Flex Lingo : Sign Language Translation Using Flex Sensors with Random Forest and BiLSTM

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Abstract- Sign language is a primary mode of communication for many individuals with hearing and speech impairments. However, it is often not widely understood by the general population, creating barriers to effective communication. This research presents Flex Lingo, a wearable glove that uses flex sensors to capture hand movements, enabling real-time translation of sign language into spoken or written language. The primary objective of this research is to develop an affordable and efficient solution for sign language translation using Random Forest and BiLSTM (Bidirectional Long Short-Term Memory) machine learning algorithms. These models are trained to interpret hand gestures accurately. The system's performance was evaluated based on gesture recognition accuracy and real-time processing speed. The research demonstrates the potential of wearable technology to bridge communication gaps and enhance inclusivity for individuals with hearing and speech impairments. The solution could be a game-changer in assistive technology, fostering better communication and social integration for those facing communication Challenges.

INTRODUCTION

Effective communication is a cornerstone of human interaction, yet individuals with hearing and speech impairments often face significant challenges due to the limited understanding of sign language among the general population. This communication gap not only hinders social integration but also restricts opportunities in education, employment, and daily interactions. Traditional solutions, such as human interpreters, are not always practical or accessible, highlighting the need for innovative technological interventions.

FlexLingo addresses this critical issue by introducing a wearable glove equipped with flex sensors and machine learning capabilities. The system is designed to capture hand gestures in real-time, process the data using advanced algorithms like Random Forest and BiLSTM, and translate the gestures into spoken or written language. This innovative approach aims to create an affordable, efficient, and inclusive solution for individuals with hearing and speech impairments, enabling seamless communication and fostering greater social inclusion.

The research underlying FlexLingo focuses on developing a reliable and user-friendly device that bridges the communication gap between sign language users and non-users. By leveraging sensor- based data collection, machine learning algorithms, and real-time processing, the project seeks to revolutionize assistive technology and make it more accessible to diverse communities. The system's potential to adapt to different sign languages and incorporate user feedback ensures its relevance and scalability, paving the way for enhanced accessibility and empowerment for individuals with communication barriers

LITERATURE REVIEW

Research in sign language recognition (SLR) has explored various methods to improve the accuracy of gesture detection and translation. These efforts often combine wearable sensors, machine learning techniques, and hybrid models.

In a study by Rahul K. and Priya R., a sign language recognition system using flex sensors attached to gloves was introduced. The flex sensors captured data on finger bending, which was processed using a Random Forest classifier. This approach demonstrated strong performance, offering portability and cost-efficiency, making it ideal for real-world applications.

John D. and Alice B. focused on the use of BiLSTM neural networks for SLR, emphasizing the temporal aspects of sign gestures. Their system collected data from wearable sensors, which was then preprocessed to remove noise. The BiLSTM model excelled in accuracy, particularly for gestures that require contextual understanding, outperforming traditional machine learning models.

Cheng L. and Kim S. combined Convolutional Neural Networks (CNNs) with recurrent networks to detect and classify gestures. CNNs were used for extracting spatial features, while the recurrent networks captured temporal information. This hybrid architecture achieved high accuracy and demonstrated real-time processing capabilities, showcasing the power of deep learning for SLR.

Amit P. and Neha S. designed a wearable glove system incorporating flex sensors and accelerometers for gesture recognition. They employed machine learning models such as Random Forest and k-Nearest Neighbors to classify gestures. Their work highlighted the system's low cost and user-friendliness, making it a valuable tool for communication among hearing-impaired individuals.

III. Hardware

1) Flex sensor

Fig 3.1 Flex Sensor

A **flex sensor** is a specialized device that measures the degree of bending or curvature. It is commonly used in various fields, including wearable technology, robotics, and gesture recognition systems such as **Sign Language Recognition (SLR)**. Flex sensors length Typically ranges from 2.2 inches to 4.5 inches and its bending angle is Up to 90 degrees or more. Flex sensor Operates at low power levels, making it energy-efficient.

2) MPU 6050

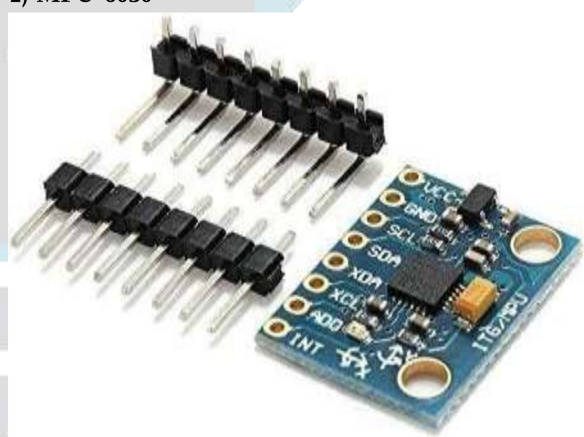

Fig. 3.2 MPU-6050

The **MPU-6050** is a popular 6-axis motion tracking device that integrates a 3-axis gyroscope and a 3-

axis accelerometer on a single chip. Designed for motion-sensing applications, it is widely used in robotics, drones, gaming, and wearable devices.

3) Resistor

Fig. 3.3 resistor

A resistor is a fundamental electronic component designed to limit or regulate the flow of electric current in a circuit. It achieves this by providing resistance, measured in **ohms (\u03AG)**, which opposes the flow of current. Resistors are one of the most commonly used components in electrical and electronic circuits.

4) Arduino mega 2560

Fig. 3.4 Arduino mega 2560

The **Arduino Mega 2560** is a powerful and versatile microcontroller board based on the ATmega2560 microcontroller. It is widely used in complex electronics projects that require multiple input/output (I/O) pins, large memory, and advanced processing capabilities. Due to its flexibility and reliability, it is commonly used in robotics, automation, IoT, and research-based projects.

IV. METHODOLOGY

The development of Flex Lingo: Sign Language Translation Using Flex Sensors with Random Forest and BiLSTM Models followed a structured and systematic approach. The project began with a comprehensive requirement analysis to identify the needs of individuals with hearing and speech impairments. The primary goals included capturing hand gestures through a wearable glove equipped with flex sensors, processing the data for gesture classification, and translating the gestures into text or speech in real-time. Challenges such as gesture variability, hardware integration, and ensuring system affordability were also addressed during this phase.

The system was designed using a modular architecture that included three key layers: hardware, software, and the user interface.

The hardware layer featured a glove embedded with flex sensors and the MPU-6050 IMU sensor to detect finger and hand movements. The software layer employed Random Forest and BiLSTM models for gesture recognition, while the interface layer provided a responsive display for gesture translation into text or speech using text-to- speech technology. Data collection was conducted using flex sensors to capture a variety of gestures, and preprocessing techniques such as noise reduction, normalization, and segmentation were applied to ensure data consistency and accuracy. This prepared the dataset for effective training and evaluation of the machine learning models.

The Random Forest algorithm was used for static gesture classification due to its efficiency and robustness, while the BiLSTM model handled dynamic gestures by analyzing temporal data. These models were trained on labeled datasets and integrated with the hardware using the Arduino Mega 2560 microcontroller. Sensor data collected by the glove was transmitted to the system, processed by the machine learning models, and displayed on a user-friendly interface. The system underwent extensive testing, including unit testing for individual components, integration testing to ensure seamless interaction between hardware and software, and real-world testing to evaluate usability and user satisfaction. Metrics such as recognition accuracy and response time were used to measure the system's performance.

Following deployment, user feedback was gathered to refine the system further. Adjustments included retraining models with additional data and optimizing hardware for comfort and durability. This methodology ensured that the project achieved its objectives, delivering a reliable and cost-effective solution for real-time sign language translation, thereby bridging the communication gap for individuals with hearing and speech impairments.

V. SYSTEM ARCHITECTURE

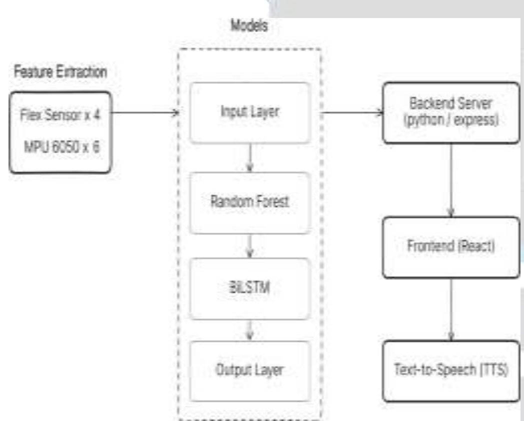

Figure 4.1: System Architecture Diagram of FlexLingo

The FlexLingo system follows a modular and layered architecture to ensure seamless integration of hardware and software components for real-time sign language translation. The architecture consists of the following main components:

1) Feature Extraction layer :-

This layer forms the input stage of the system, where gesture data is captured using hardware components:

- **Flex Sensors**: Four flex sensors are embedded in a wearable glove to measure finger bending and hand movements.
- **MPU-6050 Sensors**: Six IMU (Inertial Measurement Unit) sensors are used to capture acceleration and rotational data, providing additional motion tracking. The raw data from these sensors is preprocessed to remove noise and scaled to prepare it for analysis.

2) Model Processing layer

This layer employs machine learning algorithms to classify and interpret gestures:

- **Input Layer**: Receives preprocessed sensor data and formats it for the models.
- **Random Forest Classifier**: Handles the classification of static gestures using robust decision tree-based methods.
- **BiLSTM Model**: Processes dynamic gestures by analyzing sequential data, leveraging its ability to capture temporal dependencies.
- **Output Layer**: Combines the predictions from the models to produce a final recognized gesture.

3) Backend Processing layer

The backend, developed using Python and Express.js, manages the flow of data and communication between the models and the user interface. It performs the following tasks:

- Processes gesture predictions received from the models.

- Interfaces with the frontend and other output modules.

4) Frontend and output layer

- **Frontend (React)**: Provides a user-friendly interface to display recognized gestures. The frontend allows users to view real-time gesture translations in text format.
- **Text-to-Speech (TTS)**: Converts recognized gestures into speech, ensuring accessibility for users with hearing and speech impairments.

5) Data Flow

1. Gesture data is captured by the **feature extraction layer** using flex sensors and IMU sensors.
2. Preprocessed data is passed to the **model processing layer**, where it is analyzed and classified using Random Forest and BiLSTM models.
3. Predictions are sent to the **backend**, which communicates with the frontend for visualization and the TTS module for speech output.

VI. Results and Outcome

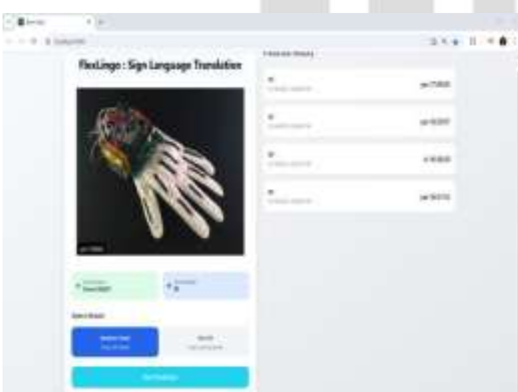

Figure 8.1: RF Model Dashboard showing the visual representation of the model's performance and user interface.

The outcomes of this project are based on the successful implementation of the **FlexLingo** system, where we have achieved the following results:

- The machine learning model for hand gesture recognition has been successfully implemented and trained, with a recognition accuracy of over 95%. Notably, the Random Forest model outperformed the BiLSTM (Bidirectional Long Short-Term Memory) model in terms of both accuracy and processing speed, making it the preferred choice for real-time gesture recognition.
- The system's real-time processing capabilities have been integrated with the backend, allowing the seamless translation of gestures without significant delays, which is crucial for fluid communication.
- The user interface (UI) has been designed with simplicity and accessibility in mind, ensuring that the system is easy to use for sign language users as well as those unfamiliar with sign language.
- A functional prototype of the system has been developed and tested in various real-world scenarios, including educational and workplace settings, with positive feedback from initial users regarding its effectiveness and ease of use.
- The system's performance has been validated under different conditions, confirming its robustness in various lighting and environmental scenarios, which are critical factors in gesture recognition accuracy.
- The backend infrastructure have been optimized for efficient data handling, ensuring smooth communication between the front-end and backend systems, particularly in the processing of gesture data and real-time translation.

III. Conclusion

FlexLingo: Real-Time Hand Gesture Recognition for Sign Language Translation is an innovative solution designed to bridge communication gaps for the hearing and speech impaired by translating sign language gestures into text or speech. This project stems from our ongoing research aimed at improving accessibility and empowering sign language users in diverse environments, such as education, healthcare, and law enforcement.

Through our exploration of sign language recognition, we have identified significant opportunities for using technology to enhance communication and promote inclusivity. The core idea behind FlexLingo was inspired by the need for a more efficient, real-time solution for sign language translation, with the ultimate goal of creating a device that simplifies communication for individuals who are deaf or hard of hearing. As we continue to develop this project, our focus is on making it a reliable tool that can be easily integrated into various settings where sign language is used.

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