor readings from flex sensors. F1 is the fourth finger, F2 is the third finger, F3 is the second finger, F4 is the first finger and F5 is the Thumb. the graph shows the reading for hand at rest.

Figure 5. Visualization of flex sensors from glove on IBM Watson IoT platform

4.2. Analyzing and decoding data

The data from the IoT platform is extracted for analyzes. The data is extracted using the python application programming interface (API) for IBM Watson IoT platform. The k-nearest neighbors (KNN) supervised machine learning model is used for classification of gestures. For training the model, 200 gestures were signed and the readings were recorded. The average value of these readings is shown in Table 1. After recording the readings, the gestures were classified using American sign language gestures and the classification were made available to KNN model.

To verify the accuracy of the system, the gesture readings were split into two parts; testing and training. 75% of the data were used as training set for KNN and 25% of data was used for testing and measuring the accuracy of the system. The bar chart in Figure 6 shows the accuracy for identifying each letter when K was set to 1 (1-NN). It can be seen from Figure 6 that majority of the gestures were identified with 100% accuracy. The dynamic gestures were identified with an accuracy less than 95%. The common mistake was in telling apart letters “i” and “j”, as they have the same sensor values except for the value of the movement sensor. The letters “j” sets the movement sensor to 1. The issue is; when the movement finishes or the glove is stationery, the “j” would be read as “i”. Aside from “j”, there were discrepancies in identifying “h” and “r”, as they had quite similar sensor readings. But by far the most problematic letter was “j”.

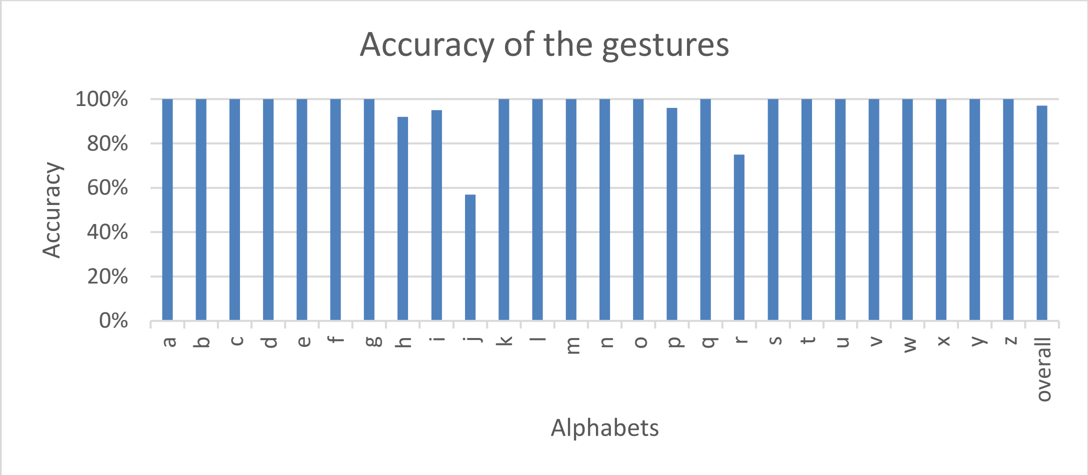

Figure 6. Accuracy of the gestures

To increase the precision of the KNN algorithm, different values of K were tested. The mean error and accuracy were generated to determine which K would be best for the existing framework. Figure 7 shows the average mean errors for various values of K. The graph shows that the best values for K are K=1 and 3 with average error rate below 0.5%.

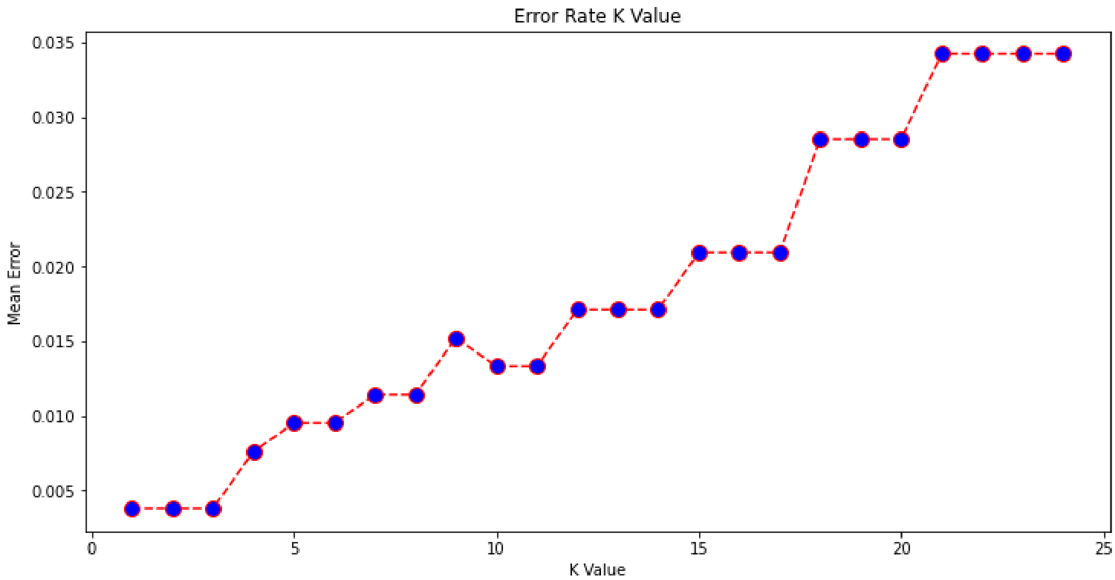

Figure 7. Mean error of K values

Figure 8 depicts the average accuracy of identifying gestures for various values of K. Similarly, Figure 8 shows that the system can achieve accuracy of more than 99.5% if the values of K are set to K=1, or 3. As the value of k increases it requires more computing power and time to analyze the data. So, the ideal choice would be to go with the lowest value of K that has acceptable accuracy and mean error rate. The ideal option here would be 1 for the value of K.

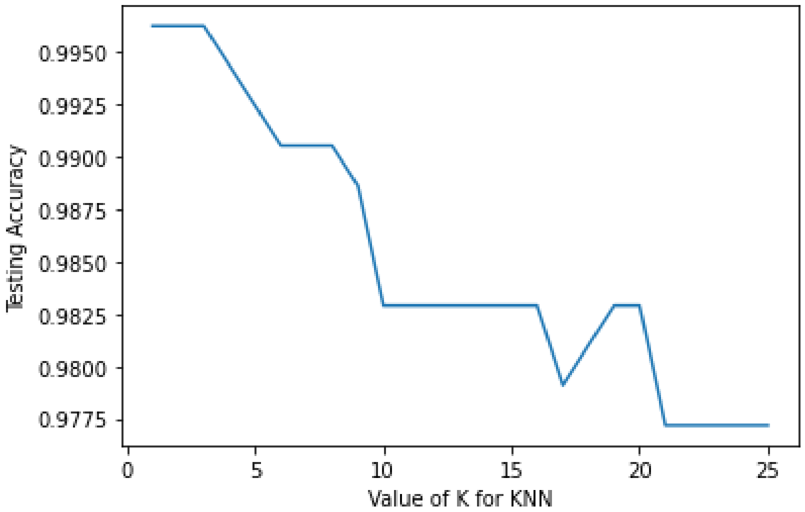

Figure 8. Accuracy of k values

The glove shown in Figure 9 was tested using pangram “The quick brown fox jumps over a lazy dog”. This pangram would be a good test to determine the efficiency of the glove in forming sentences as the pangram contains all the alphabets. The glove was powered by a battery pack that is connected at the bottom of the glove.

Figure 9. GloSign glove

Figure 10 shows the console output of the system while processing the gestures made for signing the pangram “The quick brown fox jumps over a lazy dog”. It is quite evident that there are some issues between “i” and “j” due to the movement of hands. The other issues are due to similar hand gestures. But this error is corrected by passing it through the gesture fix algorithm. In this case the algorithm was able to fix all the errors created.

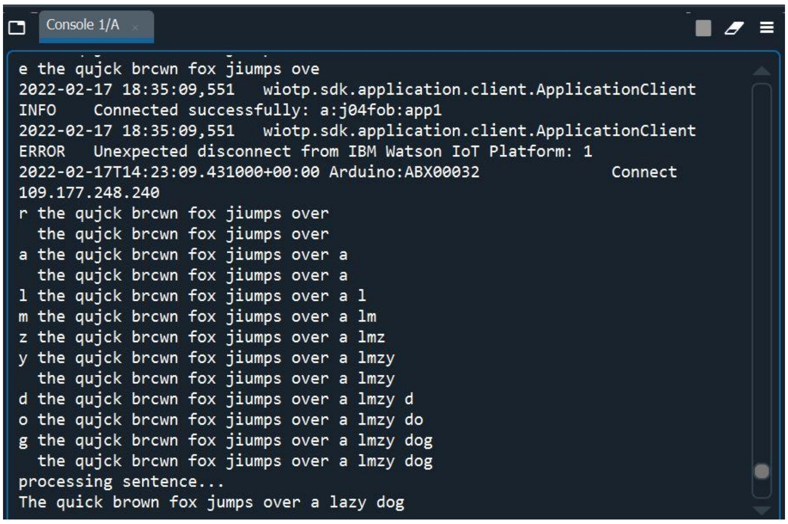

Figure 10. System output

4.3. Outputting the data

After the execution of the gesture fix program, the final sentence is displayed on the console as shown in Figure 10. It is also played using IBM Watson speech to text module. Figure 11 shows the conversion of the text to speech using IBM Watson text to speech module. The file is stored and played at the end of the program. The module can be modified to change dialects and voice.

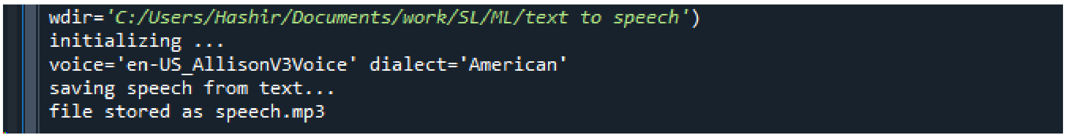

Figure 11. Speech to text

4.4. Discussion

In this paper, a glove for interpreting gestures of American Sign language has been discussed. Machine Learning and sentence level error correction has improved the output of the system for few letters with similar gestures. The glove could be further improved by utilizing additional contact sensors for identifying ambiguous gestures. The gesture fix algorithm could be optimized more to process faster. Analysis and correction at word level instead of sentence level could improve speed of the system. Similarly, further improvement could be achieved by guessing next words and sentence endings. The whole system can be placed on the IBM platform using node red. This would make the system easily accessible from anywhere and from any device. However, it can also affect the system, as processing online would be slower. Moreover, this project can be added to a video chatting software that can decode the gestures and display them on the screen. This could give a new experience of attending meetings for people who use sign language to communicate.

5. CONCLUSION

This paper proposes a glove called GloSign that translates the sign language gestures to letters and words. The system can also form sentences using the letters and words identified. This glove uses IMU and flex sensor to decode the sign language gestures. These sensor data are transmitted to IBM Watson IoT platform. The KNN machine learning algorithm is used for distinguishing between difficult or similar gestures. The letters identified from the gestures, later, are combined to form sentences. These sentences are passed through another layer of error correction which is called gesture fix algorithm to resolve the mistakes in detecting letters at word and sentence level. Finally, the output of the system is displayed on screen and converted to speech for convenience. Further studies are necessary to improve the accuracy and speed of the system, so it can aid in verifying the sign language gestures more competently.

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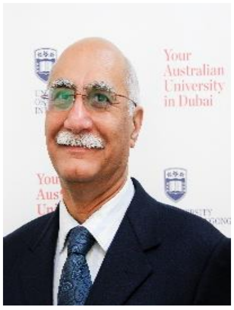

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