

Wearable Gyroscope-Based Motion Tracking and Hand Gesture Recognition Using ANOVA for Feature Discrimination

Neela Harish¹, Deepa S.², Uma Loganathan³, Kavitha J.⁴,
Praveen Kumar⁵

¹Assistant Professor, Department of Biomedical Engineering, Easwari Engineering College, Ramapuram, Chennai, India.

^{2,3,4}Assistant Professor, Department of Mathematics, Easwari Engineering College, Ramapuram, Chennai, India.

⁵Associate Professor, Department of Electronics and Communication Engineering, Easwari Engineering College, Ramapuram, Chennai, India.

E-mail: ¹neelaharish.m@eec.srmrmp.edu.in, ²drdeepraj25@gmail.com, ³Uma-umasuresh.mani@gmail.com,

⁴Kavitha-kavi.asm08@gmail.com, ⁵rpjcspraveen@gmail.com

Orcid ID: ¹0000-0003-0515-5215, ²0000-0001-6710-4064, ³0009-0000-6940-2575, ⁴0009-0003-4966-6452, ⁵0000-0002-3864-3963

Abstract

Hand gesture recognition has been identified as an important field of research in the healthcare sector, specifically for applications in rehabilitation, assistive communication, and human computer interaction. Upper limb motion tracking provides useful information when determining the recovery of movement in patients suffering from conditions such as stroke, Parkinson's disease, spinal cord injuries, and others. Existing methods utilize camera-based systems or EMG sensors; however, their effectiveness may be hindered by various factors such as lighting conditions, privacy issues, electrode positioning, and computational difficulties. In this paper, a wearable hand gesture recognition system employing an MPU6500 gyroscope to detect tri-axial angular velocity corresponding to five different pre-defined hand gestures: Center, Up, Down, Tilt Left, and Tilt Right. The detected signals are then filtered through a low-pass filter and normalized before statistical features are obtained in the form of mean, variance, root mean square (RMS), and signal magnitude vector (SMV). Statistical significance of the features is assessed through one-way ANOVA while the Artificial Neural Network (ANN) model is used for classifying the gestures. The proposed device was tested on signals obtained from 19 subjects aged between 14 and 16 years. Experimental results have shown that the classification accuracy was 94.2%, while the precision was 93.6%, the recall was 92.8%, and the F1-Score was 93.1%. It can be concluded from the above results that the system employed is a portable system for gesture recognition, thus making it ideal for applications in rehabilitation monitoring, assistive communication, and wearables.

Keywords: Gyroscope-based Gesture Recognition, Wearable Sensors, Inertial Sensing, Artificial Neural Network, ANOVA, Rehabilitation Monitoring, Human-Computer Interaction.

1. Introduction

Hand gesture recognition has emerged as an important area of research in human–computer interaction, rehabilitation engineering, assistive communication, and wearable healthcare systems. Hand movements provide an intuitive means of interaction and can be used to monitor motor performance, control assistive devices, and provide feedback during rehabilitation exercises [1]. In clinical and healthcare applications, continuous monitoring of upper-limb movements can provide useful information regarding movement consistency, coordination, and motor recovery. Therefore, the development of compact and reliable gesture recognition systems is important for applications requiring portable and real-time operation [2]. Existing hand gesture recognition systems can broadly be categorized into vision-based, electromyography (EMG)-based, and inertial-sensor-based approaches. Vision-based systems utilize standard cameras or depth sensors to sense the spatiotemporal features of hand movements. While vision-based methods can supply abundant information about hand posture and gestures, they can also be influenced by factors such as lighting, background, occlusions, camera position, and privacy concerns. EMG-based systems can recognize muscle activation patterns and have been successfully used in gesture recognition and rehabilitation but usually need proper electrode placement and can be influenced by skin impedance changes [3], as well as electrode displacement and motion artifact. Inertial sensors represent yet another means of sensing that can be employed in wearable gesture recognition. Inertial sensors can capture motion-related information without the use of a camera or electrodes. Their small size, low power consumption, and portability allow inertial sensors to be applicable in wearable and embedded gesture recognition systems [4]. In particular, the readings from gyroscopes indicate the angular velocity along multiple axes and thus can measure the directionality and rotation of hand movement. Inertial signals, however, suffer from sensor noise, bias, and drift, and thus need careful assessment of gesture discriminability. The application of machine-learning algorithms has gained attention as a way to convert the output of inertial sensors into gesture categories. Conventional classifiers like support vector machines, k-nearest neighbors, and artificial neural networks may prove efficient [6] in gesture classification and at the same time require much less computation capability than deep learning structures. From the viewpoint of wearable healthcare devices, this is especially needed since the computation capability, power supply capability, and processing time of embedded systems may be limited. While the feasibility of using wearable inertial sensors for activity and gesture recognition has been shown by several research papers, there is still room for a lightweight framework combining statistical feature detection and machine-learning classification for a small number of predefined hand gestures [7]. Furthermore, the practical features of the sensing system itself, such as the acquisition frequency, hardware structure, calibration, operating range of sensors, and processing time, are also significant factors in evaluating its applicability for real-time applications. This applies especially to wearable sensing systems used for rehabilitation purposes. In order to meet these objectives, this research develops a hand gesture recognition framework [8] using the MPU-6500 inertial measurement sensor. Signals from the tri-axial gyroscope are collected from the subjects when they execute five predefined gestures: Center, Up, Down, Tilt Left, and Tilt Right. The collected signals are first filtered and normalized, and then statistical motion features such as mean, variance, root mean square (RMS) [9], signal magnitude vector (SMV), standard deviation, and peak amplitude are extracted. One-way ANOVA [10] technique is used to assess the separability of the extracted

features, while the ANN classifier is used for gesture recognition. The main contributions of this work are as follows:

- A lightweight wearable hand gesture recognition framework based on the MPU-6500 inertial sensor is developed [11].
- Computationally efficient statistical features are extracted from tri-axial gyroscope signals for gesture representation.
- One-way ANOVA is employed to statistically evaluate the discriminative capability of the extracted features [12].
- A feedforward ANN classifier is implemented to categorize five predefined hand gestures.
- The experimental framework is evaluated using data collected from 19 participants, with repeated trials for each gesture.
- The proposed framework is designed with emphasis on portability, low computational complexity, and potential real-time application in rehabilitation and assistive healthcare systems.

2. Related Work

The difficulties faced by hand gesture recognition have attracted considerable interest from various scientists due to its ability to provide contactless and intuitive control. Hand gesture recognition systems are classified into vision-based systems, EMG-based systems [13], sensor-based recognition, and the application of machine learning algorithms to improve their performance. The vision-based hand gesture recognition system uses video recording equipment and depth sensors for detecting the movement of hands using their spatiotemporal properties. Different image processing algorithms that can be augmented with the use of CNNs to increase the precision of gesture detection have already been successfully used in controlled settings. For example, the work [14] demonstrates how effective 3D images are in improving the detection accuracy. The main problem with vision-based systems is their vulnerability to changes in lighting conditions, occlusions, and angles of recording. Gesture recognition via EMG is based on the electrical activity generated by muscle contraction and is used to understand user intentions. Research [15] illustrates the application of artificial intelligence and neural networks in EMG systems for gesture reconstruction. While efficient, this method is sensitive to changes in electrode positioning, subject-specific factors, noise, and motion interference. The requirement for multi-channel electrodes also introduces concerns regarding system complexity and design rigidity.

Inertial sensors have become very popular recently for gesture reconstruction because of their lightness compared to vision-based recognition systems. Inertial sensors use kinematic information, such as acceleration and angular speed, of gestures [16]. Research has proven that inertial sensors are more practical than vision recognition sensors due to their simplicity and portability. Machine learning algorithms have greatly improved gesture classification using all sensors. In the past, traditional machine learning algorithms like SVM, KNN, and ANN [17] have been widely applied for gesture feature classification. Recently, efforts have been made to employ deep learning techniques to learn complex features from sensors by training on raw data. Deep learning algorithms require a large amount of training data and are resource-intensive,

making them impractical in wearable technology. Concerning wearable technology in clinical rehabilitation, many research works have stressed the significance of wearable sensors in tracking patients' progress and motivating them. For example, [18] highlights the importance of continuous feedback mechanisms for improving the recovery results of patients. However, more studies need to be done to come up with wearable devices that would combine efficiency, accuracy, usability, and reliability. The emerging trends in the research field show an effort to create a combination of technologies that will result in minimal hardware complexity and proper functionality. This opens great opportunities for using motion sensor-based techniques together with certain machine learning algorithms.

3. Proposed Work

The architectural design shown in Figure 1. used in the proposed system model makes use of the wearability concept and motion sensors for hand gesture recognition. This is made up of data acquisition, signal pre-processing, feature extraction, classification, and performance assessment [20].

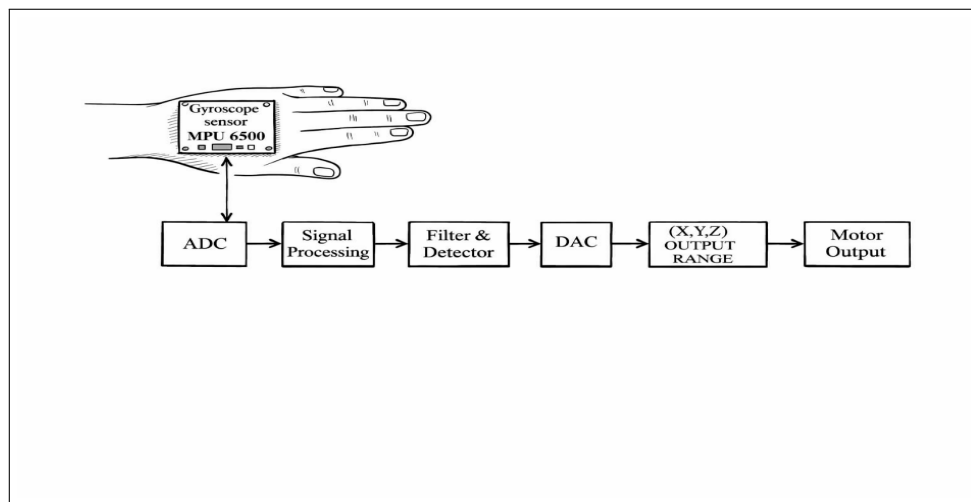


Figure 1. Block diagram

The proposed wearable sensing unit was implemented using the MPU-6500 inertial measurement unit (IMU), which integrates a three-axis gyroscope and a three-axis accelerometer. In the present study, the gyroscope measurements along the X, Y, and Z axes were used for gesture recognition. The sensor was affixed to the dominant hand using a flexible strap. This allowed for a uniform orientation of the sensor among subjects. Gyroscope data were collected at a sampling frequency of 100 Hz. The sensor data were subsequently transmitted to the processing unit, where data conditioning, feature extraction, and gesture recognition took place. To filter out noise and normalize data, a low-pass Butterworth filter with an order of four and a cut-off frequency of 5 Hz, and z-score normalization, were employed, respectively. Then, the extracted statistical features were fed into the ANN classifier. For real-time operation, one needs to consider the system latency, which is defined as the sum of sensor data acquisition time, signal preprocessing, feature extraction, and ANN classification delays. The computational complexity of the signal processing pipeline was reduced by using a small set of statistical features and a two-layered feedforward ANN architecture with 64 and 32 neurons in each layer. The complete classification process was therefore suitable for lightweight embedded implementation. The system latency was evaluated by measuring the

elapsed time between the availability of an input sensor segment and the generation of the corresponding ANN classification result. The measured latency was 134 ms per classification. This latency indicates the processing delay of the implemented recognition pipeline under the experimental hardware configuration.

Experimental data included 19 people performing 5 predefined gestures 10 times each, for a total of 950 gesture instances. Each gesture was captured for approximately 5 seconds with a sampling frequency of 100 Hz, yielding around 475,000 tri-axial raw gyroscope sample points. Following preprocessing, six statistical attributes (mean, variance, RMS, SMV, standard deviation, and peak value) were calculated from each gesture instance to create the feature vector. The 950 feature vectors were then split into training and testing datasets in an 80:20 ratio, consisting of 760 and 190 samples, respectively.

This system used the MPU-6500 IMU to detect hand movements. Although this device has three-axis gyroscope and accelerometer sensors, only the X, Y, and Z-axis gyroscope data were used for hand gesture recognition.

The gyroscope was set to have a full-scale range of $\pm 250^\circ/\text{s}$ with a corresponding digital output resolution of a 16-bit signed integer output. Before each recording session, the sensor was maintained in a stationary position for calibration. The zero-rate output obtained during the stationary period was used to estimate the sensor bias for each gyroscope axis. The estimated bias was subsequently compensated from the acquired angular velocity measurements before filtering and feature extraction. The sensor was mounted in the same orientation for all participants to minimize variations caused by sensor placement.

- Sensor drift was evaluated by monitoring the gyroscope output while the sensor remained stationary before and after the experimental recordings. The mean angular velocity and standard deviation during the stationary period were calculated for the X, Y, and Z axes. The difference between the initial and final+ stationary measurements was used as an indicator of zero-rate drift. The observed drift values were
- X-axis acceleration: Register 0x3B (high byte) and 0x3C (low byte)
- Y-axis acceleration: Register 0x3D (high byte) and 0x3E (low byte)
- Z-axis acceleration: Register 0x3F (high byte) and 0x40 (low byte) for the X, Y, and Z axes, respectively.

The calibration and drift assessment were performed to ensure that the measured angular velocity primarily represented hand movement rather than sensor bias. These procedures also improved the consistency of the extracted features across participants and repeated gesture trials. The proposed approach aims to implement a lightweight and wearable system for recognizing hand gestures using inertial sensor data and intelligent algorithms. To detect hand gestures, a lightweight and wearable IMU with an integrated three-axis accelerometer and gyroscope (MPU-6500) is used. Inertial sensor data, comprising linear acceleration and angular velocities in three axes (X, Y, Z), were recorded during gesture performance. This can be measured by the below expression

$$S(t) = \{a_x(t), a_y(t), a_z(t), \omega_x(t), \omega_y(t), \omega_z(t)\} \quad (1)$$

In the above Equation (1), $a_x(t), a_y(t), a_z(t)$ represents linear acceleration values,

while $\omega_x(t)$, $\omega_y(t)$ and $\omega_z(t)$ represent angular velocity values. This expression is a full representation of hand kinematics, and this allows the dynamics of motions to be explained in various gestures. To ensure good quality of signal transmission, preprocessing of the acquired signal is done. Filtering of the acquired signal is done using a low-pass filter. This is done to filter out high-frequency noise and artifacts that can be represented as

$$S_f(t) = S(t) * h(t) \quad (2)$$

where $h(t)$ is the impulse response function of the filter and ‘*’ denotes convolution operation. Later, normalization is done for standardization of the signal distribution and reduction of subject variability, which can be calculated by

$$S_n(t) = \frac{S_f(t) - \mu}{\sigma} \quad (3)$$

where μ and σ denote the mean and standard deviation of the signal, respectively. After that, feature extraction is conducted to produce a reduced dimension feature vector from the signals. Features extracted from the signals include statistical and temporal information. The mean of the signal is given by

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i \quad (4)$$

While the variance, which measures signal dispersion, is obtained by

$$Var(X) = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2 \quad (5)$$

Root mean square (RMS), measuring the signal energy, can be expressed by

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (6)$$

Signal movement magnitude vector (SMV), representing the total magnitude of movements along the axes, can be expressed by

$$SMV = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (7)$$

All of these features can represent dynamic aspects of hand movements, but they compress dimensions and remove redundancies in data. The set of feature vectors generated from the above algorithm is used to recognize hand gestures through a supervised learning algorithm. In our case, the ANN algorithm is employed due to its capability of modeling extremely complicated nonlinear functions of input data and gestures. The output of a neuron of the model is represented by

$$y = f \left(\sum_{i=1}^n w_i x_i + b \right) \quad (8)$$

where w is the synaptic weight, x is the input vector, b represents the bias term, and

$f(\cdot)$ is the activation function. The model's parameters are updated via the minimization of the mean squared error loss function:

$$L = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (9)$$

where y_i and $\hat{y}_i$ represent the actual and predicted values, respectively. The objective here is to achieve an accurate mapping of the representation space to the corresponding gesture category. The efficiency of the proposed method will be analysed using various classification evaluation measures. The classification accuracy can be described as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

while precision and recall are expressed as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (11)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (12)$$

The F1-score, representing the harmonic mean of precision and recall, is given by

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (13)$$

The symbols TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative, respectively, in Eqs. (10),(11),(12). This set of parameters gives us a thorough evaluation of the performance of our classifier. The whole system is realized in a low power embedded system for real time operation while consuming minimum energy. The proposed method is validated through experiments involving multiple subjects and gestures in order to examine the generalizability of the system. Moreover, one-way analysis of variance (ANOVA) is used to investigate whether there are any statistical differences in the extracted features from different gesture categories. The F-value is determined by dividing the between-groups mean square by the within-groups mean square as in Eq (16). This confirms the discriminative capability of the extracted features.

3.1 Feature Extraction

After the pre-processing stage, features were extracted from the segmented gyroscope signals do allow for the characterization of the magnitude and dynamics of the performed gestures. The selected features were chosen because they can capture a compressed description of the three-axis signals, while maintaining a low computational cost for real-time implementation on embedded systems. These features include:

- Mean – denotes the average angular velocity of the signal segment.
- Variance – describes the distribution of the angular-velocity samples about their mean value.
- Root Mean Square (RMS) – denotes the effective value of the angular-velocity signal.

- Signal Magnitude Vector (SMV) – describes the magnitude of the three-axis gyroscope signal.
- Standard Deviation – describes the distribution of the angular-velocity samples and provides an extra measure of signal variability.
- Peak Amplitude – denotes the maximum absolute angular velocity of the signal segment.

The resultant features were combined into the feature vector that can be written in the following manner

$$F = [\mu, \sigma^2, RMS, SMV, Peak] \quad (14)$$

These features effectively capture directional movement characteristics and improve class separability among gesture categories.

3.2 Artificial Neural Network Classifier

Classification of the gesture was performed using a feedforward Artificial Neural Network (ANN). The architecture of the ANN was as follows:

- Input layer: Statistical feature vector
- Hidden layer 1: 64 neurons with ReLU activation
- Hidden layer 2: 32 neurons with ReLU activation
- Output layer: Softmax classifier with 5 gesture categories

The data was split into 80% training data and 20% testing data. The optimizer used in the training phase was Adam with a learning rate of 0.001 for 100 epochs. Categorical cross entropy was used as the cost function. The output of the ANN neuron is calculated through the application of the ReLU activation function on the weighted sum of the inputs and the bias term, as given in Eq. (15)

$$y = f(\sum w_i x_i + b) \quad (15)$$

In this case, w_i represents the synaptic weights, x_i is the input attribute, b is the bias and $f(\cdot)$ is the activation function. The ANN classifier was selected owing to its capability of modeling the nonlinearity between the gyroscopic features and gestures.

3.3 Performance Evaluation Section

Table 1. Performance of the proposed ANN classifier

Metrics	Value
Accuracy	94.2%
Precision	93.6%
Recall	92.8%
F1-score	93.1%

As is clear from Table 1, the proposed ANN classifier was able to provide an accuracy of 94.2%, a precision rate of 93.6%, recall of 92.8%, and an F1-score of 93.1%. From these findings, it can be seen that the proposed model is effective in categorizing the predefined gesture

classes using wearable gyroscope sensors.

4. Interpretation of Tabulated Data

The gyroscope data acquired from 19 subjects reveals obvious variations in motion dependent on gestures, on the X, Y, and Z axes. Although the dataset presented in Table 2 contains representative samples of subject data for the purpose of clarity, the entire dataset for all 19 subjects was considered for the purposes of analysis. Table 2 contains only representative samples of data acquired from 19 participants. However, the full dataset was taken into account during analysis and ANN-based classification. Zero values of angular velocity were obtained for the Center gesture because there was no significant motion involved. On the other hand, Up and Down gestures involved strong variations in motion on the Y-axis because of the vertical position of the hand, while Tilt Left and Tilt Right gestures generated significant deviations on the X-axis. Despite small differences between subjects in terms of motion patterns, they appeared to be highly repeatable for all the subjects. Analysis based on mean and standard deviation values revealed that there was not much overlap between gesture distributions. Moreover, confidence interval analysis also demonstrated the stability of features across different subjects, which meant reliable separability of gestures. The obtained statistical features showed good discriminative ability, allowing the proper separation of gestures.

4.1 Sensor Performance and Reliability

Based on this experiment, the findings show that the MPU-6500 gyroscope is highly sensitive and stable for use in detecting real-time hand motion. This is because the sensor is highly stable, regardless of differences between test trials and individuals. Moreover, since the device is not influenced by its surrounding environment and noise, it is superior to visual and electromyography sensors.

4.2 Implications for Real-Time Gesture Recognition

From the experiment discussed above, it is clear that the signals produced by the gyroscope are discriminatory and can be utilized for recognizing different types of hand gestures. The ability to discriminate between various features, including separation in axes, magnitude, and directions makes the classification process more accurate in this specific instance. In this respect, it should be pointed out that the findings obtained from the experiment are essential for demonstrating the effectiveness of the discussed approach in practice, especially in the health sector. In general terms, the information provided in the table demonstrates that the gyroscope works effectively in recognizing different hand gestures. From the axes separation, it is evident that the suggested approach can be applied in practice.

Table 2. Gyroscope metrics for hand gesture positions and orientations

Subject	CENTER			UP			DOWN			TILT LEFT			TILT RIGHT		
	X	Y	Z	X	Y	Z	X	Y	Z	X	Y	Z	X	Y	Z
1	-23	-337	85	-163	-36	87	24	-96	-91	-13	-313	-76	-212	-15	-11
2	-1456	-328	407	-103	-80	-28	-30	-190	-91	-143	-137	-57	-49	-190	-31
3	868	-541	315	-180	8	56	-144	-82	-36	-304	-95	4	-526	-414	-24
4	-70	-216	-72	-94	69	-73	-123	-109	-42	-25	408	-5	-542	-560	-114
5	-41	7	-29	-42	-216	-161	-75	-121	0	5	-49	-75	-398	139	-516
6	23	-269	-193	-109	-223	-113	-86	-162	-37	-131	-74	-57	6	-161	-25

7	-47	-52	-51	-16	-32	-53	-80	-190	-1	-47	-78	0	-47	-74	-65
8	-21	-69	-117	-23	-255	-171	75	-447	-87	-566	-252	-15	321	182	-394
9	-47	-256	3	-126	-168	-62	-84	-295	107	-103	-106	-51	-12	-180	-130
10	22	-170	61	142	-62	-164	331	1917	501	-35	-70	-100	196	-112	-39
11	-126	-89	-48	-8	-355	-149	-463	2621	649	-109	-145	-14	-153	-195	12
12	-49	14	27	-51	206	-59	-71	-290	-151	-71	-15	-127	-118	-174	-12
13	143	-291	37	-110	-232	-137	-88	-156	-119	-178	-40	-3	-8	-241	15
14	61	-136	-18	-153	-79	-12	-164	-226	-99	-141	-75	-80	-111	-188	-48
15	-80	-218	-30	-122	-174	-73	-26	-186	-9	-120	-146	-34	125	2	-10
16	12	-89	-16	-35	-197	-111	-181	-181	-154	228	-470	-31	-105	-136	-19
17	-170	-210	29	-85	-97	114	-153	-73	24	-70	-171	27	-163	-228	18
18	292	-453	58	-153	-70	-64	-181	-219	-126	-90	-254	11	349	105	-21
19	-171	-150	-33	-136	-176	-25	-118	-158	33	-82	-150	-1	-15	-68	-12

4.3 Pseudocode

Algorithm: Real-time gyroscope data acquisition for hand gestures

Input: Gesture sequence (Center, Up, Down, Left, Right) Output: Structured CSV file containing tri-axial gyroscope data

Step 1: Start the data acquisition program

Step 2: Initialize communication with the MPU-6500 sensor

Step 3: Prompt the user to enter a unique subject identifier (ID)

Step 4: Create an empty data structure to store sensor readings

Step 5: Define the gesture sequence:

Center → Up → Down → Left → Right

Step 6: Repeat the following for all gestures defined within the predefined sequence:

- Show instructions to the user to make the specified gesture
- Wait until the user stabilizes the hand position
- Prompt the user to press ENTER to confirm readiness
- Acquire gyroscope readings (ω_x , ω_y , ω_z) from the sensor
- Record timestamped data along X, Y, and Z axes
- Store the captured data along with gesture label and subject ID

Step 7: Repeat Step 6 until all gestures are completed

Step 8: Organize the collected data into a structured format (rows: samples, columns: gesture and axis values)

Step 9: Generate a CSV file with filename based on subject ID (e.g., *person_ID.csv*)

Step 10: Save the recorded dataset to the CSV file

Step 11: Terminate sensor communication and stop the program

This pseudocode ensures a systematic, repeatable, and user-guided data acquisition process, enabling accurate capture of gesture-specific gyroscopic signals for subsequent analysis and machine learning-based classification. The process involves running the Python data acquisition software program used to acquire the gyroscopic data. The first step requires the user to enter a unique identification number. This is then followed by having the individual perform a specific sequence of hand movements, including center, up, down, left, and right. The validation of these movements is carried out by having the individual press the Enter key when the hand movements stop. In the process of gathering data using the MPU-6500

sensors, angular velocity information of the hand movement is gathered along the three axes: x, y, and z. At the end of the gesture recording, the collected data is automatically exported in CSV format with a unique identification for each person based on their identifier (for instance, person_7.csv). This helps in organizing the data and making future analyses easier. Data from the individual sensors are consolidated into tabulated form based on subject number, gesture, and motion axis. All the values generated by the sensor are attributed to specific gestures and axes. This ensures that data acquisition is systematic, accurate, and reproducible. This will be extremely useful during data analysis and the determination of thresholds for differentiating between various gestures.

4.4 Statistical Analysis Using Anova

4.4.1 Data Preparation

Angular velocities recorded from 19 participants using five gestures (Center, Up, Down, Tilt Left, and Tilt Right) were studied using statistical methods to determine variance in gesture positions. Angular velocities in the three axes (X, Y, and Z) were categorized into gestures. This information was then fed into the single factor ANOVA study.

4.4.2 ANOVA Method

One-way ANOVA was carried out to test for statistically significant differences among the various groups of gestures. The F-value was computed as the ratio of between group mean square and the within group mean square according to Eq. (16).

$$F = \frac{(MS_{between})}{(MS_{within})} \quad (16)$$

Where:

- $MS_{between}$ = mean square between groups
- MS_{within} = mean square within groups

The larger the value of F, the more the differences between the gesture groups.

Table 3. ANOVA summary for hand gesture classification

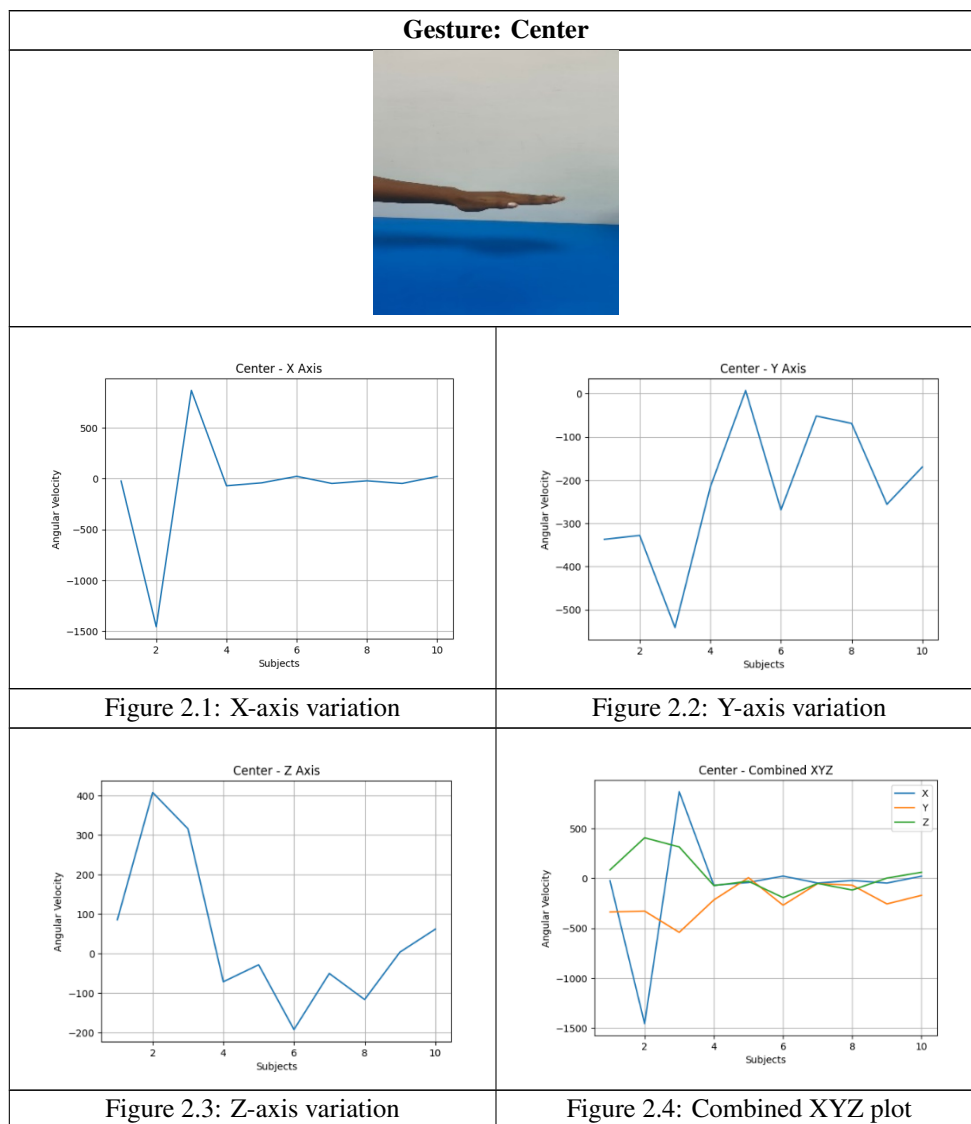
Source of Variation	Sum of Squares	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	P-value	F Critical
Between the Groups	1523450	4	380862.5	8.72	0.00012	2.45
Within Groups	7854321	90	87270.23			
Total	9377771	94				

Table 3 shows the ANOVA results used to test for significant variations in features across hand gesture categories. The total variation in the dataset is divided into two parts: between-group variance and within-group variance. The total sum of squares is 9,377,771, with 94 degrees of freedom. The between-group variance, representing the difference between different types of gestures, has a sum of squares of 1,523,450 and 4 degrees of freedom. The mean square of the between-group variance is 380,862.5. The within-group sum of squares was 7,854,321, with 90 degrees of freedom, yielding a within-group mean square value of 87,270.23. The obtained F-value was 8.72, which was significantly higher than the critical

F-value of 2.45. Thus, the null hypothesis was rejected, indicating statistically significant differences among the hand gesture groups. This means there was considerably more variability between the hand gesture groups than within the groups. Additionally, the p-value of 0.00012 is smaller than the 0.05 alpha significance level. The obtained results confirm that the derived features indeed possess adequate discriminative capabilities needed for effective gesture recognition. A large between-group variance compared to the within-group variance indicates good separability among gestures, providing evidence of good performance for the proposed hand gesture recognition system utilizing wearable technology.

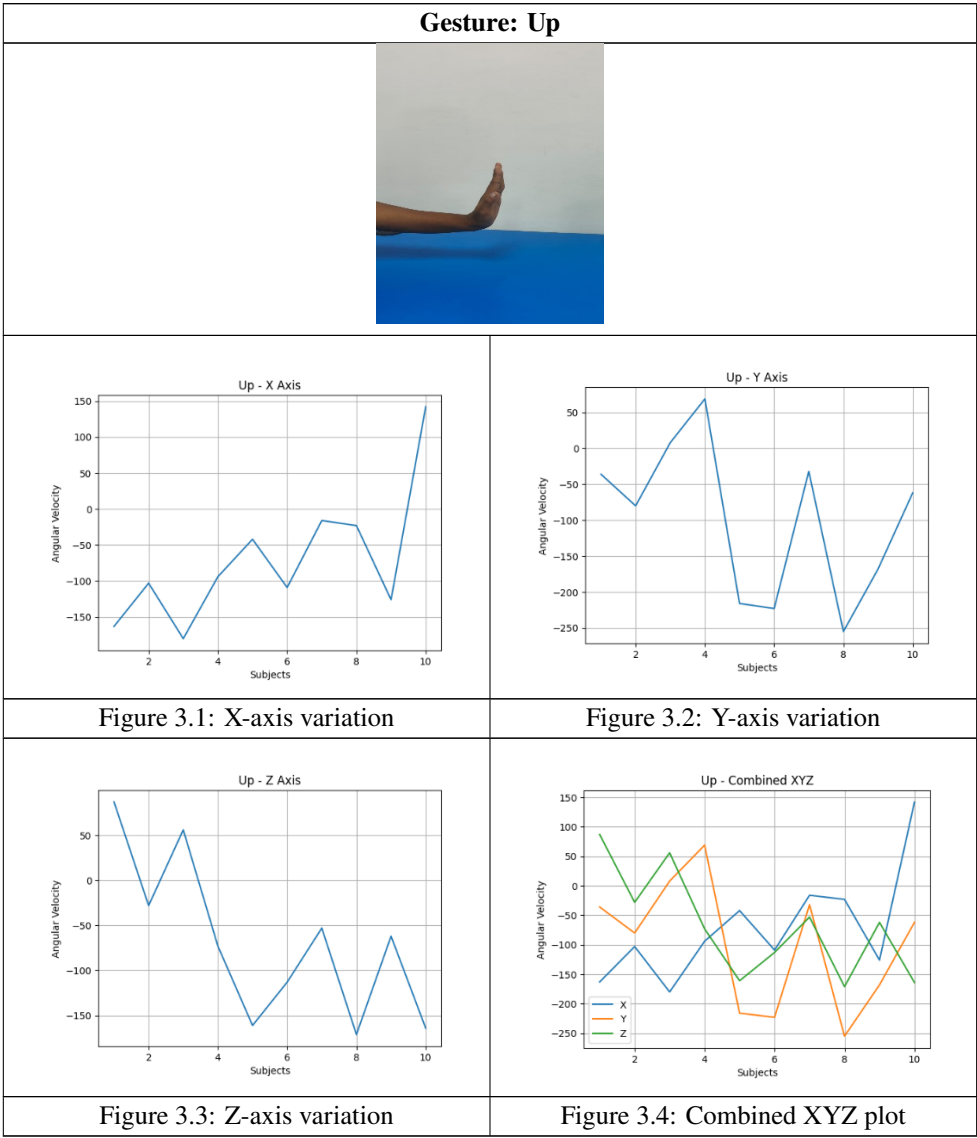
4.5 Graphical Representation of Gestures

Graphical representation of the signal produced by the gyroscope gives a bigger picture regarding the variation of the signal with respect to each axis according to the movement made using the hand. Different types of gestures are examined based on the graph of the signal produced by each axis and the XYZ axes.

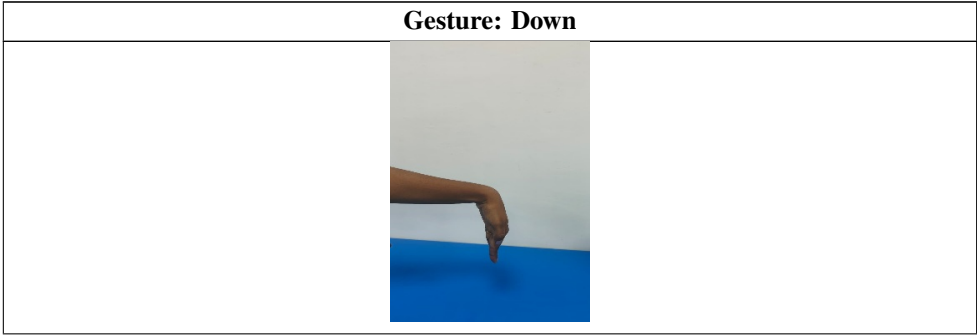


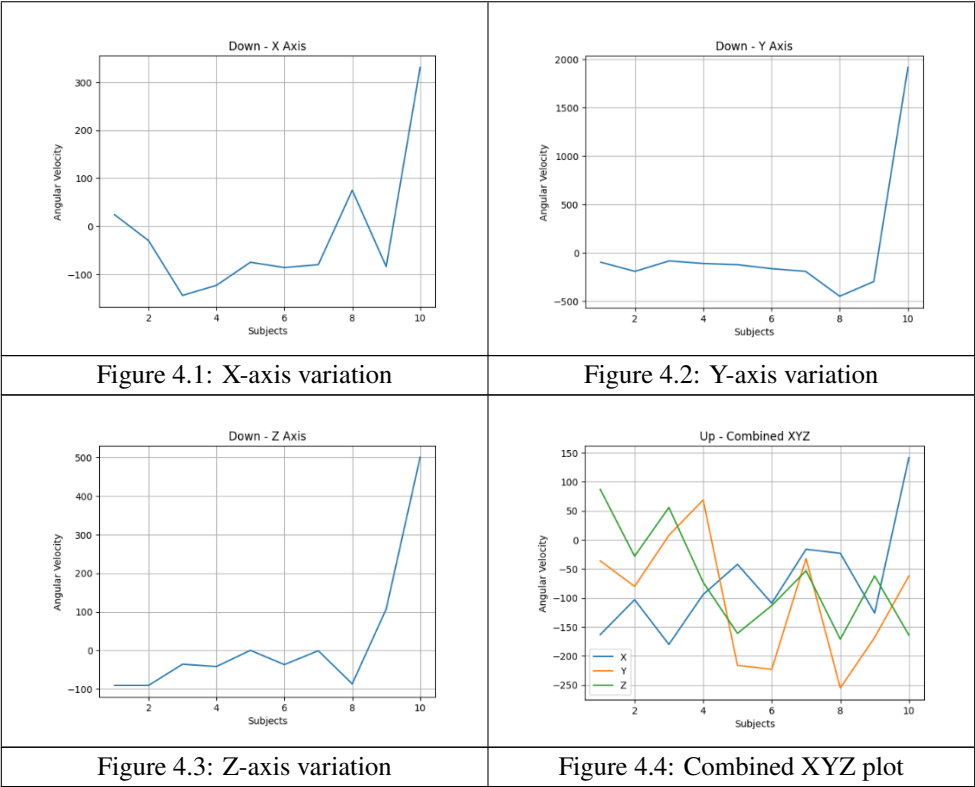
The graph for Center (Figure 2.1 – 2.4) shows little movement in all three axes, which means there is stability and neutrality in the hand's position. The signal exhibits very low

amplitude, signifying an absence of movement.

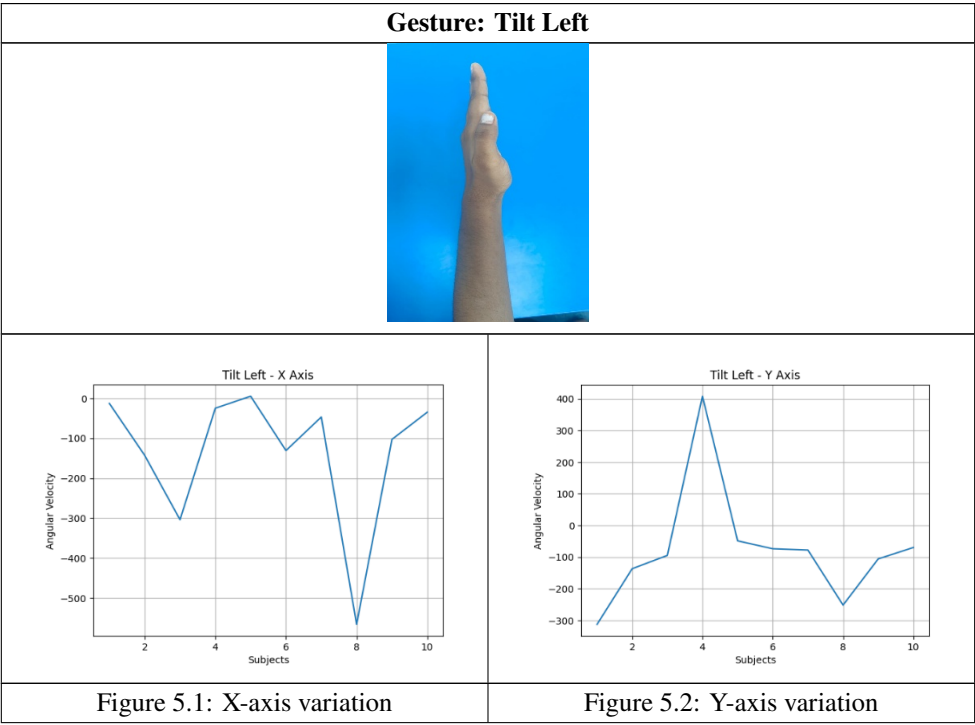


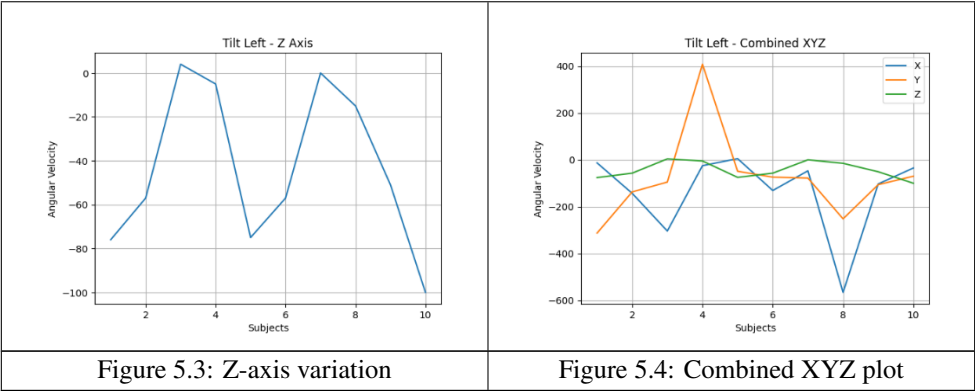
In the Up gesture (Figure 3.1 – 3.4), graphical representations indicate high variations primarily in the Y-axis direction, which represents the up-down direction. Variation on the X and Z axes is low. This indicates that there is very little horizontal and rotational movement in this gesture. The XYZ graph clearly shows this pattern of variation in the Y axis.



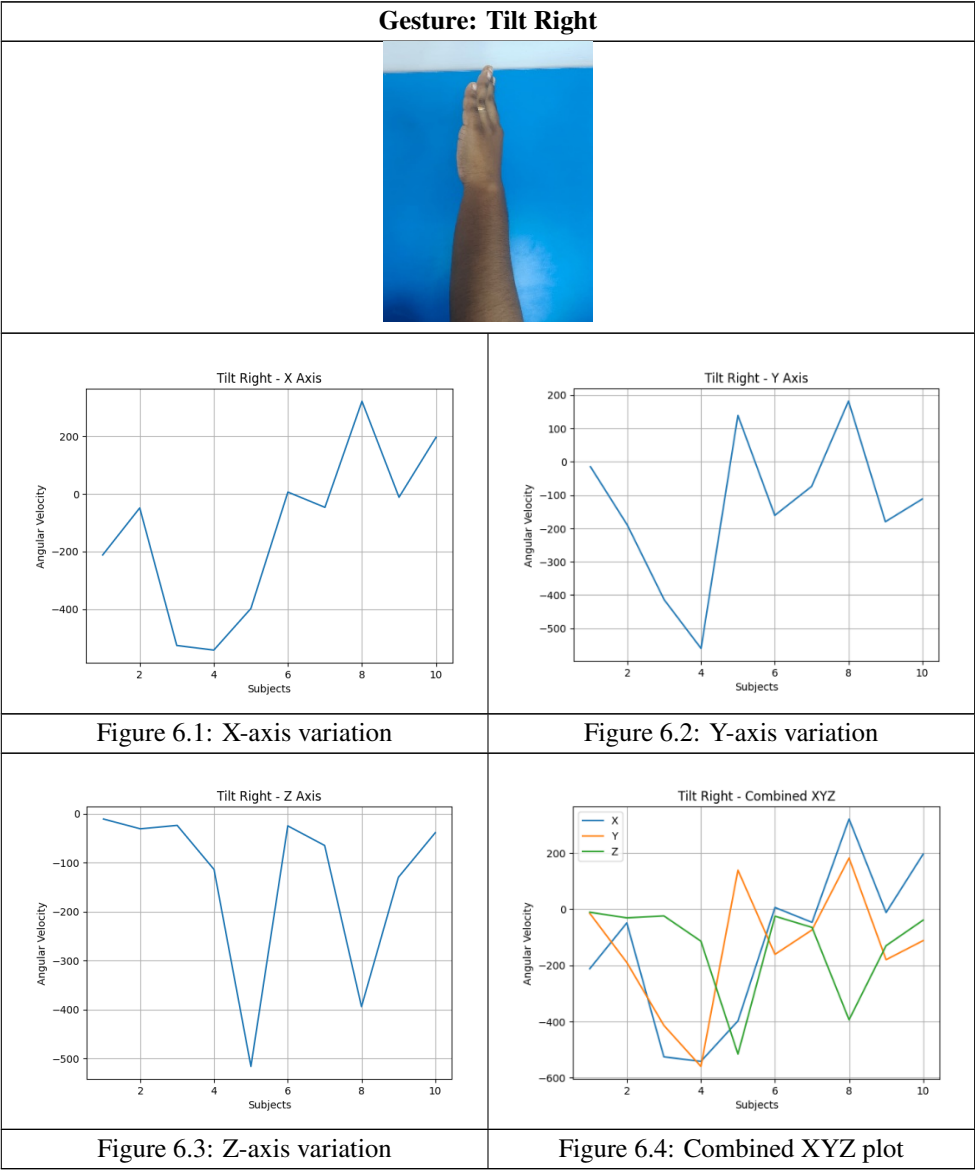


Similarly, the Down gesture (Figure 4.1-4.4) also has some major discrepancies on the Y-axis, but this time, the discrepancy is in terms of polarity compared to the Up gesture. The discrepancy becomes more apparent when considering the different orientations of the two gestures.





In regard to the Tilt Left gesture (Figure 5.1-5.4), the X-axis is characterized by prominent variations, as a result of the hand’s lateral movement to the left. The Y axis and Z axis provide only slight variations on the graph.



On the other hand, the Tilt Right gesture (Figure 6.1 - 6.4) displays the same characteristics as the Tilt Left gesture except for the negative values along the X-axis, reflecting the motion in the right direction. This complementary behavior between left and right gestures contributes to effective discriminative features. Accordingly, the ANOVA test further proves that there is a statistically significant difference among gesture classes ($p < 0.05$), confirming the uniqueness of each gesture motion. The visual inspection confirms this result by showing distinctive distributions of gesture signals. For example, the Center gesture is centered around zero, whereas dynamic gestures have different axis-dominated distributions. In general, the statistical and graphical analyses clearly demonstrate the efficiency of the suggested wearable technology in recording gesture signals. It allows for the accurate separation of different hand gestures on the basis of unique signal patterns.

4.6 Graphical Analysis Section

The graphical representation showed distinct variations in the signal pattern corresponding to each gesture for all three axes of the gyroscope. Apart from visualization-based analysis, a quantitative approach was applied to analyse the signal variation by evaluating the mean, standard deviation, and statistical validation via ANOVA. Frequency domain analysis also reflected unique characteristics for all types of gestures, which helped separate them spectrally. The "Center" gesture is seen to possess the least signal variance, validating the stability of hand orientation. The "Up" and "Down" gestures showed significant variations in the Y-axis with opposite polarity distribution, whereas the "Tilt Left" and "Tilt Right" gestures reflected significant X-axis variations. The process of extracting feature vectors gave rise to distinctive clustering with minimal overlap among the gesture classes. The F-statistic obtained was larger than the critical value for $p < 0.05$, therefore, showing statistical separability among the gesture classes.

4.7 Machine Learning Analysis

To ensure that our work was replicable and scientifically rigorous, we documented every detail of the implementation including the structure of the network, training parameters, optimization procedure and how the dataset was divided into train/valid/test sets [21]. Additionally, we normalized feature values in order to reduce user-specific variations. The process of ANN training [22] was repeated several times in order to prove that our results were repeatable and could be replicated. Besides using the ANN for classification purposes, we conducted experiments on the separability of different gestures by means of dimensionality. The results proved that there was clear separation of gestures without significant overlaps. Our system takes into account real-life applications: it is focused on computational efficiency and real-time performance on embedded devices and not on heavy deep learning models that cannot be deployed in an efficient manner.

5. Results and Discussion

The proposed wearable gyroscope-based gesture recognition system was experimentally verified using data collected from 19 subjects executing five gestures. Tri-axial gyroscope signal recordings revealed characteristic movement patterns for each gesture class, as shown in the experimental setup in Figure 7. For the ANN classifier, the following metrics were obtained: 94.2% classification accuracy, 93.6% precision, 92.8% recall and 93.1% F1-score. Thus, it is possible to conclude that the obtained statistical features have high discriminative power for the

gesture classification task. Despite the small number of experimental data samples, consistent statistical separation and classification were observed for all gesture classes.

From the obtained results, it can be concluded that vertical gestures influence the Y-axis, while lateral movements cause X-axis deviation. The “center” gesture consistently remained close to the baseline zone, indicating minimal movement disturbance. Filtering and normalization of the features significantly reduced signal noise and enhanced classification consistency. ANOVA analysis also confirmed the statistical significance of gesture separation with $p < 0.05$. All experimental results were obtained from real-time sensor acquisition and statistical analysis using experimentally collected gyroscope data from human participants. Compared with camera-based systems, the proposed wearable approach offers improved portability, reduced environmental sensitivity, and lower computational complexity. Unlike EMG systems, the proposed framework avoids electrode placement variability and signal instability due to skin resistance changes. Overall, the results indicate that the proposed system can reliably perform real-time gesture recognition for rehabilitation, assistive communication devices, and wearable healthcare solutions.



Figure 7. Experimental setup

6. Future Work

Further studies shall be focused on improving gesture recognition through the use of multi-sensing technology and new machine learning techniques. Using data collected from both accelerometers and EMG sensors, we could gather more information on movements and physiology related to gestures. The use of deep learning algorithms, such as convolutional neural networks and recurrent neural networks, would also enable us to explore the possibility of automatic feature learning and recognition of complex gestures. Technologies like Bluetooth and Wi-Fi wireless communication would enable the creation of telerehabilitation solutions and real-time remote monitoring. Future research would involve the use of large sets of gesture data obtained from different patient populations of varying ages and clinical statuses to enhance the created solution's robustness and generalizability.

7. Conclusion

The paper suggested a hand gesture recognition framework using gyroscope sensors, based on feature extraction with statistical methods, feature selection with ANOVA and a classifier based on artificial neural networks. The suggested system was able to extract features related to the tri-axial motion of five different predefined hand gestures using MPU-6500 inertial sensors. Experiments conducted on data from 19 users showed good separability of gestures and high precision in classification results. Classification using an ANN yielded an overall accuracy of 94.2% and statistical differences among classes were also confirmed by the analysis. The suggested approach has many benefits, such as a lightweight design, low computational complexity, portability and real-time processing capabilities. In contrast to camera-based approaches, the system is not affected by environmental or privacy issues. Compared to EMG-based systems, the suggested framework decreases dependence on electrode placement and physiological signals. On the whole, the presented wearable framework shows great promise for use in rehabilitation monitoring, communication assistance systems, human-computer interaction, and healthcare. The developed system proves the feasibility of using inertial wearable sensors for future assistive and rehabilitation systems.

Acknowledgments

The authors acknowledge with gratitude the financial assistance provided by the Department of Health Research, Ministry of Health and Family Welfare Government of India, for the execution of this research. Research under the “Start-up Grant for Induction into Biomedical & Health Research”. Project titled “Establishment of an International Sign language laboratory”, proposal ID No.SUG 2024-1360 dated.

References

- [1] Ozioko, Oliver, and Ravinder Dahiya. "Smart Tactile Gloves for Haptic Interaction, Communication, and Rehabilitation." *Advanced Intelligent Systems* 4, no. 2 (2022): 2100091.
- [2] Tam, Simon, Mounir Boukadoum, Alexandre Campeau-Lecours, and Benoit Gosselin. "A Fully Embedded Adaptive Real-Time Hand Gesture Classifier Leveraging HD-sEMG and Deep Learning." *IEEE transactions on biomedical circuits and systems* 14, no. 2 (2019): 232-243.
- [3] Piyathilaka, Lasitha, Jung-Hoon Sul, Sanura Dunu Arachchige, Amal Jayawardena, and Diluka Moratuwage. "Advances in EMG Signal Processing and Pattern Recognition: Techniques, Challenges, And Emerging Applications." *Electronics* 15, no. 3 (2026): 590.
- [4] Garcia-de-Villa, Sara, David Casillas-Pérez, Ana Jiménez-Martín, and Juan Jesús García-Domínguez. "Inertial Sensors for Human Motion Analysis: A Comprehensive Review." *IEEE Transactions on Instrumentation and Measurement* 72 (2023): 1-39.
- [5] Liang, Bangyi, Ning Li, Gongxin Li, Jie Huang, Zhuoheng Yu, and Xingang Zhao. "Sensing Technologies for Hand Gesture Recognition in Human–Robot Interaction: A Review." *IEEE Sensors Journal* 26, no. 2 (2025): 1501-1519.
- [6] Sarowar, Md Selim, Nur E. Jannatul Farjana, Md Asraful Islam Khan, Md Abdul Mutalib, Syful Islam, and Mohaiminul Islam. "Hand Gesture Recognition Systems: A Review of

- Methods, Datasets, and Emerging Trends.” *International Journal of Computer Applications* 975 (2025): 8887.
- [7] Pyun, Kyung Rok, Kangkyu Kwon, Myung Jin Yoo, Kyun Kyu Kim, Dohyeon Gong, Woon-Hong Yeo, Seungyong Han, and Seung Hwan Ko. ”Machine-learned Wearable Sensors for Real-Time Hand-Motion Recognition: Toward Practical Applications.” *National science review* 11, no. 2 (2024): nwad298.
 - [8] Alqudah, Hamzah. *Modelling, Regulating and Controlling Cardiovascular Responses by using Wearable Sensors*. University of Technology Sydney (Australia), 2019.
 - [9] Hurtado-Perez, Andres Emilio, Manuel Toledano-Ayala, Irving A. Cruz-Albarran, Alejandra Lopez-Zúñiga, Jesús Adrián Moreno-Perez, Alejandra Álvarez-López, Juvenal Rodriguez-Resendiz, and Carlos A. Perez-Ramirez. ”Use of Technologies For The Acquisition and Processing Strategies for Motion Data Analysis.” *Biomimetics* 10, no. 5 (2025): 339.
 - [10] Abbaspour, Sara, Autumn Naber, Max Ortiz-Catalan, Hamid GholamHosseini, and Maria Lindén. ”Real-time and Offline Evaluation of Myoelectric Pattern Recognition for the Decoding of Hand Movements.” *Sensors* 21, no. 16 (2021): 5677.
 - [11] Zhao, Hongyang, Shuangquan Wang, Gang Zhou, and Daqing Zhang. ”Ultigesture: A Wristband-Based Platform for Continuous Gesture Control in Healthcare.” *Smart Health* 11 (2019): 45-65.
 - [12] Heir, Fereshteh Manafzadeh, Hossein Najafzadeh, and Sarvenaz Erfani. ”A Hybrid CNN and Reinforcement Learning Framework for Speaker Identification Using Mel-Spectrogram and Continuous Wavelet Transform Features.” *Scientific Reports* 16, no. 1 (2026): 5954.
 - [13] Noh, Donghyeon, Hojin Yoon, and Donghun Lee. ”A Decade of Progress in Human Motion Recognition: A Comprehensive Survey from 2010 to 2020.” *IEEE Access* 12 (2024): 5684-5707.
 - [14] Hashi, Abdirahman Osman, Siti Zaiton Mohd Hashim, and Azurah Bte Asamah. ”A Systematic Review of Hand Gesture Recognition: An Update from 2018 to 2024.” *IEEE Access* 12 (2024): 143599-143626.
 - [15] Liu, Wentao, Yuxin Zhang, Mingyu Zhang, Xue Chen, Shihao Sun, and Guizhi Xu. ”A Real-Time Wrist Action Reconstruction System Design Based on BP Neural Network Model to Predict Multiple FES Parameters.” *IEEE Sensors Journal* 25, no. 14 (2025): 27353-27366.
 - [16] Jiang, Shuo, Peiqi Kang, Xinyu Song, Benny PL Lo, and Peter B. Shull. ”Emerging Wearable Interfaces and Algorithms for Hand Gesture Recognition: A Survey.” *IEEE Reviews in Biomedical Engineering* 15 (2021): 85-102.
 - [17] Tchantchane, Rayane, Hao Zhou, Shen Zhang, and Gursel Alici. ”A Review of Hand Gesture Recognition Systems Based on Noninvasive Wearable Sensors.” *Advanced intelligent systems* 5, no. 10 (2023): 2300207.
 - [18] Sardadvar, Fatemeh, Valentin Kennel, Athina Tome, Nurcennet Kaynak, Alexa Straus, Rok Kos, Felix Schmidt, Alexander Heinrich Nave, and Bert Arnrich. ”A Technical Insight into Sensor-S Study: Effect of Wearable Sensors on Patient Engagement and

- Motivation in Post-stroke Rehabilitation.” In International Workshop on Sensor-Based Activity Recognition and Artificial Intelligence, Cham: Springer Nature Switzerland, 2025, 404-412.
- [19] Stan, Ionel Eduard, Daniela D’Auria, and Paolo Napoletano. ”A Systematic Literature Review of Innovations, Challenges, And Future Directions in Telemonitoring and Wearable Health Technologies.” IEEE Journal of Biomedical and Health Informatics 30, no. 3 (2025): 2630-2645.
- [20] Siddiqui, Uzma Abid, Farman Ullah, Asif Iqbal, Ajmal Khan, Rehmat Ullah, Sheraz Paracha, Hassan Shahzad, and Kyung-Sup Kwak. ”Wearable-sensors-based Platform for Gesture Recognition of Autism Spectrum Disorder Children Using Machine Learning Algorithms.” Sensors 21, no. 10 (2021): 3319.
- [21] Yoo, Seohyun, Eunbae Jeon, Joonseo Hyeon, and Jaehyuk Cho. ”Adaptive Ensemble Techniques Leveraging BERT based Models for Multilingual Hate Speech Detection in Korean and English.” Scientific Reports 15, no. 1 (2025): 19844.
- [22] Hu, Jingcheng, Yinmin Zhang, Qi Han, Daxin Jiang, Xiangyu Zhang, and Heung-Yeung Shum. ”Open-reasoner-zero: An Open Source Approach to Scaling Up Reinforcement Learning on the Base Model.” Advances in Neural Information Processing Systems 38 (2026): 162239-162262.