Development of a Smart System to Translate Sign Language for Deaf and Mute Individuals

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A Final Year Design Project (FYDP) submitted to the Department of Electrical and Electronics Engineering in partial fulfillment of the requirements for the degree of
Bachelor of Science in Electrical and Electronic Engineering

Electrical and Electronics Engineering
BRAC University
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Electrical and Electronics Engineering
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May 2025

Declaration

It is hereby declared that

1. The Final Year Design Project (FYDP) submitted is my/our own original work while completing degree at Brac University.
2. The Final Year Design Project (FYDP) does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The Final Year Design Project (FYDP) does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. I/We have acknowledged all main sources of help.

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Approval

The Final Year Design Project (FYDP) titled "Development of a Smart System to Translate Sign Language for Deaf and Mute Individuals" submitted by

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of Spring, 2025 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of BSEEE on 15/05/25.

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Ethics Statement

Our project aims to develop a smart system that translates sign language for Deaf and Mute individuals, promoting accessibility and inclusivity. We are committed to respecting the privacy, dignity, and cultural identity of users. All data used were collected ethically, with informed consent and confidentiality ensured. We recognize that sign languages are complex and culturally rich, and we aim to reflect that in our design. Community input among the BRACU students was considered throughout the development process. This system is intended to assist—not replace—human interpreters, and to support communication in situations where traditional resources may be limited. Our goal is to create a respectful, useful, and ethically sound tool that uplifts and empowers its users.

Abstract/ Executive Summary

Communication is another major barrier that the deaf and the mutes are faced with in mostly a vocal society. More than 13 million individuals in Bangladesh experience some hearing impairments and impediments on speech. They use sign language thus they cannot communicate well most of the time because the one being signed can not understand sign language. The idea of the proposed project is to design a smart wearable device that can be used to translate sign language into speech by hard of hearing persons and actors with impaired voices. The system involves flex sensors, a 6 axis accelerometer-gyro which is mounted into a glove in order to pick up the hand motions and hand postures. The data is processed in the form of sensor data transmitted to a microprocessing unit that has a machine learning ready with such information. In case such a person is a deaf mute, he/she will move his/her hands and our model will identify it and provide us with the corresponding sign (word) by means of a speaker. This solution addresses the shortfalls of the earlier systems since it allows translation in real time regardless of the environmental situation. The solution also improves the accessibility to communication, social inclusion, and safety among the users especially in emergencies and the day-to-day situations.

Keywords: Sign Language Recognition; Smart Glove; Flex Sensors; Machine Learning; Raspberry Pi; Temporal Convolutional Network (TCN); Social Awareness.

Acknowledgement

Our team would like to express our gratitude and appreciation for the guidance and support our ATC panel has provided throughout the length of one FYDP academic year. We would like to express our appreciation to our ATC panel chair Dr. Touhidur Rahman for his immense belief and confidence in our team and project. We would also like to thank Shahed Alam Sir for his endless support in research purposes, tackling technical problems and boosting our knowledge further than what was required for our project. Last but not the least, we would like to thank Atib Mohamman Oni Sir for sharing his own FYDP experience and providing us guidelines for the fruitful completion of our project.

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Chapter 1: Introduction- [CO1, CO2, CO10]

1.1 Introduction

In the modern world where technology is rapidly developing, people cannot imagine their lives without communication. However, millions of deaf or mute people across the world encounter major challenges whenever they come across people who do not understand sign language. Such communication barriers usually result in social isolation, low access to education and employment, as well as low independence. In order to meet these challenges, it would be opportune and necessary that we develop assistive technologies to fill this gap.

This project is intended to develop and install a smart system, which is capable of converting sign language signs into audible speech by using the speaker output. The main aim would be to develop a realtime, portable, and user friendly device that would enable the deaf and mute people to communicate more freely and confidently in their day to day lives. Data collection in the system will be based on sensors and will be able to efficiently capture hand gestures in support of the common sign language. The input will be then run through machine learning models which are trained to understand and convert them to speech out.

The importance of the project is in the fact that having performed it, the project could establish a more inclusive environment, as sign language users would be able to interact smoothly with the rest of society, the hearing-speaking one. It also shows the relevance of innovation in solving the social and accessibility problems. By doing this, we are trying to make a difference in a future where no one will be unheard, no matter what their physical condition is.

1.1.1 Problem Statement

Communication is a fundamental human need and shapes everything, including friendships, lectures and first jobs. Satisfying that need can be an uphill task to deaf and mute citizens. According to the World Health Organization (WHO) more than 430 million individuals in the world have hearing loss and it is estimated that by 2050 this figure will rise to more than 700 million unless the current efforts of preventing hearing loss are able to increase [1]. In Bangladesh, the issue is acute: over 13 million citizens are challenged with some type of hearing impairment, and approximately 3 million have severe to profound hearing loss that restricts their communicative abilities [2]. The fact that most of us do not understand sign language leaves a huge gap since most of the deaf and mute individuals communicate through sign language. Consequently, a large number finds themselves on the periphery of social activities at school, in the workplace and even in classrooms, and this prompts frustration, dependency and isolation from society [3].

In order to fulfill this gap, researchers have been testing sign-recognition software, although much of that software is not ready to be used in prime-time. Systems that work by sight are super-accurate, but require perfect lighting and positioning of cameras and they are seriously computer-power hungry. The first glove-based systems based on mechanical switches or conductive fabrics have also been found to be clumsy and unreliable within a short period [4]. That is why, an actual tough user-friendly solution remains a necessity. A smart glove, with flex sensors, an accelerometer, and machine learning algorithms to read hand gestures and convert them into audible speech, is being developed by our team. Imagine having an interpreter in real time right in the palm of your hands.

1.1.2 Background Study

Hand gesture interpretation systems have over the years followed various paths and each one of the paths has had its cost in terms of recognition accuracy and speed. And here is a brief review of three of them:

1. **A CMOS Camera:**

   This arrangement has a CMOS camera that is connected to a UART serial port. The UART takes each of the camera bits and converts them to parallel where it then re-serializes that parallel data into the serial bits of the CPU. The primary disadvantage in this case is price, CMOS cameras are not inexpensive, and the latency is high, as the signal must pass through the UART and into the CPU.

2. **Glove based on Leaf Switch:**

   These gloves have a leaf switch which operates in the same way as a normal switch: press on it and the two ends touch, completing the circuit. The switches are mounted on the fingertips such that as the finger bends the switch is closed. The issue is that, under continuous abuse the switch may not open again when the finger is straight sending the wrong signal.

3. **Glove made of Copper Plate:**

   In this case, a copper plate on the palm will be used as the ground. copper strips on the glove will be at logic 1 when at rest. Contacting the ground plate causes their voltage to go to logic 0. Since the system is based on the direct connection of the copper strip with the ground plate, the connection may alter with time and thus inaccuracies.

The three solutions deal with the same issue: that of making communication between the people who use gestures and the rest of the world faster and more accurate. The interested parties in the project will be the non-verbal community, medical institutions that may in the future conduct remote surgeries, and anyone with a severe physical disability such as cerebral 3/22 palsy that can operate the single finger to choose some of the frequently used words.

1.1.3 Literature Gap

A number of research groups have investigated the methods of identifying sign language by using both image-based systems and sensor-based devices, but a certain gap regarding usability, real-time performance, and cultural flexibility remains. Image-based systems are accurate at carefully controlled situations, however, they break down when applied in real life situations where there is poor lighting, background noise or camera angles-which are not feasible in real life situations [23]. The older types of sensor gloves using either copper plates or leaf switches were often clumsy, unreliable, or even subject to eventual mechanical failure [24].

Continuing systems are also inclined towards American Sign Language (ASL) and ignore local languages such as Bangla Sign Language (BdSL), as a result of which users in such countries as Bangladesh are left alienated. The previous research also does not pay attention to ethical issues, user comfort, and viability of the off-the-shelf hardware.

Our proposal is seeking to fill these gaps by creating the sensor-based wearable glove that offers rapid gesture-to-speech translation and places affordability, comfort, and inclusivity at the center of our focus. The glove is highly customizable to the local needs and constructed of reusable, locally available parts, which makes it more feasible, scalable, and culturally applicable than the available modern assistive technology solutions.

1.1.4 Relevance to current and future Industry

Even coming up with an intelligent system that translates sign language is of great concern to where we are going with technology today and where we are going with technology tomorrow, in aspects such as assistive technology, artificial intelligence, and human-computer interaction. The assistive technology market is thriving and is expected to reach USD 32.5 billion by 2030 due to the demand of people who would like to have accessible solutions to people with disabilities [6]. Ethics is not the only driving force that makes companies take action. It also has to do with the necessity to abide by the rules and increase the number of their users.

Large companies like Google, Apple, and Microsoft are already incorporating accessibility into consumer goods and launching real-time captioning and voice-to-text functions. An intelligent sign language interpreter would be just right here to provide the deaf-mute person with an alternative means of relating with the rest of the community.

As remote services and automation increase in customer support, education, and healthcare, there is a great demand in systems capable of managing non-verbal communication [7]. The current project contributes to the expanding list of available technologies and might be used in commercial applications, particularly in combination with IoT devices.

1.2 Objectives, Requirements, Specification and Constraints

1.2.1. Objectives

- Design a smart system for non-verbal individuals.
- Smartly implement the system to comfortably meet the users' needs for everyday use.
- Implementation of Real-Time Gesture Recognition.
- Creating a smooth communication flow between the user and the next individual.
- Social awareness for non-verbal people by recognizing their presence.

1.2.2 Functional and Nonfunctional Requirements

Functional Requirements:

- A glove that is made of synthetic material since it can be slipped or taken off and on, and also holds the whole electronic system placed on the outside firmly.
- The first thing sensors should be able to identify of course is finger flexion, and the second requirement is position sensor and an angle sensor to monitor the orientation of the whole hand.
- The complex outputs are then computed by a processing unit (preferably a microprocessor) which receives these inputs.
- Lastly, a light-weight speaker is given to convey those outputs to the user.

Non-functional Requirements:

- The glove ought to be a distinctive color which will make the viewer see that the user is non-verbal.
- Insulation that is strong is needed so as to avoid electrical shock in the event of a break in the system.
- The entire system should also be lightweight so as to reduce fatigue to the user when he/she wears it over long durations.

1.2.2 Specifications

The table below lists the component level specifications for all the design approaches.

Table 1: Specifications

Specifications for all Design Approaches		
Component	**Model**	**Specification**
Flex Sensor	2.2”	• **Flex Length(mm):** 2.2” (56) • **Total length(cm):** 7 • **Life cycle:** >1 million

		• **Flat resistance:** 10K ohms ±30% • **Power rating:** 0.5W continuous; 1W peak
Accelerometer Gyroscope	ADXL335	• **Operating Voltage (VDC):** 3~5 • **Communication:** I2C protocol • **Gyro range(Â°/s):** Â± 250, 500, 1000, 2000 • **Acceleration range(g):** Â±2 Â±4 Â±8 Â±16 • **Length(mm):** 21 • **Width(mm):** 16
Speaker	1.5W*2rms	• **Output Power(W):** 1 • **S/N ratio:** ≥60dB • **Size(mm):** 64*54*73mm*2 units • **Weight(gm):** 220.8g
MPU	Raspberry Pi 5 Model B 8GB	• **Microcontroller:** BCM2712 quad-core Arm Cortex A76 processor @ 2.4GHz • **RAM:** 8 GB LPDDR4-3200 SDRAM • **Wireless Connectivity:** 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, BLE • **Networking:** Gigabit Ethernet • **USB Ports:** 2 USB 3.0 ports; 2 USB 2.0 ports • **Display:** 2 x micro-HDMI ports (up to 4kp60 supported); 2-lane MIPI DSI display port • **Camera:** 2-lane MIPI CSI camera port • **Audio and Video:** 4-pole stereo audio and composite video port • **Storage:** Micro-SD card slot for loading operating system and data storage • **Power:** 5V DC via USB-C connector; 5V DC via GPIO header
Camera	Raspberry Pi Camera Module V2	• **Resolution:** 8 Megapixel • **Sensor Resolution:** 2592 x 1944 pixels • **Video modes:** 1080p30, 720p60 & 640x480p60/90 • **Focal length:** 3.60mm ± 0.01 • **Dimensions (mm):** 25 x 23 x 9
Cooler	Raspberry Pi 5 active cooler	• Heat Sink Material: Metal • Fan Speed: Variable

Below are some points listed that represents system (device) level specifications –

- Real-time recognition of sign language.
- Provides audio output for better understanding.
- Ergonomic design allows for prolonged use without causing any discomfort.

1.2.3 Technical and Non-technical consideration and Constraint in design process

Critical Constraints:

- The system may fail to work under real life pressure.
- The system is uncomfortable after wearing it for some time.
- To effectively use the battery in the real sense, it must be larger though a larger battery increases bulkiness of the system.
- The size of hands is quite different between individuals and thus the glove should adapt to the different size.

Technical Challenges:

- The training data set must be implemented properly-an ill designed data set would lead to either over-fitting or under-fitting and lower precision.
- The flex sensors mounted onto the gloves are delicate; due to the slightest misuse one may bend them thus breaking them and increasing expenses.
- The flex sensors should as well be well calibrated as the accelerometer so that the values obtained by the sensor can be of practical relevance and can be effectively used to distinguish between different signs.
- The cables that join the glove with the computer must be long so that the user may move hand freely as he may be signing.

Non-technical Obstacles:

- Obtaining informed consent of all those interested parties who wish to share their information in the data set.
- Gathering the data of a diverse sample of participants to address different sizes of hands.
- Restrictions about the hardware of the computer imply that we are capable of designing a dataset that identifies five words only.

1.2.4 Applicable compliance, standards, and codes

Our sign language translation project does not involve the development of some specific standards that can be used to translate signs into text. Rather we are looking at adopting the type of best practices that engineers tend to subscribe to when they are working on wearable technology and human-computer interaction. That is to say that we shall count upon:

- ISO/IEC 27001: Management of information security in ensuring safety of user data--especially that the device will be capturing personal movements and gestures.

- ISO 13482: Personal-care robots safety standards, whose areas also cover other wearable robotic systems such as our smart gloves.
- IEEE 11073--this is the one whose standards you go to when dealing with interoperability among the medical devices. It has ensured that in case you plug in a pair of these gloves to any hospital system, they will work well with the remaining technology without creating a headache.
- IEC 60601-1- the so-called basic standard of medical electrical equipment safety. It defines all the rudimentary safety and performance necessities that make our glove designs reliable and secure.

Once you start discussing sign languages in an academic environment, it is very easy to understand that you require some rules of engagement. Codes and standards are useful in communicating across borders as well as ensuring that everyone is aware of who is talking. Having three-letter codes in the ISO 639-2 language standard, sign languages are sgn. There is a single code that corresponds to all signs languages of the ISO 639-2 list.

1.3 Systematic Overview/summary of the proposed project

The concept that lies in the essence of this proposed project is to fill the communication gap that may exist between people who may freely converse on the one hand and between the people who are under conditions where they have to resort to use of sign language in case they need to get their point across. Through this, the project will be aiming to exchange the older approaches we are familiar with with those that are much more effective.

1.4 Conclusion

By designing a smart device that can be used by the deaf and mutes, we would in actual sense be fighting the issue of isolation which is surely brought about by lack of hearing abilities. This system enables a person who cannot hear, to exchange thoughts and feelings with others and be treated and viewed like any other person. Since this is machine learning that we are depending on, we might as well have an expansion in terms of it growing with the community- someone should only need to come up with a document of the phrases and words used mostly by the community, train the model on it and then, anyone can pick up the device in the future and talk out what he or she might be having in mind. In other words, as a way of summarizing our mission statement, we want to assist in creating a society in which no individual, regardless of his or her physical capabilities, needs to ask a question about whether anyone is listening.

Chapter 2: Project Design Approach [CO5, CO6]

2.1 Introduction

In our project, 'Development of a Smart System to Translate Sign Language of Deaf and Mute People', there are two approaches of design as every single approach has its advantages and disadvantages. The purpose of both strategies is the same, but it is quite simple to understand the idea, namely, to relieve the communication inconvenience of the hearing impaired. Two of our methods involve machine learning algorithms applied on predicting what the person is attempting to communicate to the person capable of uttering. In both systems, we attempted to seek the excellent parts among numerous variations that are long lasting as well as cost efficient. Both the methods bring our final goals vividly but in their unique style.

2.2 Identify multiple design approach

2.2.1 Design Approach 1

Image Based Hand gesture Detection using Deep Learning

In this design plan, the device will capture a picture of the sign language that the user does using a camera and transmit it to the Raspberry Pi module. The main objective is that the process of processing the picture taken (gathering the needed features) will be followed by training the Raspberry Pi module to use an image-processing model that will execute the gathered features taken out of the picture taken and deliver the result in the form of an audio output through the speaker.

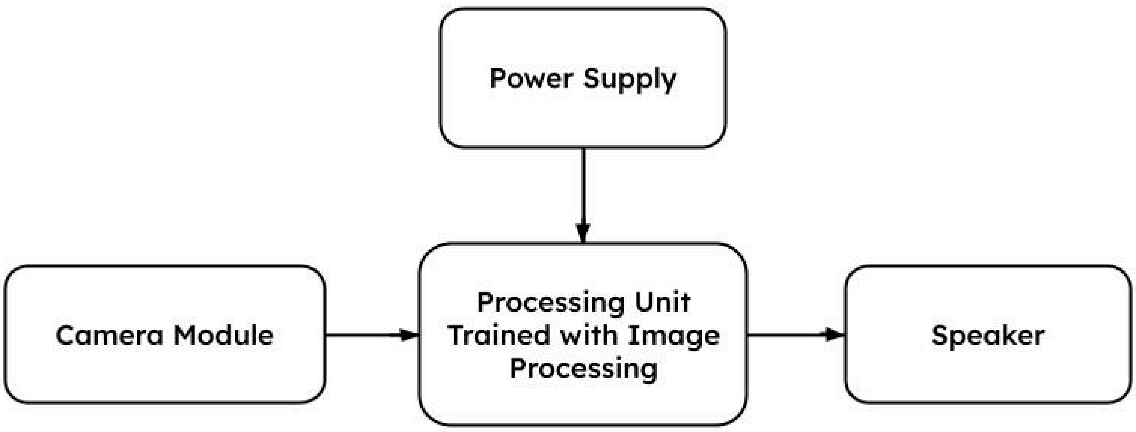


Figure 1: Design Approach 1

2.2.2 Design Approach 2

Sensor-Based Hand Gesture detection using ML

In this design approach, we have inserted five flex sensors to monitor finger flexion and a grove 6 axis accelerometer and gyroscope to monitor the movement and orientation of the hand in the 3 dimensional space. The flex sensors and accelerometer have been connected with a Raspberry Pi microprocessor to process the raw data of both the sensors which are complex in nature and simplify them. A trained machine learning model would be installed in the microprocessor and would execute the gathered features of the simplified sensor data and would give the audio output generated on it, to the speaker. To supply power in the system we have attached a power supply unit in the system.

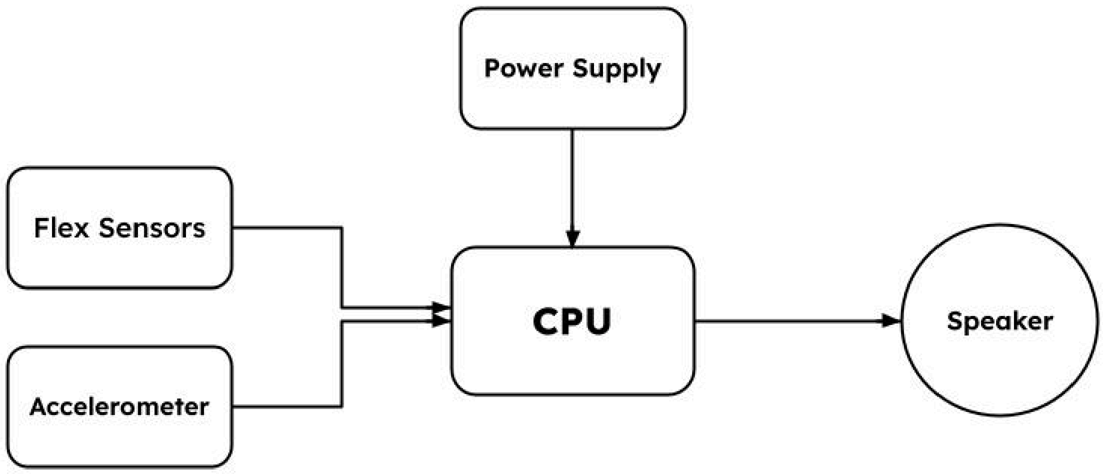


Figure 2: Design Approach 2

2.3 Describe multiple design approach

2.3.1 Design Approach 1

The first design can be divided into two parts: Image detection and image processing. In detecting the image to be used, an 8 megapixel raspberry pi camera module is employed to clearly capture our sign made. The captured image will separate it into various features in various frames which makes it to have a higher training accuracy. All the amassed features are written in an Excel file as our input data which is then to be fed to the raspberry pi 5 tool. Within the tool, there is a machine learning algorithm of image processing named CNN (Convolutional Neural Network). The machine learning model is trained by being fed with the dataset. In this case, because the data relies on the images of the sign aimed at the sign that the user captures, there is a need to provide a good background lighting condition, in order to identify the gesture accurately. In darker settings, the camera may obtain parts of the pixels of the acquired image leading to loss of features and null values. Once the process of training is complete a test case is conducted by a new person to cross check whether there are any further adjustments in an algorithm or if it is fully functional. The camera will capture the sign made by a new user, extract the features required and eliminate any error values and lastly, it would go through the input log of the model that we have developed. When training is done correctly, then the relationship between the sign and the output will be precise and the new user will be predicted to output.

2.3.2 Design Approach 2

In our second design solution we are going to use five flex sensors and a grove-6-axis accelerometer and gyroscope. These sensors will give us our last output which shall be predicted via a trained machine-learning model on our own dataset. Every flex sensor will be put on every finger of a hand. The sensors are responsive resistors and their home is relative to their radius of bend. Hence when the user bends or curved the fingers it gives a value of the voltage. The finger orientation is sensed with the use of finger flex sensors placed in the back of the finger. The fabrication of the flex sensor will lie in the fact that the bend mechanism will also induce a bend in the radius curvature of the flex sensor resulting in a change in resistance. Grove-6-axis accelerometer and gyroscope monitors the movement of the hand in three dimensional space by measuring acceleration of the hand and its orientation. In order to know where the hand is within the space of 3-D coordinates the angular position of the hand is used (pitch, roll and yaw) that are computed using the data collected by the IMU module. We will acquire the angle of flexion in every finger at 20 frames as well as the acceleration of the hand in the 3D plane at 20 frames and orientation of the hand in the 3D space at each frame to create a data set. It is with this dataset that we would establish a machine learning model pre-train. The model under consideration is Temporal Convolutional Network (TCN). As the central unit of computation, we are using Raspberry Pi 5. We will incorporate our trained model into Raspberry pi. Raspberry Pi will receive the data value received by the flex sensor and the grove-6-axis accelerometer and gyroscope to predict the hand gesture. And on prediction, should it identify a matching pattern then it will speak the word.

2.4 Analysis of multiple design approach

Table-2: Comparison Table for Different approaches

Criteria	Design 1	Design 2
Functionality	Non-versatile	Versatile
Complexity	More Complex; difficult	Less complex; simple
Usability	No wearable hardware required	Requires the user to wear a glove
Computational Load	More computationally demanding	Less computationally demanding
Cost	Reasonable	Relatively High

In the comparison table, it is obvious that the Design 1 is less versatile than Design 2, as well as less functionality. The former is easier in terms of usability, as there is no need of wearing anything to the system, all we need is to show the hand gesture to the camera, and we are in business. Nevertheless, it is computationally more expensive, a little more difficult to process and that may lag things down. Design 2, on the contrary, is so much more versatile and efficient. Computationally, it is more simple and provides quicker processing of input, yet the user needs to wear a glove with sensors, which is not a desirable solution in every case. In terms of price, one can certainly say that Design 1 is more cost effective, whereas Design 2 is quite an expensive venture with additional hardware. However, we believe that the additional expense may be compensated by the performance and flexibility, which Design 2 has.

2.5 Conclusion

After rigorous analysis of both the design approaches, one of image based detection and the other of sensor based detection, we can conclude that design approach 2 plays a greater advantage with respect to design approach 1. This is because in terms of complexity (the machine learning model and the setup), design approach 2 has computationally less demanding algorithms than design approach 1. This means the specifications required for a computer to run the algorithm of design 1 smoothly is immensely high as it takes up a lot of storage. On the other hand, design approach 2 is more environment independent meaning it is more versatile than design 1 as it only requires the user to make a sign gesture without having the need to be standing socially awkward in public. Lastly, the device in design 2 uses up components that are cheap and readily available if any of them gets damaged, resulting in less recurring costs.

Chapter 3: Use of Modern Engineering and IT Tool. [CO9]

3.1 Introduction

Simulation and imaging of the design solutions have been performed with the help of various contemporary engineering and information technology facilities. The hardware tools are applied to collection and data storage. In the meantime the work is carried out using the software tools in adopting and analyzing the data that is gathered.

3.2 Select appropriate engineering and IT tools

Hardware Tools:

- Flex Sensors
- 6-axis Accelerometer and Gyroscope
- Arduino Mega 2560 Pro Mini
- Raspberry Pi 5
- Camera

Software Tools:

- Proteus Design Suite 8.13
- Python Language
- Google Colab
- Arduino IDE

3.3 Use of modern engineering and IT tools

1. **Proteus 8 professional:**

Proteus will be best fit when it comes to designing and simulating a microcontroller based project hence it will be applicable during the firmware and hardware integration step of the smart glove. It supports sensor, microcontroller [e.g. Arduino] and peripheral device real-time simulation. This becomes essential to conduct the test in the interaction between the two tools of the glove [e.g., flex sensors, accelerometers] and the microcontroller without involving physical objects. Microcontrollers can be easily programmed because there is inbuilt support since the firmware can be uploaded and microcontroller behaviour can be simulated hence aiding in debugging the code and simulation of the hardware. Proteus is an integrated circuit, simulation, and PCB layout in a single software, so as to use fewer software platforms. The major strength of Proteus is that one can simulate real time circuits that aids in detecting any issues with a circuit before one set-ups actual hardware and tests it. Simulink is not circuit level simulation, or tying together embedded systems. It needs training in Simulink, which can be a long hill to an hardware-focused developer. And a simulink license may cost a lot. Pspice, however, does not specialize in programming microcontrollers or writing software. It fails to promote the integration of firmware and hardware development which is essential to the smart glove.

2. **Google Colab:**

Google Colab allows you to access GPUs and TPUs at no cost; this is useful when training-deep learning models that require a quick turnover, e.g., in case you are planning to apply complicated algorithms to recognize sign language. It also provides smooth cooperation like Google Docs. It is simpler to work in the team as multiple team members may edit and comment on the same notebook in real-time. Since the many machine learning libraries that are available to use in Colab are already loaded [e.g., TensorFlow], a lot of time is saved on their setup. It is also accessible via all browsing devices. The user end does not need any set up, which is ideal with teams working at different locations. It is also compatible with Google Drive that allows storing results and datasets. It is convenient to test real-time data processing on sensors of the smart glove. Colab is free and ready-to-use, and we also could access the free GPU/TPU resources to train the machine learning models of recognizing sign language. In contrast to this, however, the use of VS code and Jupyter notebook is only possible with local hardware resources, unless you install a remote development environment, which can be cumbersome. In VS code, the collaboration can be done through extensions, which necessitate some set up. Jupyter requires manual configuration of your libraries unless you have a ready-made environment.

3. **Raspberry Pi:**

Raspberry Pi can also be described as a good device to be used in the software part of a project since it is small, lightweight, and has a lot of processing power that will enable it to perform operations such as gesture recognition and speech generation in projects involving wearable technologies. A wide range of programming languages and libraries [e.g., Python] can be applied to it and used to classify gestures and generate audio, which is the case here.It also has GPIO pins that can be directly connected to many sensors such as accelerometer, gyroscopes, and flex sensors, which are used in this smart gloves to detect hand gestures and movements. Its libraries and machine learning and audio processing frameworks are well developed and, as such, systems can be developed and tested quickly within the gesture-to-audio translation space. They are relatively cheap as compared to other single board computers with the same functions whereby they can serve in the prototype and scaling of smart gloves. Being small in size, and with low power needs, it is a suitable solution to consider when the device used is a wearable device, such as a smart glove that will be powered by a small battery.

3.4 Conclusion

All the contemporary IT tools that we employed were recommended by the various research papers that we based our project on by the Institute of Electrical and Electronics Engineers (IEEE). The chapter snatches the significance and utilization of the contemporary IT tools during our time schedule of the project.

Chapter 4: Optimization of Multiple Design and Finding the Optimal Solution. [CO7]

4.1 Introduction

The design selection is never an easy task in any engineering or machine learning project. There is frequently a range of designs that need to be considered whereby every design has its advantages and compromises. Here optimization comes in handy. As opposed to trial-and-error or relying on gut-feel, a systematic process of compounding and optimization of various designs has beneficial effects of providing the optimal result. In the present section, we pay attention to the procedure of optimization of two various designs created to recognize sign language on sensor data. These models can be evaluated, by comparing their performance according to consistency. Our objective is to come up with the best approach of gesture recognition that is real-time and accurate. The optimization does not only enhance the performance of the system but also strengthens the confidence of the robustness and generalizability of the design made. It is with such systematic optimization that we eventually settle on the optimal system to be used in the practical implementation of sign to speech application, one which is sufficiently accurate, fast and able to survive the noise in the environment.

4.2 Optimization of multiple design approach

4.2.1 Design Approach 1:

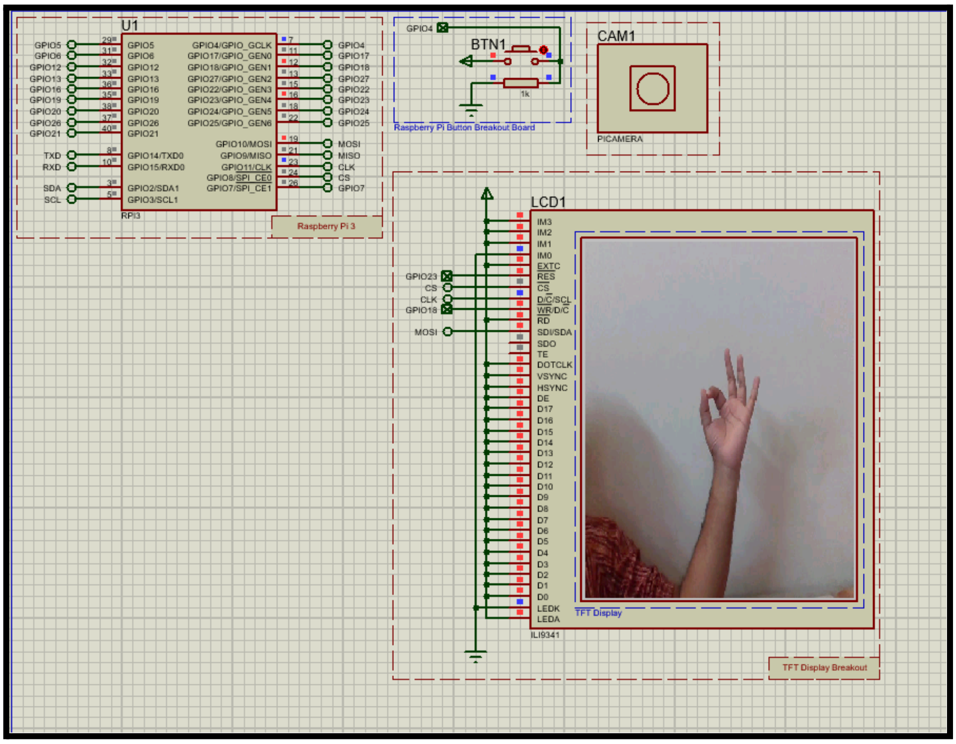
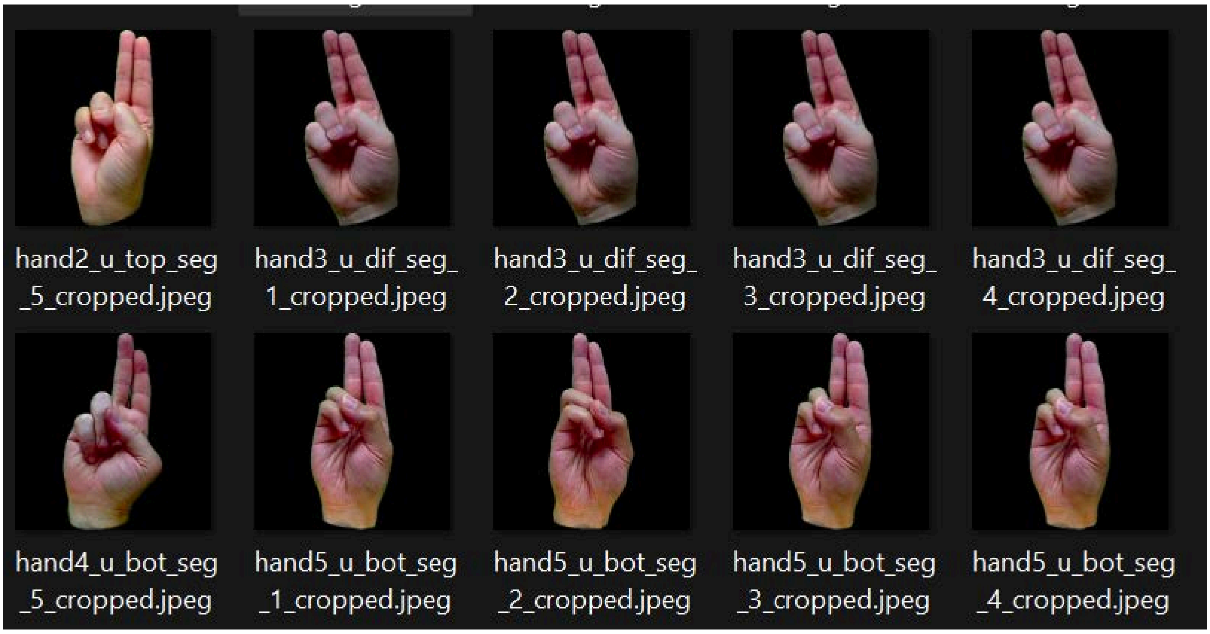


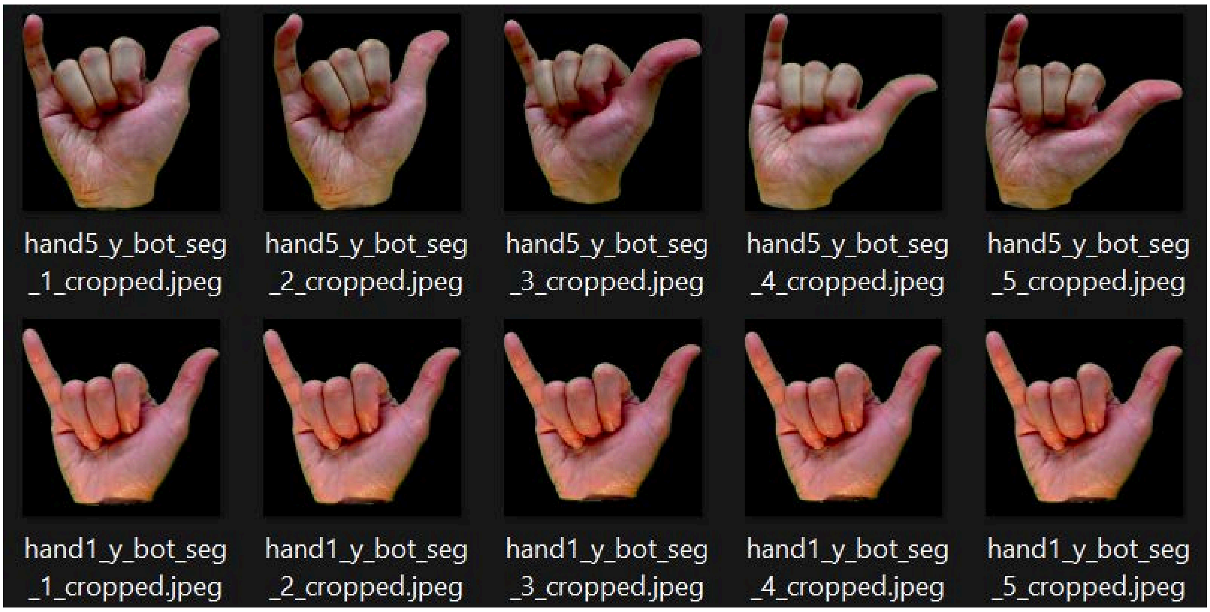
Figure 3: Circuit Diagram Design 1 in proteus

DataSet:

Sample 01:



Sample 02:



Sample 03:

Sample 04:

Sample 05:

Training Result:

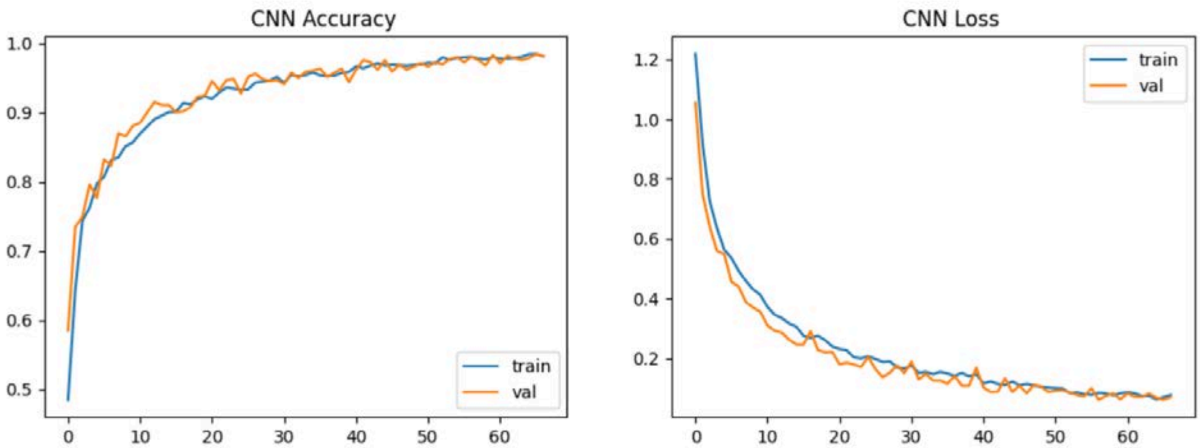


Figure 4: Training and Validation accuracy and loss

Training curves of the CNN model show well that they correspond to substantial and steady learning. As it can be seen in the left figure of CNN Accuracy, both the training and validation accuracy begin below 0.6 but quickly rise above 0.6 in the few epochs. The model achieves more than 90 percent accuracy around epoch 20 and subsequently continues to improve almost to over 98 percent accuracy in the sixth 5 epochs of training and validation. It is a sign of great generalization, and there is no overfitting.

In the right plot in the CNN Loss, the training loss and the validation loss reduce rapidly during the initial epochs indicating good learning. The validation loss closely follows training loss in a big way that it finally remains constant around zero, which is further testament of no overfitting and of good convergence. On the whole, these plots indicate that CNN model is very efficient in learning the characteristics out of the image-based dataset and it works quite well on the unknown validation data thus it can be used as a method of recognizing sign language using image data accurately.

Output:

We also conducted the sign language recognition project using an image-based dataset, here each gesture was represented by corresponding hand sign images. For this task, a Convolutional Neural Network (CNN) was employed due to its proven efficiency in image classification tasks. The CNN model was trained on a well-labeled custom dataset, and it effectively learned the spatial patterns and features associated with each gesture class. After training, the model achieved an impressive accuracy of 98%, demonstrating its strong performance in recognizing sign language from static images. This approach validates the effectiveness of CNNs for visual gesture recognition and offers an alternative method to sensor-based classification.

4.2.2 Design Approach 2

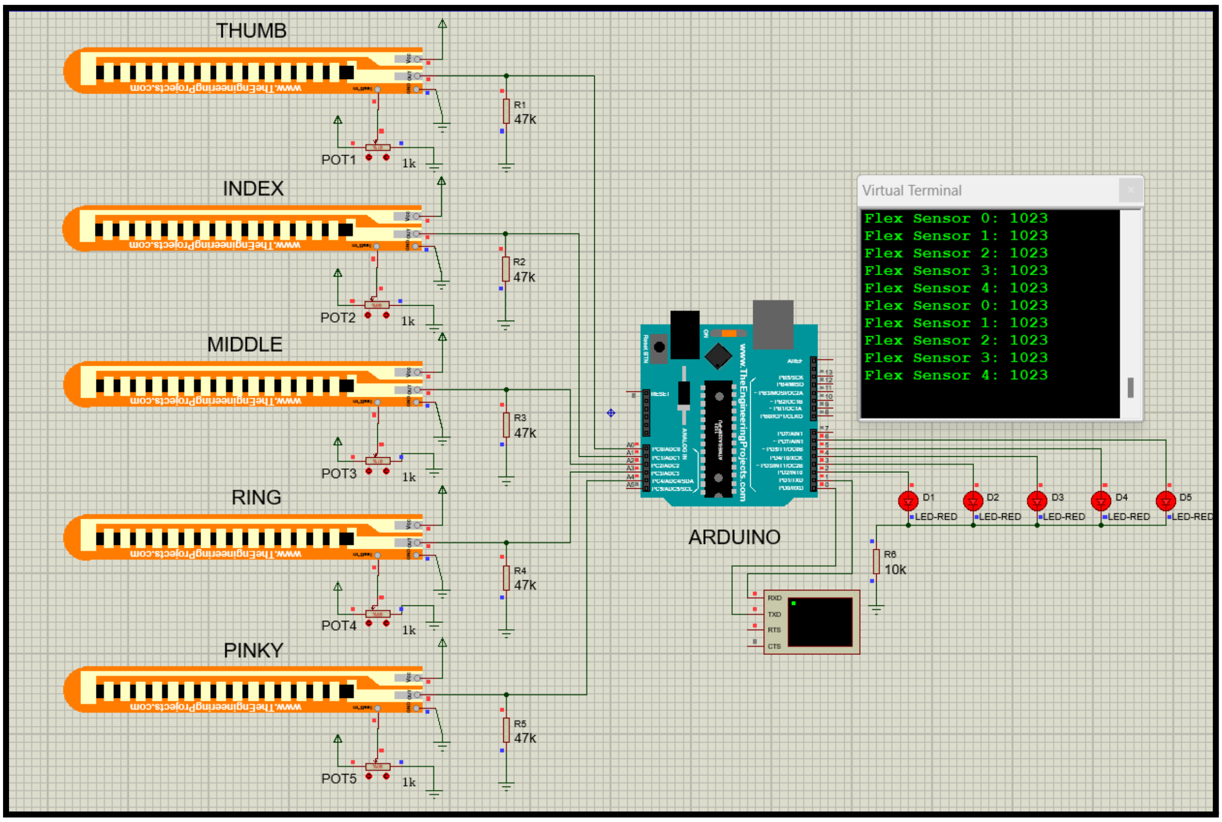


Figure 5: Circuit Diagram In Proteus

Dataset:

Hello:

250	255	258	272	249	474	299	331	Hello
253	259	260	272	251	312	295	404	Hello
253	261	259	269	253	289	310	412	Hello
237	254	247	269	243	330	321	421	Hello
238	256	245	267	242	333	318	419	Hello
236	254	244	267	241	315	321	419	Hello
248	260	248	269	246	389	274	365	Hello
249	258	251	270	247	420	275	348	Hello
249	261	254	268	248	396	279	356	Hello
249	251	240	264	249	380	294	366	Hello
250	252	238	262	249	349	308	380	Hello
249	251	237	264	249	390	300	355	Hello
257	262	253	260	244	328	372	455	Hello
258	260	252	260	242	398	278	345	Hello

Yes:

157	114	112	173	194	381	356	441	Yes
185	131	132	183	197	393	224	332	Yes
173	135	133	191	206	367	281	344	Yes
242	158	148	216	221	453	368	371	Yes
223	168	157	214	216	388	302	369	Yes
232	168	152	216	218	409	340	413	Yes
218	154	149	176	203	347	301	354	Yes
217	151	137	182	207	364	275	376	Yes
200	134	130	178	192	336	265	354	Yes
156	123	124	186	181	437	355	397	Yes
152	120	120	184	185	342	320	356	Yes
165	129	135	177	188	356	422	320	Yes
242	130	121	177	191	335	246	354	Yes
199	132	134	187	198	424	339	387	Yes
242	128	119	175	189	329	279	342	Yes

No:

251	222	191	206	173	328	272	353	No
254	257	251	206	177	345	261	349	No
253	264	256	209	189	348	278	372	No
256	257	244	241	236	338	271	362	No
247	251	240	240	230	332	274	355	No
251	260	240	238	235	332	275	358	No
253	260	257	203	181	349	275	355	No
249	246	226	215	193	362	265	344	No
253	260	253	215	201	352	266	358	No
252	231	194	215	183	346	264	362	No
256	232	197	223	198	351	272	367	No
256	246	219	224	207	349	279	364	No
246	250	246	243	231	345	295	359	No
248	251	240	234	232	354	275	353	No
248	253	238	226	228	343	273	361	No

Eat:

246	249	232	265	253	357	265	334	Eat
249	250	238	266	250	349	283	384	Eat
247	253	238	267	255	355	253	311	Eat
247	253	238	268	255	351	254	306	Eat
247	250	236	267	254	346	301	409	Eat
247	251	236	267	257	343	258	319	Eat
246	249	232	267	256	355	304	442	Eat
246	249	230	267	257	352	292	407	Eat
246	252	233	268	257	340	252	305	Eat

Okay:

171	147	203	267	242	303	286	355	Okay
160	161	253	271	237	268	294	361	Okay
171	139	251	269	240	274	300	370	Okay
184	141	257	272	241	306	286	366	Okay
154	150	254	269	243	272	296	382	Okay
148	163	260	272	239	392	263	371	Okay
154	156	253	271	238	335	278	365	Okay
171	147	261	272	239	411	268	376	Okay
166	153	258	273	235	441	246	376	Okay
160	147	260	272	237	304	296	381	Okay

Training Configuration	
Configuration	Data
Epochs	300
Data Size	160
Total Sample	3316
Train, Test Sample (Yes)	542,135
Train, Test Sample (Hello)	539,135
Train, Test Sample (Okay)	531,132
Train, Test Sample	525,131

Training Configuration	
(No)	
Train, Test Sample(Eat)	516,129
Train Model	TCN

Hardware:

As a training and evaluation environment, we relied on Google Colab using the T4 GPU runtime because it allows performing computations in high speed when working with sequential data. TCN model is CPU as well as GPU friendly. Raspberry Pi 5 equipped with a Quad-core ARM cortex A76 was deployed. Although we had experienced latency problems with the initial inference based on standard methods, we have optimized the model to run on the ARM platform with the NCNN framework and its performance improved considerably on the Pi.

Evaluation:

In training, we used the flag plots=True to create real-time visual display of model performance accuracy and loss. TCN model showed good sequential gesture data, efficient training convergence characteristics, as well as minimal validation loss. It has performed more than 120 FPS on T4 GPU. Once optimized in the Raspberry Pi 5, the inference time went up to about 150-180 milliseconds by frame, which gave it 6-7 FPS in a real-life situation, i.e. suitable to responsive activities like sign language detection.

Model Size:

The TCN model that is trained comprises around 1.2 million parameters with total model file size being approximately 5 MB. This minimal footprint made it suitable to be deployed on edge devices with minimal memory and storage capacity e.g. the Raspberry Pi 5.

Layers:

Our TCN structure consists of several stacked causal convolutional layers with a bigger dilation factor. These blocks stem into residual blocks and these blocks comprise the ReLU activations and normalization layers such that the model could be efficient in considering long-range dependencies in input sequence.

Loss Function:

TCN model applies Categorical Cross-Entropy Loss that can be applied in multi-classification tasks such as gesture or sign recognition. This loss measures the accuracy of the model comparing the probability of each class that the model predicted with the one hot encoded real labels. It encourages classification individually and punishes wrong classification efficiently when training.

Inference Speed:

The TCN model had very quick inference speeds on the T4 GPU provided by Google Colab, with an average speed of input sequences being carried out at 120-140 frames per second (FPS) when experimented on using batch-inference parameters. The rate of inference, however, depends on hardware configuration. Even on mid-range CPUs (e.g. Intel i7) it still performs reasonably, 1520 FPS, so it can be useful in real-time or near-real-time applications prior to optimization at the edge.

Latency Mitigation Procedure:

At first, when testing the TCN model on Raspberry 5 Pi with conventional frameworks, the latency was considerably high, that is, a single frame consumed about 380 to 425 milliseconds, which does not warrant real-time detection, where 23 FPS would be sufficient. That was a bottleneck because of the difference in architecture between x86 (on which it was developed) and ARM (the architecture on which Raspberry Pi 5 was based). To address this, we deployed the trained TCN model to NCNN format, a low-profile neural network inference engine which is optimised to run on ARM-based devices. NCNN was made to achieve high performance improvement through the ability to use quantization, layer fusion, and hardware acceleration on the Pi. When converted, the mean inference time would go down to 150ms to 180ms per frame or an approximately 6 to 7 frames per second on Raspberry Pi 5 without thermal throttling (provided with proper cooling). This effective latency reduction allowed the real-time operation of a fixed set of gestures in USB-powered tiny device.

Training Results:

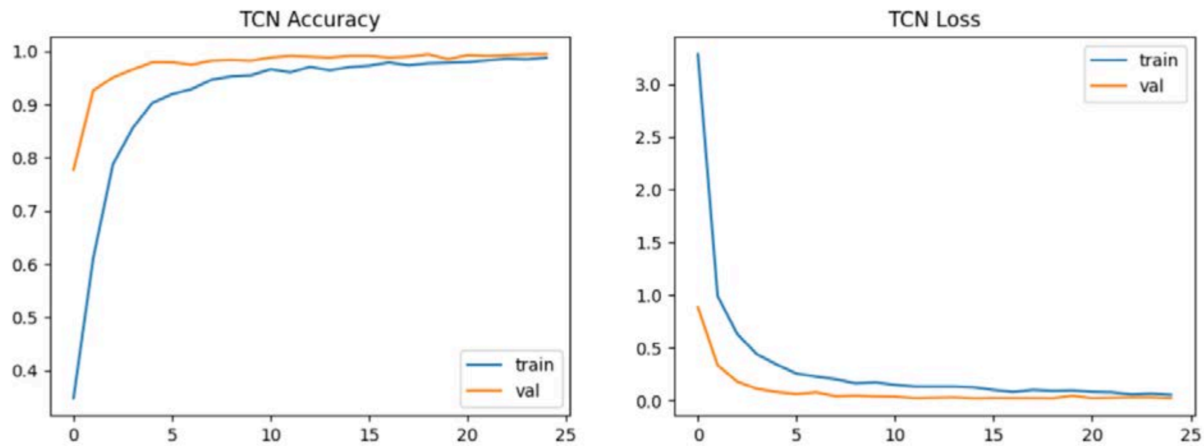


Figure 6: Training Result

Figure: Here training and validation accuracy and training and validation loss curves over various epochs showing the performance improvement for our TCN model.

As the validation accuracy graph and the validation loss graph is optimum and stable in the last which indicates efficient validation. Furthermore, the train accuracy and train loss is also optimized and output a steady result as to entails that the model is well trained. These graphs represent the chart of the convergence over time of model.

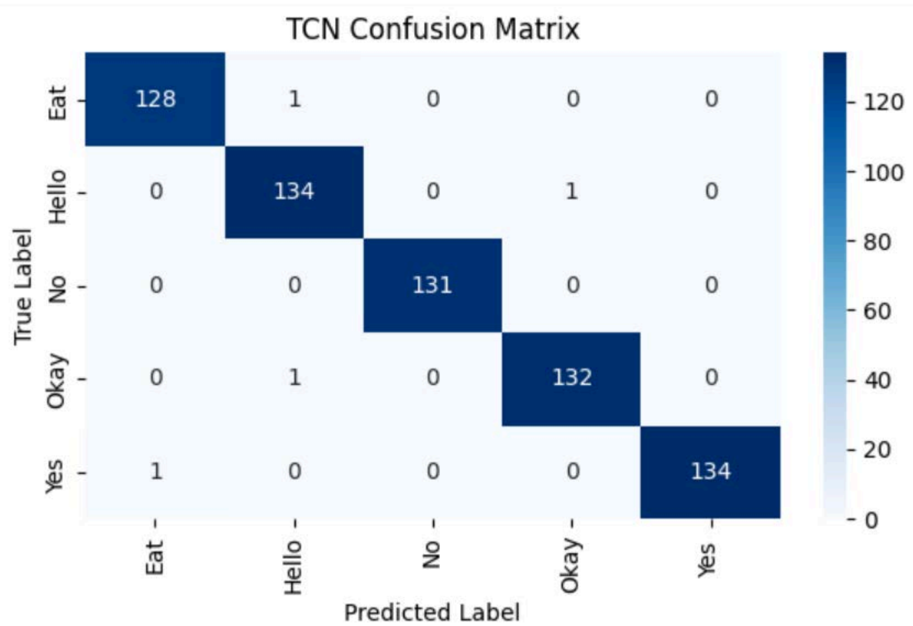


Figure 7: Confusion Mtrix

The given confusion matrix represents the results of the TCN (Temporal Convolutional Network) model, which predicts whether five sign language gestures, including Eat, Hello, No, Okay, and Yes, are correct or not. The amount of effectively classification is high in the matrix, where most predictions are along the diagonal line meaning correct classification in each class. In particular, there were 128 correctly classified Eats, 134 Hellos, 131 No, 132 Okay, and 134 Yes. The misclassifications are small both in terms of overall number of misclassifications and the number in each class having been set as the wrong type but, e.g., one label with the value of Eat being misclassified as Hello and the label with the value of Hello being misclassified as Okay. This shows that TCN model is very effective and reliable in recognition of sign language in real time due to accuracy of near perfect precision and recall in all classes with very low confusion.

Output:

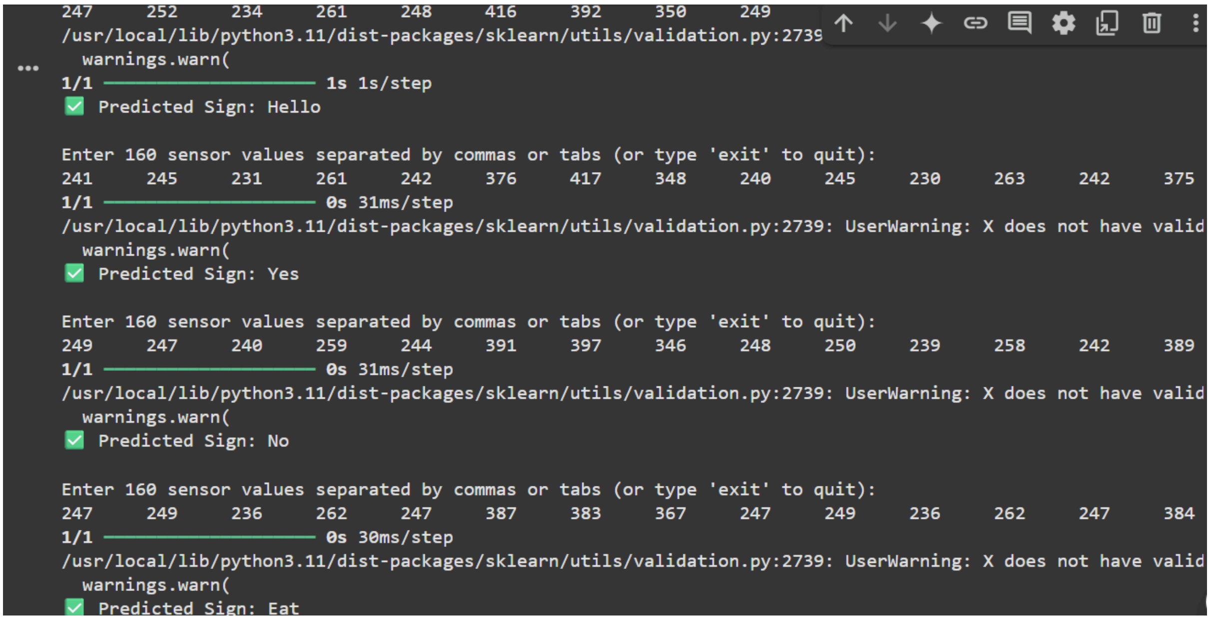


Figure 8: Sign Prediction

We are developing a Temporal Convolutional Network (TCN) to classify sign language gestures when given time-series sensor data. The model is implemented by using a custom training set with the features of 160 features by sample, and five gesture classes. TCN is most suitable in modeling the temporal dependencies and time-varying patterns in a data set which is sequential in nature. This training process performed 80 epochs which enabled the model to converge well and produce high levels of classification accuracies. TCN balances learning capacity against computing performance very well, so it is a suitable model at least for real time operations (as experienced on the Raspberry Pi device).

4.3 Identify optimal design approach

In this report two alternative solutions are investigated that could be implemented into a real-time fire detection system utilising sign languages that would fall within the PyroSentry project. The image-processing design solution consists of processing the images using a CNN model configured with the dataset based upon an image to obtain the fire or to read sign language based on visual information. This technique achieves great accuracy (98 %) and yields good results when illumination is good but such an algorithm is sensitive to clutter in the background, needs higher resolution cameras and thus expensive and slow to process. The second design approach has an underlying sensor-based detection with Temporal Convolutional Networks (TCN) which has been considered as the best design. This model uses the time-series sensors data of smart gloves to identify signs or detect thermal/fire anomalies with high accuracy and as latency is significantly reduced. It is harder to be knocked out of shape by environmental noise, light-weight in computational terms, and simpler to deploy on edge accessories such as Raspberry Pi. Though the sensor integration is complex in nature, the advantage of the sensor based TCN architecture is the high scalability, good real time properties, and reliability which made it the preferred option in real world deployment.

SWOT Analysis

Strengths:

1. Low latency and high real time responsiveness (6 FPS on Raspberry Pi 5)
2. Strength in fluctuating environmental circumstances (e.g. murk, smoke)
3. Thin client designed to work on the edge (e.g., Raspberry Pi, microcontrollers)
4. Extremely precise in regulated orderly data (sensor data of a gesture or fire signature)

Weaknesses:

1. Demands combining several physical sensors (e.g. smart gloves, thermal sensors)
2. Greater preprocessing of data because of time-series format
3. Hardware cost can increase if large-scale deployment is needed
4. Needs consistent sensor calibration and maintenance over time

Opportunities:

1. It can be scaled to many uses - gesture control, fire alert, industrial safety
2. Scalable education, medical and intelligent safety environments
3. Development cost goes down with open-source framework and hardware such as Arduino, Raspberry Pi

Threats:

1. May be subject to sensor failure or noise in signal, which may affect accuracy
2. Security and privacy issues of continuous sensing within the personal environment
3. Other technologies (e.g. vision-based AI, thermal, cameras) can be more effective in some specialties
4. Performance of the model can decline, in case the quality of sensor data falls in the field

4.4 Performance evaluation of developed solution

We tested widely on our sensor-based gesture recognition system which is created with a Temporal Convolutional Network (TCN) model. The system was trained on five of sign languages: Eat, Hello, No, Okay, and Yes on wearable smart sensors gloves dataset. Analysis was achieved by way of repeated test runs amongst these classes of gestures. Performance of the model was gauged on the accurate detection of the gestures using real-time sensor values.

Table 3: Accuracy and Successful Detection of Gestures from Test Dataset

Gesture	Train Samples	Test Samples	False Detections	Mean Accuracy
Yes	542	135	0	100.00%
Hello	539	135	1	99.26%
Okay	531	132	1	99.24%
No	525	131	0	100.00%
Eat	516	129	1	99.22%

4.5 Conclusion

In this project, we have had a look at several strategies of creating intelligent fire detection and suppression system, as well as an assistive sign language recognition tool. All the strategies were well planned, trained, practiced, and tested in terms of their suitability to the real world. The Temporal Convolutional Network (TCN), powered our sensor-based design and produced extremely high classification accuracy in gesture classification across the different gestures used as part of sign language recognition with a mean of over 99 per cent in our 5 classes. NCNN conversion optimized the system to run fastest in real-time on the resource-starved devices such as the Raspberry Pi 5 minimizing the latency and enhancing the usability. Multi-point verification, confusion matrix testing, precision-recall, and servo alignment verification validates the strength and stability of our combined 3D-FX product. Our multi-strange approach is promising with smart safety systems as well as with assistive communication technologies.

Chapter 5: Completion of Final Design and Validation. [CO8]

5.1 Introduction

In the last section, we have broadly compared and contrasted most of the proposed system designs in order to come up with the best solution. The chosen sensor-based solution was pointed out to be the most feasible after all simulation, testing, and design improvements were held. In this chapter, the entire process of developing the finished design has been described, which includes the shift of the simulation to its hardware implementation. Owing to such test runs, detailed validation processes were performed that covered the practical use issues and consistency of performance. The sections below offer close evaluation of the functionality, accuracy, and responsiveness of the final prototype on different operating conditions.

5.2 Completion of final design

In order to achieve the final design, we used the two steps process. The initial stage was concentrated on the development of hardware and building of the data set through a specially designed data acquisition system. Our main controller was Arduino Mega 2560 Pro Mini, and we added five flex sensors and accelerometer to the system that was placed in a wearable glove. This glove was built such that high-quality data on the capture of hand gestures would be taken to build the dataset. To guarantee uniformity in recording of data, we designed a control button in the system. When the button is pushed a red LED will come up to show that preparation mode. A blue active data-recording window indicator LED illuminates during the opt-out period and is pulsed on (5 second delay) exactly 2.4 seconds and pulsed off. Here in this window data was put inside to make up a total of 20 frame. In this period, collection of sensor readings is automatically done and published to a CSV file that is stored on memory card mounted on the system. With this arrangement, we obtained 3, 316 gesture samples of various persons. The following examples are the reps of the five predetermined classes of our word recognition using sign language. Such a systemized and automated system of data collection provided consistency, higher quality of data and an opportunity to train and validate the model, during which the next phase can follow.

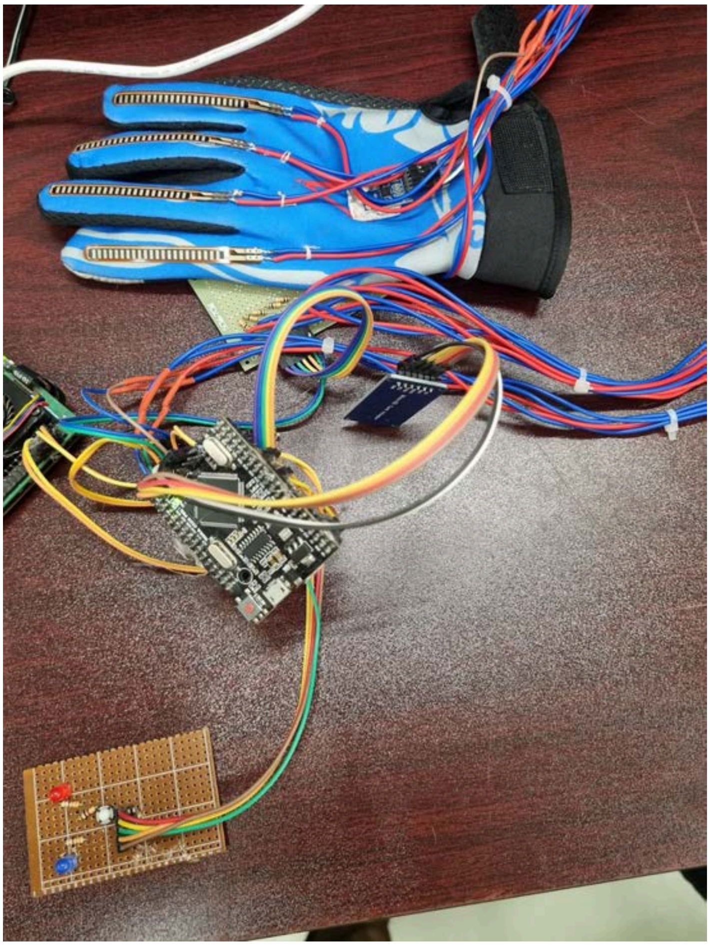


Figure 9: System For Taking the Dataset

The second phase involved before the collection of data, we built and trained our model after collecting data and then coupled the system to Raspberry Pi to facilitate real-time sign detection. A hand sign applies through the sensor-equipped glove that transmits the input values to the Raspberry Pi. We use our prepared model to predict the sign corresponding to these inputs by processing these inputs. There is also a speaker attached to the system that speaks out the sign that it predicts, thus the set up is a full gesture-to-speech communication system.

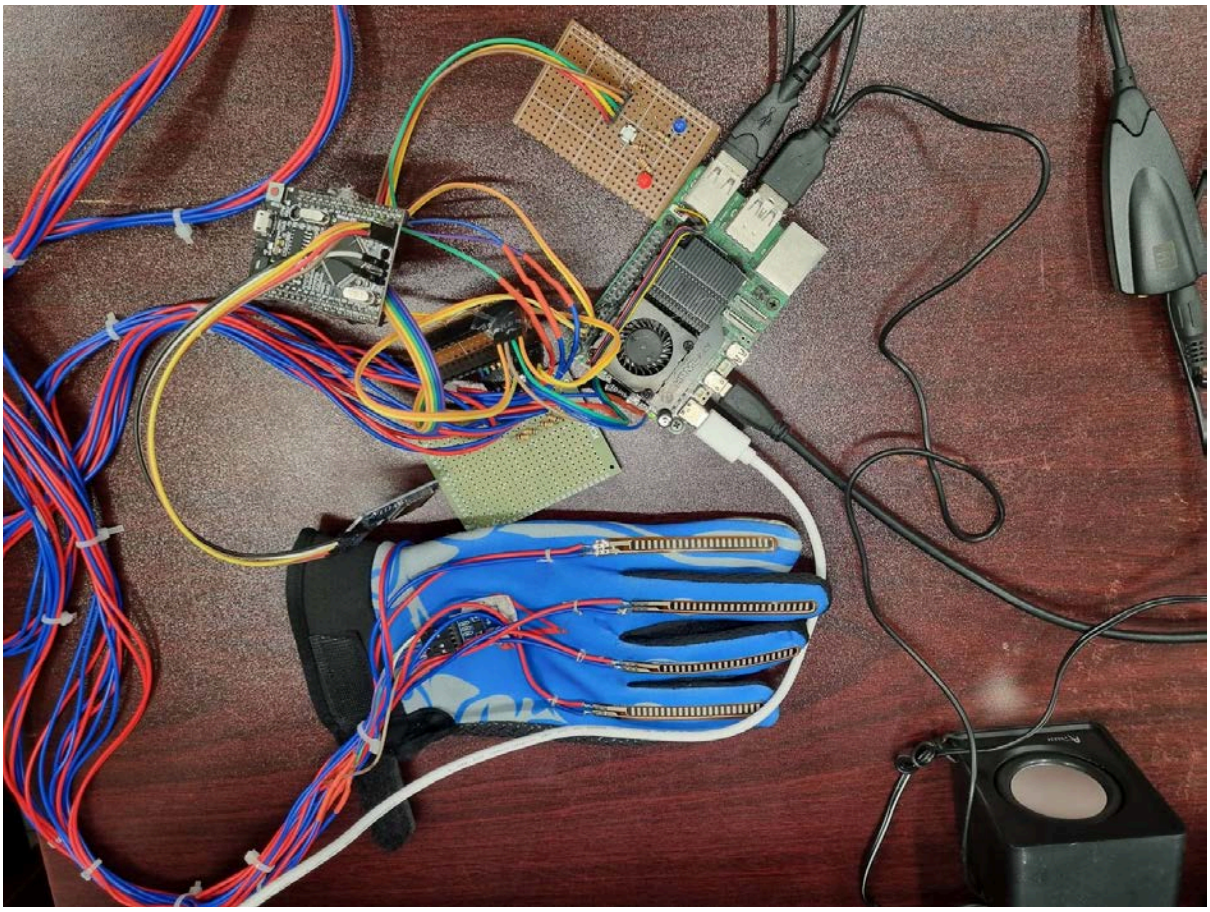


Figure 10: Whole Integrated System

5.3 Evaluate the solution to meet desired need

In order to test the solution and make it sure that it addresses the needed purpose, we performed several test runs with the help of making new, previously unseen hand signs enter the system of gesture recognition via the wearing of the glove system. The data of both flex sensors and accelerometer could be taken in real-time and fed to the trained model running on the Raspberry Pi. The model distinguished the class of the corresponding sign quite well and the system declared a confident voice message via the speaker connected. This ascertains that the provided solution can intelligently convert hand gestures into speech, which was the essence of offering sign-to-voice communication to enhance accessibility.

5.4 Conclusion

To sum up, it is possible to note that the given project manages to present a feasible and effective technique of real time capture of gesture-to-speech translation through glove based sensor system. Coupling the acquisition of an extensive dataset of hand gestures and training a consistent TCN model, we managed to provide precise identification of five primary classes of signs. The development of the trained model and its combination into a Raspberry Pi and audio output would mean smooth translation of gestures into spoken words that would meet the fundamental communication requirements of people with predisposed speech or hearing particularities. This is a potential assistive technology that can grow more and has practical usage due to the performance, ease of use and portability of the system.

Chapter 6: Impact Analysis and Project Sustainability. [CO3, CO4]

6.1 Introduction

In a world which is moving in leapfrog toward the more rational technologies and higher inclusion in societies, our project will fill one of the huge communication gaps, or rather, we will crochet the way by creating a smart glove system, which will help the deaf and mute people communicate. It is not where we come up with a project idea by chance in order to gain some academic validation, it is making a difference. With social inclusion, mental well-being, and emergency safety being the primary spheres covered by our solution, we enable a section of the population, which is commonly disrespected and dismissed. Meanwhile, we are making an effort to make it as sustainable as possible. Conservation of the environment to energy-efficient components, we have made our project aligned with the global SDG goals, because it is not only beneficial at the present moment, but is also responsible enough to create the future.

6.2 Assess the impact of solution

For the solution we have identified in our project of creating a smart system for deaf and mute individuals, below is the context in which our solution aligns with –

★ **Societal Impact**

It enhances communication by making it more accessible and thus facilitates social integration, interaction and functionality between them and the rest of the society.

★ **Health Impact**

Healthwise, this can help to eliminate part of the psychological pressure presented by the communication barrier i.e. frustration, anxiety or depression. Their freedom of expression and the comprehension of others may affect mental health positively and levels of cognitive burden.

★ **Safety Impact**

Regarding the aspect of safety, the glove system may in some particular cases prove handy even in cases of an emergency such as conveying important information such as where they are or the nature of any kind of medical assistance. What is more is that this technology would offer safer communication when sign language might be impractical (e.g. in the dark or at a distance).

6.3 Evaluate the sustainability

Sustainability is having the ability to meet the needs of the present generation without compromising the capacity of the future generation to conduct their business in the future. In our project, it is definitely important that our system/prototype together with the contents and components that have been utilized to construct the system must not undermine the capacity of the future generations to satisfy their own wants and needs. Once the project has been cross-checked with the 17 Sustainable Development Goals (SDGs), we identified a match with the SDG-10 that is meant to guarantee incomes are reduced and inequalities based on the grounds of age, sex, disability, race, ethnicity, origin, religion, or economic or any other status of a country. The following are the three key pillars of sustainability–

Environmental Sustainability

1. **Energy Efficiency**: The system will be built through energy conservation at the basis of low-power components, e.g. energy-efficient sensors/processors and rechargeable batteries. This will enable fewer replacements to be made and therefore minimize wastes.
2. **Material Selection**: The nylon gloves used by our system is a manmade product made out of petrochemicals that has more of an environmental impact when compared to natural fibers. The gloves can however be produced to be more durable and less replacements there to reduce long term waste. Another thing is the repairability and sellability of the electronic components which we are utilizing which further makes sure there is reduction of e-waste as time passes by.

Social Sustainability:
The smart glove system makes the lives of deaf and mute people more inclusive and better since the system offers them a more efficient way of communication and accessibility. It gives individuals who are disabled increased access to society as there are fewer barriers to communication. The user-friendly design of the glove as it is comfortable, lightweight and easy to put on means that the glove is within reach of a large number of people who will not feel uncomfortable wearing it.

6.4 Conclusion

This project is underlining a fundamental human right to communicate and all voices are going to be heard, in one way or another. In conclusion, this intelligent glove is not only a device, it is one of the steps to make the world more inclusive, safe, and mentally supportive to those people who communicate differently. Our project with an environmentally-positive backbone and social focus shows that tech can be significant and conscious.

Chapter 7: Engineering Project Management. [CO11, CO14]

7.1 Introduction

Project management is the key to the successful implementation of engineer projects and interdisciplinary technologies including artificial intelligence, computer visualization and embedded systems. This has to be planned well, resource allocation, management of risks and coordination of different technical and non-technical stakeholders.

The project will take a systematic engineering project management approach which starts with the analysis of requirements and consultation to the stakeholders to make sure that the solution is able to satisfy the needs of the users. Major stages are the development of the system design, combination of hardware and software, the development of a prototype, testing and implementation. The specific deliverables, schedules and budgetary limits are outlined per stage and handled through mechanisms like Gantt charts.

Due to the nature of social and technical aspects of the project, risk management procedures-frequent checking of milestones, contingency plans, and quality assurance of any project are some of the key areas to ensure that performance and usability levels are up to mark. The end-user also provides feedback in terms of end-users (especially in the case of deaf and mute community) of the project in order to develop an inclusive approach, as well as applicability to the real world. Altogether, the given project is indicative of how innovative ideas and concepts should be transformed by means of disciplined engineering project management into practical, user-reasonable solutions that provide more accessibility and social inclusion.

7.2 Define, plan and manage engineering project

EEE499P

Table 4: EEE499P Project Plan

Task	Start Date	End Date	Duration
Topic Selection	11th June	21st June	10 days
Finding Complex Engineering Problems	11th June	16th June	5 days
Review of Related Research Papers	16th June	21st June	5 days
Selection of Research Topic	18th June	21st June	3 days
Project Concept Note	23rd June	27th June	4 days
Tentative Objective and Problem Statement	23rd June	24th June	1 day
Multiple Design Approach	24th June	25th June	1 day
Specification, Requirements, and Constraints	25th June	26th June	1 day

Comparison Between Design Approaches	26th June	27th June	1 day
Preparation of Progress Presentation	27th June	4th July	7 days
FYDP P Progress Presentation	1st July	4th July	3 days
Project Proposal	2nd September	26th September	24 days
Background Research and Methodology	2nd September	17th September	15 days
Project Plan	6th September	17th September	11 days
Budget and Expected Outcome	8th September	11thSeptember	3 days
Sustainability, Safety, and Ethical Consideration	12th September	14th September	2 days
Risk Factor Management	12 September	15th September	3 days
Final Project Proposal Note	15th September	17th September	2 days
Preparation of Final Presentation	21st September	21st September	1 day
Mock Presentation	23rd September	23rd September	1 day
Final Presentation	26th September	26th September	1 day

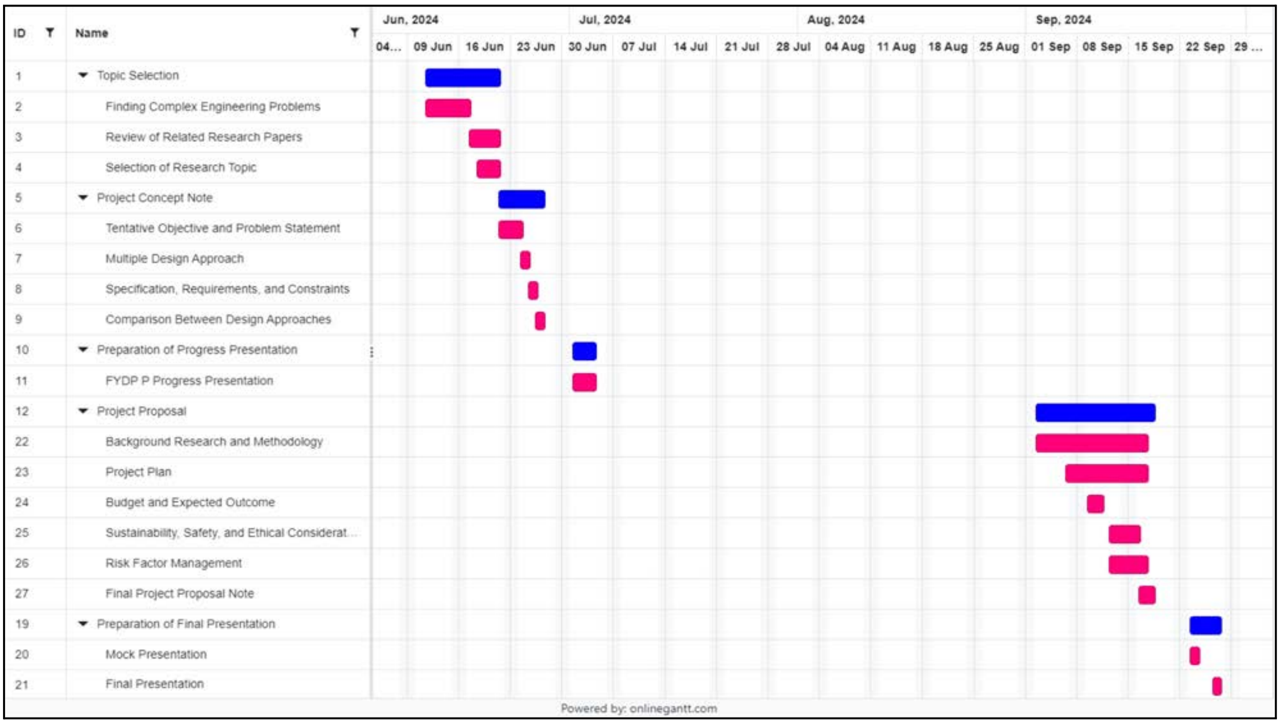


Figure 11: Gantt chart for EEE499P

EEE499D

Table 4: EEE499D Project Plan

Task	Start Date	End Date	Duration
Market Analysis	29th October	29th November	30 days
Engaging the Stakeholders	2nd November	29th November	27 days
Evaluation of Similar Products Available in the Market	29th October	6th November	8 days
Simulation of Optimal Approach	10th November	11th December	31 days
Analyzing Optimal Approach	7th November	19th November	12 days
Modification of Design Approach if needed	14th November	19th November	5 days
Software Simulation	14th November	10th December	26 days
Debug Software Simulated Results	18th November	24th November	6 days
Simulated Result Analysis	30th November	5th December	5 days
Project Report Submission and Presentation	2nd December	22nd December	20 days
Preparation for Presentation	2nd December	17th December	15 days
Mock Presentation	16th December	16th December	1 day
Progress Presentation	26th December	26th December	1 day
Project Report Submission	2nd January 2025	2nd January 2025	1 day

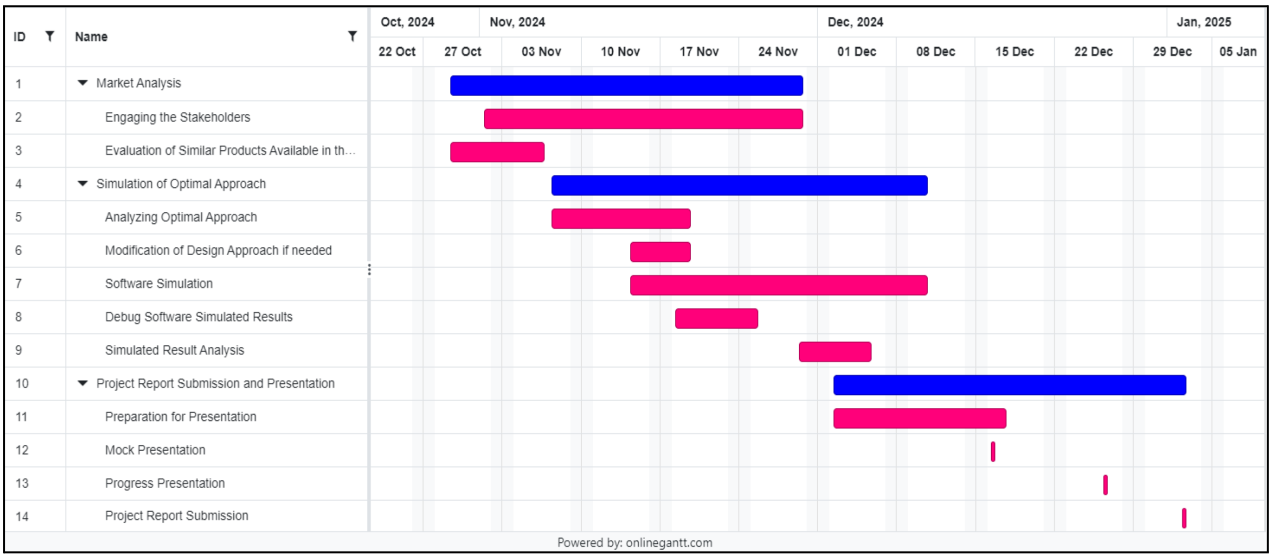


Figure 12: Gantt chart for EEE499D

EEE 499C

Table 5: EEE499C Project Plan

Task	Start Date	End Date	Duration
Prototype Implementation	27th January 2025	4th March 2025	35 days
Designing PCB	27th January	16th February	20 days
Components Testing	6th February	19th February	16 days
Compilation of components	20th February	2nd March	10 days
Develop the Prototype	17th March	19th April	32 days
Trial & Error Phase 1	17th March	22nd March	6 days
Trial and Error Phase 2	22nd March	30th March	8 days
Trial and Error Phase 3	30th March	13th April	14 days
Troubleshooting	28th March	17th April	20 days
Final Prototype	18th April	18th April	1 day
Final Prototype Presentation	22nd April	15th May	14 days
Preparation for Presentation	19th April	30th April	11 days
Mock Presentation	25th April	25thApril	1 day
Project Report Submission	14th May	14th May	1 day
Final Presentation	15th May	15th May	1 day

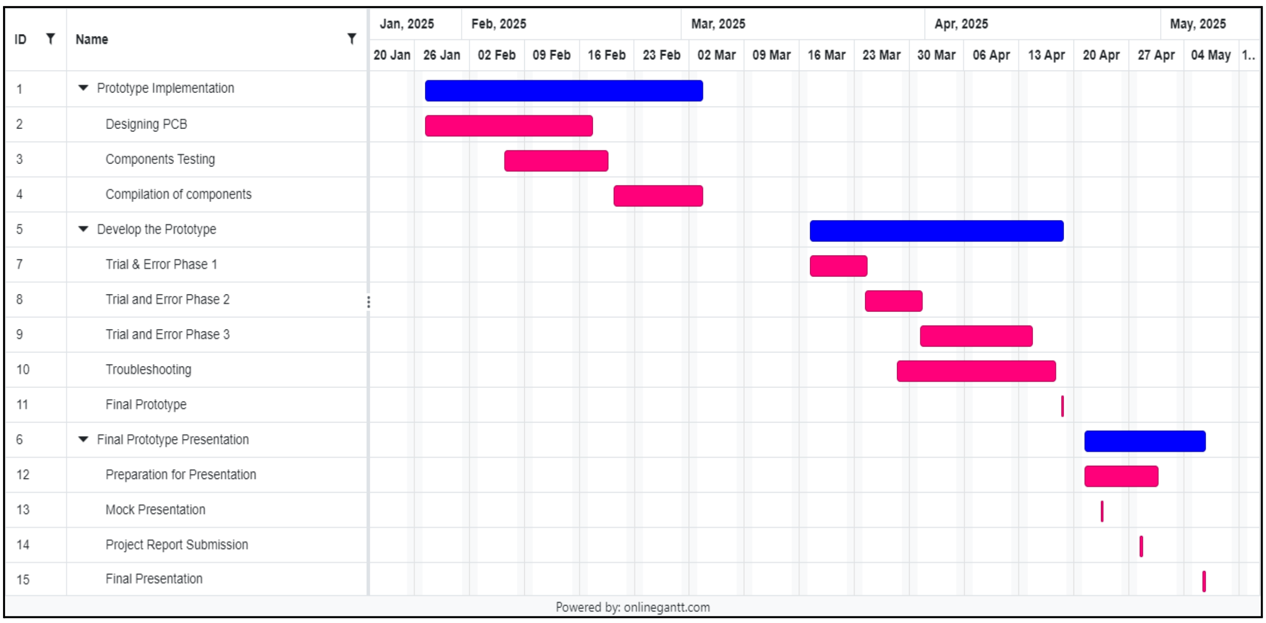


Figure 13: Gantt chart for EEE499C

7.3 Evaluate project progress

No.	*Risk Event*	*Management Procedure*	*Contingency Plan*
1	Gesture Recognition Accuracy	Use high-quality datasets for training; implement adaptive learning models for personalization.	Allow manual correction input or fallback to basic gesture set in low-confidence scenarios.
2	Discomfort/ Irritation	Use soft, breathable, hypoallergenic materials; offer adjustable glove sizes.	Provide glove-free alternative options(e.g., camera-based recognition) for sensitive users.
3	Data Security	Encrypt all transmitted data; implement secure authentication and access control.	Disconnect system from external networks if breach is suspected; restore from secure backup.
4	Short Circuiting	Waterproof casing and protective coatings; educate users on safe usage and storage.	Include automatic shutdown circuit; replace damaged components with spares.
5	Sharp Endings	Ensure all hardware is properly enclosed; use rounded and insulated materials.	Provide safety gloves for handling; redesign hardware layout to eliminate exposed edges.

The table describes some of the risks that may arise in coming up with a smart system to translate sign language with how the risks will be mitigated and what alternative contingency plans there are. In any engineering work, particularly one that has both a hardware and software component, it is always wise to plan beforehand on what might cause problems. This assists in making the system to be safe, reliable and comfortable to the person using it.

The correctness in gesture recognition is one of the issues that arise. Each person uses a different sign and a sign may be similar and therefore the system must be trained using good data and intelligent methods of learning. In case it continues to err, backup measures such as manual correction can be adopted and it will ensure that users do not end up frustrated as a result of its errors. Comfort and safety of the user is of high importance too. The gloves have to be of materials which will not aggravate the problems on the skin. Camera-based solutions can be provided in such a case. On the same note, cutting edges or bad designed components of the hardware may lead to harm. That is the reason why the design will be based on smooth finishing and excellent casing.

Under the technical aspect such risks as data security and short circuiting are being considered. With likely incidents of capturing of personal movement information in the system, encryption will be applied to maintain all the information impenetrable. And in order to avoid electrical damages, water proofing and safety tips will be employed. In general, this project will become effective and convenient in usage due to its attentive planning and safety-first design and support measures.

7.4 Conclusion

Project management is the core of a successful project. Lack of definite planning and organized control make it difficult to remain consistent and reach the objectives of the project. No matter how well the management is made and the procedures followed, random risks might yet emerge. Thus, contingency plans are necessary in order to curb the problems in advance. These plans are crucial towards the realization of the main goals of the project effectively and in time.

Chapter 8: Economical Analysis. [CO12]

8.1 Introduction

Economical Analysis is very significant in measuring the economics of a project in terms of its long-term viability and whether investments can be sustained. It represents an in-depth analysis of other financial aspects aiming to ascertain whether the planned initiative would be economically feasible with respect to the limits of the resources that would be in place. In this section, a value judgment on overall cost consequences of the operation (both direct and indirect), the effectiveness of allocation of resources and any kind of possible return on investment within a specified duration of time shall be made. Strongly evaluating the amount of initial capital spent and other operational expenses plus the estimated financial and non-financial returns, the analysis provides a complete insight into the economic value of the said project. Moreover, it considers other criteria such as market trends, risk analysis and cost benefit analysis to make sure that all the financial decisions made have considered the overall strategic objectives of the projects. The holistic analysis allows stakeholders to make informed decisions based on the data being analyzed, promotes accountability in financial planning, guarantees effective budget oversight, and finally facilitates the feasibility and practical sustainability of the suggested solution in real-life application settings.

8.2 Economic analysis

Economic analysis can enable any company to reach and achieve an effective resource allocation which will create revenues out of a project or a product. It assists in undertaking difficult economic trade-offs and also knows the optimal resource placement in terms of a trade-offs and cost-effectiveness approach with regards to the performance capabilities. Based on our design strategy, we definitely can indicate that it is cost-effective due to a variety of reasons. Initially materials that were used were easily available in Bangladesh hence reducing costs of transporting parts abroad. This makes replacement of components a less bigger problem. Second, the type of hardware IT tools that we have utilized, including Raspberry Pi 5 and Arduino Mega Pro mini, is reusable meaning that there will be less e-waste in the long run. Finally, the glove incorporated in our design strategy is constructed out of heavy material that renders it to be tear and wear prone. This will reduce maintenance fees hence illustrating the economic viability of our preferred design.

8.3 Cost benefit analysis

Cost Benefit Analysis is a critical instrument with the help of which the economic efficiency and feasibility of a project can be considered with reference to systematic comparison of cost and anticipated benefits. This technique of analysis enables one to come up with a price-effective alternative among the existing alternatives, as the intangible and tangible variables are quantified. It offers a systematic way to assess value that a project has created compared to the input resources, hence decisions are arrived at with resort to both the financial and strategic sides. In this section, a detailed analysis is performed in order to compare the various design or implementation methods that consider the initial investment, operational cost, long-term pay backs and risks involved. The analysis will assist in the evidence-based decision-making process and increase the sustainability and impact of the entire project by calculating net benefit, benefit-cost ratio, and payback period indicators. This will help the concerned parties apply the model that ensures the highest gain at minimal use of resources.

Design approach 1 may look simple and necessitates minimal components at a first look. Design Approach 1 that operates image processing with a Raspberry Pi 5 and an 8MP camera module is cheaper as the estimated total cost is around 20,000 BDT. It is easy to integrate with and easy to use, the only component needed would be a camera to follow hand gestures, so it is suited to simple programs or small-scale prototypes. Its functions, however, are very sensitive to the environment, and they can only work well with respect to lighting and the clarity of the background. The deep learning image processing model which it will apply to select the features of the gesture reveals that it will have high computer specification requirements/GPU to operate and deliver an output within minimal time possible. Thus we have latency problems as well as scalability dilemmas in our initial design strategy.

Design Approach 2, in its turn, requires considerably more complicated hardware, featuring five flex sensors, a Grove 6-axis accelerometer and Gyroscope, an SSD to store the data on and other peripherals, roughly estimating its price range at 47,000. Although the approach is more expensive and the hardware more complex, it offers hugely better performance in terms of accuracy, the speed of response, and robustness under a variety of conditions. It is more scalable and ready to apply on time-sensitive applications, because it comprehends dynamic movements of fingers and 3D hand orientation. In addition, when a component breaks, only that component will need to be replaced and not all the sensors since each component is independent of the others. Comparing it to the design approach 1, all problems experienced on any of its parts (e.g- camera module) will need to be changed wholesomely which will make it more expensive.

8.4 Evaluate economic and financial aspects

Our project provides an investor with an opportunity to invest his money and gain a good deal of profits on that. Originally investments towards our chosen approach of design may prove to be expensive (roughly two times more expensive when compared to approach 1) but in the long-term potential benefits that can be derived in the light of economic and financial terms is a case in point. The method chosen which is very accurate, faster, more environmentally self-sufficient that results in reduced errors as well as costs of maintenance and high reliability to handle real world situations is chosen by us. The project is super scalable in economic terms because in the future it is possible to add new components/functions or customize datasets to specific users and, therefore, capture the niche population living in various cultures. Regarding the economic one, it is the fact that its initial cost rate is high, but the prices do not ignore its usefulness to various communities like healthcare devices or education facilities to the hearing-impaired individuals. The value added Health benefits is sufficient to vindicate the product price in terms of reliability, speed and environment independency. The table below represents the budget allocated in order to develop a prototype of our chosen approach.

Table 6: Budget for Design Approach 02

For Design Approach- 02				
SL.	**Components**	**Unit**	**Product Link**	**Price (BDT)**
1.	Flex Sensor 2.2”	5	https://store.roboticsbd.com/robotics-parts/169-flex-sensor-bangladesh.html	9,250
2.	ADXL335	1	https://store.roboticsbd.com/sensors/1913-adxl335-module-3-axis-analog-output-accelerometer-gy-61-robotics-bangladesh.html	630
3.	Raspberry Pi 5	1	https://store.roboticsbd.com/raspberry-pi/2439-raspberry-pi-5-8gb-robotics-bangladesh.html	15,420
4.	Cooler	1	https://store.roboticsbd.com/raspberry-pi/1081-raspberry-pi-5-active-cooler-robotics-bangladesh.html	740
5.	Raspberry Pi 5 M.2 HAT	1	https://www.bdtronics.com/raspberry-pi-5-m-2-hat-for-nvme-ssd-drives.html?srsltid=AfmBOoql_lYqPDqwro8an1uxdy-Xj-S5jCmWy9t-YL3fYgJemls_MAeG	4990
6.	27W USB-C PD Power Supply	1	https://store.roboticsbd.com/raspberry-pi/1082-official-27w-usb-c-pd-power-supply-for-raspberry-pi-5-white-robotics-bangladesh.html	3480
7.	128 GB M.2	1	https://www.startech.com.bd/hikvision-e1000-128gb-m-2-nvme-pcie-ssd	1850
8.	Micro HDMI make to HDMI Cable	1	https://store.roboticsbd.com/raspberry-pi/1145-micro-hdmi-male-to-hdmi-male-cable-for-pi-4-or-5-robotics-bangladesh.html	400
5.	Nylon Gloves	1	https://www.daraz.com.bd/products/nylon-safety-hand-gloves-anti-cut-cut-reseistant-industrial-domestic-hand-gloves-1-pair-i185679779.html	400
6.	Portable Speaker	1	https://store.roboticsbd.com/robotics-parts/1044-15w-8ohm-mini-speaker-diy-robotics-bangladesh.html	1500
			Total	**38,660**

8.5 Conclusion

By conducting a detailed assessment of economic analysis, cost-benefit analysis and economic and financial feasibility, it could be concluded that the design approach 2 has the potential of being a success-story product and that too to the investors and to the hearing impaired users. The economic analysis has guaranteed us the sustainability of our product in the long-run whereas the financial analysis has assured us the total funds needed in the years to come toward our growth. Therefore a completely comprehensive perspective that may involve economic and financial perspectives would be required as regards strategic decision making regarding the survival of the project.

Chapter 9: Ethics and Professional Responsibilities CO13, CO2

9.1 Introduction

Ethics and professional responsibilities provide the core of every engineering project which will guarantee safety, integrity and accountability in the entire design, development and implementation process. The engineers should put the interest of the population first as they have to follow the guidelines that protect health and safety and the environment. It is important to tell the truth, be honest, and transparent with reporting, limitations, awareness of the risks. Professionalism demands that engineers should not have conflicts of interests, honor confidentiality and respect intellectual property rights. Moreover, the engineers should be able to address the issues of related laws, standards, and codes and promote the environment of inclusiveness and respect to their work. Lifetime learning and keeping abreast of emerging technologies also fall in their list of ethical responsibilities. Communications and mutual respect makes cooperation and trust stronger especially when operating in groups or with clients. Finally, ethical engineering also makes innovation sustainable and responsible and brings a positive change to society without doing harm. By focusing on these duties, engineers preserve the integrity of their job and work in the common good.

9.2 Identify ethical issues and professional responsibility

A. **User Consent and Privacy -** In this project, the participants were used to provide real data about qualitative gestures, which was used to train the machine learning model. Because we understood the basis to use hand gesture patterns as personal and biometric data, we were concerned with collecting informed consent forms of all contributors. Prior to the data extraction, participants were explained in a clear manner whether verbally or in manuscript on the manner in which their gesturing would be taken, archived and utilized solely on the basis of study and development. Ethical research guidelines were implemented by the signing of consent forms. All data on gestures were not gathered without any voluntary agreement and this corresponds to ethical principles of transparency and autonomy.

B. **System Reliability -** Because our system translates the hand movement into the hearable speech, any faulty classification can cause dangerous communication failure. As one intake, the misinterpretation of the word Help as the word Yes may be a safety issue. So, it was important to achieve system reliability and accuracy. We clarified that the glove is not supposed to substitute human translators at high stakes scenarios (e.g., hospitals or law scenarios) but be something that helps them in the communication process. We have added protective measures, like the use of confidence thresholds with the ML model, such that the system will not speak when it cannot be reasonably sure of how it has interpreted.

C. **Fair Representation -** Another issue of AI systems is bias, models trained on small or homogeneous data sets do not generalize. To prevent this we trained the machine learning model with data obtained by users of various hand sizes, skin tones, and signing styles. This went towards eliminating bias and enhancing recognition of the glove within different user groups. Through a wide representation, we performed our duty related to the ethical aspect of fairness, which meant that the system was accessible to all users irrespective of some physical aspect.

D. **Safety and Comfort -** Since the glove is meant to be worn, the physical comfort and safety of users were the key aspects of our hardware design. To ensure that no irritation occurs after wearing over a long period of time, we chose skin friendly, breathable and heat insulated materials. We have also put the system to test in real time usage to ensure it does not overheat, it did not become fatigued due to weight and that material sensitivity was to be expected. Ethically, any assistive device should not hurt or pain the user- this observation is in line with the engineering code of not harming and guarantees the safety of the user.

9.3 Apply ethical issues and professional responsibility

I. **Gaining Trust Through Responsible Data Collection -** Within the work of our smart glove, one of the central needs was to build trust in the persons who provided gesture data. We came up with a clear consent form and outlined what our project was all about, in a simple language, before we started gathering some data. Known to contributors, their data of gestures would not be shared or published and would only be used as a method of training the model. We highlighted the importance of voluntariness and made sure that users can withdraw any time with no implications. Such a cautious data collection allowed achieving a certain transparency and attention to the autonomy of our contributors.

II. **Safeguarding Information with Secure Data Handling -** We utilized strict measures to ensure the collected data was secured and non-disclosable. All information in all datasets was depersonalized by assigning them coded identifiers rather than by personal names. Only members of the team were allowed access to the data, and all files were safely located on encrypted drives. We never used cloud storage on any sensitive data when there was no guarantee of encryption. Such practices took care of the privacy of the contributors and did not reveal their individual pattern of gestures.

III. **Designing for Accuracy Without Over-Promising -** Our glove will read gestures and translate them to speech, and it was thus important that their reliability was high. The machine learning model was trained to some minimum degree of confidence so that the speech output will be spoken out. Where there was an unclear or low confidence gesture, the system just held the output to escape miscommunication. We were also categorical in indicating that the glove is not an actual replacement to professional human interpreters during emergencies that may arise in hospitals or in a court of law. The strategy prevents the misunderstandings that may affect the safety of the users.

IV. **Building for Everyone, Not Just the Majority -** To avoid situations where the system would give favor to a certain group, we made sure that our training data resembled different users. We gathered the gesture data of participants with different size of hands, skin tones, and signing styles. This assisted in eliminating prejudice in the model and enhanced general acknowledgement. With this method of measuring performance on various groups of users, we narrowed down the dataset until the model was performing in a fair way on all groups of users. This pledge to diversity would result in a system that functions effectively on many users, rather than on a small elite group of users.

V. **Putting User Safety and Comfort First -** The fact that the device is put directly on the body simplified the selection of materials, we focused on the skin-safe, breathable, and lightweight materials. We also chose the low-voltage components without causing heating problems and used the glove over long periods of time, trying to find out possible discomfort. The size of gloves and cushioning materials were also made adjustable to suit different users. The measures allowed the device to be comfortable to wear on an everyday basis and will not cause any distress (physical or psychological).

9.4 Conclusion

In designing a smart sign language translation system, ethical considerations were taken first and professional responsibilities observed at all stages of the design process. Since we wanted to observe the user privacy and dignity, we began with respecting the user privacy at the moment of obtaining informed user consent, data storage security, and anonymity. The reliability aspect had to be pointed out since our approach to the creation of this system was a communication tool and not a substitute human interpretation in sensitive situations. We made conscious efforts as well to consider a variety of user data when training models to prevent skewed performance based on demographics as well. With regard to hardware planning we focused on safety, comfort and future applicability to avoid exposing the user to injury. Our goal was to construct a solution that is not only technologically sound but ethically competent; through compliance with the standards of ethical engineering and the principles of a human-centered design incorporated into our practices, we sought to become a socially responsible organization. This strategy will enhance our efforts to embrace inclusive innovation and emphasize the need of ethics in developing meaningful assistive technologies to marginalized groups.

Chapter 10: Conclusion and Future Work.

10.1 Project summary/Conclusion

The project aimed to design a smart wearable glove-based system that will allow translation of sign language to audible speech to fill the communication gap between the deaf/mute and the rest of the population. This system combines five flex sensors and a 6 axis accelerometer-gyroscope into a single system so that the position of the finger as well as the orientation of the hand is followed. The system will be able to capture data that is on sensors to be able to recognise hand gestures that present standard sign language. This will be followed by interpretation via machine learning models trained to interpret the gestures and translate the output to verbal.

Another advantage of a sensor-approach as opposed to an image-recognition based system is environmental flexibility (can be used in low-light conditions), reduced computational requirements, as well as real-time capability. The design is aimed towards the comfort of use, portability, and cost-effectiveness with the purpose to engage in daily use by non-verbal persons.

Besides facilitating regular communication, this glove system will find some use in education, healthcare, and emergencies. It enables a person to deliver a very basic value in terms of conveying either Yes, No or Okay with a minimum number of efforts. On the whole, the system shows encouraging outcomes in respect to usability, accuracy, and accessibility. The successful implementation of this project marks a significant step forward in assistive communication technology, contributing to a more inclusive society where individuals with speech and hearing impairments can communicate more independently and confidently.

10.2 Future work

Although this project has managed to exemplify how a smart glove can be developed so as to assist in converting sign language into written words that can be heard, it still has a few areas that can be polished. Among the major advancements possible, it would be essential to increase the vocabulary of the glove and introduce it to a wider number of signs, not only full phrases and their interpretation regarding the context. That would demand a bigger and more assorted training dataset and a high level of natural language processing integration.

The other potential development involves surveillance to identify non manual signs which include facial expression and body language which form part of the major sign languages. Camera-based modules or wearable facial sensors might assist such extra steps in communication, though this adds complexity to both the computing hardware and data processing.

The glove can also be made wireless and even more ergonomic in the future versions with smaller and even more efficient electronics and the more efficient battery. The interface optimization of the smartphone application with regard to the multilingual output and offline capabilities would make it more accessible in the rural or non-resource-rich locality as well. All in all, the continued-grade product could alter lives in a larger way.

Chapter 11: Identification of Complex Engineering Problems and Activities.

11.1 Identify the attribute of complex engineering problem (EP)

Attributes of Complex Engineering Problems (EP)

	Attributes	Put tick (√) as appropriate
P1	Depth of knowledge required	✓
P2	Range of conflicting requirements	
P3	Depth of analysis required	✓
P4	Familiarity of issues	
P5	Extent of applicable codes	✓
P6	Extent of stakeholder involvement and needs	✓
P7	Interdependence	✓

11.2 Provide reasoning how the project address selected attribute (EP)

P1. Depth of Knowledge Required: The project required high levels of expertise in a variety of engineering fields such as sensor interfacing, embedded systems, signal processing, machine learning and human-centered design. An advanced integration of the hardware and software was involved in implementation of a working prototype, which was by no means a routine application, and so this attribute is very relevant.

P3. Depth of Analysis Required: We were working with significant analytical depth in training and validating machine learning model, analysing and interpreting real time data on gesture extraction and developing accuracy in the system to reduce miscommunication. Each one of the stages, such as sensor calibration or audio output, required thought-provoking decisions, which were carefully tested and analyzed in terms of their performance ability, emphasizing the importance of a top-notch analytical mind and problem-solving skills.

P5. Extent of Applicable Codes: This is portrayed in the fact that we observe a lot of standards and ethical requirements. Though a project is not regulated by one regulatory body, we have conducted informed consent on the data privacy, electrical safety regulations of wearable technology and good practices of assistive technology design standards. This variated use of codes makes the project distinctive underlining the multiplicity and interdisciplinarity of the project.

P6. Extent of Stakeholder Involvement and Needs: This was important in the structuring of the system. The deaf and mute users were the focus of our design approach, and they affected everything, including the used gesture set, queasy comfort of gloves, and the user interface design. Their opinion has contributed to the fact that the system proved not only functional, but also practical and inclusive and highlighted the reflection of the real consequences of our engineering solution.

P7. Interdependence: It was a defining characteristic of our system. The functionality of the glove depended on the harmonious collaboration of the hardware sensors, the data processing algorithms, the machine learning models and the output devices. The issue in one particular component might result in the sacrifice of the overall user experience. To design such a tight-coupled system, the development, validation, and troubleshooting had to be holistic, which confirmed that interdependence was the fundamental parameter of sophistication in this project.

These attributes collectively demonstrate that our project required not just technical skills but thoughtful consideration of ethical, practical, and social factors—hallmarks of a complex engineering challenge.

11.3 Identify the attribute of complex engineering activities (EA)

Attributes of Complex Engineering Activities (EA)

	Attributes	**Put tick (√) as appropriate**
A1	Range of resource	✓
A2	Level of interaction	✓
A3	Innovation	✓
A4	Consequences for society and the environment	
A5	Familiarity	✓

11.4 Provide reasoning how the project address selected attribute (EA)

A1. Range of Resources: This can be well applied. In our project, we placed emphasis on uniting a variety of sources, both hardware (the use of flex sensors, accelerometers, microcontrollers, etc.), involves the use of software (machine learning with Python, TensorFlow, Google Colab), and development environments (Proteus, Raspberry Pi OS, etc.).

It took coordination of all these different hardware and software platforms, which should have consisted of compatibility and planning of the task which made the task even more complicated. The attribute of A1 is observed in the diversity of physical, digital, and intellectual resources that were applied in this project.

A2. Level of Interaction: This activity is also strongly present. The project needed a lot of collaboration between several systems and stakeholders. The operation of the glove was conditional on a coordination of sensors and processing algorithms in real-time with user interfaces. Also, the team needed to communicate with the people that might use a product (the deaf and mute people); they needed to receive the feedback, perfect gestures, and also check the usability. The multi-level interaction between systems, users, and the development team illustrates the extent of interaction which takes place.

A3. Innovation: It is one of the attributes of this project. A solution that was proposed by us is not a routine or an off-the-self product. We developed a machine learning applied wearable real-time gesture system that translates the speech turned into machine learning. Bringing all of this functionality into a wearable, easy to carry device--and making it both accessible and affordable to underserved groups, is an innovation new to the world of assistive technology. The innovative nature of the system is further evidenced by its capability of being used in different environments such as in the low light conditions in which vision-based systems could not be applied.

A5. Familiarity: This makes the complexity of this activity even more. We started with little knowledge of the project problem and the environment. It was the first time sign language was recognized, and assistive devices were designed, and this demanded a lot of background research, user feedback, and trials and errors. When working in such a relatively unknown area, it poses a higher learning curve and design problems in coming up with a working prototype, that satisfies both technical and human-centered objectives. This unfamiliarity necessitated creativity, flexibility and versatile problem solving- it is an out-and-out characteristic of a complex engineering exercise.

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Appendix

FYDP (P) Summer 2024 Summary of Team Log Book/ Journal

Title: Development of a Smart System to Translate Sign Language for Deaf and Mute Individuals

Group 6

Final Year Design Project (P) Summer 2024				
Student Details	**Name**	**ID**	**Email Address**	**Phone No.**
Member 1	Raheela Rubaiyat Khan	20221009	raheela.rubaiyat.khan@g.bracu.ac.bd	1931200600
Member 2	Modassir Billah	20221019	modassir.billah.nirjon@g.bracu.ac.bd	1749684613
Member 3	Md. Shahriar Rahman Rounok	20321044	md.shahriar.rahman.rounok@g.bracu.ac.bd	1707998756
Member 4	Md. Forhad Hossain	20321020	md.forhad.hossain1@g.bracu.ac.bd	1318613493

ATC Details		
ATC 8		
ATC	**Name and Designation**	**Email Address**
Chair	Dr. Touhidur Rahman (Chair) Professor, Department of EEE, BRAC University	touhidur.rahman@bracu.ac.bd
Member 1	Dr. Shahed Alam (Member) Senior Lecturer, Department of EEE, BRAC University	shahed.alam@bracu.ac.bd
Member 2	Mr. Atib Mohammad Oni (Member) Lecturer, Department of EEE, BRAC University	atib.mohammad@bracu.ac.bd

General Notes:

1. In addition to detail journal/logbook fill out the summary/key steps and progress of your work
2. Reflect planning assignments, who has what responsibilities.
3. The logbook should contain all activities performed by the team members (Individual and team activities).

FYDP (P) Summer 2024 Summary of Team Log Book/ Journal

Date/Time	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
11.6.2024 [Offline]	**Faculty Members** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	Introduction of tentative topics for the project and presenting it to the ATC members.	**Presenting different ideas** 1. Raheela- Inspection of Fruit Quality and Detection of Lifespan Based on Iot. 2. Modassir- Developing Flood Detection and Warning System 3. Shahriar- Development of a smart system to translate sign language 4. Forhad- Autonomous system for food and water supply for Home alone pets(Birds) and plants	1. Slides must be prepared with good contrast. 2. Use bullet points instead of sentences. 3. Use more images for the audience to visualize easily.
16.6.2024 [Online]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Explaining in detail about the ideas (including a few new ideas) and discussing them with the ATC members.	**Presenting different ideas** 1. Modassir- Inspection of Fruit Quality and Detection of Lifespan Based on Iot 2. Raheela- Face Recognition Smart Doorbell System 3. Shahriar- Development of a smart system to translate sign language 4. Forhad- Enhancing Search and Rescue in Building Collapses with GPR (Ground Penetrating Radar)	1. Face recognition cannot be accepted as it has already been chosen in past papers. 2. Enhancing search and rescue, it will be a very expensive and big project to implement. 3. Unable to to get data for Fruit quality detection.

21.6.2024 [Online]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Finalizing the project.	Discuss among ourselves to shortlist and finalize a project - Raheela, Modassir, Shahriar & Forhad	Make a comparison table for the 2 shortlisted topics so that it's easy to choose.
	Students 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok			
24.6.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Project is finalized [Development of a Smart Glove System for Deaf and Mute Individuals Using Gesture Recognition and Real-time Speech Synthesis]	Presentation on shortlisted 2 topics to make a comparison on which project will be better - Raheela, Modassir, Shahriar & Forhad	Confirming the project 'Development of a Smart Glove System for Deaf and Mute Individuals Using Gesture Recognition and Real-time Speech Synthesis'
	Students 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok			
1.7.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Mock Progress Presentation	1. Raheela- Problem Statement, Objectives, Complex Engineering Problems 2. Modassir- Requirements, Specifications and Constraints 3. Shahriar- Design Approaches 1, 2 and 3	1. Presentation must be rehearsed and try to finish it in 10 mins. 2. Put more images about the components and points mentioned. 3. Avoid writing long sentences.

			explanations 4. Forhad- Applicable standards and codes and Conclusion	
8.7.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Discussion about the feedbacks and questions given but all the ATC members present during the progress presentation	Discussing strategies and thinking of ideas to improve.	Make our project title shorter so that it's easier to get an idea of our project.
2.9.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Discussion on the new topic included and how to proceed with the project proposal.	1. Raheela- Project Plan and Ethical Consideration 2. Modassir- Impact, Expected Outcome and Budget 3. Shahriar- Methodology and Design Approach 1,2 &3 4. Forhad- Sustainability, Risks, Safety consideration	1. Show the price of each component in the budget table. 2. Give names for each design approach.
9.9.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Showing our progress to the atc on our project proposal report.	1. Raheela- Project Plan and Ethical Consideration 2. Modassir- Impact, Risks, and Budget 3. Shahriar- Methodology , Expected Outcome And Design Approach 1,2 &3 4. Forhad- Sustainability, Safety consideration	Use proper flowchart format to prepare a flowchart
17.9.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni	Discussing our completed project proposal and taking feedback from the ATC for the necessary	1. Raheela- Project Plan and Ethical Consideration 2. Modassir- Impact, Expected Outcome and	Put Risk management and Safety Consideration in the same slide.

	Students 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	improvements.	Budget 3. Shahriar- Methodology and Design Approach 1,2 &3 4. Forhad- Sustainability, Risks, Safety consideration	
	Students 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok			
24.9.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Mock Final Presentation to the ATC and taking feedback for improvement.	1. Raheela- Problem Statement & Background Research, Scopes & Objectives, Requirements, Specifications & Constraints 2. Modassir- Project Plan, Expected Outcome, Impact & Sustainability 3. Shahriar- Multiple Design Approaches, Methodology & Budget 4. Forhad- Codes, Ethical Consideration, Risk & Safety consideration	1. Presentation must be rehearsed and try to finish it in 10 mins. 2. Merging the budgets beside each design approach. 3. Adding images which are more related with the topics being presented. 4. Use more colors to differentiate. 5. Don't explain points in detail, better to explain briefly but with accurate information.

FYDP (D) Fall 2024 Summary of Team Log Book/ Journal

Title: Development of a Smart System to Translate Sign Language for Deaf and Mute Individuals

Group 6

Final Year Design Project (D) Fall 2024				
Student Details	**Name**	**ID**	**Email Address**	**Phone No.**
Member 1	Raheela Rubaiyat Khan	20221009	raheela.rubaiyat.khan@g.bracu.ac.bd	1931200600
Member 2	Modassir Billah	20221019	modassir.billah.nirjon@g.bracu.ac.bd	1749684613
Member 3	Md. Shahriar Rahman Rounok	20321044	md.shahriar.rahman.rounok@g.bracu.ac.bd	1707998756
Member 4	Md. Forhad Hossain	20321020	md.forhad.hossain1@g.bracu.ac.bd	1318613493

ATC Details		
ATC 8		
ATC	**Name and Designation**	**Email Address**
Chair	Dr. Touhidur Rahman (Chair) Professor, Department of EEE, BRAC University	touhidur.rahman@bracu.ac.bd
Member 1	Dr. Shahed Alam (Member) Senior Lecturer, Department of EEE, BRAC University	shahed.alam@bracu.ac.bd
Member 2	Mr. Atib Mohammad Oni (Member) Lecturer, Department of EEE, BRAC University	atib.mohammad@bracu.ac.bd

General Notes:

4. In addition to detail journal/logbook fill out the summary/key steps and progress of your work
5. Reflect planning assignments, who has what responsibilities.
6. The logbook should contain all activities performed by the team members (Individual and team activities).

FYDP (D) Fall 2024 Summary of Team Log Book/ Journal

Date/Time	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
31.10.2024 [Offline]	**Faculty Members** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Introduction to overall FYDP-D project methods. 2. General guidelines on how to develop and design simulations. 3. Brief on tentative time schedules on FYDP-D and design report writing		
4.11.2024 [Offline]	**Faculty Members** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	1. Brief on how the FYDP-D curriculum will be held. 2. General guidelines on design report writing 3. Briefing on simulation for 2 design approaches.		
11.11.2024 [Offline]	**Faculty Members** 1.Shahed Alam 2.Atib Mohammad Oni **Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	1. Discussion on creating our own dataset set to train the model and get output. 2. Discussion on different approaches to get proper accuracy		It will be better to create your own dataset as the ones which are found online can have multiple flaws which might not give proper output.
15.11.2024 [Online]	**Students** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Planning on how to collect the datas manually and when to start preparing for those		
18.11.2024	**Faculty Members**	1. Discussion on	**Task 1:** Rounok and	Prepare an algorithm

[Offline]	1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	project plan. 2. Brief on various algorithms for training the dataset.	Forhad **Task 2:** Raheela and Modassir **<u>Progress:-</u>** **Task 1:** In progress **Task 2:** In progress	for design approach 2
25.11.2024 [Offline]	**<u>Faculty Members</u>** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	1. Design approach 1 research on algorithms. 2. Design approach 2 research on algorithms. 3. Gantt chart listing	**Task 1:** Rounok and Forhad **Task 2:** Raheela and Modassir **<u>Progress:-</u>** **Task 1:** In progress **Task 2:** In progress	
28.11.2024 [Online]	**<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Discussion about our respective tasks for the mock presentation and rehearsing accordingly.	**Task 1:** Raheela **Task 2:** Modassir **Task 3:** Rounok **Task 4:** Forhad **<u>Progress:-</u>** **Task 1:** Complete **Task 2:** Complete **Task 3:** Complete **Task 4:** Complete	
1.12.2024 [Offline]	**<u>Faculty Members</u>** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah	1. Review of the logbook 2. Review of design report and gantt chart. 3. Discussions on design approach 1 simulation.		1. Update the design report. 2. Include all the research papers in IEEE format. 3. Work on the design approach 2 simulation.

	3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	4. Discussion on design approach 2 simulation		4. Make preparation for the mock presentation.
2.12.2024 **[Offline]**	**<u>Faculty Members</u>** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Mock Progress Presentation	**Task 1:** Raheela **Task 2:** Modassir **Task 3:** Rounok **Task 4:** Forhad **<u>Progress:-</u>** **Task 1:** Complete **Task 2:** Complete **Task 3:** Complete **Task 4:** Complete	1. No need to give screenshots of the codes. 2. You can put a video link on the slide so that you can show when asked to. 3. Shorten the sentences.
5.12.2024 **[Offline]**	**<u>Faculty Members</u>** 1. Tashfin Mahmud 2. Md. Ehsanul Karim 3. Bristi Das 4. Md. Mahmudul Islam **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Progress Presentation	**Task 1:** Raheela **Task 2:** Modassir **Task 3:** Rounok **Task 4:** Forhad **<u>Progress:-</u>** **Task 1:** Complete **Task 2:** Complete **Task 3:** Complete **Task 4:** Complete	

26.12.2024 [Offline]	**<u>Faculty Members</u>** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Submission of draft design report		
2.1.2025 [Offline]	**<u>Faculty Members</u>** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Final mock presentation with the ATC members		
9.1.2025 [Offline]	**<u>Faculty Members</u>** 1.Dr. Touhidur Rahman 2.Shahed Alam 3.Atib Mohammad Oni **<u>Students</u>** 1.Raheela R Khan 2.Modassir Billah 3.Md. Forhad Hossain 4.Md. Shahriar Rahman Rounok	Final presentation day and submission of final design report		

FYDP (C) Spring 2025 Summary of Team Log Book/ Journal

Title: Development of a Smart System to Translate Sign Language for Deaf and Mute Individuals

Group 6

Final Year Design Project (C) Spring 2025				
Student Details	**Name**	**ID**	**Email Address**	**Phone No.**
Member 1	Raheela Rubaiyat Khan	20221009	raheela.rubaiyat.khan@g.bracu.ac.bd	1931200600
Member 2	Modassir Billah	20221019	modassir.billah.nirjon@g.bracu.ac.bd	1749684613
Member 3	Md. Shahriar Rahman Rounok	20321044	md.shahriar.rahman.rounok@g.bracu.ac.bd	1707998756
Member 4	Md. Forhad Hossain	20321020	md.forhad.hossain1@g.bracu.ac.bd	1318613493

ATC Details		
ATC 8		
ATC	**Name and Designation**	**Email Address**
Chair	Dr. Touhidur Rahman (Chair) Professor, Department of EEE, BRAC University	touhidur.rahman@bracu.ac.bd
Member 1	Dr. Shahed Alam (Member) Senior Lecturer, Department of EEE, BRAC University	shahed.alam@bracu.ac.bd
Member 2	Mr. Atib Mohammad Oni (Member) Lecturer, Department of EEE, BRAC University	atib.mohammad@bracu.ac.bd

General Notes:

7. In addition to detail journal/logbook fill out the summary/key steps and progress of your work
8. Reflect planning assignments, who has what responsibilities.
9. The logbook should contain all activities performed by the team members (Individual and team activities).

FYDP (C) Spring 2025 Summary of Team Log Book/ Journal

Date/Time	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
28.01.2025 [Offline]	**Faculty Members** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Discussion about when to start working after buying the components. 2. Scheduling when the next meetings along with the updates will be taken. 3. Estimated day on which we will show our progress has been discussed		
10.02.2025 [Online]	**Faculty Members** 1. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Showing the data of the flex sensors in Excel sheet	**Task 1:** Md. Shahriar Rahman Rounok **Progress:** **Task 1:** Half done	1. Fix the issues of the sensor values as they are not updating when changes are made
17.02.2025 [Online]	**Faculty Members** 1. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Showing the record of the bill of components 2. Discussion about how to bring the sensor values within acceptable range	**Task 1:** Md. Shahriar Rahman Rounok **Task 2:** Md. Shahriar Rahman Rounok **Progress:** **Task 1:** Completed **Task 2:** Incomplete	
24.02.2025 [Offline]	**Faculty Members** 1. Shahed Alam	1. Discussion about how to optimize the sensor values in order to be detected accurately	**Task 1:** Md. Shahriar Rahman Rounok **Progress:**	

	Students 1. Raheela R Khan 2. Modassir Billah 3. Md. Shahriar Rahman Rounok		**Task 1:** Completed	
12.03.2025 [Offline]	**Faculty Members** 1. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Showcasing our prototype progress so far 2. Checking if the flex sensors change values according to the dataset we were using 3. Suggestion by Atib sir to create our dataset if the dataset we were previously using was causing a problem.	**Task 1:** All **Task 2:** Modassir Billah and Md. Shahriar Rahman Rounok **Progress:** **Task 1:** Completed **Task 2**: Giving values within a low range	
17.03.2025 [online]	**Faculty Members** 1. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Announcement about progress presentation date which was taken online 2. Start preparing the slides for progress presentation	**Task 2:** Modassir Billah, Md. Shahriar Rahman Rounok, Raheela Rubaiyat Khan, Md. Forhad Hossain **Progress:** **Task 2:** Completed	
24.03.2025 [Online]	**Faculty Members** 1. Atib Mohammad Oni 2. Shahed Alam **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	Progress presentation delivered	**Task:** All members **Progress:** **Task:** Delivered by all	

16.04.2025 [Offline]	**Faculty Members** 1. Shahed Alam **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Shahriar Rahman Rounok	1. Flex sensors got damaged which was informed to Shahed Sir 2. Suggested to buy new flex sensors and to work on one hand only	**Task 1&2:** Md. Shahriar Rahman Rounok **Progress:** **Task:** Completed	
1.05.2025 [Offline]	**Faculty Members** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Shahriar Rahman Rounok	1. Starting from 1st May to 7th May, new dataset was created using peer volunteers from BRAC	**Task 1:** Raheela Rubaiyat Khan, Modassir Billah, Md. Shahriar Rahman Rounok **Progress:** **Task 1:** Ongoing	
7.05.2025 [Offline]	**Faculty Members** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah 3. Md. Shahriar Rahman Rounok	1. Dataset has been successfully created	**Task 1:** Raheela Rubaiyat Khan, Modassir Billah, Md. Shahriar Rahman Rounok **Progress:** **Task 1:** Completed	
10.05.2025 [Online]	**Faculty Members** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **Students** 1. Raheela R Khan 2. Modassir Billah	1. Initial model training has been carried out to fix the errors and optimize the algorithm	**Task 1:** Raheela Rubaiyat Khan, Modassir Billah, Md. Shahriar Rahman Rounok **Progress:** **Task 1:** Half completed	

	3. Md. Shahriar Rahman Rounok			
12.05.2025 [Online]	**<u>Students</u>** 1. Raheela R Khan 2. Modassir Billah 3. Md. Shahriar Rahman Rounok	1. Successful completion of training the algorithm with our dataset. 2. Test cases has given accurate outputs 3. Start writing the book	**Task 1:** Raheela Rubaiyat Khan, Modassir Billah, Md. Shahriar Rahman Rounok **Task 2:** All members **Progress:** **Task 1:** Completed **Task 3:** Ongoing	
14.05.2025 [Online]	**<u>Faculty Members</u>** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **<u>Students</u>** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	1. Demonstration of our prototype device 2. Finalizing the poster details 3. Finalizing and verifying the official FYDP book by ATC 4. Finalizing the video which will be played at the showcase day 5. Completing chapters that are still incomplete	**Task 1:** All members **Task 2:** Raheela Rubaiyat Khan **Task 3:** All members **Progress:** **Task 1:** Completed **Task 2:** Completed **Task 3:** Completed **Task 4:** Completed	
15.05.2025 [Offline]	**<u>Faculty Members</u>** 1. Dr. Touhidur Rahman 2. Shahed Alam 3. Atib Mohammad Oni **<u>Students</u>** 1. Raheela R Khan 2. Modassir Billah 3. Md. Forhad Hossain 4. Md. Shahriar Rahman Rounok	Showcase Day		

Codes

TCN Model Training Code:

New Feature!

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Input
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tcn import TCN
import seaborn as sns

# Load data
data = pd.read_csv('/content/8-5-25 lebeled.CSV')

# Show class counts
print("Sample count per class (before filtering):")
print(data['Sign'].value_counts())

# Filter out classes with fewer than 2 samples
class_counts = data['Sign'].value_counts()
valid_classes = class_counts[class_counts >= 2].index
```

```python
filtered_data = data[data['Sign'].isin(valid_classes)]

# Features and Labels
X = filtered_data.drop('Sign', axis=1)
y = filtered_data['Sign']

# Encode labels
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
y_encoded = tf.keras.utils.to_categorical(y_encoded)

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y_encoded, test_size=0.2, stratify=y_encoded,
random_state=42
)

# Reshape for model input
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

# Callbacks
callbacks = [
    EarlyStopping(patience=10, restore_best_weights=True),
    ReduceLROnPlateau(patience=5, factor=0.5, min_lr=1e-6)
```

```python
]


# TCN model
def build_tcn(input_shape, num_classes):
    model = Sequential([
        Input(shape=input_shape),
        TCN(nb_filters=64, kernel_size=3, dropout_rate=0.2,
return_sequences=False),
        Dense(32, activation='relu'),
        Dropout(0.2),
        Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
    return model


# Predict from manual input
def predict_from_input(model, encoder, scaler):
    while True:
        try:
            user_input = input("\nEnter 160 sensor values separated by
commas or tabs (or type 'exit' to quit):\n")


            if user_input.lower() == 'exit':
                break
            input_list = [float(x.strip()) for x in
user_input.replace('\t', ',').split(',')]
            print(input_list)
            if len(input_list) != 160:
```

```
                print(f"❌ Error: Expected 160 values, but got
{len(input_list)}.")
                continue
            input_array = np.array(input_list).reshape(1, -1)
            input_scaled = scaler.transform(input_array)
            input_reshaped = input_scaled.reshape(1, 160, 1)
            prediction = model.predict(input_reshaped)
            predicted_class = np.argmax(prediction)
            predicted_label =
encoder.inverse_transform([predicted_class])[0]
            print(f"✅ Predicted Sign: {predicted_label}")
        except Exception as e:
            print(f"❌ Input error: {e}")

# Train and evaluate
def train_and_evaluate(model_fn, name):
    print(f"\nTraining {name} model...")
    model = model_fn(X_train.shape[1:], y_train.shape[1])
    history = model.fit(X_train, y_train, epochs=300, batch_size=32,
                        validation_data=(X_test, y_test),
callbacks=callbacks, verbose=0)

    loss, acc = model.evaluate(X_test, y_test, verbose=0)
    print(f"{name} Test Accuracy: {acc:.4f}")

    # Accuracy and Loss Plots
    plt.figure(figsize=(12, 4))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='train')
```

```
    plt.plot(history.history['val_accuracy'], label='val')
    plt.title(f'{name} Accuracy')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='train')
    plt.plot(history.history['val_loss'], label='val')
    plt.title(f'{name} Loss')
    plt.legend()
    plt.show()

    # Confusion Matrix
    y_pred = model.predict(X_test)
    y_pred_classes = np.argmax(y_pred, axis=1)
    y_true_classes = np.argmax(y_test, axis=1)

    cm = confusion_matrix(y_true_classes, y_pred_classes)
    class_names = encoder.classes_
    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=class_names, yticklabels=class_names)
    plt.title(f'{name} Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.xticks(rotation=90)
    plt.tight_layout()
    plt.show()
```

```
    print(f"\n{name} Classification Report:")
    print(classification_report(y_true_classes, y_pred_classes,
target_names=class_names))

    return model

# Train and allow manual testing
model = train_and_evaluate(build_tcn, "TCN")
predict_from_input(model, encoder, scaler)
```

CNN Model Code:

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout, BatchNormalization
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
import numpy as np
import os
import cv2
from tqdm import tqdm
import matplotlib.pyplot as plt

# Load and preprocess the dataset
def load_images_and_labels(image_dir, labels_dict, img_size=(64, 64)):
    images = []
    labels = []
    for label, value in labels_dict.items():
```

```
        folder_path = os.path.join(image_dir, label)

        for img_file in tqdm(os.listdir(folder_path), desc=f"Loading {label}"):

            img_path = os.path.join(folder_path, img_file)

            img = cv2.imread(img_path)

            if img is not None:

                img = cv2.resize(img, img_size)

                images.append(img)

                labels.append(value)

    return np.array(images), np.array(labels)

# Specify dataset path and labels dictionary

image_dir = "/content/drive/MyDrive/asl_dataset"  # Replace with your dataset path

labels_dict = {

    "0": "0", "1": "1", "2": "2", "3": "3", "4": "4", "5": "5", "6": "6", "7": "7", "8": "8", "9": "9",

    "a": "a", "b": "b", "c": "c", "d": "d", "e": "e", "f": "f", "g": "g", "h": "h", "i": "i",

    "j": "j", "k": "k", "l": "l", "m": "m", "n": "n", "o": "o", "p": "p", "q": "q", "r": "r",

    "s": "s", "t": "t", "u": "u", "v": "v", "w": "w", "x": "x", "y": "y", "z": "z"

}

  # Update as per your classes

import os


# Features data types and information

# Get information about the directory using os.stat

stat_info = os.stat(image_dir)

print(f"File Size: {stat_info.st_size} bytes")
```

```python
print(f"Last Modified: {stat_info.st_mtime}")


# Or, list files in the directory
print("Files in the directory:")
for file in os.listdir(image_dir):
    print(file)


# If you want to analyze the images, you can load them and print their shapes
# and data types using:
# import cv2
# img = cv2.imread(os.path.join(image_dir, "some_image.jpg"))
# print(f"Image Shape: {img.shape}")
# print(f"Image Data Type: {img.dtype}")
# Load images and labels
img_size = (64, 64)  # Resize images to 64x64
images, labels = load_images_and_labels(image_dir, labels_dict, img_size)
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, BatchNormalization


# Assuming labels_dict is already defined
# Verify the number of classes
num_classes = len(labels_dict)
print("Number of classes in labels_dict:", num_classes)
```

```
# Convert labels to numerical format using LabelEncoder before one-hot
encoding
label_encoder = LabelEncoder()
labels_encoded = label_encoder.fit_transform(labels)

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = stratified_split(images,
labels_encoded, test_size=0.3, random_state=42)

# One-hot encode the labels
y_train = tf.keras.utils.to_categorical(y_train,
num_classes=num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes=num_classes)

# Define the CNN model
def create_cnn_model(input_shape, num_classes):
    model = Sequential([
        Conv2D(256, (3, 3), activation='selu',
input_shape=input_shape),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Conv2D(128, (3, 3), activation='selu'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Conv2D(64, (3, 3), activation='selu'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Conv2D(32, (3, 3), activation='selu'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
```

```
        Flatten(),
        Dense(256, activation='relu'),
        Dropout(0.3),
        Dense(num_classes, activation='softmax')  # Ensure this matches
num_classes
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )
    return model

# Create model
input_shape = (img_size[0], img_size[1], 3)
model = create_cnn_model(input_shape, num_classes)

# Train the model
history = model.fit(
    data_gen.flow(X_train, y_train, batch_size=32),
    epochs=30,
    validation_data=(X_test, y_test),  # Make sure to use y_test here
    callbacks=[
        tf.keras.callbacks.EarlyStopping(monitor='val_loss',
patience=30, restore_best_weights=True),
        tf.keras.callbacks.ReduceLROnPlateau(monitor='val_loss',
factor=0.5, patience=3)
    ]
```

```
)
```

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Input
from tensorflow.keras.callbacks import EarlyStopping,
ReduceLROnPlateau
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tcn import TCN
import seaborn as sns
import pickle
import serial
import pygame
import time

pygame.init()
pygame.mixer.init()
ser = serial.Serial("/dev/ttyAMA0",9600,timeout=2)

# Load data
with open('/home/rounok/Desktop/Sign/model.pkl', 'rb') as file:
    clf = pickle.load(file)
data = pd.read_csv('/home/rounok/Desktop/Sign/8-5-25 lebeled.CSV')
```

```
# Show class counts
print("Sample count per class (before filtering):")
print(data['Sign'].value_counts())

# Filter out classes with fewer than 2 samples
class_counts = data['Sign'].value_counts()
valid_classes = class_counts[class_counts >= 2].index
filtered_data = data[data['Sign'].isin(valid_classes)]

# Features and Labels
X = filtered_data.drop('Sign', axis=1)
y = filtered_data['Sign']

# Encode labels
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
y_encoded = tf.keras.utils.to_categorical(y_encoded)

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y_encoded, test_size=0.2, stratify=y_encoded,
random_state=42
)

# Reshape for model input
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
```

```
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)


# Callbacks
callbacks = [
    EarlyStopping(patience=10, restore_best_weights=True),
    ReduceLROnPlateau(patience=5, factor=0.5, min_lr=1e-6)
]


# Predict from manual input
def predict_from_input(model, encoder, scaler):
    while True:
        try:
            ser.write(bytearray('1200','ascii'))
            #print('sts')
            tmp = ser.readline().strip().decode("utf-8")
            done = 0
            if len(tmp) > 0 :
                done = 1
                print(tmp)
            user_input = tmp
            if done == 1 :
                ##user_input = input("\nEnter 160 sensor values separated by commas or tabs (or type 'exit' to quit):\n")
                if user_input.lower() == 'exit':
                    break
                input_list = [float(x.strip()) for x in user_input.replace('\t', ',').split(',')]
                if len(input_list) != 160:
                    print(f"❌ Error: Expected 160 values, but got {len(input_list)}.")
                    continue
```

```
                input_array = np.array(input_list).reshape(1, -1)
                input_scaled = scaler.transform(input_array)
                input_reshaped = input_scaled.reshape(1, 160, 1)
                prediction = model.predict(input_reshaped)
                predicted_class = np.argmax(prediction)
                predicted_label =
encoder.inverse_transform([predicted_class])[0]
                print(f"✅ Predicted Sign: {predicted_label}")
                status = str(predicted_label)
                if status == 'Yes ' :
                    print(predicted_label)

pygame.mixer.music.load('/home/rounok/Desktop/Sign/sounds/Yes.mp3')
                    pygame.mixer.music.play()
                    while pygame.mixer.music.get_busy():
                        time.sleep(.01)
                elif status == 'Hello' :
                    print(predicted_label)

pygame.mixer.music.load('/home/rounok/Desktop/Sign/sounds/Hello.mp3'
)
                    pygame.mixer.music.play()
                    while pygame.mixer.music.get_busy():
                        time.sleep(.01)
                elif status == 'No' :
                    print(predicted_label)

pygame.mixer.music.load('/home/rounok/Desktop/Sign/sounds/NO.mp3')
                    pygame.mixer.music.play()
                    while pygame.mixer.music.get_busy():
                        time.sleep(.01)
                elif status == 'Okay' :
```

```
                    print(predicted_label)

pygame.mixer.music.load('/home/rounok/Desktop/Sign/sounds/Okay.mp3')
                    pygame.mixer.music.play()
                    while pygame.mixer.music.get_busy():
                        time.sleep(.01)
                elif status == 'Eat' :
                    print(predicted_label)

pygame.mixer.music.load('/home/rounok/Desktop/Sign/sounds/Eat.mp3')
                    pygame.mixer.music.play()
                    while pygame.mixer.music.get_busy():
                        time.sleep(.01)
        except Exception as e:
            print(f"❌ Input error: {e}")
            continue


model = clf
pygame.mixer.music.load('/home/rounok/Desktop/Sign/sounds/starting.m
p3')
pygame.mixer.music.play()
while pygame.mixer.music.get_busy():
    time.sleep(.01)
predict_from_input(model, encoder, scaler)
```

Arduino Code :

```
#include <SD.h>

#define bottom       2
#define led1         12
#define led2         13

const int chipSelect = 53;
File myFile;

#define xPin1     A0
#define yPin1     A1
#define zPin1     A2

#define F1        A4
#define F2        A3
#define F3        A6
#define F4        A5
#define F5        A7

void setup() {
  Serial.begin(9600);
  Serial1.begin(9600);
  pinMode(xPin1, INPUT);
  pinMode(yPin1, INPUT);
```

```
  pinMode(zPin1, INPUT);

  pinMode(F1, INPUT);
  pinMode(F2, INPUT);
  pinMode(F3, INPUT);
  pinMode(F4, INPUT);
  pinMode(F5, INPUT);

  pinMode(bottom, INPUT);
  pinMode(led1, OUTPUT);
  pinMode(led2, OUTPUT);

  digitalWrite(led1, LOW);
  digitalWrite(led2, LOW);

  if (!SD.begin(chipSelect)) {
    Serial.println("initialization failed. Things to check:");
    Serial.println("1. is a card inserted?");
    Serial.println("2. is your wiring correct?");
    Serial.println("3. did you change the chipSelect pin to match
your shield or module?");
    Serial.println("Note: press reset button on the board and reopen
this Serial Monitor after fixing your issue!");
    while (true);
  }

  Serial.println("initialization done.");
}

void loop() {
  int FValue1 = analogRead(F1);
```

```
int FValue2 = analogRead(F2);
int FValue3 = analogRead(F3);
int FValue4 = analogRead(F4);
int FValue5 = analogRead(F5);

//  FValue1 = map(FValue1, 0, 1023, 0, 255);
//  FValue2 = map(FValue2, 0, 1023, 0, 255);
//  FValue3 = map(FValue3, 0, 1023, 0, 255);
//  FValue4 = map(FValue4, 0, 1023, 0, 255);
//  FValue5 = map(FValue5, 0, 1023, 0, 255);

// Read the analog values from the first ADXL335
int xValue1 = analogRead(xPin1);
int yValue1 = analogRead(yPin1);
int zValue1 = analogRead(zPin1);

// Process the data (example: print to serial monitor)
Serial.print("F1=");
Serial.print(FValue1);
Serial.print(", F2=");
Serial.print(FValue2);
Serial.print(", F3=");
Serial.print(FValue3);
Serial.print(", F4=");
Serial.print(FValue4);
Serial.print(", F5=");
Serial.print(FValue5);

Serial.print(", ADXL335 1: X=");
Serial.print(xValue1);
```

```
  Serial.print(", Y=");
  Serial.print(yValue1);
  Serial.print(", Z=");
  Serial.print(zValue1);

  Serial.println();

  int Bottom_v = digitalRead(bottom);

  if (Bottom_v == 1) {
    String send_data;
    digitalWrite(led1, HIGH);
    digitalWrite(led2, LOW);
    delay(5000);
    digitalWrite(led1, LOW);
    digitalWrite(led2, HIGH);
    for (int i = 0; i < 20; i++) {
      int d1 = analogRead(F1);
      int d2 = analogRead(F2);
      int d3 = analogRead(F3);
      int d4 = analogRead(F4);
      int d5 = analogRead(F5);
      int d6 = analogRead(xPin1);
      int d7 = analogRead(yPin1);
      int d8 = analogRead(zPin1);

      if (i == 0) {
        send_data = String(d1) + "," + String(d2) + "," + String(d3)
+ "," + String(d4) + ","
                    + String(d5) + "," + String(d6) + "," +
String(d7) + "," + String(d8);
```

```
      }
      else {
        send_data = send_data + "," + String(d1) + "," + String(d2)
+ "," + String(d3) + "," + String(d4) + ","
                    + String(d5) + "," + String(d6) + "," +
String(d7) + "," + String(d8);
      }
      delay(120);
    }
    Serial.println(send_data);
    Serial1.println(send_data);

    myFile = SD.open("data.csv", FILE_WRITE);
    if (myFile) {
      Serial.print("Writing to test.csv...");
      myFile.println(send_data);
      myFile.close();
      Serial.println("done.");
    } else {
      Serial.println("error opening data.csv");
    }

    digitalWrite(led1, LOW);
    digitalWrite(led2, LOW);
  }
  else {
    digitalWrite(led1, LOW);
    digitalWrite(led2, LOW);
  }

  delay(50); // Delay for stability
```

```
}
```

```
#include <SD.h>

#define bottom       2
#define led1         12
#define led2         13

const int chipSelect = 53;
File myFile;

#define xPin1     A0
#define yPin1     A1
#define zPin1     A2

#define F1        A4
#define F2        A3
#define F3        A6
#define F4        A5
#define F5        A7

void setup() {
  Serial.begin(9600);
  pinMode(xPin1, INPUT);
  pinMode(yPin1, INPUT);
  pinMode(zPin1, INPUT);

  pinMode(F1, INPUT);
  pinMode(F2, INPUT);
```

```
  pinMode(F3, INPUT);

  pinMode(F4, INPUT);

  pinMode(F5, INPUT);


  pinMode(bottom, INPUT);

  pinMode(led1, OUTPUT);

  pinMode(led2, OUTPUT);


  digitalWrite(led1, LOW);

  digitalWrite(led2, LOW);


  if (!SD.begin(chipSelect)) {

    Serial.println("initialization failed. Things to check:");

    Serial.println("1. is a card inserted?");

    Serial.println("2. is your wiring correct?");

    Serial.println("3. did you change the chipSelect pin to match your
shield or module?");

    Serial.println("Note: press reset button on the board and reopen
this Serial Monitor after fixing your issue!");

    while (true);

  }


  Serial.println("initialization done.");

}


void loop() {

  int FValue1 = analogRead(F1);

  int FValue2 = analogRead(F2);

  int FValue3 = analogRead(F3);
```

```
int FValue4 = analogRead(F4);
int FValue5 = analogRead(F5);

//  FValue1 = map(FValue1, 0, 1023, 0, 255);
//  FValue2 = map(FValue2, 0, 1023, 0, 255);
//  FValue3 = map(FValue3, 0, 1023, 0, 255);
//  FValue4 = map(FValue4, 0, 1023, 0, 255);
//  FValue5 = map(FValue5, 0, 1023, 0, 255);

// Read the analog values from the first ADXL335
int xValue1 = analogRead(xPin1);
int yValue1 = analogRead(yPin1);
int zValue1 = analogRead(zPin1);

// Process the data (example: print to serial monitor)
Serial.print("F1=");
Serial.print(FValue1);
Serial.print(", F2=");
Serial.print(FValue2);
Serial.print(", F3=");
Serial.print(FValue3);
Serial.print(", F4=");
Serial.print(FValue4);
Serial.print(", F5=");
Serial.print(FValue5);

Serial.print(", ADXL335 1: X=");
Serial.print(xValue1);
```

```
  Serial.print(", Y=");

  Serial.print(yValue1);

  Serial.print(", Z=");

  Serial.print(zValue1);


  Serial.println();


  int Bottom_v = digitalRead(bottom);


  if (Bottom_v == 1) {

    String send_data;

    digitalWrite(led1, HIGH);

    digitalWrite(led2, LOW);

    delay(5000);

    digitalWrite(led1, LOW);

    digitalWrite(led2, HIGH);

    for (int i = 0; i < 20; i++) {

      int d1 = analogRead(F1);

      int d2 = analogRead(F2);

      int d3 = analogRead(F3);

      int d4 = analogRead(F4);

      int d5 = analogRead(F5);

      int d6 = analogRead(xPin1);

      int d7 = analogRead(yPin1);

      int d8 = analogRead(zPin1);


      if (i == 0) {

        send_data = String(d1) + "," + String(d2) + "," + String(d3) +
"," + String(d4) + ","
```

```
                    + String(d5) + "," + String(d6) + "," + String(d7)
+ "," + String(d8);
      }
      else {
        send_data = send_data + "," + String(d1) + "," + String(d2) +
"," + String(d3) + "," + String(d4) + ","
                    + String(d5) + "," + String(d6) + "," + String(d7)
+ "," + String(d8);
      }
      delay(120);
    }
    Serial.println(send_data);

    myFile = SD.open("data.csv", FILE_WRITE);
    if (myFile) {
      Serial.print("Writing to test.csv...");
      myFile.println(send_data);
      myFile.close();
      Serial.println("done.");
    } else {
      Serial.println("error opening data.csv");
    }

    digitalWrite(led1, LOW);
    digitalWrite(led2, LOW);
  }
  else {
    digitalWrite(led1, LOW);
    digitalWrite(led2, LOW);
```

```
  }



  delay(50); // Delay for stability

}
```