Wearable IOT based Malaysian sign language recognition and text translation system

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Abstract*—Sign language recognition devices are gaining tremendous attention in recent years for helping speech and hearing-impaired community. The idea of fusing technology and sign language knowledge together to create a smart system is still being tried and developed all over the world with implementation with many different sign languages. In this paper, Malaysian Sign Language is given importance with 5 Malaysian Sign Language words being selected for recognition and prediction with new combination of sensor used compared to previous researches done for Malaysian Sign Language recognition and prediction. The combination of sensors used are 1 MPU9250, 1 MyoWare and 2 Force Sensitive Resistor sensors. 1D CNN time-series model is implemented with prediction accuracy ranging from 80 to 91 percentage.

***Keywords*— Wearable IOT, Malaysian sign language, text translation system, hand gestures, Force Sensitive Resistor.**

I. INTRODUCTION

Communication is the first tool used by a human being to convey thoughts, opinions, ideas, emotions and generally spoken words as a contribution to an ongoing conversation. Unfortunately, some human beings have certain barriers to communicate in an ordinary way, these group of people falls among hearing or speech impaired groups. Hearing and speech impaired people are individuals whom has difficulties in listening to a voice or a sound and also those whom are not able to talk. It is stated that statistically 160,000 Malaysian are found to belong in the hearing-impaired category according to [1]. A direct solution for the obstacle faced is communicating through sign language which has different grammatical representation and also classified as a visual language.

Sign language employs signs made with the hands and other movements, including facial expression and postures of the body, used primarily by people who are deaf [2]. According to [3] there are 300 different sign languages in the world, Malaysian Sign Language (MSL) is also one of them. As for this project, Malaysian Sign Language is the main element to be discussed and the chosen sign language for recognition process. The MSL has its own way of representation of alphabets and common words which can be categorized by static signs and dynamic signs that has motion in hand gesture representation. Referring back to history, Malaysia had signed the United Nations Convention on the Right of People with Disabilities (UNCRPD) and passed the people with Disability Act (Act 685) to give the people with disabilities the opportunity to live as a normal citizen of Malaysia.

At first instance, sign language has a lot of benefits for hearing and speech impaired individuals to communicate or convey information to others whom also possess the same knowledge as the conveyer. As this situation is seen in a deeper manner, the impaired individuals suffer in conveying the thoughts, opinions, or having a normal conversation to the majority of people that does not possess the same sign language knowledge that requires hours and multiples class of trainings. This situation is usually the main reason for the implementation of sign language interpreter job although it is indicated by the Malaysian Federation of the Deaf in 2018, there are under 100 affirmed gesture-based communication mediators in Malaysia.

The described problematic situation will create a social gap between those with and without the knowledge of Malaysian Sign Language. To overcome this barrier, a substantial research is gaining attention all over the world, it is exclusively about a creating a smart predictive system to recognize and translate sign language into text or speech through the implementation of sensor and microcontroller. The explained advancement inspired to create this project of developing a Malaysian Sign Language recognition and translation system that uses Surface Electromyography (sEMG) sensors, Force Sensitive Resistor (FSR) sensor and one 6-axis motion sensor where 3-axis accelerometer and 3-axis gyroscope are used which is also called inertial measurement unit (IMU) sensor. Hand orientation, position and individual fingers movements are crucial elements analysed through this proposed system. The analysing process is performed through machine learning algorithm to train and test the data collected for the sensors to make an accurate prediction of possible output datasets that will be translated to text and speech.

As the research is based on sensor data analysing system, it explains that sensors are being used in countless applications as we move to even more connected world in terms of technology [4] Plenty of applications require various inputs from sensors with no less in performance and used with exceptionally low power consumption. Combination of the useful sensor and machine learning algorithms will be substantial components for the solution of targeted problems of this research as listed below.

- Recognition of two types of hand gestures that are classified into static hand gesture and dynamic hand gestures (gesture with motion).
- Training and testing the system model by choosing a suitable machine learning classification method to get

a higher accuracy and performance of predictive output.

- Extraction of useful data from the raw data sensors.
- Creating the prototype that is wearable.
- Producing a sensor-based device with cost effective hardware components

The common researches done for Malaysian Sign Language recognition are based on vision, Kinect and using flex sensors with incorporation of accelerometer. The most common method used for every sign language is vision-based recognition system, it captures hand gestures through image processing and certain structure machine learning algorithm analyses the data to give an output. Image processing or vision method is a famous technique, according to [5] researchers predict that the global market of image recognition will reach $38.92 billion by 2021. The vision-based technique is the most common for sign language recognition but the system is vulnerable and fails to captures in dynamic background, bad lighting and other variables.

Consideration were taken from all possible researches for Malaysian Sign Language to analyse a cost efficient and a newly explored method for recognition in this proposed paper. Fusion of sEMG, IMU and FSR sensors are a unique and new combination to be explored in MSL recognition system although there are several researches done for American Sign Language (ASL) by using the mentioned sensor combination. Therefore, the main aim of this research is to develop a portable device or system to translate MSL to text and voice for hearing and speech impaired person.

A research of "New Data Glove Approach for Malaysian Sign Language Detection" is conducted by [6] A method proposed to overcome the difficulty of deaf and mute people in order for them to communicate with normal people. Three different method were analysed and reasoned from the paper before finalizing one method which are visual-based approach, data-glove based approach and virtual button-based approach, the data-glove based approach were chosen by the researcher.

Second research paper is about creating the ASL recognition system, a data-glove approach is proposed as the comfort of use is prioritized by using Bluetooth module to transmit data written by [7]. The researcher uses 5 flex sensors and an accelerometer to recognise American Sign Language with output displayed on LCD and speech form. Arduino Mega is used to analyse the data from sensors and 0.5W audio speaker used with amplifier module to play the sound of the output dataset, the voice of corresponding datasets is stored in a SD card module which is connected to ICSP (In-Circuit Serial Programming) pins in Arduino Mega. Advancing to next step, the glove-based prototype is made with personalised PCB to connect the microcontroller and sensors and also a main box is created for storage of components.

An analysis of vision based Malaysian Sign Language recognition method is done [8]. The main topic focuses in Human Computer Interaction (HCI) research reviews. The research reviews 3 different approaches for gesture interpretation which are data glove, colour glove and bare hand approaches. Data glove approach uses flex or tactile sensor and motion sensor, the colour glove approach is done by tracking the hand gestures through different marked colours. The colour approach is stated unnatural and not suitable for many users. Third approach implements a bare hand recognition method through computer vision that is processed to extract features from hand gestures made. The researchers also reviewed some hand gesture recognition algorithms which gives many ideas and explanation for further progress towards recognition, the algorithms used are Artificial Neural Network (ANN) and Hidden Markov Model (HMM).

A research titled "Using FSR based muscle activity monitoring to recognize manipulative arm gestures" was done [9]. FSR sensor is mounted on forearm to manipulate performance of 16 different gestures performed by 2 subjects. The main effort made is to improve the muscle activity reading by incorporating 3D acceleration and gyro sensors with FSR sensors to obtain results with high accuracy. The FSR sensor is made of piezoelectric plates that change electrical resistance value when any forces are applied as written in the research paper. 8 FSR sensors of 46mm x 46mm are placed equally divided on lower and upper forearm instead of wrist to get more detailed information directly from particular muscles. Wearable hardware system is prepared by inclusion of motion sensor and FSR sensors into a long bicycler's glove with power directly supplied from a mobile computer.

A 'Malaysian Sign Language Dataset for Automatic Sign Language Recognition System" research is done by [10]. Different kind of feature extractions are proposed for Microsoft Kinect to recognize the gestures shown. A Kinect based system is used to create a dataset for MSL, there are 3 steps in methodologies for the creation of MSL dataset which starts with data capturing, data processing and data organization. Data capturing is done through the Microsoft Kinect with help of capturing features like RGB, Skeleton and Depth analysis, each signer is asked to sign the same gesture for 5 times with 130 cm apart from the Microsoft Kinect sensor and lastly data recorded are kept in a file. As for Data Processing, raw data collected from RGB, skeleton and depth frames are used for extracting import hand segment to assign it to appropriate hand gestures. Data organization is a process of grouping datasets based on static and dynamic signs which are motionless sign and sign with motions respectively.

In the recent years, advancement of technology has led to an increase in research and development of IoT devices [11-17]. IOT is one of the main components of the project, an extensive research has been done in this area for further understanding of IOT. [18] written a paper titled "Home Automation Using Bluetooth and IOT", although the topic discussed is related to home automation but the Bluetooth and IOT components are essential area to be reviewed. The method proposed for IOT purpose is low cost method that includes connection with Bluetooth (HC-05) as for method one and ESP8266 Wi-Fi for internet connectivity as second method. Additional components used are Relay Module and Arduino Uno R3. The working concept of Bluetooth (HC-05) connection is explained as a wireless system that transmits data using Master and Slave configuration through Serial Port Communication and it operates for a short distance data transfer.

Machine learning analysis is important for projects in order to train the data in predictive model that give outcomes with better accuracy and performance, a research titled "A comparative study of machine learning algorithms for physiological signal classification" written by [19]. The research is regarding finding the performance of famous machine learning techniques like support vector machine, logistic regression, neural networks and so on. The research outlines an accurate method of machine learning technique to be used for physiological signal like EEG, gait dynamic signal and speech. Materials used are the datasets that related to physiological signals to test the best classification method among the datasets, the first dataset is "The Parkinson Disease (PD) data set (DS1)" which has 195 voice recordings from 23 subjects with PD and from 8 healthy subjects where a total of 22 features are extracted.

Wearable body pressure sensing is explored by using force sensing resistor that also known as FSR sensor by [20]. The accuracy and reliability are focused on the research paper where wearables can collect more important information regarding activities or physiological parameters which can be analysed for different purposes. Overview of the force sensing technologies are explained with inclusion of different phenomena behind the contact pressure sensing technique with multiple tests on pressure sensors.

Surface electromyography signal collection for artificial hand controlling purposes are one of the main methods for experiments of hand muscle signals information utilisation [21]. Electromyography signal is exerted electrical signal from skeletal muscle that represents activity of electrical during contraction of muscle from any movements. The EMG signal is often comes in very high noise which can be excluded with the help of electrodes to obtain and extract useful information from muscle contraction.

Next research is regarding auto classification of vibration data from smartphone by using deep learning technique [22]. The analysation of data and real-time classification techniques and information are useful from the mentioned research paper. Incidents with bridges around the US and Italy were inspiration to proposed project on visual illustration of different vibration types on the bridge. There are four mainly focused type of vibrations explored and stated in the research done which are the device bias, ambient, traffic and earthquake.

Another research is reviewed which uses Optical Fiber Force Myography (FMG) sensor to identify and classify hand postures [23]. The work is an effort towards advanced human-computer interaction, an intensity-based optical fiber FMG sensor is used with utilisation of ANN for hand posture prediction. Progressing to next procedure which is the sensor design from scratch to place the proposed sensor comfortably on hand to collect the appropriate data regarding different hand postures.

II. SYSTEM IMPLEMENTATION

According to the Fig 1., there are 3 parts of the entire system that falls under category of system implementation, the first part is circuit and prototype creation with all the sensor and components, second part is the dataset creation from 3 subjects which also includes data analyzation and pre-processing and last part is 1D CNN model building to predict new data through IOT for MSL sign translation.

The MPU9250 has additional feature called magnetometer that combines with accelerometer and gyroscope to produce a 9 degree-of-freedom sensor that increase accuracy of data to obtain from MSL gestures. Prototype creation is also an integral part of the whole implementation of MSL translation system, this part covers the appropriate placement of the MPU9250, 2 FSR and MyoWare sensors to obtain low noise and useful signal that flows into ESP32 for dataset creation. The FSR sensors are placed on wrist which is a new placement compared to the proposed model, the sensitivity of FSR sensor to static hand gestures are important to classify the MSL signs, so after different placement testing in practical, it was concluded that the sensitivity due to finger movement increases when placed on wrist. MPU9250 sensor is integral to find the dynamic movement from the MSL gesture, so it is placed slightly above the wrist to capture the appropriate movements from values generated by accelerometer, gyroscope and magnetometer.

Furthermore, second part of the system starts with dataset obtaining from users or volunteers that offered to perform the MSL gestures, dataset acquisition is collected from selected MSL words or gesture which are "Siapa", "Nama", "Awak", "thankyou" and "understand", these are the 5 selected MSL signs that selected to be performed. MSL words selected contains a combination of "Bahasa Malaysia" and "English", these words are some of the commonly used words between MSL community. The number of words proposed initially to be recognized were 12 MSL signs before implementing the sensors and prototype but it has been changed to 5 words. There were 3 volunteers chosen for the collection of datasets where each person requested to perform each MSL signs for 10 trials, before the data acquisition process start, volunteers were shown video on how the selected MSL gestures are performed. After all the procedures done which includes volunteers wearing the prototype comfortably, data from ESP32 were recorded by using serial port at 10HZ which represents 10 data points per second. Finally, the sensor data are collected from serial monitor and stored into separate excel file for future data analysation and pre-processing which was done in python environment.

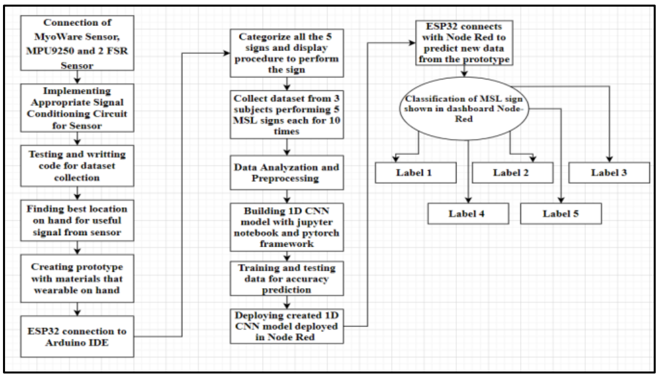

Fig. 1. Overall block diagram of the system

Next is the third part of block diagram of entire system that discusses about elements needed and steps taken for prediction of MSL signs performed. First, the collected data need to be labelled according to the MSL signs performed, this can be done in Excel software with help of tools provided by Excel platform. Then, data analysation, pre-processing and prediction related procedures are done in Jupyter Notebook environment with usage of Python 3 programming language. IOT is also one of the major parts of the entire system, Node-Red is used as the IOT platform to deploy the 1D CNN models for performing prediction and classification elements by accepting sensor values from ESP32.

Based on Fig 2, there are 4 main things to explain for the circuit diagram which are microcontroller (ESP32), MPU9250 sensor, FSR sensors and lastly MyoWare sensor. Additional components are only added for FSR sensors for the purpose of creating a signal-conditioning circuit to output stable and useful data. First, the ESP32 is brain of the circuit diagram where it obtains signals and data from all the sensors, three GPIO pins (32,35,34) are used for inputting data that is capable of reading 16-bit analog data. ESP32 is supplied power with USB cable and also it distributes power for all the components and sensors used, this scenario is only valid during dataset creation from volunteers' phase where the data will be used for training, testing and creation model. This scenario becomes different during the final prediction phase after creating the IOT application, when the IOT application used through WIFI, the ESP32 will be powered up by a converted 5V battery with 850mAh. The explained implementation is done because, during dataset creation by volunteers, the data acquisition frequency is high which is 10HZ, to avoid loss of any data when transferring data to laptop, the WIFI option is neglected and a normal USB cable is used. This reason is why there is a difference in technique of powering up the circuit.

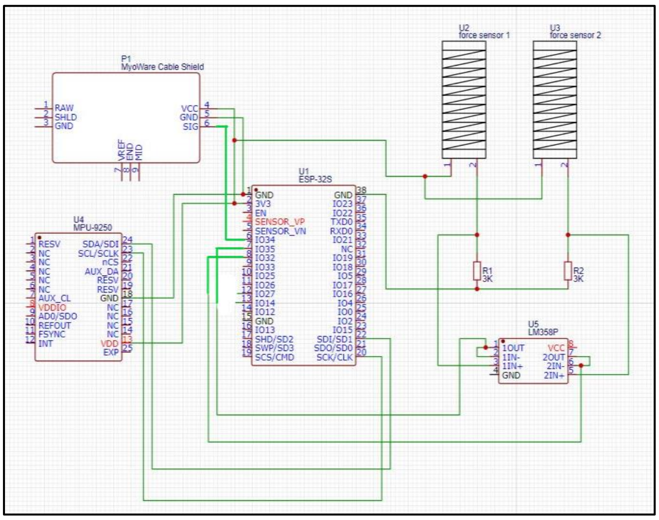

Fig. 2. Circuit diagram of the entire data acquisition system

Next, 2 FSR sensors can be seen in the circuit diagram, as for this type of sensor, the data acquisition should not be directly read without any signal conditioning circuit because the signals will be weak and not stable. A dual operational amplifier named LM358P is used for both the FSR sensor with a voltage dividing circuit from help of 3K ohms resistor for each FSR sensor. Outputs across 3K resistors were fed into LM358P for signal amplification and stabilization, the value 3K is chosen after doing testing in practical to determine the best resistor for this project application which needs a highly sensitive FSR sensor with less actuation force. Besides, the MyoWare sensor is connected to GPIO pin 34 of the ESP32, this sensor does not have any signal condition circuit because the MyoWare sensor comes with a board that has all features and functions to amplify, rectify and stabilize the output signal. As can be seen from the circuit diagram, there are choices for user to choose between raw signal output or the other output option that had gone through signal conditioning. In this system, the signal conditioned output is chosen to be supplied into ESP32. Lastly, the MPU9250 is connected to SDA and SCL of ESP32 which represents the I2C communication between two-wired interface. Another additional info is all the sensors and components used are powering up from 3.3V pin by ESP32 microcontroller.

Node-Red flows and connections are also part of coding of the entire systems in a graphical manner. The Node-Red is the integral part of the entire system when the built prototype is tested by MSL sign performers or users with help of ESP32, the Node-Red receives the data from sensors and execute the saved CNN model with help of Pytorch module. Then, the execution of 1D CNN model will output the classified categorical variable which is the MSL words that will be displayed in Node-Red dashboard. The explanation given is general term of working of the flow shown in Fig. 3., but there are more detailed explanations behind the nodes shown where each node has a purpose. Firstly, the techniques of data transfer from ESP32 to Node-Red are done by using WIFI as the project is proposed to be IOT based, in Fig. 3., there is a node specialised for MQTT (MQ Telemetry Transport or Message Queuing Telemetry Transport) messages coming from ESP32 through WIFI. MQTT is a data exchange technique used for IOT purposes, as for this project there is a built-in MQTT module called AEDES in Node-Red, this MQTT protocol can be taken advantage to transfer the MPU9250, FSR and MyoWare sensors.

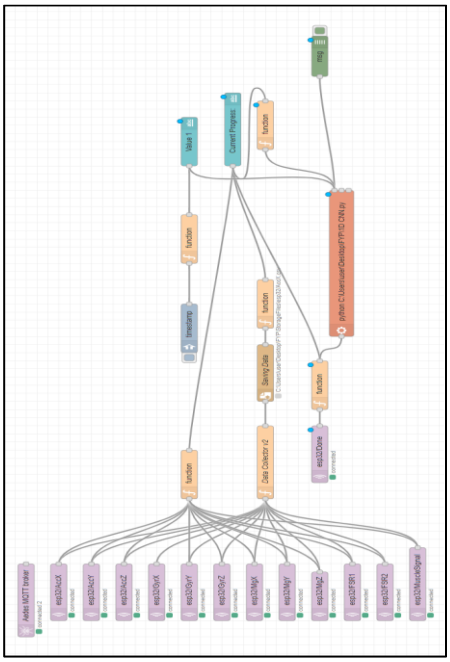

Fig. 3. Node connections in Node Red between python and

Furthermore, the data collected for prediction has to be changed stored into an array technique for inserting as the inputs to the "execution" node which executes the 1D CNN time-series model saved locally. The dimension of array that are inserted into the "execution" node will be "[20,12]" which has 12 inputs features in one array with a total number of 20 arrays. This specification is done to get more useful information from the data collection without losing data due to WIFI error or other issues during data transfer.

Fig. 4. shows the full flowchart of steps and procedures taken for the dataset creation and pre-processing phase. The

flow starts with circuit building of circuit with MPU9250, FSR and MyoWare sensors connected with ESP32 which is the microcontroller for this MSL recognition and detection project. Connections are troubleshot and process of creating dataset with volunteers will be initialised if the data, sensor values and connection are working as desired. Sign performing videos of the selected MSL words will be shown to volunteers and certain time will be allocated for the volunteers to learn and repeat the gesture without any major errors. 3 volunteers accepted to contribute towards the dataset creation process, the 3 volunteers consist of 2 boys and 1 girl. The volunteers had to perform the each of the 5 selected MSL words for 10 trials with the starting position of the hand is at rest position without any movement on table. Data acquisition frequency will be 10Hz while volunteers doing the MSL words as requested. After, collection of data, the pre-processing of data phase is performed with Jupyter Notebook that runs on Python 3 programming language.

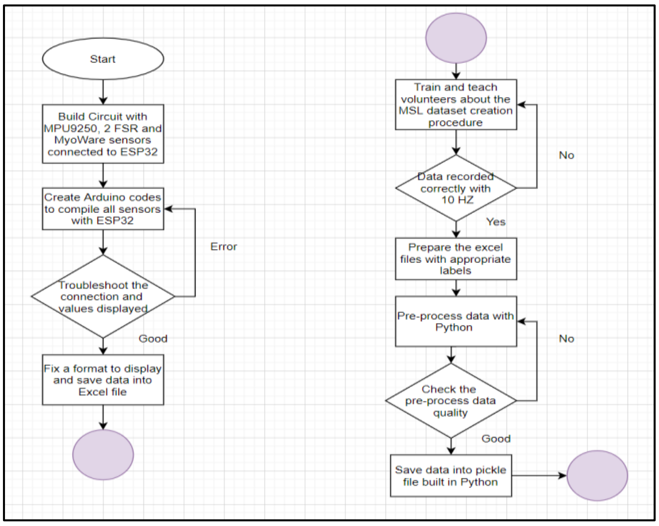

Fig. 4. Flowchart of dataset creation and pre-processing

Fig. 5. shows the flowchart of how the dataset is trained and also the creation of 1D CNN model. All specific details about the flow of model creation and dataset training are explained and covered under explanation for coding which includes the model details, parameters and other test metrics.

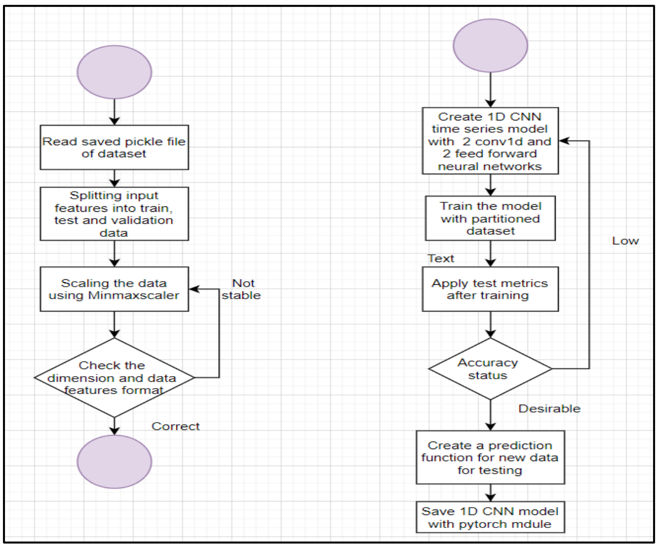

Fig. 5. 1D CNN model creation and dataset training

Fig. 6. shows the IOT flowchart that explains the flow of how IOT is implemented in this project. The ESP32 does the main contribution for IOT by contributing the ability of transferring sensor's data through WIFI with MQTT protocol. Connection of the MQTT should be troubleshoot many times to avoid losing of any sensor data while data transfer process. Node-Red has built-in nodes to transform and create array by joining all the sensors value into recognizable format array type during execution of 1D CNN model which was saved in local disk. Lastly, the classification will be done after the execution of 1D CNN-time series model, the output will be shown in Node-Red Dashboard.

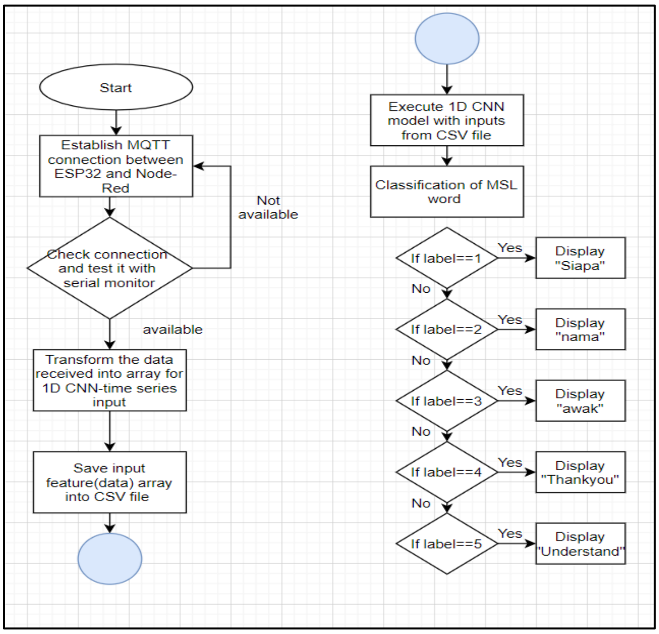

Fig. 6. IOT flowchart

III. Hardware and Simulation Results

Fig. 7. and 8. shows the whole prototype made for the MSL recognition and prediction project, as shown Fig. 7, there are 3 types of sensors which are MyoWare sensor on the top left, 2 FSR sensors place on a Velcro tape that can be found at top middle position in Fig 7. and MPU9250 on top right which is placed on plastic bendable bracelet. The main circuit that contains ESP32, LM358P, 3K resistors, LiPo 3.7V 850mAh battery and 3.7V to 5V linear voltage convertor are soldered on a prototype board and glued on an arm pouch bag.

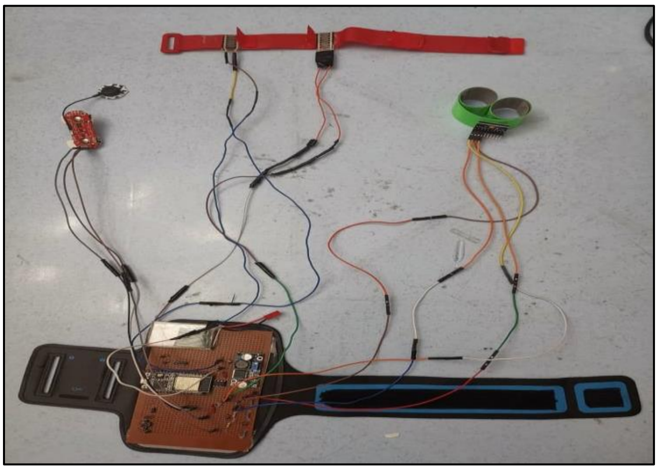

Fig. 7. IOT flowchart prototype for MSL recognition

This configuration and implementation will give users the wearable ability for the prototype as shown in Fig. 8. The placement of the sensors on hand can be seen in Fig. 8. where the 2 FSR sensors placed on top and down part of wrist, MyoWare sensor on Extensor Carpi Ulnaris muscle and MPU9250 slightly above wrist section. Although the connections of wires are not comfortable to look because of long wires, it actually gives freedom of movements for user to do the MSL gestures.

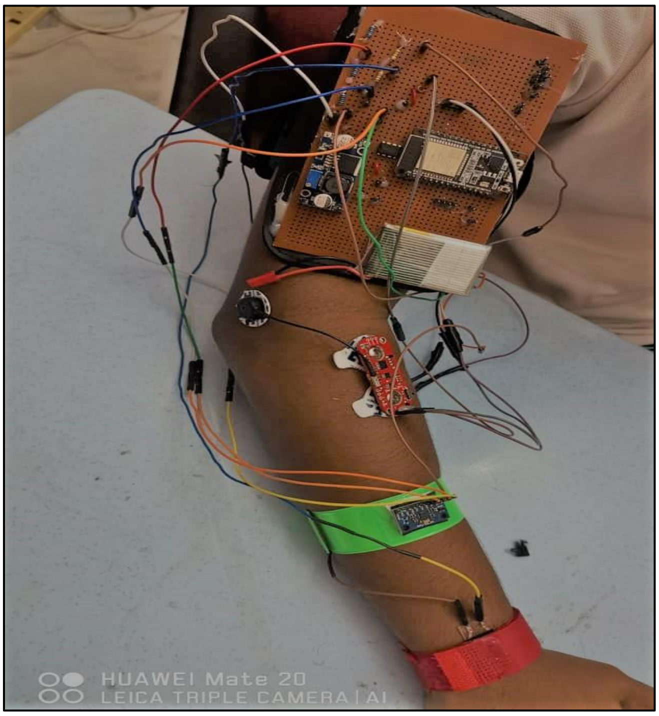

Fig. 8. Prototype placed on right hand

IV. TESTING OF THE PROPOSED DESIGN

A) *CNN Model Accuracy Test*

The 1D CNN model is used to test the accuracy of prediction from data that are totally new for the neural network, this can further determine the performance of the model created with specific tunings and optimization. The experimental setup is done by performing 2 of the selected MSL words that contains frequency of 10Hz, there will be around 40 arrays of 12 input features sent into the model because 20 arrays of 12 input features are there for each label.

The data transfer will be through IOT when prediction is being done and finally the created array will be fed into the 1D CNN time series. Table I. shows the sensor's data collected and the appropriate label. Table I shown is in excel spreadsheet format with the appended data from data acquisition of new gesture performing trials done to test the accuracy of the created 1D CNN time series model, the labels are also written in the spreadsheet Table shown for plotting the accuracy graph appropriately.

Fig. 9. shows the overall accuracy for the 2 MSL words that were tested with new set of data, the inference can be made that the model created is performing at a good level of accuracy around 83 percent with 200 epochs. Although, the results of accuracy will vary slightly if the other MSL words are also added into testing.

TABLE I. MSL WORD "SIAPA" AND "NAMA" SENSOR DATA

AccX	AccY	AccZ	GyrX	GyrY	GyZ	MgX
-0.89548	0.052675	-7.79113	0.203664	0.061718	0.528634	58.61793
0.251404	0.052675	-7.79113	0.203664	0.061718	0.528634	58.61793
0.251404	-0.17479	-7.9731	0.227899	0.401277	0.476435	58.61793
0.768578	-0.17479	-7.9731	0.227899	0.401277	0.476435	58.61793
0.272953	-0.3807	-8.58365	0.189549	0.3576	0.438617	58.61793
0.272953	-0.08859	-8.56689	0.118708	0.169045	0.39281	58.61793
0.31232	-0.08859	-8.56689	0.118708	0.169045	0.39281	58.61793
0.311262	0.014366	-8.40887	0.070238	0.171176	0.325964	58.61793
0.186757	0.014366	-8.40887	0.070238	0.171176	0.325964	58.61793
0.186757	0.287319	-8.1814	0.043073	0.176502	0.276695	57.71888
0.227461	0.287319	-8.1814	0.043073	0.176502	0.276695	57.71888
0.227461	0.220278	-8.22211	0.076097	0.165317	0.245535	57.71888
0.004789	0.220278	-8.22211	0.076097	0.165317	0.245535	57.71888
0.004789	0.174786	-8.29633	0.083021	0.084888	0.243671	57.71888
-0.4621	0.174786	-8.29633	0.083021	0.084888	0.243671	57.71888

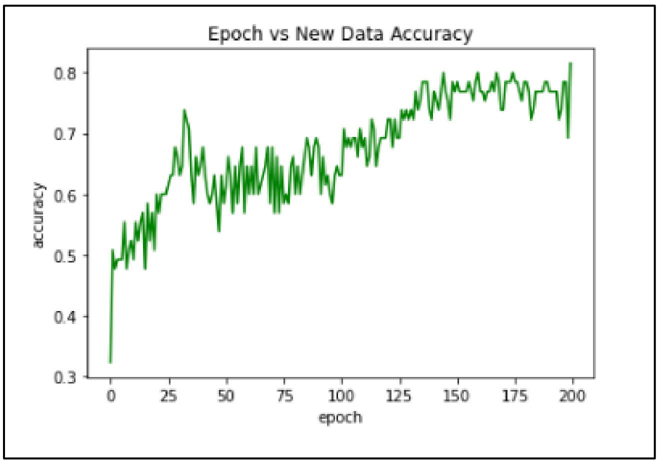

Fig. 9. Overall accuracy shown after testing with new data of selected 2 words

B) *Test for FSR resolution based on 3K and 10K resistor*

The test is regarding the resolution which means the smallest change of voltage output when testing against input forces gradually increasing from zero. The experimental setup is done by using FSR 408 sensor connected with 3K and 10K resistor, 5V is supplied for both of the testing with resistors and the force is applied by placing the FSR sensor on electronic weighing scale and finally applying specific force onto the FSR sensor with force being managed with virtual confirmation by the scale. The voltage in Table II and III. are measured with multi-meter across the resistor used.

TABLE II. RESULTS FOR 10K RESISTOR

Force(g)	Vout (V)
20	0.82
40	1.51
60	1.96
80	2.32
100	2.84
120	3.27

TABLE III. RESULTS FOR 3K RESISTOR

Force(g)	Vout (V)

20	0.24
40	0.48
60	0.75
80	0.79
100	0.87
120	1.2

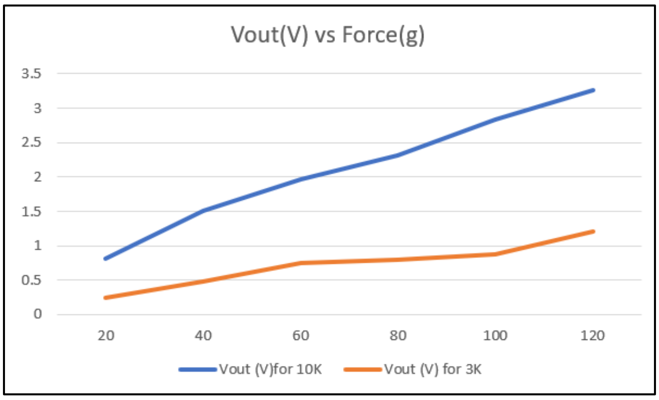

Fig. 10. Comparison of output voltage for 3K and 5K resistors application

According to Fig. 10, it can be seen that the circuit with 3K resistor gives the smallest change when linear and same force is applied on the FSR 408 sensor, the mentioned scenario is the reason for choosing 3K resistor for voltage divider circuit used in the prototype.

C) *Test for stability and strength of MyoWare sensor signal on different muscle group*

MyoWare sensor is used mainly to read and collect the electrical signals generated by muscle, so in order for a more successful data acquisition for the MSL project, MyoWare sensor is placed on 2 different groups of muscle and tested with selected MSL word "nama" which involves high number finger movement. Two muscle groups from right hand are targeted which named extensor carpi ulnaris and extensor carpi radialis longus, the signing gesture were done slowly to check performance and stability of the signal produced in a clear manner. Table IV below consists of time, "signalval1" which is the data collected when MyoWare sensor is placed on extensor carpi ulnaris and "signalval2" is data collected from extensor carpi radialis longus.

TABLE IV. RESULTS SHOWN FROM MYOWARE SENSOR

Time(s)	Signal val1	Signal val2
0s	1742	1647
1s	1745	1821
2s	1833	1845
3s	1965	1875
4s	2745	1888
5s	2910	2223
6s	2875	1900
7s	2606	2231
8s	2273	1489
9s	2379	1888
10s	2258	1807
11s	2140	1930
12s	2213	1983

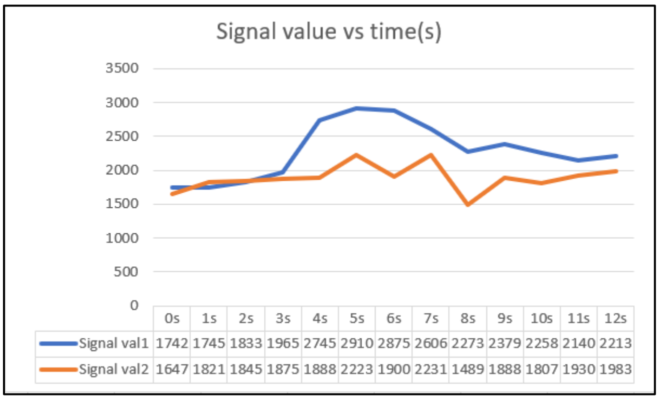

Fig. 11. Muscle signal value vs Time(s) graph

According to the Fig. 11., the gesture performing is done between 4s to 8s, at that instances the "signal val1" line is more stabilized and has higher intensity compared to other line. The mentioned statement explains that the muscle group extensor carpi ulnaris is the right location for placement of MyoWare sensor to acquire useful and stable signals or data.

V. CONCLUSION

The ESP32 is used as the microcontroller to integrate all the components into one single controller, it can be stated that the objective is successfully achieved. The objective of evaluate the data of sensor with deep learning algorithms was achieved successfully as the collected sensors were evaluated in Jupyter Notebook environment with help of deep learning algorithm provided by Pytorch and Scikit-learn modules. The objective of manage recognised MSL words classified which is shown in text in dashboard is achieved by displaying and managing the Node-Red dashboard where the classified output from the 1D CNN will be shown as text. The process is made possible with Node-Red ability to communicate with ESP32 sensor values and 1D CNN model created which is deployed in Node-Red environment.

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