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IoT-Enabled Assistive Glove for Real-Time Sign Language Translation Using Machine Learning

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This paper presents a real-time system for translating gestures from American Sign Language (ASL) using an IoT-enabled smart glove. The glove is equipped with five flex sensors and an MPU-6050 gyroscope to capture finger movements and wrist orientation, processed by an Arduino Nano. Sensor data is transmitted via a Bluetooth module to a mobile application, where a Random Forest machine learning model with 97% accuracy classifies the gestures. The recognized gestures are displayed as text and vocalized through a speaker. Moreover, the app has a feature that allows users to see ASL signs with their corresponding vocabulary, thus enabling accessibility and making language more accessible to learn. It enhances the communication between the deaf and the hearing community since it offers an accurate, portable, and interactive sign recognition application.

Keywords: Sign Language (SL), American Sign Language (ASL), Machine Learning (ML)

Introduction:

The deaf and speech-impaired community represents a substantial segment of the global population, with an estimated 430 million people, about 5% of the world's population, experiencing some form of disabling hearing loss [1]. In Pakistan alone, there are approximately 244,196 individuals who are either deaf or have speech impairments [2]. Such individuals, like other members of the community, possess unique abilities and talents that contribute immensely to social value. The lack of adequate means of communication has been a barrier, restricting them from society and its opportunities.

Sign language plays a vital role in the lives of deaf and mute individuals, serving as their primary mode of communication. It enables them to convey their thoughts, emotions, and needs through gestures and expressions, fostering independence and interaction [3][4]. However, the lack of knowledge of sign language among the general population exacerbates communication challenges, creating a gap that hinders inclusivity and mutual understanding.

In the last few years, IoT has made tremendous progress and has created new opportunities to bridge this communication gap [5]. Solutions derived from IoT are equipping individuals with disabilities by providing intelligent devices and supportive technologies that improve their overall quality of life. IoT technologies have opened new avenues for the deaf and speech-impaired community by enabling real-time translation, smart wearables, and mobile apps that support smooth and accessible communication [6].

One of the innovations that gained significant popularity for translating sign language into text or speech is sign language gloves. These gloves have gone through significant evolution from sensors to machine learning techniques to effectively recognizing and interpreting gestures [6]. These systems using wearable technology avoid the problems of visual recognition, such as variability in lighting and dependency on camera functionality.

The objective of this study is to design a novel IoT-enabled smart glove that can translate both static and dynamic American Sign Language (ASL) gestures into real-time text and speech using a Random Forest machine learning model. Thus, it connects the world of the deaf with its counterpart by integrating flex sensors, MPU-6050 gyroscope, and their incorporation into machine learning-based algorithms. By offering a portable, low-latency, and intuitive communication tool, the system seeks to increase accessibility for deaf and speech-impaired people. Unlike previous works, it offers instant feedback through a Bluetooth-connected mobile app that converts gestures into speech and text, while also providing a learning module for non-signers. Its key innovation lies in delivering a low-cost mobile solution that bridges the communication gap between the deaf and hearing communities.

Related Work:

The development of real-time sign language translation through IoT-enabled assistive gloves is the next big leap in communication technology for the hearing-impaired community. This comparative study discusses how such research projects make use of sensor technologies and machine learning algorithms to further enhance the accuracy and efficiency of sign language recognition. We critically reviewed these works to determine their key findings, their limitations, and how our project builds on those foundations to offer improved functionality and user experience.

Based on comparative analyses, the following important details emerge: Several projects effectively work with flex sensors along with motion detection technologies while frequently facing problems concerning accurate gesture recognition and the capability of user in relation to adaptability.

Table 1. A Comparative Analysis of Existing Sign Language Recognition Systems and the Proposed IoT-Enabled Assistive Glove

References	Key Findings	Limitations	How our Proposed Solution Improves Upon It
American Sign Language using Hand Gloves [7]	Used flex sensors to recognize ASL gestures with reasonable accuracy. Focused on static gestures.	Limited to static gestures.	Supports both static and dynamic gestures with MPU6050 and machine learning for real-time processing.
Matiwade & Dixit, (2016) [8]	Created an electronic glove for basic sign language interpretation.	Focused on limited vocabulary; no mobile app integration.	Mobile app allows scalability with a broader vocabulary and additional learning features.
Dalal et al., 2022 [9]	Combines flex sensors and deep learning models for improved gesture recognition and translation capabilities.	Requires extensive training data.	Our Proposed Solution leverages a more efficient ML approach (Random Forest), which requires less training data while maintaining accuracy.
Ambar et al. (2018) [10]	Designed a glove with flex sensors to identify gestures and transmit data wirelessly.	Did not handle dynamic gestures effectively; limited range for data transmission.	Enhances data transmission range with Bluetooth and processes dynamic gestures with the gyroscope.
Amin et al. (2023) [11]	Explored wearable IoT solutions for gesture-based communication.	IoT implementation lacked real-time feedback for users.	Ensures real-time feedback through a mobile app with text and vocalized outputs.
A Wearable Smart Glove and Its Application of Pose and Gesture Detection to Sign Language Classification (2022) [12]	Used machine learning for gesture recognition in sign language.	Relied heavily on training dataset size; lacked gyroscope integration for dynamic gestures.	Optimized Random Forest model performs well even with limited training data; includes gyroscope for dynamic gesture support.
Amin et al. (2022) [13]	Comprehensive review of various sensor- and vision-based methods.	Discussed limitations of individual methods but did not present a unified solution.	Combines the best of sensor-based systems with real-time IoT capabilities for a unified approach.

Study Contributions:

Examples of such illustrative works include those whose primary focus is on basic sign interpretation; however, our project is based on a Random Forest machine learning architecture, which has promising results in the sense that it achieves superior predictive accuracy for various signing patterns. In addition, most commercial products available today do not support real-time feedback.

Our proposed solution fills this gap by providing instant voice output of interpreted signs through an application. This study, therefore, calls for continuous improvements in assistive technologies to adequately address the needs of the deaf community.

Methodology:

System Architecture Overview:

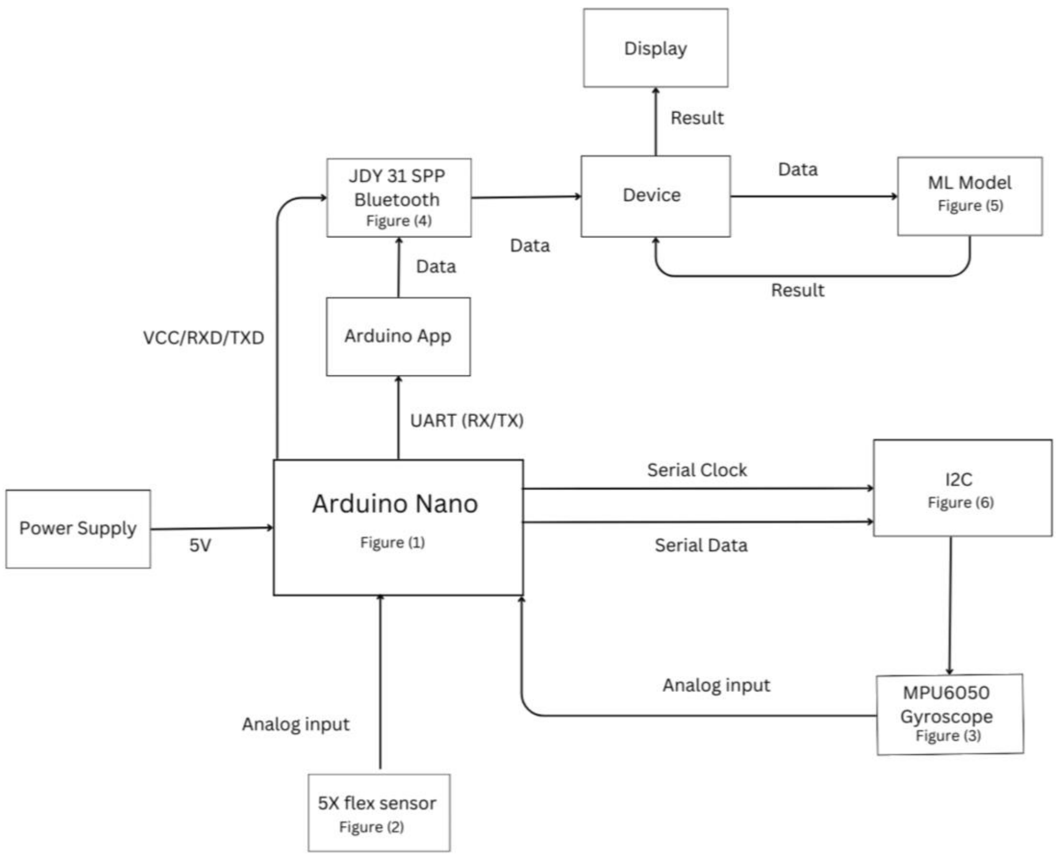

Figure 1. Block Diagram

The IoT-enabled assistive glove system is developed on an interconnected architecture integrating sensors, microcontrollers, and communication modules for real-time gesture recognition and translation. The system comprises three layers: data acquisition, where hand gestures and orientation are captured with embedded sensors; five flex sensors attached to the fingers of the glove for bending angle detection, and an MPU-6050 module measuring wrist orientation and dynamic hand motions. Using the available Bluetooth technology, the transmitted data is received by the mobile application and, using a Random Forest machine learning model, the signs are classified into their related ASL vocabulary with accuracy as high as 97%. It uses a Bluetooth module in the communication layer to enable real-time interaction with the mobile application. It translates identified gestures to text and voices through its text-to-speech capability while also providing features such as word-to-sign mapping for educational purposes. The process flow involves collecting data from sensors, preprocessing it, transmitting it to the mobile application, recognizing gestures, and delivering feedback through the user interface.

Hardware Design:

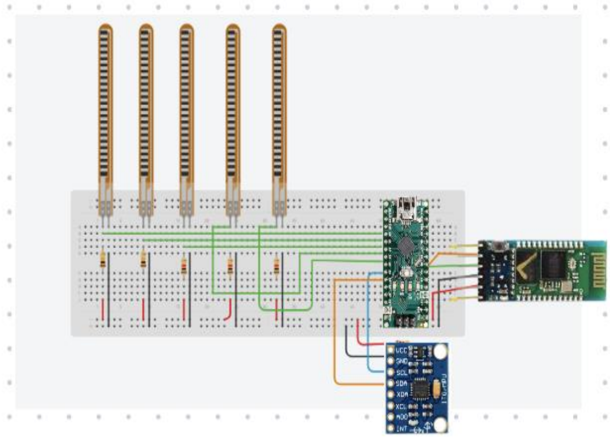

Figure 2. Circuit Diagram

Components Used:

Arduino Nano: The Arduino Nano served as the primary microcontroller, responsible for processing data received from the flex sensor and the MPU-6050 module. It also facilitated communication with the Bluetooth module for data transmission to the mobile app.

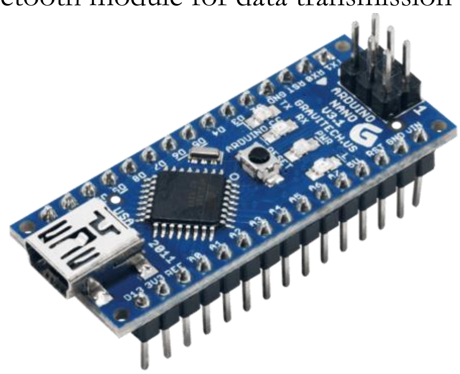

Figure 3. Arduino Nano

Table 2. Arduino Nano Specifications

Parameter	Specification
Type	Microcontroller
Specifications	ATmega328P, 8-bit, 32 KB Flash memory, 16 MHz clock speed
Power Supply	External power or USB
Operating Voltage	5V
Current Consumption	19 mA in active mode
Interface	UART, SPI, I2C

Flex Sensors: The flex sensors are designed to detect finger bending by tracking resistance changes, allowing the system to capture static hand gestures that are important to ASL recognition.

Figure 4. Flex Sensor

Table 3. Flex Sensor Specifications

Parameter	Specification
Type	Sensor (Variable Resistor)
Specifications	Length: 2.2 inches, Resistance: ~10 kΩ (flat) to ~30-40 kΩ (bent), Response Time: Fast (<1 ms)
Power Supply	Passive
Operating Voltage	None
Current Consumption	None
Interface	Voltage divider output to analog input

MPU-6050: The MPU-6050 incorporates a gyroscope and accelerometer for measuring wrist orientation and dynamic hand movements, hence making it possible to clearly distinguish both static and dynamic ASL gestures.

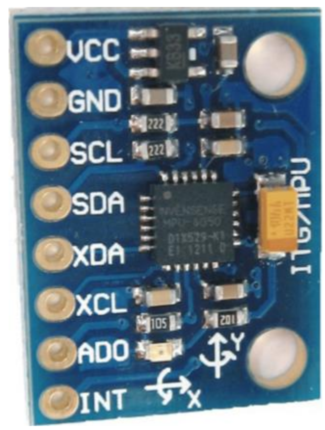

Figure 5. MPU 6050 Module

Table 4. Gyroscope Specifications

Parameter	Specification
Type	Sensor (6-axis IMU: Gyroscope + Accelerometer)
Specifications	Gyro range: ±250°/s to ±2000°/s, Accelerometer range: ±2g to ±16g
Power Supply	External 3.3V/5V power
Operating Voltage	3.3V to 5V
Current Consumption	~3.9 mA
Interface	I2C (SDA, SCL)

Bluetooth Module: This module enables wireless transmission of sensor data from the Arduino Nano to the mobile application so that there will be seamless real-time interaction and feedback.

Figure 6. Bluetooth Module

Sensor Placement: The Flex Sensors are strategically placed along the length of each finger on the glove to measure the bend angles accurately during gestures. The Flex Sensors detect resistance variations to determine finger motion, while static gestures are detected. On the back of the hand, the MP-6050 module is mounted and has a gyroscope and accelerometer. This placement allows for the data from both static and dynamic gestures to be collected extensively so that accurate American Sign Language (ASL) translations can be made. The ergonomic positioning of these sensors ensures comfort and reliability during prolonged use.

Table 5. Bluetooth Specifications

Parameter	Specification
Type	Wireless Communication Module
Specifications	Bluetooth v4.0, Transmission range: ~30 m
Power Supply	External 3.3V/5V power
Operating Voltage	3.6V to 5V
Current Consumption	~10 mA in standby, ~40 mA during transmission
Interface	UART (RX, TX)

Data Acquisition: The data acquisition process for the IoT-enabled assistive glove was based on collecting signals from two types of sensors: flex sensors and an inertial measurement unit (IMU). The flex sensors measured resistance changes caused by finger bending and were positioned along each finger. The MPU6050 IMU, which consists of a gyroscope and an accelerometer, captured angular velocity and linear acceleration to detect wrist movement and hand orientation. Each flex sensor was connected to the analog pins of an Arduino Nano microcontroller. The resistances of the flex sensors fluctuate as a result of each user's finger bend. These changes are in an analog signal that Arduino captures with the analogRead() function to give raw values.

The MPU6050 sensor was initialized using the Adafruit MPU6050 library, which enabled real-time motion data acquisition. The captured motion data included angular velocity along the X, Y, and Z axes, and linear acceleration along the Ax, Ay, and Az directions.

All the processed data was transmitted via a Bluetooth module and accessed on a mobile application, which displayed the recognized gestures in real time.

Data from the IMU was accessed using the MPU.getEvent() function, which performed auto-calibration during initialization to minimize sensor drift and variations in installation. Flex sensors were calibrated using their minimum and maximum values during a steady-state phase. The gyroscope was calibrated by averaging several initial readings to determine offset, reducing sensor noise. Signal preprocessing consisted of two main steps. First, the raw values from flex sensors were scaled between 0 and 1023 using the map () function to normalize inputs for the machine learning model. Second, values were averaged to improve precision and reduce random fluctuations. Gyroscope data was bias-corrected by subtracting offset values to reduce drift over time.

Machine Learning Model:

Model Selection: In this study, the Random Forest algorithm was employed as the machine learning model. Simple, real-time applicable, and very effective, it was chosen for this purpose. This algorithm is very general and is used in all forms of classification and regression with low computational needs. This is because the ensemble approach that is used in this study, where multiple decision trees are combined, has been shown to perform well even for small to medium-sized datasets and thus makes a good choice for the IoT-enabled assistive glove system. Random Forest was chosen for the reason that it offers a good tradeoff between accuracy and the time complexity of the algorithm. While other sophisticated models are computationally intensive, the Random Forest Algorithm works very well with embedded systems. Since the goal of the project was to make it portable with low latency, the system can run in real time without the need for a lot of hardware, which is needed for things such as assistive gloves. The built-in capacity of the algorithm for preventing overfitting made it a good choice. This is because, by aggregating the predictions from many decision trees, the Random Forest reduces the risk of model bias but maintains a high degree of generalization. This robustness is particularly useful in gesture recognition, where data from sensors may be different because of differences in the movement of the user. It can also deal with mixed data types, for instance, the continuous data from accelerometers and the categorical output for gesture labels in this particular application. Random Forest was trained on a diverse dataset of static and dynamic ASL gestures for the case of an IoT-enabled glove. The model had an excellent classification accuracy of 97% in the testing. The level of accuracy is important for gesture detection, which is important for the correct functioning of the system. Furthermore, since the algorithm has simple installation needs and low processing requirements, it was well suited to the embedded nature of the glove, which made it a good match with the Bluetooth module and the mobile application.

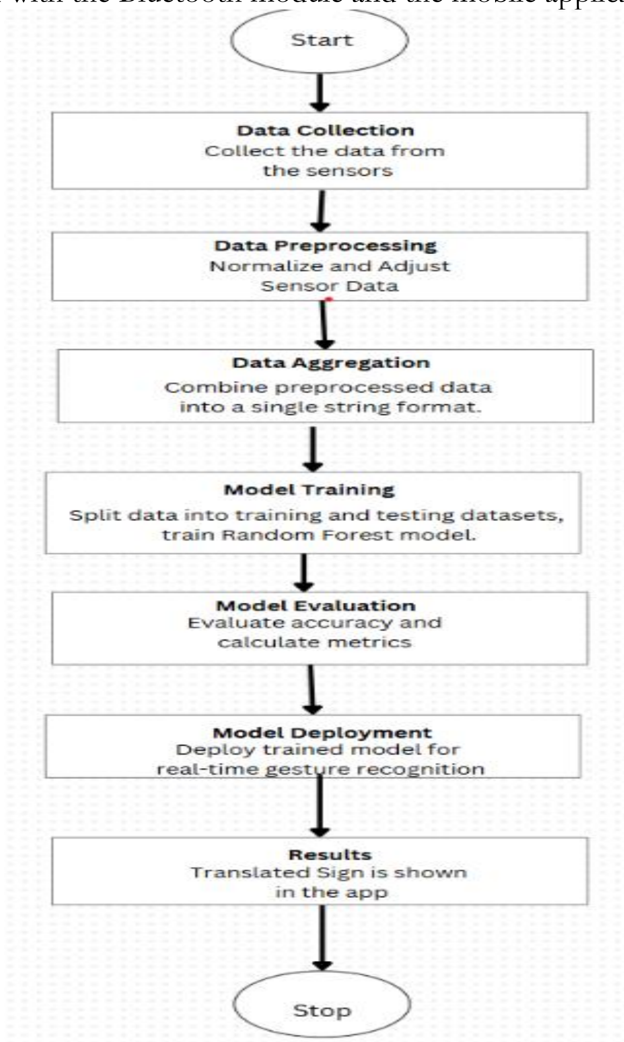

Figure 7. Flow Chart for the Testing and Training Stages

Dataset: This dataset was created to support the training and testing of the Random Forest model for American Sign Language (ASL) gesture recognition. It contained numerous features from the glove to guarantee the precise classification of both static and dynamic gestures. In this dataset, we used the assistive glove with five flex sensors and an MPU-6050 that integrated a gyroscope, an accelerometer, and a timestamp for each measurement to collect gesture data from 5 participants, right-handed males around 18-22 years of age. The recorded attributes include bend angles that were measured with the help of flex sensors placed on the fingers and motion data extracted by the accelerometer and the gyroscope on the axes of X, Y, and Z. The axes signify the movement and orientation of the wrist. The timestamping has been provided to sync with other records, while every record is assigned its appropriate ASL gesture, which will be marked as categorical. The dataset contains approximately 14,000 gesture points as well as static gestures (A through F) and 10 dynamic gestures across frequent words in ASL, such as "hello" and "sorry".

	Timestamp	Flex1	Flex2	Flex3	Flex4	Flex5	AccelX	AccelY	AccelZ	GyroX	GyroY	GyroZ	label
0	2024-12-25 18:47:59	790	792	805	778	772	-1.45	1.88	10.64	-0.57	1.21	0.41	a
1	2024-12-25 18:47:59	784	784	793	774	771	-3.19	1.33	10.11	0.29	1.10	-0.05	a
2	2024-12-25 18:47:59	775	777	785	767	769	-3.21	2.02	9.56	0.04	0.30	0.08	a
3	2024-12-25 18:47:59	772	775	782	767	767	-3.26	1.76	9.42	-0.68	0.11	0.32	a
4	2024-12-25 18:47:59	776	776	785	769	768	-3.88	1.29	9.48	-0.03	-0.19	-0.07	a

Figure 8. Dataset labels

Before training, the following preprocessing steps were applied to the data. First, we normalized the readings for accelerometers and gyroscope sensors. Also, time-based features were obtained through feature engineering in order to improve the ability of the model to identify dynamic gestures. The dataset was divided into an 80/20 train-test split in order to make sure that the evaluation was unbiased. This is a strong base to train the Random Forest model, and it is able to work with different users and gesture variations.

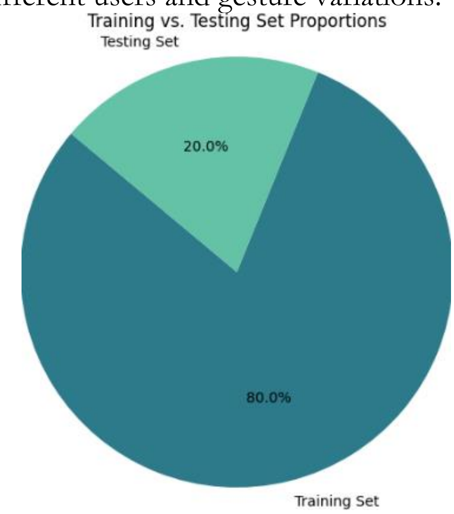

Figure 9. Train and Testing Data Split

To ensure effective data exploration, various kinds of visualizations were developed to represent both the dataset's characteristics and its structural configuration. For instance, Fig. 9 illustrates the proportion of the training and testing sets, clearly showing an 80-20 split.

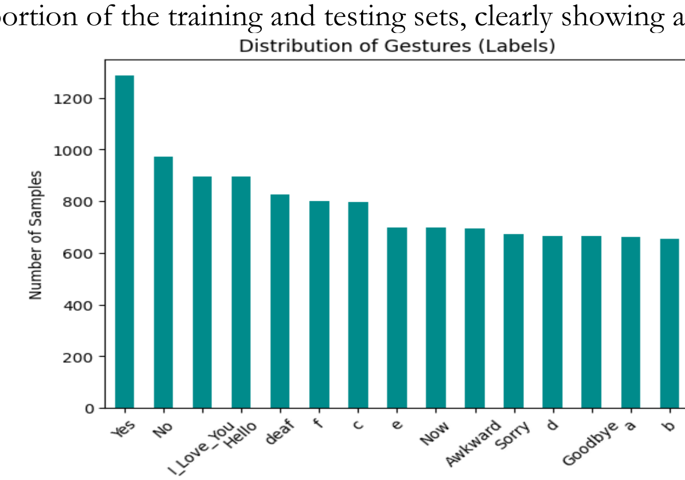

Figure 10. Bar chart showing the label distribution

A bar chart (Fig. 10) was created to demonstrate the distribution of gestures and the number of each kind of gesture present in the dataset.

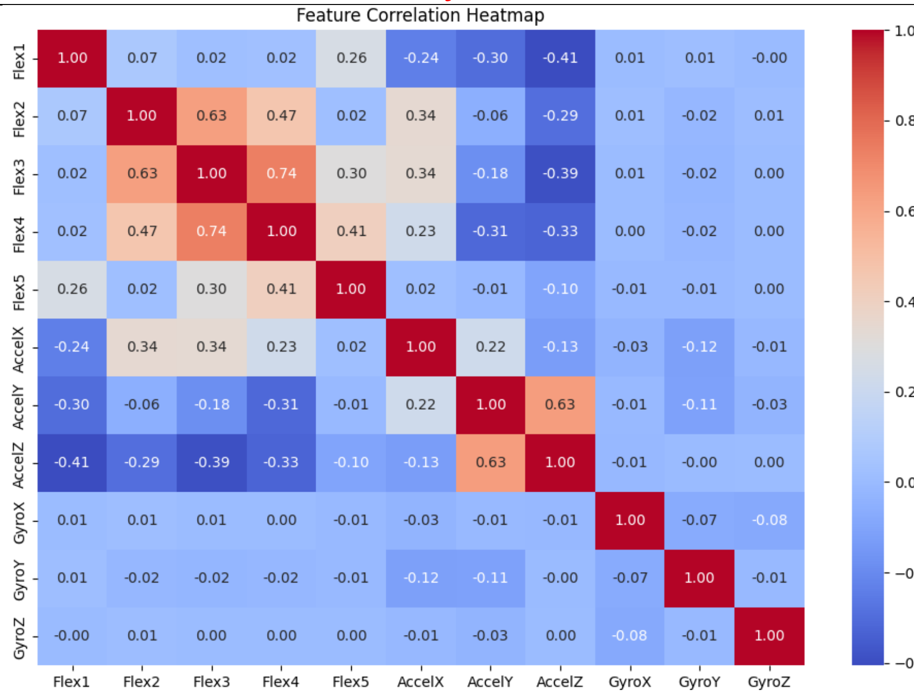

Figure 11. Heatmap between the features of the model

To better interpret the dataset, a feature correlation heatmap (Fig. 11) was employed to highlight the relationships between various input features, including flex sensor values and gyroscope readings. This approach helps reveal any underlying dependencies or overlaps, which can be valuable for optimizing feature selection and improving model performance.

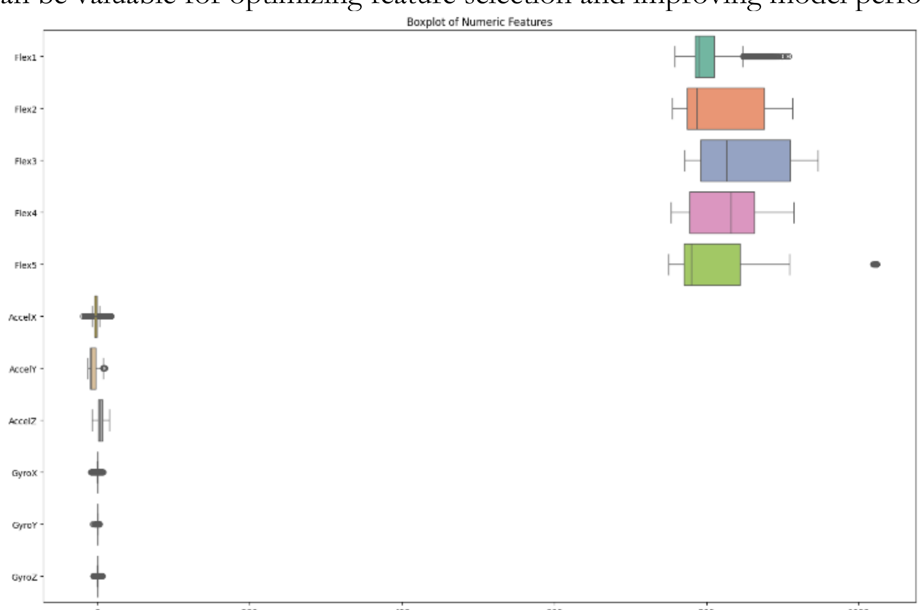

Figure 12. Boxplot between the sensor readings

Boxplots (Fig. 12) for each sensor reading representing variability, median, and outlier values of flex sensor resistance, accelerometer readings, and gyroscope values were investigated further for the statistical properties of numerical features.

Violin plots (Fig. 13) were developed to describe data distribution through a combination of the box plots with kernel density estimation; this described the overall shape of the distribution for every feature.

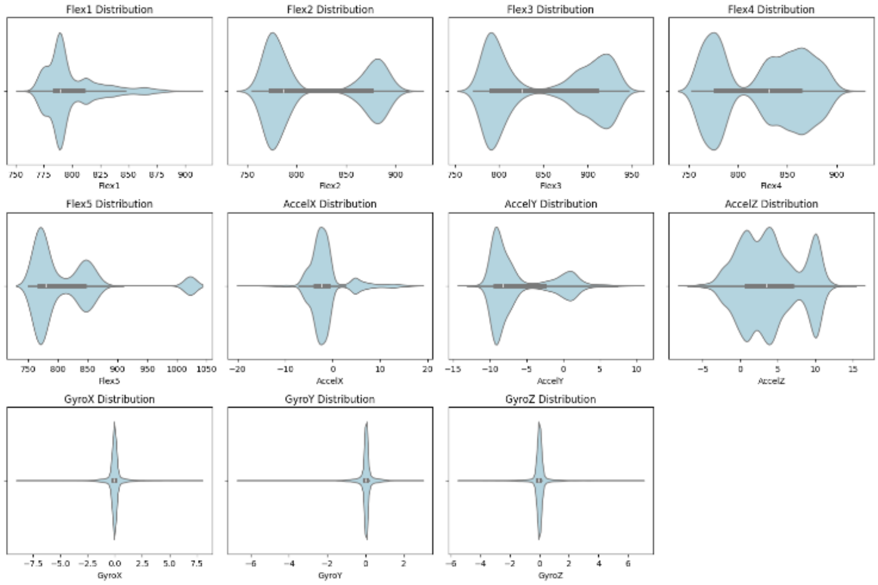

Figure 13. Violin Plot of the readings

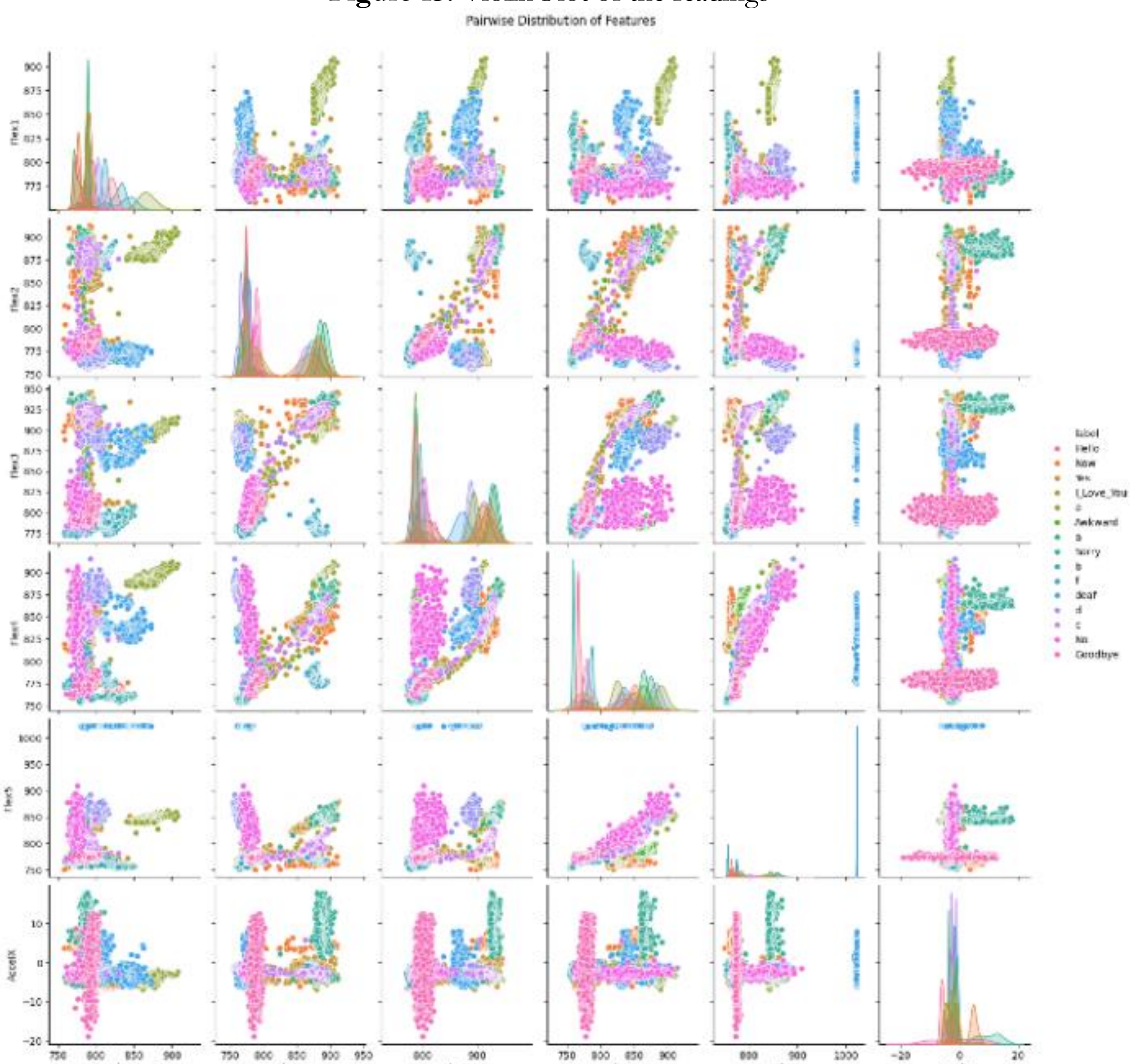

Figure 14. Pairwise distribution of the labels and sensor readings

In addition, pairwise distribution plots (Fig. 14) were generated to illustrate the interaction between feature pairs, thus helping to detect both linear and non-linear patterns that might influence model performance.

Training Process: The training process of the Random Forest model is designed to improve optimal efficiency and robustness of gesture recognition in American Sign Language. The dataset comprises preprocessed values on different attributes like flex sensor resistance, accelerometer measurements, and data captured by the gyroscope, which were extracted using the glove. Normalization helps bring all feature values into a common range to reduce the effects of features with larger scales, making it easier for the model to search for meaningful patterns. The dataset was divided into 80% training data and 20% testing data, which gave a good balance in terms of sufficient training samples and an unbiased evaluation dataset. To improve the model's performance, Hyperparameter tuning was carried out using GridSearchCV, which is a systematic process to completely cover the parameter space. Among these parameters, the number of estimators (the trees in the forest), the maximum depth of the trees, the minimum number of samples required to split an internal node, and the minimum number of samples at a leaf node were optimized. This process tested the combinations of the parameters by three-fold cross-validation to identify the configuration that maximized the model's accuracy while avoiding overfitting. This ensured that the Random Forest model was accurate and efficient, and hence could be used for real-time applications. The model achieved a test accuracy of 97%, indicating strong generalization performance on previously unseen data. The enhanced performance, in addition to the success of the pipeline used in training, justified the use of the Random Forest model for gesture recognition.

Mobile Application:

Features: The mobile application of the IoT-enabled assistive glove serves as the means through which signers or non-signers can reach out to the system effortlessly. It is designed according to accessibility and usability characteristics and incorporates several key features. For signers, it provides real-time, gesture-to-text translation and depicts recognized ASL gestures, presented on the screen as associated text. The app further provides vocalization functionality that converts the recognized gestures into speech. Therefore, the signers can easily communicate with people who do not understand ASL. The application for the non-signers has an educational module where words are assigned to their respective ASL gestures. This enables the user to learn and practice the language interactively. Therefore, it is inclusive and bridges gaps in communication.

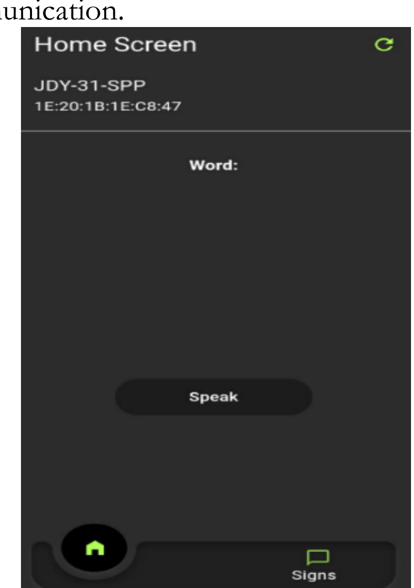

Figure 14. User Interface

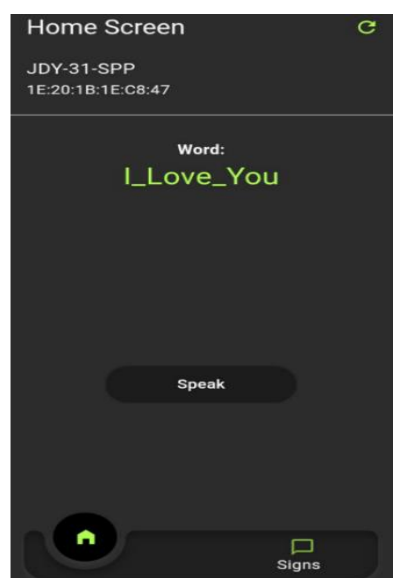

Figure 15. Module for signers

Integration: The integration of the mobile application with the glove system was designed to enable real-time functionality and robust performance. Data collected by the glove's sensors is transmitted to the app via Bluetooth, ensuring wireless and efficient communication. The app receives this sensor data and passes it through the embedded Random Forest machine learning model to classify the gestures through Fast API. Then the application renders the predicted gesture to text, voices this text through text-to-speech technologies, or produces visual ASL references when working within the learning module. This seamless data flow makes sure that the system reacts rapidly to the inputs provided by the user and is highly engaging and usable.

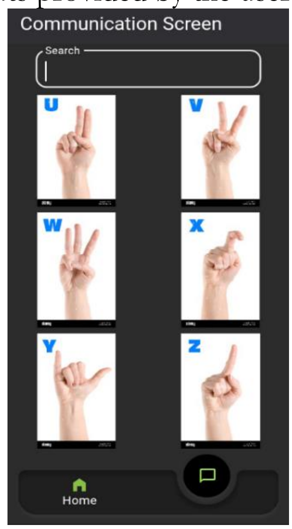

Figure 16. Module for non-signers

Results:

Mobile Output:

The mobile application provided a user-friendly interface that displayed recognized ASL gestures in real-time, improving accessibility and ease of communication. Once a gesture was recognized, it was translated into text and then vocalized. Additionally, the application included a vocabulary section that allowed learners to view ASL signs alongside their corresponding words, thereby supporting learning and practice.

Classification Report:

The effectiveness of the Random Forest model used for gesture recognition was evaluated using a classification report, which measured precision, recall, F1-score, and support for each gesture class. The model achieved an overall accuracy of 97%, with a micro average precision of 98% and a weighted average F1-score of 98% across all classes.

Table 6. Classification Report

Gesture	Precision	Recall	F1-Score	Support
Awkward	1.00	0.96	0.98	140
Bathroom	1.00	1.00	1.00	149
Deaf	1.00	1.00	1.00	136
Goodbye	0.99	1.00	1.00	129
Hello	0.97	0.98	0.98	170
I_Love_You	0.95	0.96	0.95	198
No	0.94	0.95	0.94	202
Now	0.99	0.98	0.98	130
Sorry	1.00	1.00	1.00	132
Yes	0.96	0.98	0.97	231
a	1.00	0.96	0.98	140
b	1.00	1.00	1.00	132

c	0.99	0.99	0.99	156
d	1.00	1.00	1.00	132
e	1.00	0.99	0.99	153
f	0.99	1.00	1.00	150

Confusion Matrix:

The confusion matrix provided a visual representation of the model's classification performance across all gesture classes. Correct predictions were concentrated along the diagonal, while off-diagonal elements indicated misclassifications. For example, the gesture "No" was occasionally misclassified as "I_Love_You," which was reflected in the corresponding cells of the matrix. Similarly, slight confusion was observed between gestures "Hello" and "Goodbye," though these instances were minimal, as indicated by the high precision and recall values in the classification report.

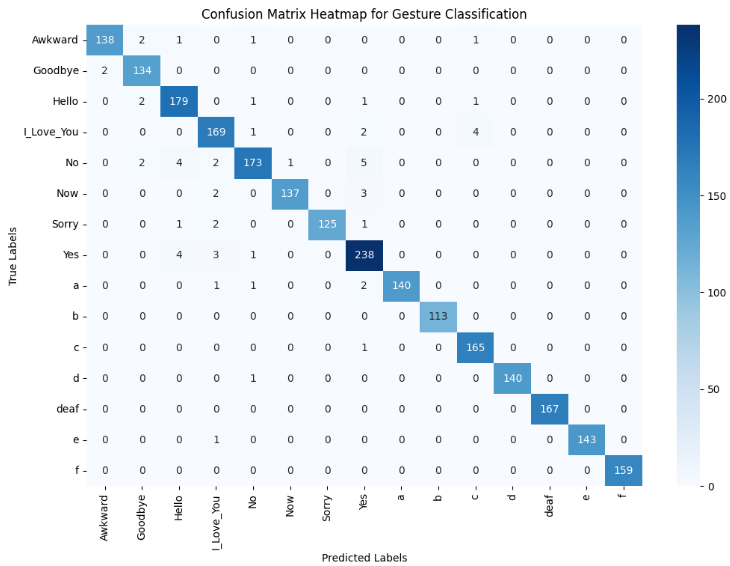

Figure 17. Confusion Matrix Heatmap for Gesture Classification

Discussion:

Compared to existing studies, our proposed solution achieved superior performance in both accuracy and functionality. For instance, while the work of Dalal et al. (2022) [9] used deep learning models requiring extensive training data, our system achieved 97% accuracy using a Random Forest model that performs well even with less data, making it more efficient for real-time applications. Similarly, Matiwade & Dixit (2016) [8] and Ambar et al. (2018) [10] relied on gloves limited to static gestures and offered no mobile app integration. In contrast, our system supports both static and dynamic gestures using the MPU6050 sensor and provides real-time feedback via a mobile application with text and voice output.

Amin et al. (2023) [11] proposed a wearable IoT system but did not include real-time user interaction. Our solution bridges this gap by providing instant recognition and output, enhancing communication for the deaf and hard-of-hearing community. Furthermore, while the study "A Wearable Smart Glove..." (2022) [12] employed machine learning, it lacked gyroscope integration and was heavily dataset-dependent. By incorporating both gyroscope data and an optimized model, our system offers better support for dynamic gestures with reduced computational demand.

Limitations:

Incomplete Data Set: While our model is trained to recognize both static and dynamic gestures, currently, it's only trained to recognize 10 letters and 10 gestures. Furthermore, some hand signs are quite similar to others, and differentiating between them is difficult.

The system requires a stable internet connection to work: Fast API is used to send data to the Python module for predicting the results, and then send data back to the mobile app to be displayed on screen. This process requires the user to have a stable internet connection, which may not always be available to users in remote or low-connectivity regions.

Battery requirement: The glove requires power to function. This means that the battery used to supply power to the glove would need to be replaced every time it runs out, creating an inconvenience for the user.

The system works only on English and ASL While there are multiple sign languages, our system is designed to recognize only letters and words in the American Sign Language (ASL). The system cannot be used to detect signs in other languages. Additionally, regional variations in hand signs are also not taken into account.

Lack of Contextual Understanding: The system currently focuses solely on recognizing individual gestures without incorporating contextual understanding of sentence structure, grammar, or the flow of communication. This limitation prevents the system from accurately interpreting complete phrases or sentences, especially in cases where meaning depends on the sequence of gestures or facial expressions commonly used in sign languages. As a result, the system may misinterpret gestures or fail to provide coherent translations.

Future Improvements:

Dataset Expansion: Use a larger dataset that includes the full alphabet and commonly used phrases in sign language to train our Machine Learning model. The dataset should represent diverse users to improve generalization.

Offline Mode Development: Implement on-device sign recognition by integrating lightweight machine learning models capable of operating on smartphones. This will enable predictions to be performed locally without internet dependence.

Use of piezoelectric sensors: Since piezoelectric sensors can generate power from hand movements, by incorporating them into our system, we can reduce the need for batteries as power sources.

Incorporate more languages into the system: The glove can be expanded to detect different languages by training the machine learning model to recognize these gestures. However, it is quite difficult to find data that takes into account the regional sign variations. This data could be obtained by collaborating with local sign language communities.

Sequential Gesture Recognition: Incorporate advanced natural language processing (NLP) techniques to understand and translate sequences of gestures into meaningful phrases or sentences. This would involve training recurrent neural networks (RNNs) or transformer-based models on gesture sequences to capture context.

Conclusion:

The paper brings a holistic solution to the communication gap between the deaf and hearing communities by developing an IoT-enabled smart glove. The glove captures both static and dynamic ASL gestures using flex sensors, an MPU-6050 gyroscope, and an Arduino Nano. The classification is further ensured by integrating a Random Forest machine learning model into the glove, while text and voice outputs are produced in real time through the Bluetooth-enabled mobile application. An educational module further complements the integration of sign language among non-signers into the community, making people more accessible and inclusive.

The proposed system addresses shortcomings in the current solutions. It is portable, provides real-time feedback, and supports dynamic gestures, hence making it a powerful tool for communication and learning. Its scalable design and performance efficiency underline its potential for widespread adoption and continuous improvement in assistive technologies. This way, the system helps create a deeper relationship between the deaf and hearing communities, which, in itself, is a step towards making society more inclusive.

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