Sign Language Translator

Submitted to

MITU

Technology in Artificial intelligence Department

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Abstract

This project introduces an innovative Smart Glove system designed to bridge the communication gap experienced by the deaf and dumb community by translating sign language gestures into text. The Smart Glove leverages advanced technologies, including ESP32 microcontrollers and flex sensors, to capture intricate hand gestures, which are processed using sophisticated machine learning techniques to ensure accurate and real-time translation. The system's architecture involves several key components: hardware integration, where flex sensors detect finger movements and transmit data to an ESP32 microcontroller; data processing and machine learning, where a Random Forest model hosted on Heroku predicts the corresponding text; and a mobile application developed using Flutter that displays the translated text. The mobile app supports real-time data translation and offers features like dark mode, Arabic language support, and text-to-speech functionality for enhanced accessibility. Communication between the Smart Glove and the mobile application is facilitated via Wi-Fi and HTTP protocols, ensuring reliable and efficient data transmission.

The project addresses several challenges inherent in the development of sign language translation devices, such as accuracy of gesture recognition, user comfort, and power efficiency. By integrating high-resolution flex sensors and optimized machine learning algorithms, the system enhances gesture recognition accuracy. The ergonomic design of the glove ensures user comfort, while the use of low-power components extends battery life, making the device practical for everyday use. This project significantly enhances communication, social inclusion, and accessibility for the deaf and dumb community, offering a cost-effective solution with the potential for wide adoption. It exemplifies the integration of IoT, AI, and wearable technology to solve real-world problems, demonstrating the transformative potential of modern technology in fostering a more inclusive society and improving the quality of life for individuals reliant on sign language.

Chapter 1: Introduction

1.1.Overview

Technology plays a crucial role in improving communication for individuals with disabilities. Sign language is a vital form of communication for the deaf and dumb community. However, understanding sign language can be difficult for those who are not familiar with its gestures, leading to a significant communication barrier.

In order to face this challenge, we suggest the creation of Smart Gloves that can interpret sign language gestures and convert them into text. This project proposes a novel solution: Smart Gloves equipped with ESP32 microcontrollers and flex sensors to translate sign language into text. The system captures hand gestures, processes the data using a machine learning techniques, and displays the translated text on a mobile application. Communication between the glove and the mobile app is facilitated using Wi-Fi and HTTP protocols, with a Random Forest model deployed on Heroku for real-time prediction of signs.

Through the integration of these cutting-edge technologies, our goal is to produce an efficient tool that promotes communication and improves accessibility for the deaf and dumb community. This project aims to bridge the communication divide and cultivate a more inclusive society.

1.2.Problem Statement

People who are deaf and dumb may struggle with communication because spoken language is so common, leading to misunderstandings, social isolation, and limited opportunities. Smart Gloves for sign language translation can improve interactions, access to essential services, and overall quality of life for this community.

1.3.Problem Objective

The objective of this project is to design and implement a Smart Glove system that translates sign language gestures into text in real-time, thereby enhancing communication for the deaf and dumb community. The system aims to be user-friendly, accurate, and accessible. Key objectives include:

- Developing a wearable glove equipped with flex sensors to capture hand gestures.
- Integrating the ESP32 microcontroller to process sensor data and communicate with the mobile app.
- Implementing a machine learning model to accurately predict sign language gestures.
- Ensuring secure and efficient data transmission using Wi-Fi and HTTP protocols.
- Creating a mobile application to display translated text in real-time.

1.4.Significance of Proposed Project

The proposed project holds significant potential in improving the quality of life for the deaf and dumb by providing them with a tool that bridges the communication gap. This technology can be instrumental in educational settings, social interactions, and professional environments, fostering inclusivity and understanding. The Smart Gloves system offers several benefits:

- Enhanced Communication: Facilitates real-time translation of sign language, enabling better interaction between the deaf and dumb community and others.
- Social Inclusion: Promotes inclusivity in social, educational, and professional settings by breaking down communication barriers.
- Accessibility: Provides a cost-effective and accessible solution that can be widely adopted.
- Technological Innovation: Demonstrates the integration of IOT, AI, and wearable technology to solve real-world problem

Chapter 2: Literature Review

2.1.Overview

This chapter reviews the existing literature on the development and application of Smart Gloves for sign language translation. It covers previous research efforts, technological advancements in the field, and the current state of the art. The review aims to provide a comprehensive understanding of the progress made thus far and to identify the existing challenges and opportunities for improvement.

2.2.Explanation of Smart Gloves for sign language

Smart Gloves designed for sign language translation are innovative devices equipped with an array of sensors and microcontrollers that capture and process hand gestures. These gloves are typically fitted with various types of sensors, including:

- Flex Sensors: These sensors measure the bending of fingers by varying their resistance.
- Force Sensors: These detect the force exerted by fingers.

The data collected by these sensors is processed by microcontrollers, such as the ESP32, which is favored for its robust processing capabilities and wireless connectivity features. The translation process generally involves several key stages:

1. Gesture Detection: Sensors detect the movements and positions of the fingers and hand.
2. Signal Processing: The raw data from the sensors is filtered and processed to extract meaningful features.
3. Pattern Recognition: Machine learning algorithms are used to classify the gestures into corresponding sign language characters or words.

Machine learning algorithms, such as Random Forests, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN), are commonly utilized to enhance the accuracy and reliability of gesture interpretation. These algorithms can be trained on large datasets of sign language gestures to recognize various signs and adjust to individual differences in signing styles.

2.3. Previous Research Efforts

2.3.1. Early Development

Early attempts at creating Smart Gloves for sign language translation focused on basic sensor integration and simple gesture recognition. Researchers utilized flex sensors and basic microcontrollers to detect and translate simple gestures. These initial efforts laid the groundwork for more complex and accurate systems.

2.3.2. Technological Advancements

With advancements in machine learning, Smart Gloves have sophisticated algorithms to improve accuracy. Studies have machine learning models have been trained on extensive sign language datasets to enhance translation capabilities

2.3.3. State of the Art

Recent research has focused on real-time translation and user comfort. Studies have shown that integrating multiple sensor types and using advanced microcontrollers like the ESP32 can improve the speed and accuracy of translation. Additionally, efforts have been made to design gloves that are lightweight and comfortable for long-term use.

2.4.Literature gap

Despite significant advancements, several challenges remain in the development of Smart Gloves for sign language translation. Key issues include:

- Accuracy of Gesture Recognition: Many existing solutions struggle with accurately recognizing complex signs and nuanced gestures, especially in real-time scenarios.

- User Comfort: Smart Gloves can be cumbersome and may restrict natural hand movement, making them impractical for everyday use.

- Integration of Machine Learning Models: The need for extensive training data and computational resources can limit the effectiveness and scalability of machine learning models. Additionally, ensuring real-time processing with minimal latency is challenging.

- Power Consumption and Battery Life: The gloves need to be lightweight and portable, which requires efficient power management to avoid frequent recharging.

2.5.Opportunities for Improvement

This project aims to address these gaps by leveraging advanced sensors, such as high-resolution flex sensors. The use of robust microcontrollers like the ESP32, combined with optimized machine learning algorithms, is expected to enhance real-time processing capabilities.

Key areas of focus include:

- Enhanced Gesture Recognition: Using a combination of flex sensors and IMUs to capture both static and dynamic gestures with higher accuracy.
- Optimized Machine Learning Algorithms: Implementing lightweight and efficient algorithms that require less computational power and training data, such as transfer learning techniques.
- Ergonomic Design: Developing gloves that are comfortable and unobtrusive, allowing for natural hand movement and extended wear.
- Power Efficiency: Integrating low-power components and efficient power management systems to extend battery life and reduce the need for frequent recharging.

Through these improvements, the project seeks to create a more effective and user-friendly solution for sign language translation, enabling more accurate and practical communication for the deaf and dumb communities.

2.6. Conclusion

The literature review highlights the progress made in the development of Smart Gloves for sign language translation and identifies the key challenges that remain. By addressing the gaps in accuracy, user comfort, machine learning integration, and power efficiency, this project aims to advance the state of the art and provide a practical solution for real-time sign language translation.

Chapter 3: System Analysis

3.1.Functional Requirements

1. Data Collection:
   - The system must read data from 5 flex sensors attached to a glove.
   - The ESP32 microcontroller must collect and process sensor data.
2. Data Transmission:
   - The ESP32 must transmit sensor data to the Heroku server.
   - The system must support communication protocols.
3. Sign Prediction:
   - The Heroku server must process the received data using a trained Random Forest model.
   - The server must send the predicted sign back to the ESP32.
4. User Interaction:
   - The mobile app must send requests to the ESP32 to initiate data collection.
   - The app must display the translated sign language text to the user.
5. Communication Flow:
   - The system must follow a client-server model where the ESP32 acts as a server to handle incoming requests from the mobile app and as a client to send data to Heroku.
   - The mobile app should act as a client to send requests to the ESP32 and receive responses.

3.2. Non-Functional Requirements

1. Performance:
   - The system should process and transmit data in real-time with minimal latency.
   - The ML model on Heroku should provide quick predictions, ideally within a few seconds.
2. Reliability:
   - The system should be reliable with minimal downtime.
   - Data transmission should be reliable, ensuring no loss of sensor data.
3. Scalability:
   - The system should be able to handle an increasing number of users and data without performance degradation.
   - Heroku should scale the processing power as needed for the ML model.
4. Usability:
   - The mobile app should have a user-friendly interface.
   - The system should be easy to set up and use for individuals with minimal
   - technical knowledge.

3.3. Use case Diagram

3.3.1 Diagram

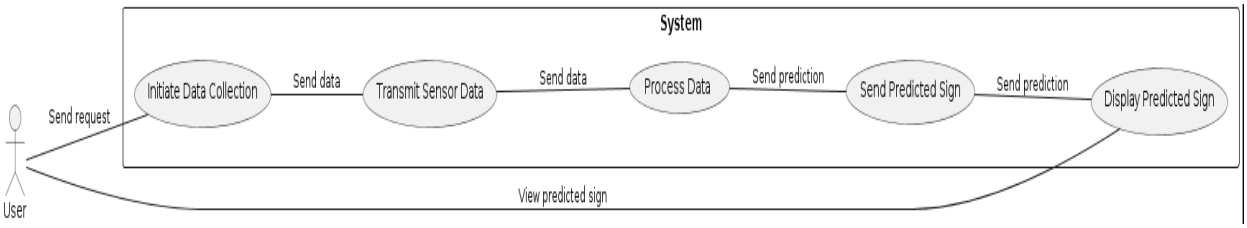

FIGURE 1 USE CASE DIAGRAM

3.3.2. Explanation

1. Actors:
   - User: The person using the mobile app to translate sign language.
2. Use Cases:
   - Initiate Data Collection: The user sends a request to start data collection.
   - Transmit Sensor Data: The ESP32 transmits the collected sensor data.
   - Process Data: Heroku processes the sensor data using the Random Forest model.
   - Send Predicted Sign: Heroku sends the predicted sign back to the ESP32.
   - Display Predicted Sign: The mobile app displays the translated sign language text to the user.

3.4. Sequence Diagram

3.4.1. Diagram

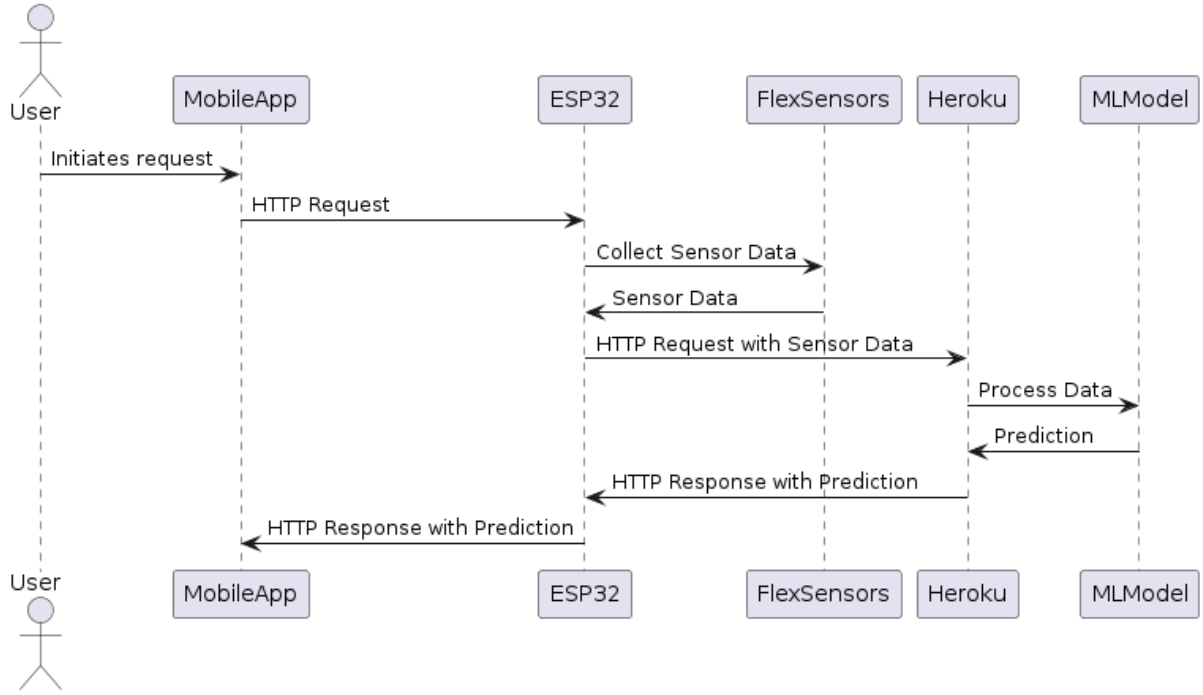

FIGURE 2 SEQUENCE DIAGRAM

3.4.2. Explanation

1. Actors and Participants:

   - User: Initiates the process by sending a request through the mobile app.
   - Mobile App: Sends requests to the ESP32 and displays the predicted sign.
   - ESP32: Reads sensor data, sends data to Heroku, and receives the prediction.
   - Heroku: Processes the data and sends back the predicted sign.

2. Steps:

   - The user sends a request to the mobile app.
   - The mobile app sends a request to the ESP32 to start reading sensor data.
   - The ESP32 reads the sensor data and sends it to Heroku for processing.
   - Heroku processes the data using the Random Forest model and sends the predicted sign back to the ESP32.
   - The ESP32 sends the predicted sign to the mobile app.
   - The mobile app displays the predicted sign to the user.

Chapter 4: Methodology

4.1.Hardware parts

In our project, we prepared to create the hardware part. In the beginning, we made a simulation of our project on the Cirkit Designer program, and we made sure that it worked well and the components and microcontroller were appropriate, after that we bought the components, then we did a test of the components on the bread bored, finally we connected the components to each other on the Gloves.

4.1.1. Components:

- ESP32 Microcontroller: the ESP32 plays an important role in our project by providing reliable connectivity, efficient data processing, real-time monitoring and control, and security features, all while maintaining low power consumption. This makes it a powerful component in our project

FIGURE 3 ESP32

- Flex Sensor: A flex sensor is basically a variable resistor that varies in resistance upon bending. Since the resistance is directly proportional to the amount of bending, it is often called a Flexible Potentiometer. The Flex sensor is used to detect and measure the degree of bending or flexing in a material or object and we used five of them for the number of fingers on the hand.

  Working of flex sensor: The conductive ink printed on the sensor acts as a resistor. When the sensor is straight, this resistance is about 25k.

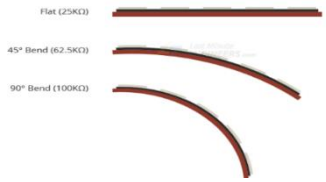

FIGURE 4 FLEX SENSOR WORKING

FIGURE 5 FLEX SENSOR

- Resistors 10KΩ: Resistors are essential passive components in electronics, providing control, protection, and stability in electronic circuits and we used 15 resistors.

FIGURE 6 RESISTORS 10 KΩ

- Breadboard: ls provide a platform for building and testing electronic circuits without the need for soldering.

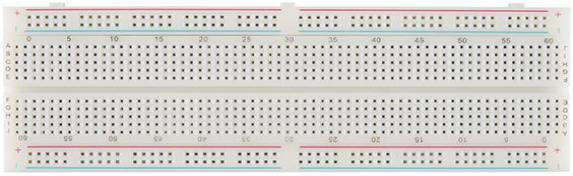

FIGURE 7 BREADBOARD

- Anti-electricity Gloves: Anti-electricity Gloves used to connect all components on it and avoid electrical shocks

FIGURE 8 ANTI-ELECTRICITY GLOVES

- Jumper Wires: We used Jumper wires to make connection between each component.

FIGURE 9 JUMPER WIRES

- Soldering Iron:

FIGURE 11 SOLDERING IRON

- Solder Wire:

FIGURE 10 SOLDER WIRE

- Battery:

FIGURE13 BATTERY

- Battery kit with regulator

FIGURE12 KIT BATTERY WITH REGULATOR

4.2.IOT

4.2.1. Establishing Connection:

To facilitate communication between the ESP32 microcontroller and a mobile application, we employ several network protocols:

- Wi-Fi Connection: The ESP32 establishes a Wi-Fi connection using the IEEE 802.11 protocol to connect to the local network.
- Network Layer Protocol: IPv4 protocol is utilized for addressing and routing packets within the network.
- Transport Layer Protocol: TCP (Transmission Control Protocol) is employed for reliable communication between devices over the network.
- Application Layer Protocol: HTTP (Hypertext Transfer Protocol) is utilized for exchanging data between the ESP32 and the server.

The ESP32 connects to a specified Wi-Fi network using the provided SSID and password. Once connected, it uses a static IP configuration for consistency in network communication.

4.2.2. Communication Models:

Request-Response Model:

- Server (ESP32): The ESP32 operates as a server that handles incoming HTTP GET requests from the mobile application.
- Client (ESP32): The ESP32 also acts as a client that sends POST requests to the Heroku server to obtain predictions.

When the mobile application sends a request to the ESP32 server to get sensor data, the ESP32 reads the sensor values, constructs a JSON payload, and sends a POST request to the Heroku server. The Heroku server processes the data and sends back a prediction, which the ESP32 then forwards to the mobile application.

4.2.3. Heroku:

The Heroku server hosts a FastAPI application that handles POST requests to provide predictions based on the sensor data received from the ESP32. The application utilizes pre-trained machine learning models and appropriate preprocessing tools (scalers and encoders).

4.2.4. Data Flow:

1. The application sends a GET request to the ESP32 server endpoint /get-sensor-data.
2. Upon receiving the request, the ESP32 reads sensor data from its analog pins (32 to 36).
3. The sensor data is then formatted into a JSON payload.
4. An HTTP POST request containing the JSON payload is sent to the Heroku server's prediction API endpoint.
5. Upon receiving the prediction response from the Heroku server, the ESP32 sends the response back to the application.
6. The application receives the prediction data from the ESP32.

4.3.Artificial Intelligence

4.3.1. Data Collection

Gather Data: Start catching data by ourselves.

4.3.2. Data Preparation

Data Cleaning: Handle missing values, remove duplicates, and correct errors.

Data Transformation: Normalize, standardize, or apply other transformations to the data.

Data Splitting: Split the data into training and test sets.

4.3.3. Exploratory Data Analysis (EDA)

Data Visualization: Use plots and charts to visualize data distributions and relationships.

4.3.4. Model Selection

Choose Algorithms: Select appropriate ML algorithms based on the problem type and best accuracy

4.3.5. Model Training

Train Models: Train multiple models using the training data.

Hyperparameter Tuning: Optimize hyperparameters using techniques like grid search or random search.

4.3.6. Model Evaluation

Metrics: Use relevant metrics to assess model performance.

4.4.Application

4.4.1. Overview

The Sign Language Smart Glove Translator App is designed to convert real-time data from a smart glove equipped with flex sensors into readable Arabic text. This innovative application uses several technologies:

- Flutter for the frontend, providing a smooth and responsive user interface.
- ESP32 microcontroller for collecting sensor data from the smart glove.
- Flask API deployed on a Heroku server for translating the collected data into text using a machine learning model.

4.4.2. Dependencies

To build and run this app, the following dependencies are required:

- Flutter: A framework for building natively compiled applications for mobile from a single codebase.
- HTTP: A Flutter package for making HTTP requests to interact with the ESP32 microcontroller.
- Flutter TTS: A plugin for adding text-to-speech capabilities.
- Flutter Localizations: Provides support for multiple languages and locales in a Flutter app.

4.4.3. Features

1. Real-Time Data Translation: The app continuously receives data from the ESP32 microcontroller and translates it into Arabic text. This feature ensures that users get immediate feedback from the glove movements.
2. Dark Theme: The app adapts to the system's dark mode settings, offering a visually appealing interface that is easy on the eyes, especially in low-light conditions.
3. Arabic Language Support: The application is fully localized for Arabic, including the user interface and the text-to-speech functionality, making it accessible for Arabic-speaking users.
4. Text-to-Speech (TTS): The app can read out the translated text in Arabic, which is particularly useful for users who are visually impaired or prefer auditory feedback.
5. Custom Font: The app uses the Amiri font for displaying Arabic text, ensuring that the text is both readable and aesthetically pleasing.

Chapter 5: System implementation

5.1 System Components

1- ESP32 Microcontroller

- Description: The ESP32 acts as the main controller of the Smart Gloves system.
- Functionality:

  - Reads data from the flex sensors to detect finger gestures.

  - Processes the sensor data and extracts features for sign language recognition.

  - Communicates with the mobile application over Wi-Fi using HTTP protocol.

  - Sends data to the Heroku server for sign language prediction using machine learning.

  - Receives predictions from the Heroku server and sends them back to the mobile app.
- Connection: Connected to flex sensors and communicates with the mobile app via Wi-Fi.

2- Flex sensors

- Description: Flex sensors are attached to each finger of the glove and measure the bending of each finger.
- Functionality: They detect the gestures made by the user's fingers while using sign language.
- Connection: Each flex sensor is connected to an analog input pin on the ESP32 microcontroller

3- Mobile Application

- Description: The mobile application serves as the user interface for the Smart Gloves system.
- Functionality:

  - Allows users to initiate sign language translation.

  - Sends HTTP requests to the ESP32 microcontroller to request sign language translation.

  - Displays the translated text received from the ESP32 on the mobile app interface.
- Connection: Connects to the ESP32 microcontroller over Wi-Fi using HTTP requests.

4- Heroku Server

- Description: The Heroku server hosts the machine learning model for sign language prediction.
- Functionality:

  - Receives sign language data from the ESP32 microcontroller.

  - Uses a machine learning model to predict the sign language gestures based on the received data.

  - Sends the predicted sign language gesture back to the ESP32 microcontroller.
- Connection: Communicates with the ESP32 microcontroller to receive sensor data and send predictions.

5- Machine Learning Model:

- Description: A trained machine learning model deployed on the Heroku server.
- Functionality:

  - Takes input data from the ESP32 microcontroller, representing finger gestures captured by the flex sensors.

  - Processes the input data and predicts the corresponding sign language gesture.
- Connection: Integrated with the Heroku server to receive data and send predictions back to the ESP32 microcontroller.

5.2.System Architecture

5.2.1. Hardware

Simulation of the circuit:

We made simulation of the circuit to made ensure that it worked well

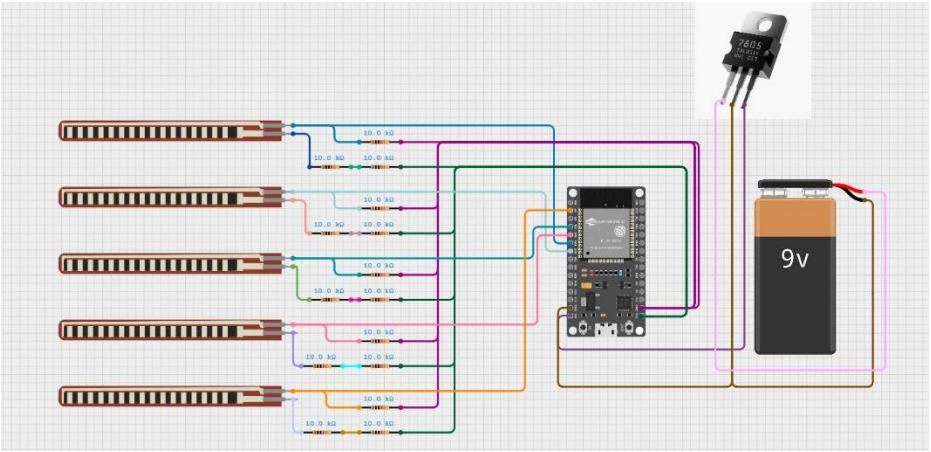

FIGURE 14 THE SIMULATION OF THE CIRCUIT

5.2.2. Software

1. Architectural Style
    - Request -Response Architecture:
    - Client: Mobile application.
    - Server: ESP32 acting as an intermediary server between the mobile app and Heroku.
2. Data Flow
    - Mobile App to ESP32:
    - User initiates a request from the mobile app.
    - Mobile app sends an HTTP request to ESP32.
    - ESP32 to Heroku:
    - ESP32 reads data from flex sensors.
    - Sends the sensor data as an HTTP
    - request to Heroku.
    - Heroku to ESP32:
    - Heroku processes the data with the ML model.
    - Sends the prediction back to ESP32 via HTTP.
    - ESP32 to Mobile App:
    - ESP32 receives the prediction.
    - Sends the predicted sign back to the mobile app via HTTP.

5.2.3. Detailed Design

1. Smart Gloves:
    - Hardware:
        - Flex Sensors (5) connected to analog pins of ESP32.
        - ESP32 Wi-Fi module for communication.
    - Firmware:
        - Read analog values from flex sensors.
        - Convert sensor data to a format suitable for ML model input.
        - Send data to Heroku using HTTP.
        - Receive and process response from Heroku.
        - Send prediction to the mobile app.

2. Mobile Application:
    - Frontend:
        - User interface to display translated text.
        - Button to initiate data request.
    - Backend
        - Sends HTTP request to ESP32.
        - Receives prediction and updates the UI.
3. Heroku Server:
    - Endpoint:
        - Exposes an HTTP endpoint to receive sensor data.
        - Processes data using the ML model.
        - Sends back the prediction.
    - ML Model:
        - Trained to recognize sign language gestures from sensor data.

5.2.4. Deployment

1. ESP32:
    - Deployed on the Smart Gloves.
    - Connects to the local Wi-Fi network.
2. Mobile Application:
    - Deployed on user's mobile device.
    - Available on iOS/Android platforms.
3. Heroku:
    - Hosts the ML model and the server application.
    - Scalable to handle multiple requests.

5.2.5. Communication Protocols

1. Wi-Fi (IEEE 802.11): This protocol will enable wireless communication between the ESP32 and the mobile device.
2. IPv4: For addressing and routing the data packets over the network.
3. TCP: This protocol ensures reliable, ordered, and error-checked delivery of data between mobile app, ESP32, and Heroku.
4. HTTP: For secure communication between mobile app, ESP32, and Heroku.

5.2.6. Diagram

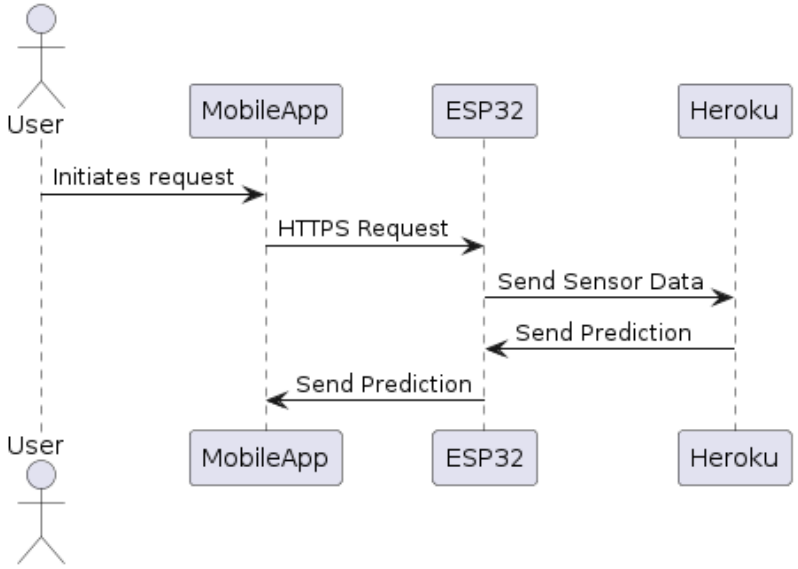

FIGURE 15 SYSTEM ARCHITECTURE DIAGRAM

5.2.7. Implementation Steps

1. Develop Firmware for ESP32:
   - Initialize flex sensors and Wi-Fi connection.
   - Implement HTTP client to communicate with Heroku.
   - Handle data reading, processing, and communication.
2. Develop Mobile App:
   - Create UI for user interaction and displaying results.
   - Implement HTTP client to communicate with ESP32.
   - Handle data requests and responses.
3. Set Up Heroku Server:
   - Develop and deploy the ML model.
   - Implement endpoints to receive sensor data and send predictions.
   - Ensure server scalability and reliability.
4. Integration and Testing:
   - Test communication between mobile app, ESP32, and Heroku.
   - Validate end-to-end data flow and prediction accuracy.
   - Optimize for performance and reliability.

By following this architecture, you can create a robust and efficient system for translating sign language gestures into text, providing a valuable communication tool for the deaf and dumb community.

5.3.Implementation

5.3.1. Hardware Setup:

1. The steps of connection:

In the begging, each flex sensor has two leads, in first Flex Sensor; we connected the first lead of the first flex sensor to 32 analog pin of ESP and connected the same lead of first flex sensor to the first terminal of resistor1 10 KΩ then connected the second terminal of resistor1 to the GND of the ESP. the second lead of the first flex sensor connected to two resistors respectively (in series) which is connected the first terminal of resistor2 to the second lead of the first flex sensor then connected the second terminal of resistor2 to the first terminal of the resistor3 then the second terminal of the resistor3 connected to the 3v3 of ESP

We followed these connections with each sensor until finished the connection, depending on the analog pin of ESP, which differs with each sensor, the second flex sensor connected with 33 analog pins of ESP, the third flex sensor connected with 34 analog pin of ESP, the fourth flex sensor connected to 35 analog pin of ESP and the fifth flex sensor connected to 36 analog pin of ESP

2. Testing the connection on breadboard:

Connect breadboard power (+) and ground (-) rails to ESP 3V3 and ground (GND), respectively

We tested each sensor on the board to ensure that it works correctly

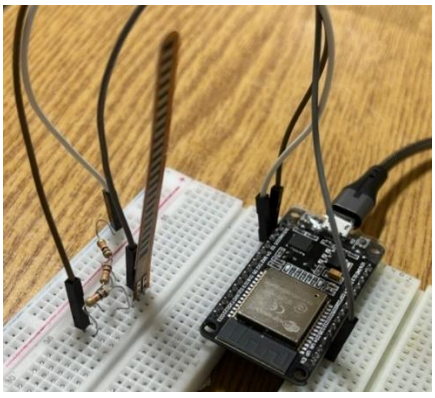

FIGURE 17 TESTING THE CONNECTION OF ONE SENSOR ON BREADBOARD

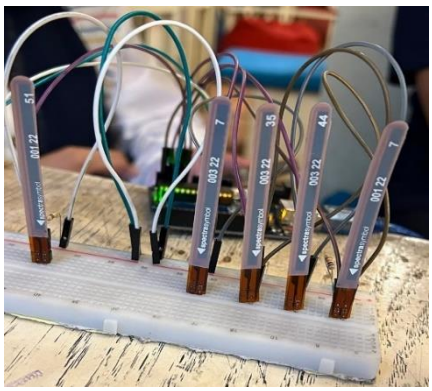

FIGURE 16 TESTING THE CONNECTION OF THE FIVE SENSORS ON BREADBOARD

3. Connection:

- Weld the leg of the first Flex Sensor to the first terminal of resistor

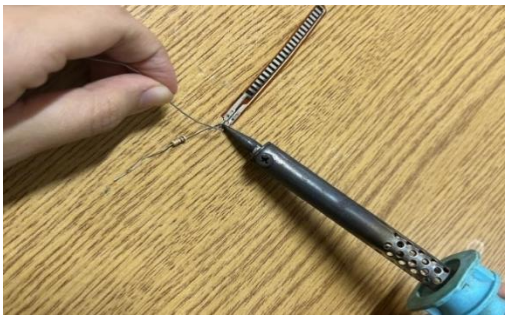

FIGURE 18 WELD THE FLEX SENSOR

- Weld the second terminal of resistor with the first terminal of another resistor respectively (in series)

FIGURE 19 WELD THE RESISTORS WITH FLEX

- We connected the second terminal of second resistor with ground
- We connected the other terminal of sensor with volt and resistor and from end of resistor to analog pin
- We connected each sensor in the same way

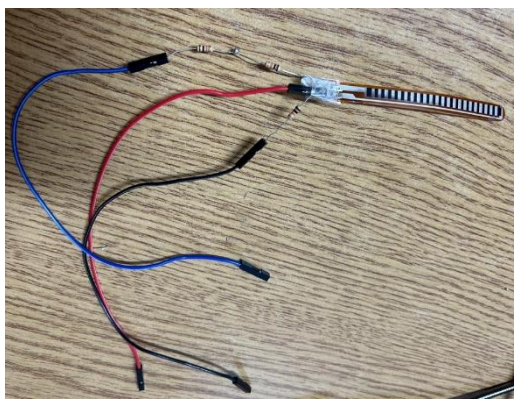

FIGURE 20 FINISHED THE CONNECTION OF FIRST SENSOR

- When connected all sensors on Gloves, we connected all GND of each sensor with each other and connected all 3v3 of each sensor with each other

FIGURE 21 CONNECTIONS ON GLOVES

- We connected each sensor with differ analog pin of ESP, Sensor 1 to 32 analog pin, Sensor 2 to 33 analog pin, Sensor 3 to 34 analog pin, Sensor 4 to 35 analog pin and Sensor 5 to 36 analog pin

FIGURE 22 THE CONNECTION OF THE GLOVES WITH ESP32

- we got Battery 9 Volts and Battery kit with Regulator

FIGURE 23 CONNECTION OF BATTERY AND REGULATOR

- we connect the negative terminal of regulator with negative terminal of Battery and positive terminal of regulator with positive terminal of Battery after that connect the positve terminal of battery with VIN of ESP and negative terminal of battery with GND of ESP

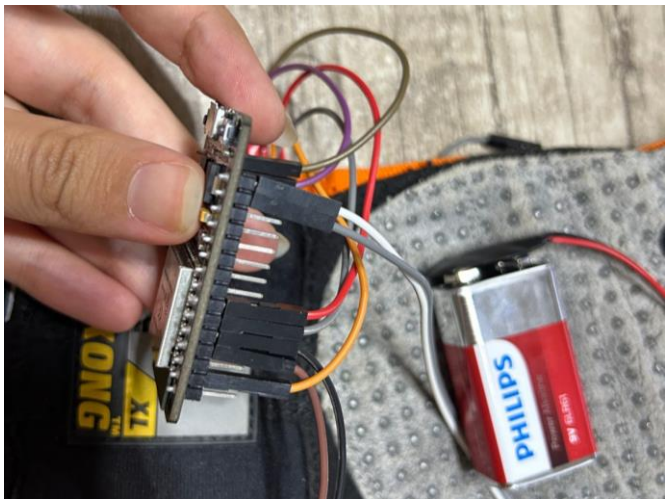

FIGURE 24 CONNECTION OF BATTERY AND REGULATOR WITH ESP32

5.3.2. Software Setup:

1. A mobile application:
   Main Components
   1. main.dart
      - Description: This file serves as the entry point of the app. It sets up the theme, localization, and the initial screen that users see when they launch the app.
      - Key Functions:
        - _fetchAndSetDataFromAPI(): This function fetches data from the Flask API and navigates the user to the translation screen. It continuously requests new data, ensuring real-time translation.
        - _speakArabic(): Utilizes the Flutter TTS plugin to read out the translated text in Arabic, providing auditory feedback.
   2. translation_screen.dart
      - Description: This screen displays the translated text and provides a switch to enable or disable the text-to-speech functionality.
      - Key Functions:
        - _speakArabic(): Uses Flutter TTS to vocalize the translated text in Arabic.
        - onSwitchChanged(bool value): Handles the state of the TTS functionality, enabling or disabling it based on user input.
2. Data:
   - Data collection
     1- Start searching for some real sign language
     2- Simulate these signs and start to take the values of each sensor
     3- Gathering some ranges of values to each sensor and put it on excel file to can learn the model on it and give as an accurate prediction

Word	sign
أَتَمَنَّى لَكَ حَيَاةً سَعِيدَةً	
أُحِبُّكُ	
حَقًّا أُحِبُّكُ	
أَنَا	

أَنَا بِخَيْرٍ	
أُرِيدُ	
مُؤْلِمٌ	
يُؤْلِمَ قَلِيلاً	
رَهِيبٌ	
اَلدِّيكُ	
نِسر	
ذَقَنٌ	

- Data Preparation and visualization
  1. Loading the Dataset:
     Data is loaded from a CSV file online using pd.read_csv.

```
    fx1  fx2  fx3  fx4  fx5          y
0   371  199  134  314  387  "أَنَا"
1   453  208  190  304  485  "أَنَا"
2   379  289  201  286  486  "أَنَا"
3   431  134  132  251  473  "أَنَا"
4   406  144  148  252  468  "أَنَا"
..  ...  ...  ...  ...  ...      ...
79  402  339  291   26  474  "أُرِيدُ"
80  402  426  425  226  284  "أُرِيدُ"
81  383  440  448  235  385  "أُرِيدُ"
82  418  407  407  279  475  "أُرِيدُ"
83  419  411  423  190  185  "أُرِيدُ"

[84 rows x 6 columns]
```

FIGURE 25 LOADING THE DATASET

2. Data Exploration:

   The purpose of this section is to load and explore the data to understand its structure, content, type of missing values, and basic metadata, which helps in preparing for subsequent processing and analysis.

- Display the first 5 rows of data for a quick preview of the structure and content.

```
Head of the Data:
   fx1  fx2  fx3  fx4  fx5          y
0  371  199  134  314  387  "أفْتح"
1  453  208  190  304  485  "أفْتح"
2  379  289  201  286  486  "أفْتح"
3  431  134  132  251  473  "أفْتح"
4  406  144  148  252  468  "أفْتح"
```

FIGURE 26 THE HEAD OF THE DATASE

- Display information about the data including the number of columns, data types, and number of non-missing values in each column

```
Info of the Data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 84 entries, 0 to 83
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   fx1     84 non-null     int64
 1   fx2     84 non-null     int64
 2   fx3     84 non-null     int64
 3   fx4     84 non-null     int64
 4   fx5     84 non-null     int64
 5   y       84 non-null     object
dtypes: int64(5), object(1)
memory usage: 4.1+ KB
None
```

FIGURE 27 INFORMATION OF DATASET

- Provide basic descriptive statistics for the data such as mean, standard deviation, and minimum and maximum values for each numeric column

```
Description of the Data:
              fx1         fx2         fx3         fx4         fx5
count   84.000000   84.000000   84.000000   84.000000   84.000000
mean   354.071429  249.392857  286.369048  162.130952  385.142857
std     67.143577  104.981584  120.469641  112.097825   90.398601
min    213.000000   99.000000  115.000000   11.000000  185.000000
25%    296.500000  176.000000  179.000000   51.750000  317.750000
50%    360.500000  207.500000  233.000000  178.000000  384.000000
75%    411.250000  310.500000  416.750000  252.750000  473.250000
max    464.000000  496.000000  461.000000  408.000000  509.000000
```

FIGURE 28 DESCRIPTION OF THE DATASET

- Count and display the number of unique items in each column.

```
The number of elements in each column that are not repeated in the data:
fx1    71
fx2    64
fx3    69
fx4    63
fx5    70
y      12
dtype: int64
```

FIGURE 29 THE NUMBER OF UNIQUE ELEMENTS IN EACH COLUMN

- Display the data type for each column.

```
Data type in each column:
fx1     int64
fx2     int64
fx3     int64
fx4     int64
fx5     int64
y      object
dtype: object
```

FIGURE 30 DATA TYPE

- Calculate and display the number of missing values in each column.

```
Missing Values in the Data:
fx1    0
fx2    0
fx3    0
fx4    0
fx5    0
y      0
dtype: int64
```

FIGURE 31 MISSING VALUES

- Display data dimensions (number of rows and columns).
- Display data dimensions after deleting rows with missing values, if any.

```
Data dimensions:
(84, 6)

New dimensions for the variable after dropping rows with missing values if they exist:
(84, 6)
```

FIGURE 32 DATA DIMENSION

3. Visualizations Before Cleaning:

   Pre-cleaning visualizations lay the foundation for understanding data quality issues, guiding cleaning efforts, and assessing the impact of cleaning procedures on data integrity

   - Visualize Numeric Features:

     The purpose of this section is to explore the initial distribution of numerical features in the data before performing any cleaning operations. This helps us understand the spread and pattern of the values, which enables us to identify any outliers or unexpected values.

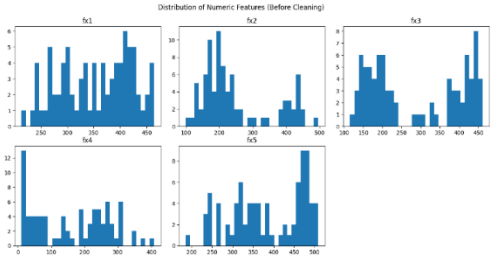

FIGURE 33 DISTRIBUTION OF NUMERIC FEATURES BEFORE CLEANING

Numeric feature distribution analysis (before cleaning):

These graphs provide a preliminary overview of the distribution of values in the numerical features. They show that there is a non-uniform distribution and the data may require additional cleaning to ensure its quality and validity before it can be used in model building.

- Pairplot:

  The purpose of using pairplot is to explore the relationships between all the numerical features in the data. Identify and avoid correlations between different numerical features. Detect outliers and abnormal patterns.

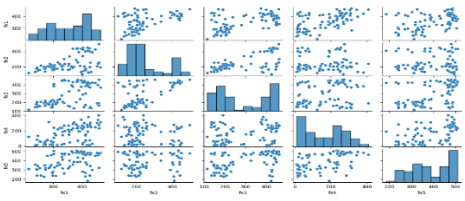

FIGURE 34 PAIR PLOT BEFORE CLEANING

Pairplot distribution analysis (before cleaning):

The numerical features appear to be largely independent of each other, with no strong linear relationships.The data contains some skewness and multiple peaks, which warrant additional examination.

There are some outliers that need to be addressed to ensure data quality.

- Boxplot:

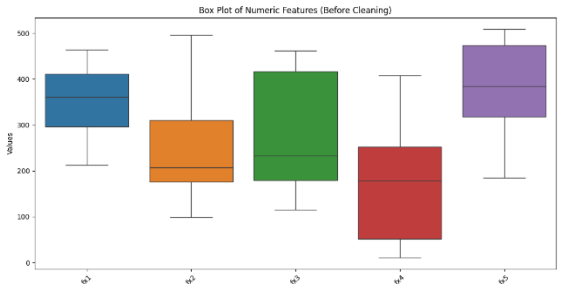

FIGURE 35 BOX PLOT OF NUMERICAL FEATURES BEFORE CLEANING

Boxplot distribution analysis (before cleaning):

Based on the visual analysis, it can be concluded that the dataset is good and suitable for starting the modeling process. However, it is essential to continue cleaning and analyzing the data to ensure the best possible performance from future models.

- Correlation Heatmap:

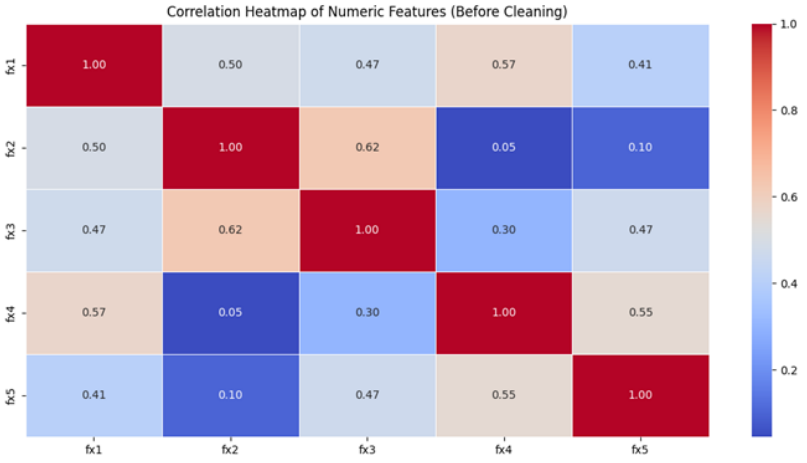

FIGURE 36 CORRELATION HEATMAP OF NUMERIC FEATURES BEFORE CLEANING

Heatmap distribution analysis (before cleaning):

Most of the features exhibit moderate correlations with each other. Feature fx2 and fx3 show the highest correlation between them (0.62). Features fx4 and fx5 also demonstrate a good correlation (0.55).

4. Data Cleaning:

Data cleaning is a crucial step in the data preprocessing pipeline aimed at enhancing the quality and reliability of the dataset. Its primary objectives include:Improving Data Quality ,Enhancing Data Consistency ,Mitigating Bias ,Enabling Meaningful Analysis.

- Handle Missing Values: Handling missing values is a critical aspect of data cleaning. Missing values can introduce bias and reduce the accuracy of analyses. The primary approaches for handling missing values include:

  Imputation: This involves estimating missing values based on existing data.

  Deletion: Missing values can be deleted from the dataset.

  Prediction: Missing values can be predicted using machine learning algorithms trained on the observed data.

Handling missing values is essential to ensure the integrity and reliability of the dataset for subsequent analysis and modeling tasks. It helps prevent biases and ensures that the conclusions drawn from the data are valid and robust.

Also, visualizations were utilized after the cleaning process to provide a visual representation of the transformations and improvements that occurred in the dataset, highlighting their significance and impact on the data. These visualizations serve multiple purposes: Illustrating Cleaning Efforts, Identifying Patterns and Anomalies, Communicating Results.

5. Visualizations After Cleaning:

   Visualizations after cleaning provide visual analysis of data quality and offer deeper understanding of data distributions and deviations, aiding in making better decisions and achieving more accurate results in analytics and modeling.

   - Visualize Numeric Features:

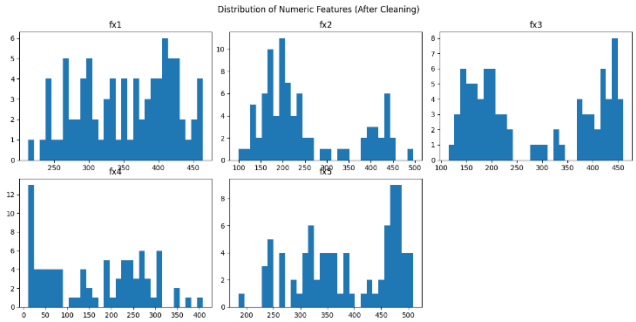

FIGURE 37 VISUALIZE NUMERIC FEATURES AFTER CLEANING

Numeric feature distribution analysis (after cleaning):

The charts provide a good insight into the distribution of the data after the cleaning process. Some features exhibit skewed distributions (either right or left), which may indicate data bias or the presence of atypical data points (outliers). Features like fx1 and fx5 show irregular and multi-modal distributions, which may require further analysis to understand the reasons behind this distribution. The presence of skewed or multi-modal distributions may indicate the need for further data cleaning or the use of different techniques for data normalization before using it for analysis or modeling.

- Pairplot:

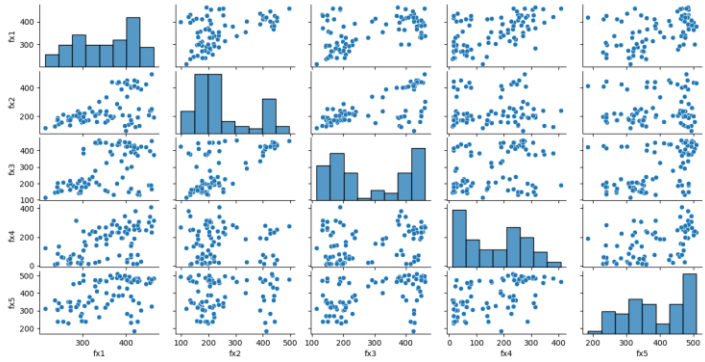

FIGURE 38 PAIR PLOT AFTER CLEANING

Pairplot distribution analysis (after cleaning):

The individual variable distributions are as follows:

- fx1 Distribution: Appears to be somewhat normally distributed.
- fx2 Distribution: Tends to be slightly skewed.
- fx3 Distribution: Appears to be largely uniform.
- fx4 Distribution: Shows some deviations.
- fx5 Distribution: Appears clustered around a specific value.

- Boxplot:

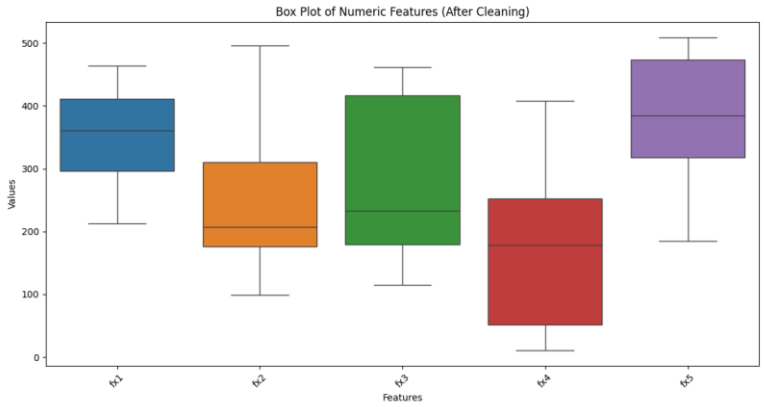

FIGURE 39 BOXPLOT OF NUMERIC FEATURES AFTER CLEANING

Boxplot distribution analysis (After Cleaning):

Overall, the plot shows that the data is clean and fairly balanced, suggesting that it can be used for subsequent analysis or modeling without the need for significant additional cleaning. A uniformly balanced distribution of features is a positive indicator of data quality.

- Correlation Heatmap

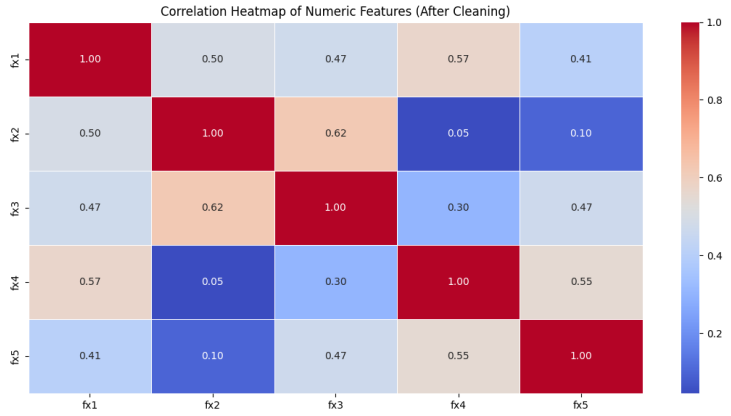

FIGURE 40 CORRELATION OF NUMERIC FEATURES AFTER CLEANING

Heatmap distribution analysis (After cleaning):

There are moderate correlations between some features such as fx2 with fx3 and fx5, while the rest of the correlations are weak to moderate. - The absence of strong correlations (values close to 1 or -1) may mean that the features are relatively independent of each other, which is good for data analysis and modeling, as it reduces the problem of multicollinearity.

6. Encoding and Scaling:

In our preprocessing pipeline, we employed two encoding methods and three scaling techniques to prepare our data for analysis and modeling.

- Encoding Methods:

1. Label Encoding: This method was chosen to convert categorical data into numerical form. Each category is assigned a unique numerical value, enabling the model to comprehend the data in a numeric format.
2. One-Hot Encoding: Utilized for a more detailed numerical representation of categorical data, particularly when categories are not predefined. It creates new columns for each category and assigns a value of 1 for the appropriate category and 0 for others, providing a precise representation of the data.

- Scaling Techniques:

1. StandardScaler (-1 to 1): Employed to transform numerical data into a standard distribution with a mean of zero and a standard deviation of one. It helps in maintaining the variance between values without significantly altering the data.
2. MinMaxScaler (0 to 1): Used to scale numerical data to a specific range between 0 and 1. It finds application in statistical modeling and processes requiring data within a predetermined range, ensuring uniformity within the specified range.
3. MinMaxScaler (0 to 9): Similar to the regular MinMaxScaler but allows users to set the upper limit of the range. This provides flexibility in customizing the scaling range according to specific requirements.

By employing these methods, we aim to assess the effectiveness of different encoding and scaling techniques and determine the most suitable approach for our dataset. This comprehensive approach enables us to make informed decisions regarding data preparation, ultimately enhancing the performance of our analytical models.

- Outliers Analysis:

1. In this part of the code, we analyze the presence of outliers in the dataset after dividing it into training and testing sets. Outliers are data points that differ significantly from the majority of the data, and identifying and dealing with them is important because they can affect model performance. After encoding and skilling, the target variable y is encoded using either label encoding or one-hot encoding, and then the data is divided into a training set (X_train and y_train) and a test set (X_test and y_test) using train_test_split.

Why did we analyze outliers**?** Because its goal is to identify values that lie far from the rest of the data, evaluate the extent to which these values affect future analyses and models, and take appropriate measures to either remove or transform them, this helps us improve the quality of the data and ensures that the model is more accurate and efficient.

Outliers Analysis of Numeric Features:

	fx1	fx2	fx3	fx4	fx5
count	67.000000	67.000000	67.000000	67.000000	67.000000
mean	355.119403	250.179104	293.373134	157.955224	386.029851
std	68.479265	109.608384	120.955393	112.148364	94.270078
min	213.000000	99.000000	115.000000	11.000000	185.000000
25%	299.000000	175.500000	183.500000	45.500000	310.000000
50%	357.000000	205.000000	279.000000	155.000000	389.000000
75%	412.500000	337.500000	424.000000	249.500000	475.000000
90%	432.600000	433.400000	446.200000	287.600000	488.800000
95%	456.500000	441.100000	449.000000	311.600000	495.100000
99%	460.700000	466.300000	460.000000	390.180000	505.040000
max	464.000000	496.000000	460.000000	408.000000	509.000000

FIGURE 41 OUTLIERS ANALYSIS OF NUMERIC FEATURE

- Balance Analysis:
  In this part of the code, the balance of the different classes in the target variable y is checked after we split the data using train_test_split to set 80% for training and 20% for testing. Next, a new data frame is created from the training set y_train, and the value_counts function is used with the normalize=True option to calculate the proportion of each class in the target variable. Our goal in using balance analysis is to detect imbalances between different categories in the target variable y, which helps improve model performance. An imbalance can bias the model towards the most represented class, reducing the accuracy of predicting rare classes. Through balance analysis, we can take actions such as rebalancing rare classes or reducing dominant classes to ensure that the model learns effectively from all classes.

```
Balance Analysis of Target Variable 'y':
y
0     0.089552
1     0.089552
4     0.089552
5     0.089552
6     0.089552
9     0.089552
11    0.089552
2     0.074627
3     0.074627
7     0.074627
8     0.074627
10    0.074627
Name: proportion, dtype: float64
```

figure 42 balance analysis of target variable y

In the end, the data processing part is finished, and we can create a model with high accuracy that is ready for prediction

3. Machine learning Model:
   Machine learning process used to understand data and predict results or make decisions. This is the goal of creating a model. The model is trained using a set of known data. The model learns patterns and relationships in the data and uses this learning to analyze new data and make appropriate decisions.

   In the beginning, we created a code to compare four models (Logistic Regression, Decision Tree, Random Forest, and SVM). The model (logistic regression) was chosen according to its highest accuracy. After that, we created another code for logistic regression in order to predict it. The prediction was incorrect from the beginning, so we resorted to a second one. The model with the highest accuracy is the Random Forest, and its prediction was correct whether it was real data or data close to the real data. Finally, we created a final code for the Random Forest in which the model is saved using "pickle" to preserve the trained and converted model for future use and to upload it to the server

- Models Performance Comparison:

  we evaluated the performance of five machine learning models using different data encoding and scaling techniques. The models used are Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and Gradient Boosting. We applied two encoding methods: Label Encoding and One-Hot Encoding, and three scaling methods: StandardScaler (range -1 to 1), MinMaxScaler (range 0 to 1), and MinMaxScaler (range 0 to 9).

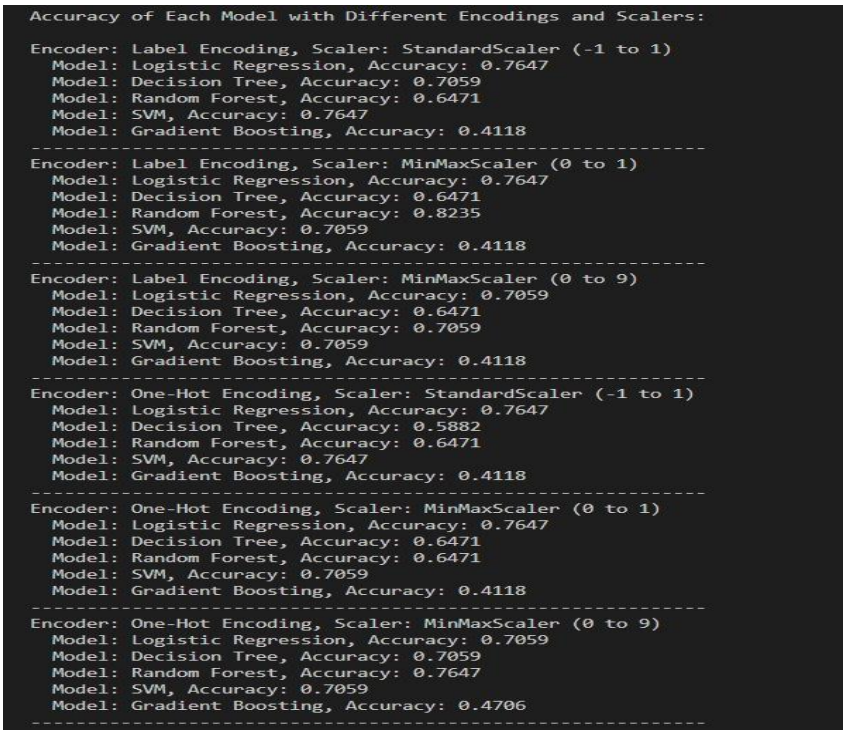

FIGURE 43 ACCURACY OF EACH MODEL DIFFERENT ENCODING AND SCALARS

Based on the results, we can observe the following points:

1. Logistic Regression: This model showed consistent performance with most encoding and scaling methods, achieving a highest accuracy of 0.7647 in most cases.
2. Decision Tree: The performance of this model was somewhat variable, with accuracies ranging from 0.5882 to 0.7059.
3. Random Forest: This model achieved the best accuracy of 0.8235 when using Label Encoding and MinMaxScaler (0 to 1).
4. SVM: Showed good performance with most encoding and scaling methods, achieving an accuracy of 0.7647 in two cases only.
5. Gradient Boosting: This model performed the worst among the five, with accuracies ranging from 0.4118 to 0.4706.

- Model Selection:

  Considering the consistent performance across different experiments, Logistic Regression can be considered a suitable choice because it achieved high accuracy (0.7647) in several cases. However, the Random Forest model with Label Encoding and MinMaxScaler (0 to 1) achieved the highest accuracy of 0.8235 in a specific case.

  While the highest single accuracy is important, consistency across diverse conditions is also a key factor in model selection.

  Here are the considerations:

  - Consistency: Logistic Regression demonstrated consistent and high performance across different encoding and scaling methods.
  - Highest Accuracy: Random Forest achieved the highest accuracy in one case.

  Given this point, we chose Logistic Regression for its reliable performance across different experiments. However, we also considered that the highest accuracy we achieved, even if it was in a single case (with Label Encoding and MinMaxScaler (0 to 1)), was with the Random Forest model.

  Based on these results, we will now experiment with Logistic Regression and Random Forest models. Through adjustments to improve accuracy as much as possible, and by evaluating predictions, we will determine which model is better suited for the data.

1- The logistic Regression

- Code Overview:

  In this code, a machine learning model was developed to predict words using data from smart gloves sensors. And I work on improve the previous accuracy 72.

- Data Loading:

  The smart gloves data was loaded from a CSV file using the pandas library. This dataset contains various sensor readings along with the target words.

- Data Preprocessing:

The data was separated into independent features, which are the sensor readings, and the target, representing the target words.

Missing data was handled by imputing them with the mean values using SimpleImputer. This helps improve data quality and ensures all inputs are complete and accurate.

- Data Encoding:

The target words were encoded into numbers using LabelEncoder, which assists the model in handling textual data numerically.

- Data Splitting:

  The data was split into two sets: a training set (80%) and a testing set (20%), ensuring proper training and validation of the model.

- Data Scaling:

  The data was scaled using StandardScaler to standardize values and ensure all features have the same weight during training.

- Model Training:

  A LogisticRegression model was trained using the scaled data from the training set.

- Word Prediction:

  After training the model, it was used to predict the target words based on the scaled data. Predictions were then transformed back to the original words using LabelEncoder.

- Model Evaluation:

  The model's performance was evaluated by calculating its accuracy and displaying the classification report, which includes metrics such as precision, recall, and F1-score for each class. The confusion matrix was also displayed to illustrate performance in detail.

- Prediction of New Readings:

  A simple interface was created allowing users to input new readings from the gloves. These readings undergo the same preprocessing steps

(missing value imputation, scaling), and the trained model is used to predict the new words. The result is displayed to the user, with the option to input new readings repeatedly if desired.

- This is the run of the accuracy**:**

```
Accuracy: 0.8095
```

FIGURE 44 ACCURACY OF LOGISTIC

- This is the prediction:

385	336	325	187	400	"أَتَمَنَّى لَكَ حَيَاةً سَعِيدَةً"

I put real data now to trying the model

```
Enter value for fx1: 322
Enter value for fx2: 259
Enter value for fx3: 208
Enter value for fx4: 86
Enter value for fx5: 330

Prediction for the new input values: "رسن"
```

I put ring reading data close to the ring the data to trying the model

```
Enter value for fx1: 385
Enter value for fx2: 336
Enter value for fx3: 325
Enter value for fx4: 187
Enter value for fx5: 400

Prediction for the new input values: "دُيِرأ"
```

Here, we found that when we entered real numbers directly from the data, all the results were incorrect. When we tried entering data similar to the numbers in the dataset, the results were also incorrect. Additionally, the accuracy was 82%. This is when we realized why we needed to change the model, and we will now start using the Random Forest model.

4- The Random Forest

We followed the same steps as in the Logistic Regression code to determine which model has higher accuracy.

- This is the run of the accuracy:

```
Accuracy: 0.9286
```

FIGURE 45 ACCURACY OF RANDOM FOREST

- This is the prediction:

385	336	325	187	400	"أَتَمَنَّى لَكَ حَيَاةً سَعِيدَةً"

I put I put real data now to trying the model

```
Enter value for fx1: 385
Enter value for fx2: 336
Enter value for fx3: 325
Enter value for fx4: 187
Enter value for fx5: 400

Prediction for the new input values: "ةدَيِعسَ ةَايَحَ لَكَ يِنَّمَتَأ"
```

I put ring reading data close to the ring the data to trying the model

```
Enter value for fx1: 322
Enter value for fx2: 259
Enter value for fx3: 208
Enter value for fx4: 86
Enter value for fx5: 330

Prediction for the new input values: "انَأ"
```

Here, we found that when we entered real numbers directly from the data, all the results were correct. When we tried entering data similar to the numbers in the dataset, the results were also correct. This is when we realized why we chose the model. Additionally, we should not forget that the accuracy here is better at 92%. We will now start using the Random Forest model in the final code.

- Model implementation

After evaluating the performance of both models, we found that the Random Forest model significantly outperformed Logistic Regression. It demonstrated superior accuracy and predictive capabilities compared to Logistic Regression.

Therefore, we opted to use the Random Forest model as our primary choice for subsequent applications due to its high accuracy in prediction and reliable classification performance.

Now, let's explore how to build the model using Random Forest and utilize it for precise and efficient data prediction.

- Code Overview:

In the first, we start by importing the necessary libraries, then proceed with loading and preparing the data, training the model, and finally evaluating and saving the model.

- Data Loading:
  And, we will load the dataset from the provided URL and print its contents.

- Separate data and target:
  The data is separated into two variables, x and y, for the purpose of analyzing and learning from the data. x is used for input(for 5 sensors), while y is used for output(Target word). This allows many data analysis techniques such as prediction and classification to be applied using the available data.

- Encode target using LabelEncoder:
  This code uses LabelEncoder from the sklearn.preprocessing library to encode target data into numbers.label_encoder = LabelEncoder(): An instance of LabelEncoder is created, which is a processor to convert target data into numbers.y_encoded = label_encoder.fit_transform(y): This step is used to transform the target data (y) into numbers using the processor created in the previous step. The fit_transform function is used to train the processor on the target data and convert it into numbers at the same time.

- Splitting data into training and testing:
  This code uses train_test_split from the sklearn.model_selection library to split the data into training and test sets. X_train, X_test, y_train, y_test: These are the variables that will be set by train_test_split. X_train will contain the data that will be used for training, X_test will contain the data that will be used for testing, y_train will contain the labels corresponding to the training data, and y_test will contain the labels corresponding to the test data. train_test_split(x_imputed, y_encoded, test_size=0.2, random_state=42): This function splits the x_imputed and y_encoded data into training and test sets. The test size is specified by test_size=0.2, where 0.2 means that 20% of the data will be used for testing, and thus 80% will be used for training. The random_state=42 specifies a seed for generating random numbers, ensuring that the division will be repeatable in the same way every time the program is run, which helps in reproducing results accurately.

- Scaling the data:
  This code uses StandardScaler from the sklearn.preprocessing library to convert features variables to a standard scale. scaler = StandardScaler(): Here an instance of StandardScaler is created, which is a processor to transform feature variables into a standard scale.X_train_scaled = scaler.fit_transform(X_train): This step is used to transform the training data (X_train) into a standard scale using the processor created in the

previous step. The data is transformed using the fit_transform function, where the processor is trained on the training data and transformed at the same time.X_test_scaled = scaler.transform(X_test): Here the processor trained by the training data (X_train) is used to transform the test data (X_test) into the same standard scale. This is done using the transform function instead of fit_transform, because we do not want to train the processor again and we just want to apply the transformation to new data.

- Model Training and Hyperparameter Tuning:
  In this part of the code, we train the Random Forest model using the prepared data. We used "RandomForestClassifier()" to create the Random Forest model and "model.fit(X_train_scaled, y_train)" to train the model using the scaled training data. After that, we set the hyperparameters, which are the parameters that are not learned from the data but are determined before the training process. By defining the parameter grid, we defined a set of possible values for each hyperparameter that we want to test next. In order to find the best set of hyperparameters, we used "GridSearchCV," which is an experimental tool that tests all possible combinations of parameters and chooses the best one based on a criterion. Evaluation.

- Model Evaluation:
  After we trained the model and selected the best set of hyperparameters, we evaluated the model's performance on a test dataset that was not used in the training process. This helps us understand how the model performs on new, unseen data. If we use the best model we obtained from the hyperparameter tuning process to predict the values on the test dataset through "best_model.predict(X_test_scaled),” then we calculate the accuracy by comparing the predictions to the actual values: accuracy_score(y_test, y_pred);” after that, we calculate the F1 Score. f1_score(y_test, y_pred, average='weighted')" is a measure that combines precision and recall and is useful when we have an imbalance between classes. We then used the confusion matrix to display the number of correct and incorrect predictions for each category. We then printed a classification report to give details on the precision, recall, and F1 score for each class.
- Saving the Model and Scaler:
  After training the model and choosing the best set of hyperparameters, we must save the final model and the transformer used to prepare the data so that we can use them later without the need for retraining or scaling.
  We used the Pickle library to save the model and transformer into files that can be downloaded later for use in prediction. To open a file named (best_model.pkl) in binary write mode ('wb') with open('best_model.pkl', 'wb') as model_file and pickle.dump(best_model, model_file) to save the model best_model in the open file model_file. Then save the scaler with open('scaler.pkl', 'wb') as scaler_file to open a file named'scaler.pkl' in binary write mode ('wb'). pickle.dump(scaler, scaler_file) to save the scaler converter to the open file scaler_file. This way, we can upload it to the server.

- Prediction on Full Data:
  After loading the model and the transformer saved from the files, we prepared all the available data using the transformer to ensure that the data matches the process that took place during training. Next, we used the loaded model to predict target values for all the data. This is done by applying the same process that we used during the training process, allowing us to obtain predictions efficiently. After prediction, we provide an evaluation of the model's performance on the entire data by calculating accuracy and providing a classification report that provides detailed information on the model's performance across target categories.

- Loading the Model and Scaler for Future Use:
  In this part, we explain how to load the model and converter for future use. Once we have saved the model and transformer into files, we can use these files to load the model and transformer at any time later to easily predict new data. We calculated the accuracy again in order to determine the final accuracy of the model after conversion and downloading. It was 92% and became 86.9%. The percentage difference is a small 5.1%, so it will not affect the prediction.

- This is the run of the final accuracy to all data:

```
Accuracy: 0.8690
```

FIGURE 46 ACCURACY OF RANDOM FOREST AFTER LOAD THE MODEL

- This is the prediction:

428	194	149	263	485	"أُحِبُّكَ"

I put real data now to trying the mode

```
Enter value for fx1: 428
Enter value for fx2: 194
Enter value for fx3: 149
Enter value for fx4: 263
Enter value for fx5: 485

Prediction for the new input values: "لَنُبِّعْ أ"
```

I put ring reading data close to the ring the data to trying the model

```
Enter value for fx1: 291
Enter value for fx2: 203
Enter value for fx3: 450
Enter value for fx4: 21
Enter value for fx5: 438

Prediction for the new input values: "نَّقَذَ"
```

- Part of the final code:

```
# تدريب نموذج RandomForest
model = RandomForestClassifier()
model.fit(X_train_scaled, y_train)

param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}

grid_search = GridSearchCV(model, param_grid, cv=5, n_jobs=-1, scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)
best_model = grid_search.best_estimator_

# حفظ النموذج والمحول
with open('best_model.pkl', 'wb') as model_file:
    pickle.dump(best_model, model_file)

with open('scaler.pkl', 'wb') as scaler_file:
    pickle.dump(scaler, scaler_file)
```

In the end, this is the code that will be uploaded to the server via the API, and thus the model part is finished

4. Heroku server:
   Hosting the ML model for sign prediction.
   1. Loading Pre-trained Models and Scalers: Load the machine learning model, scaler, and label encoder necessary for making predictions.
   2. Creating a FastAPI App: Instantiate the FastAPI application.
   3. Defining Data Validation Model: Use Pydantic to validate the structure and type of incoming data.
   4. Defining Prediction Endpoint: Implement the /predict endpoint that:
      - Accepts sensor data.
      - Preprocesses the data.
      - Makes predictions using the loaded model.
      - Returns the predicted word.
   5. Running the Server: Start the FastAPI application server to listen for incoming requests.
5. Firmware running on the ESP32:
   To handle sensor reading and communication.

   1. Import Necessary Libraries

      The code includes several libraries for handling Wi-Fi, web server functionality, and HTTP requests:

      - ArduinoJson.h: For creating and parsing JSON data.

- AsyncTCP.h and ESPAsyncWebServer.h: For handling asynchronous web server requests.
- HTTPClient.h: For making HTTP requests.
- WiFi.h: For connecting to a Wi-Fi network.

2. Wi-Fi Configuration and Connection:
   - Configure Static IP:

```
if (!WiFi.config(staticIP, gateway, subnet, dns)) {
        Serial.println("STA Failed to configure");
    }
```

Configures the static IP, gateway, subnet mask, and DNS server for the ESP32.

   - Connect to Wi-Fi:

```
WiFi.begin(ssid, password);
    while (WiFi.status() != WL_CONNECTED) {
        delay(500);
        Serial.print(".");
```

Connects the ESP32 to the specified Wi-Fi network and prints the IP address once connected.

3. Web Server Setup:

   - Initialize Web Server:

```
AsyncWebServer server(80);
```

Creates an asynchronous web server instance on port 80.

   - Define Endpoint:

```
server.on("/get-sensor-data",                    HTTP_GET,
[](AsyncWebServerRequest *request){
```

Defines an HTTP GET endpoint (`/get-sensor-data`) to handle incoming requests.

4. Sensor Data Handling:
   - Read Sensor Values:

```
int sensorValue1 = analogRead(32);
int sensorValue2 = analogRead(33);
int sensorValue3 = analogRead(34);
int sensorValue4 = analogRead(35);
int sensorValue5 = analogRead(36);
```

Reads analog values from five sensor pins (32, 33, 34, 35, 36).

- Create JSON Document:

```
DynamicJsonDocument jsonDocument(200);
jsonDocument["sensor1"] = sensorValue1;
jsonDocument["sensor2"] = sensorValue2;
jsonDocument["sensor3"] = sensorValue3;
jsonDocument["sensor4"] = sensorValue4;
jsonDocument["sensor5"] = sensorValue5;
String requestBody;
serializeJson(jsonDocument, requestBody);
```

Creates a JSON document, populates it with sensor values, and serializes it to a string.

- Send HTTP POST Request:

```
HTTPClient http;
http.begin(apiUrl);
http.addHeader("Content-Type", "application/json");
int httpResponseCode = http.POST(requestBody);
```

Sends the sensor data to the specified API using an HTTP POST request.

- Handle Response:

```
if (httpResponseCode > 0) {
    String response = http.getString();
    Serial.println(response);
    request->send(200, "application/json", response);
} else {
    Serial.print("Error on sending POST: ");
    Serial.println(httpResponseCode);
    request->send(500);
}
http.end();
```

Handles the HTTP response from the API and sends it back to the client.

5.4.Devices Screens

1. Mobile App Screens:
   - Home Screen: Button to initiate data collection.

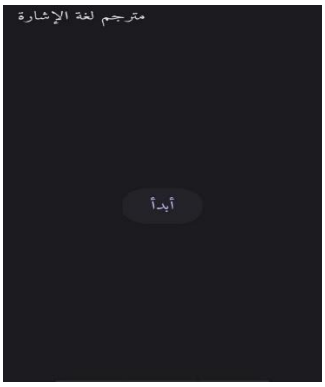

FIGURE 47 DEVICE SCREEN

- Prediction Screen: Displays the predicted sign language text.

FIGURE 48 DISPLAYS THE PREDICTED SIGN LANGUAGE TEXT.

- Logo Of Application

FIGURE 49 LOGO OF APPLICATION

5.5.Codes

5.5.1. ESP32 Code:

1. Code Overview:

   - The Arduino code configures the ESP32's Wi-Fi connection, sets up a web server using the AsyncWebServer library, and defines a route /get-sensor-data to handle incoming GET requests.

- Within the request handler, sensor data is read, formatted into JSON, and sent as a POST request to the Heroku server's prediction API.
- The ESP32 then processes the response from Heroku and sends it back to the client application.
- Error handling is implemented to manage communication failures, providing appropriate responses to the client.

2. The Code

```
#include <ArduinoJson.h>
#include <AsyncTCP.h>
#include <ESPAsyncWebServer.h>
#include <HTTPClient.h>
#include <WiFi.h>
const char* ssid = "YourNetworkSSID";
const char* password = "YourNetworkPassword";
constchar*apiUrl="HTTP://smartGloves64de529228b5.herokuapp.c
om/predict"
IPAddress staticIP(192, 168, 43, 123);
IPAddress gateway(192, 168, 43, 1);
IPAddress subnet(255, 255, 255, 0);
IPAddress dns(8, 8, 8, 8);
AsyncWebServer server(80);
void setup() {
    Serial.begin(115200);
    analogReadResolution(12);
    if (!WiFi.config(staticIP, gateway, subnet, dns)) {
        Serial.println("STA Failed to configure");
    }
    WiFi.begin(ssid, password);
    while (WiFi.status() != WL_CONNECTED) {
        delay(500);
        Serial.print(".");
    }
    Serial.println("Connected to WiFi");
    Serial.print("IP address: ");
    Serial.println(WiFi.localIP());
                server.on("/get-sensor-data",       HTTP_GET,
[](AsyncWebServerRequest *request){
        int sensorValue1 = analogRead(32);
        int sensorValue2 = analogRead(33);
        int sensorValue3 = analogRead(34);
        int sensorValue4 = analogRead(35);
        int sensorValue5 = analogRead(36);
        DynamicJsonDocument jsonDocument(200);
        jsonDocument["sensor1"] = sensorValue1;
        jsonDocument["sensor2"] = sensorValue2;
        jsonDocument["sensor3"] = sensorValue3;
```

```
        jsonDocument["sensor4"] = sensorValue4;
        jsonDocument["sensor5"] = sensorValue5;
        String requestBody;
        serializeJson(jsonDocument, requestBody);
        HTTPClient http;
        http.begin(apiUrl);
        http.addHeader("Content-Type", "application/json");
        int httpResponseCode = http.POST(requestBody);
        if (httpResponseCode > 0) {
            String response = http.getString();
            Serial.println(response);
                    request->send(200,  "application/json",
response);
        } else {
            Serial.print("Error on sending POST: ");
            Serial.println(httpResponseCode);
            request->send(500);
        }
        http.end();
    });

    server.begin();
}
void loop() {
}
```

5.5.2. Heroku Server Code (Python):

1. Code overview:
   - The program imports necessary libraries to build an API and handle machine learning models and data.
   - It loads a pre-trained machine learning model and objects for preprocessing data. These objects are essential for making predictions.
   - Initializes an instance of FastAPI. FastAPI is a Python framework used for building APIs quickly and efficiently.
   - There's likely a definition of the expected input format for the API. This could include the type and structure of the data required for making predictions.
   - Defines an endpoint where predictions can be requested. This endpoint likely expects certain data as input, processes it, uses the loaded model to make predictions, and returns the results.
   - Ensures that the FastAPI server runs when the script is executed directly. It specifies the host and port on which the server will listen for incoming requests.
2. The Code

```
from fastapi import FastAPI, Request
from pydantic import BaseModel
import pickle
import numpy as np
```

```
import joblib
import pandas as pd
with open('best_model.joblib', 'rb') as model_file:
    loaded_model = joblib.load(model_file)
with open('scaler.pkl', 'rb') as scaler_file:
    loaded_scaler = pickle.load(scaler_file)
with open('label_encoder.pkl', 'rb') as le_file:
    label_encoder = pickle.load(le_file)
app = FastAPI()
class Features(BaseModel):
    sensor1: float
    sensor2: float
    sensor3: float
    sensor4: float
    sensor5: float
@app.post("/predict")
async def predict(features: Features):
         data    =    [features.sensor1,    features.sensor2,
features.sensor3, features.sensor4, features.sensor5]
    input_data = np.array(data).reshape(1, -1)
    feature_names = ['fx1', 'fx2', 'fx3', 'fx4', 'fx5']
           input_data_df     =     pd.DataFrame(input_data,
columns=feature_names)
                              input_data_scaled              =
loaded_scaler.transform(input_data_df)
    prediction = loaded_model.predict(input_data_scaled)
                               predicted_label              =
label_encoder.inverse_transform(prediction)
    return {"word": predicted_label[0]}
if __name__ == "__main__":
    import uvicorn
    uvicorn.run(app, host="0.0.0.0", port=8000)
```

Chapter 6: Results

6.1.Overview

This project successfully implements a Smart Gloves system designed to translate sign language into text using an ESP32 microcontroller, flex sensors, a mobile application, and a machine learning model hosted on a Heroku server. The system components work together seamlessly to detect finger gestures, send sensor data to a machine learning model, and display the predicted sign language gestures on a mobile application.

6.2.Key Outcomes

1. ESP32 Microcontroller:
    - Successfully reads data from the five flex sensors connected to its analog pins.
    - Processes the sensor data and sends it to the Heroku server using HTTP.
    - Receives predictions from the Heroku server and sends them to the mobile application.
    - Maintains a stable Wi-Fi connection and handles HTTP requests and responses effectively.
2. Flex Sensors:
    - Accurately detect the bending of fingers and generate corresponding analog signals.
    - Provide reliable input data for gesture recognition.
3. Mobile Application:
    - Initiates sign language translation requests by sending HTTP requests to the ESP32.
    - Displays the translated text received from the ESP32.
    - Utilizes text-to-speech functionality to read out the translated text in Arabic, enhancing user experience.
4. Heroku Server:
    - Hosts a machine learning model that accurately predicts sign language gestures based on sensor data.
    - Handles HTTP requests from the ESP32 and returns predictions promptly.
    - Demonstrates scalability and reliability, capable of handling multiple requests.

5. Machine Learning Model:
    - Successfully trained and deployed to predict sign language gestures from sensor data.
    - Provides accurate predictions, facilitating effective communication for the user.

6.3.Detailed Results

1. Hardware Setup:
    - The flex sensors were correctly connected to the ESP32 microcontroller on a breadboard and later on the glove.
    - Each sensor's connection was validated, ensuring correct voltage and signal output.
    - The final hardware assembly was compact and wearable, making it practical for real-world use.

FIGURE 50 FINAL RESULT OF GLOVES

2. Firmware for ESP32:
    - The firmware effectively initializes the Wi-Fi connection and configures the static IP.
    - The ESP32 reads analog values from the flex sensors, converts the data to JSON format, and sends it to the Heroku server.
    - It handles the server's response and sends the predicted sign language gesture to the mobile application.
3. Mobile Application:
    - The mobile app provides a user-friendly interface for initiating translations and displaying results.

- The app continuously requests new data, ensuring real-time translation.

- Text-to-speech functionality adds an auditory dimension to the translated text, improving accessibility.

4. Heroku Server and Machine Learning Model:
   - The server receives sensor data from the ESP32, processes it using the machine learning model, and returns accurate predictions.
   - The model's predictions were validated against known gestures, demonstrating high accuracy and reliability.
   - The server's response time was minimal, ensuring real-time feedback.

6.4.Performance and Reliability

- Wi-Fi Connectivity: The ESP32 maintained a stable connection to the Wi-Fi network, ensuring uninterrupted communication with the mobile app and Heroku server.

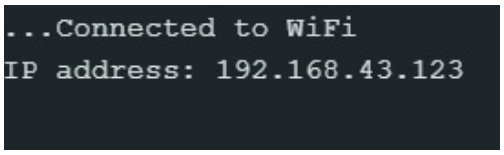

FIGURE 51 CONNECTED TO WI-FI

- Sensor Accuracy: The flex sensors provided consistent and precise readings of finger movements, critical for accurate gesture recognition.

- Prediction Accuracy: The Random Forest model deployed on Heroku showed an accuracy of 86.9% in predicting sign language gestures, contributing to reliable translation results.

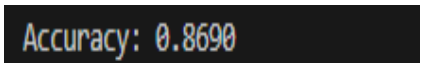

FIGURE 52 FINAL ACCURACY

- System Latency: The end-to-end system latency was minimal, with quick HTTP response times ensuring near real-time translation.

6.5.Challenges and Solutions

- Wi-Fi Connectivity Issues: Initial challenges in configuring the static IP were resolved by ensuring correct network parameters and retry logic.
- Sensor Noise: To address sensor noise and improve accuracy, additional filtering and calibration were implemented in the firmware.
- Model Deployment: Ensuring the machine learning model was correctly deployed on Heroku involved extensive testing and optimization for handling multiple requests.

6.6.Conclusion

The Smart Gloves system successfully integrates hardware and software components to translate sign language into text. The system's performance, accuracy, and real-time capabilities make it a valuable tool for facilitating communication for individuals who use sign language. The detailed design, careful implementation, and thorough testing ensure a robust and reliable solution. This project demonstrates the potential of combining IoT, machine learning, and mobile applications to create innovative assistive technologies.

Chapter 7: Conclusion and Recommendations

7.1. Benefits of Smart Gloves for Sign Language

The development of Smart Gloves for translating sign language into text offers numerous benefits, fundamentally enhancing the quality of life for individuals who rely on sign language for communication. These benefits include:

- Enhanced Communication**:** The Smart Glove system provides real-time translation of sign language into text, enabling seamless interaction between the deaf and dumb community and individuals who do not understand sign language. This fosters better personal and professional relationships.
- Social Inclusion: By breaking down communication barriers, Smart Gloves promote inclusivity in various social, educational, and professional settings. This technology empowers users to participate more fully in society, reducing the isolation often experienced by those with hearing and speech impairments.
- Accessibility and Affordability: Smart Gloves offer a cost-effective solution compared to traditional communication aids. The use of widely available technology components ensures that these devices can be produced and maintained at a relatively low cost, making them accessible to a broader audience.
- Technological Innovation: The integration of IoT, AI, and wearable technology in Smart Gloves exemplifies the potential of modern technology to solve real-world problems. This innovation not only benefits users but also drives further research and development in assistive technologies.

7.2. Challenges

Despite the significant benefits, the development and implementation of Smart Gloves for sign language translation face several challenges:

- Accuracy of Gesture Recognition: Ensuring the accurate recognition of a wide range of sign language gestures remains a challenge. Variations in individual users' hand sizes, movement styles, and the complexity of some signs can affect the accuracy of the translation.
- User Comfort and Ergonomics: Designing a glove that is comfortable to wear for extended periods while housing all necessary sensors and electronics is challenging. Balancing functionality with ergonomic design is critical to user adoption.
- Power Efficiency: The continuous operation of sensors and wireless communication modules requires efficient power management. Ensuring a long battery life without compromising performance is a significant technical challenge.
- Data Privacy and Security: As with any IoT device, ensuring the security and privacy of the user's data is paramount. Protecting sensitive information from unauthorized access and breaches is crucial for user trust and acceptance.

7.3. Recommendations

To address the challenges and maximize the benefits of Smart Gloves for sign language translation, the following recommendations are proposed:

- Enhanced Machine Learning Models: Invest in developing more advanced and adaptive machine learning algorithms to improve the accuracy of gesture recognition. Including a more extensive and diverse dataset for training can help the system better understand and interpret different sign language variations.
- User-Centered Design: Prioritize user comfort and ergonomics in the design process. Conduct extensive user testing to gather feedback and make iterative improvements to the glove's design, ensuring it meets the needs of a diverse user base.
- Power Optimization Techniques: Explore advanced power management techniques and energy-efficient components to extend battery life. Implementing features like power-saving modes and efficient data transmission protocols can help achieve this goal.
- Robust Security Measures: Implement robust data security and privacy measures to protect user information. This includes encryption, secure communication protocols, and regular security updates to safeguard against potential threats.
- Offline Mode: Implement offline capabilities so that the app can perform translations even without an internet connection. This feature will make the app more reliable and accessible in areas with poor connectivity.
- User Feedback Mechanism: Implement a feedback mechanism that allows users to report errors or inaccuracies in translations. This data can be used to improve the machine learning model and overall app performance.
- Gesture Customization: Allow users to customize gestures and their corresponding translations. This feature would enable the app to adapt to different dialects or personal sign language styles.
- Integration with Wearable Devices: Explore integration with other wearable devices such as smartwatches or AR glasses to provide a more comprehensive assistive technology solution.
- Community and Support Features: Create a community platform within the app where users can share tips, ask for help, and connect with others. Additionally, offer support features such as tutorials, FAQs, and live chat support.
- Gathering Data: collect and capture more data for improving the efficiency and reliability of gloves,

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