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Precision Gait Stability Analysis Combining Hardware and Software

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Abstract: *Maintaining stable gait and avoiding falls require effective control of the body's center of mass (CoM) relative to the base of support (BoS), defined by the feet's contact points with the floor. Quadrupeds have an advantage over bipeds but share common spinal neural control mechanisms. Human walking poses stability challenges since the CoM often extends beyond the BoS. This project aims to monitor gait stability by integrating advanced hardware and software solutions. Machine learning algorithms, such as Random Forest, will be employed to predict gait instability by capturing foot positions and sensor data. Inertial measurement sensors will track stability changes, and hardware outputs will be validated against software predictions for accuracy. A mobile app developed using React Native will display predicted parameters and indicate gait instability (yes/no). In case of detected instability, a wearable buzzer will alert the user. This system promises a more accurate solution for monitoring gait stability compared to existing models, by combining real-time data collection and sophisticated algorithms*

Keywords: Precision Gait stability, Random Forest Algorithm, Parkinson disease, Machine Learning Algorithm

I. INTRODUCTION

The pursuit of universal gait stability represents a fundamental challenge in robotics, biomechanics, and assistive technologies. Essential for efficient locomotion across various terrains, gait stability is a complex interplay of biomechanical principles, sensory feedback, and control mechanisms. Achieving this stability necessitates a comprehensive approach that integrates hardware and software solutions, leveraging advancements in robotics, sensor technology, and control algorithms.

Recent years have seen a surge in developing robotic systems and assistive devices capable of emulating human-like locomotion while ensuring stability. From bipedal robots navigating uneven terrain to exoskeletons supporting individuals with mobility impairments, the quest for universal gait stability has fueled interdisciplinary research spanning engineering, neuroscience, and rehabilitation.

This paper explores state-of-the-art approaches to achieving gait stability by synergistically combining hardware and software advancements. Key components include:

- **Biomechanical Insights:** Understanding human locomotion and balance control dynamics informs the design of stable gait systems, aiding in the development of robotic platforms and prosthetic devices.
- **Hardware Solutions:** Innovations in materials science, lightweight structures, and robust actuators enhance the stability and agility of gait-assistive devices
- **Sensory Feedback Systems:** Proprioceptive, vestibular, and tactile sensors enable real-time monitoring and adjustment of gait patterns, facilitating adaptive control strategies.
- **Control Algorithms:** Sophisticated algorithms, from traditional PID controllers to machine learning-based approaches, maintain stability and optimize performance.
- **Integration and Optimization:** Seamless integration of hardware and software, along with optimization methodologies, refines system performance and addresses inherent challenges.

By synthesizing advances in biomechanics, robotics, and computational intelligence, the vision of universal gait stability moves closer to fruition. This paper provides a comprehensive overview of multidisciplinary efforts, highlighting emerging trends, challenges, and future directions in the pursuit of stable and adaptive locomotion across diverse environments and user populations.

II. PROBLEM DEFINITION

Gait instability is one of the major problems and there occurs a major necessity to determine it in people with those symptoms to provide an effective treatment. Difficult to determine the gait instability by manual means. Parkinson's disease (PD) is mainly characterized as a degenerative disorder of the brain which destroy parts of the brain that control movement. Shuffling gait, impaired balance, and freezing of gait are main motor dysfunctions shown in patients with PD. Postural control and gait dysfunction may occur in early stages of PD. They are characterized by slowing of gait, reduced arm swing, shorter step length, postural instability, and loss of disassociated arm and trunk movements during gait.

Many patients with PD trend to suffer the risk of falls due to occurrence of gait disturbance and freezing of gait. Prospective studies have reported that 70% of patients with PD have at least one fall in a year and 39% fall recurrently. Consequences of falls include fractures and injury, fear of future falls, hospital admission, and increased caregiver burden. Median survival in patients with recurrent falls is 6 years. Falls are correlated with multiple factors, including postural, gait, and cognitive dysfunctions.

Walking is a complex task in which cognitive resources continuously monitor bilateral coordination and dynamic postural control are both necessary for the walking process, including cognitive motor control.

III. THEORETICAL BACKGROUND

As the population ages, the emergence of diseases such as lower extremity diseases or motor nerve dysfunction have increased leading to an increased rate of elderly adults falling on flat ground. Approximately 32% of community-dwelling elderly adults over 75 years of age will fall at least once during a one-year interval and 24% of these individuals will sustain serious injuries. In the United Kingdom (UK), the medical costs related to falls are substantial; fall-related injuries in adults greater than 60 years have been reported to cost more than £981 million pounds per year. Total healthcare spending for elderly falls ranged from $48 million in Alaska to $4.4 billion in California. Medicare spending attributable to older adult falls ranged from $22 million in Alaska to $3 billion in Florida, as reported in 2014. The lifetime medical costs of fall-related injuries ranged from $68 million in Vermont to $2.8 billion in Florida. As such, falling has become a costly problem in the growing elderly population. For that reason, the detection and recognition of fall risk has been growing due to the implementation of safety measures in high-risk work environments, hospitals, and nursing homes. A person’s pattern of walking can be understood by gait analysis. Gait and balance functions decline through the course of disorders including stroke, dementia, Parkinson’s disease, arthritis, and others. Gait can serve as a marker of changes in physical status and fall risk. The gait of the human body refers to the behavioural characteristics of the lower limbs of the human body in the process of upright walking. A normal human gait cycle usually needs to meet the characteristics of natural, coordination of the legs, labour saving, and periodicity. Abnormal gait can develop before the human body falls. Numerous possibilities may cause an abnormal gait. In the field of medical rehabilitation, 1 identification and evaluation of abnormal gait patterns significantly guide lower limb training regimens and flat ground falls prevention strategies. By monitoring the gait patterns of elderly patients, proper preventive measures can be recommended to reduce the risk of flat ground falls. Human vision may not accurately recognize or quantify the changes in the gait pattern. Therefore, automatic gait recognition using computer vision has become a hot research topic in the biomechanics and healthcare literature in recent years. Computer-vision technology is used to acquire gait kinematics information, including angles, velocity, and acceleration of the joints based on Kinect skeletal tracking sequences. The gait analysis involves many interdependent measures that can be difficult to interpret due to a vast amount of data and their inter-relations, and a significant amount of labour is required in off-line data analysis.

IV. PROPOSED WORK

In this project, we will be using Machine Learning algorithm such as Random Forest to predict the gait instability by capturing the foot position of humans as well as integrate with sensor data to predict the gait presence in a person. The Inertial measurement sensor will be utilized to fetch the change in the stability of motion while walking along with the

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AI based prediction. The hardware units output will get compared with the software 18 outputs to arrive at a much stable outcome of gait monitoring. In the dataset collection, we are going to collect the real time dataset. Data preprocessing method is used to preprocess the datasets. Applying machine learning algorithms such as Random Forest is used to determine gait instability. A mobile application using react native will be developed in which the predicted parameters along with gait instability (yes or no) will be displayed. If the gait instability is yes, a buzzer integrated in the wearable will be switched on to alert the person. Thus, this project helps in effective determination of monitoring the gait instability with higher accuracy of combining hardware and software than the existing models.

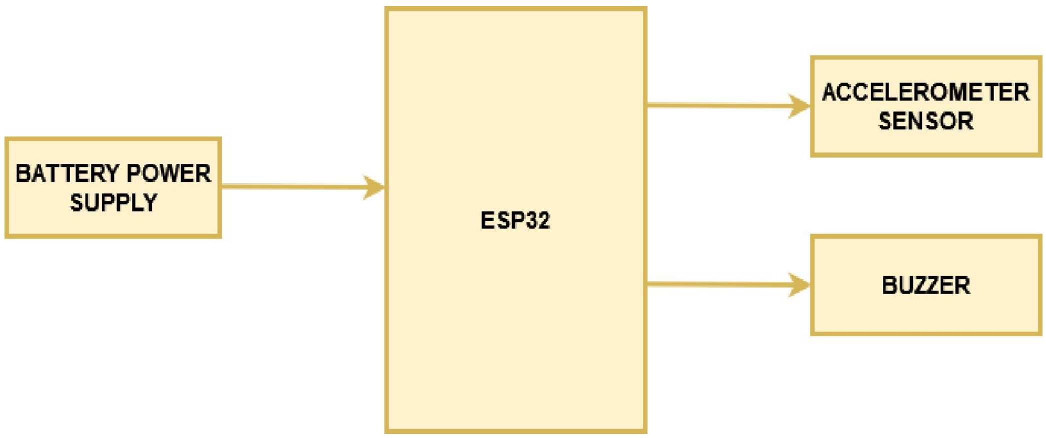

Figure 1 Hardware block diagram

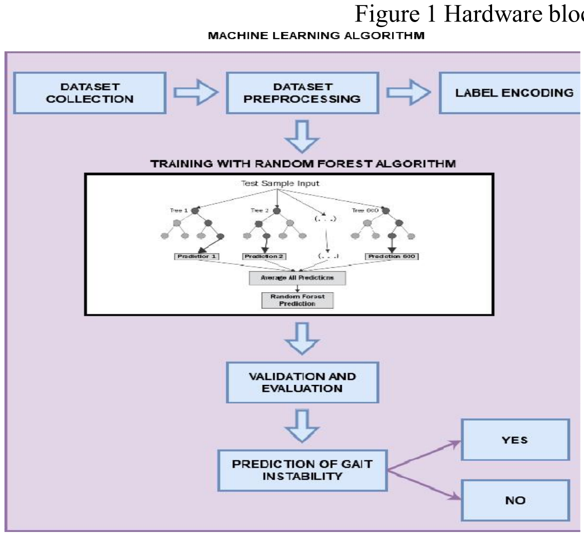

Figure 2 Proposed system architecture

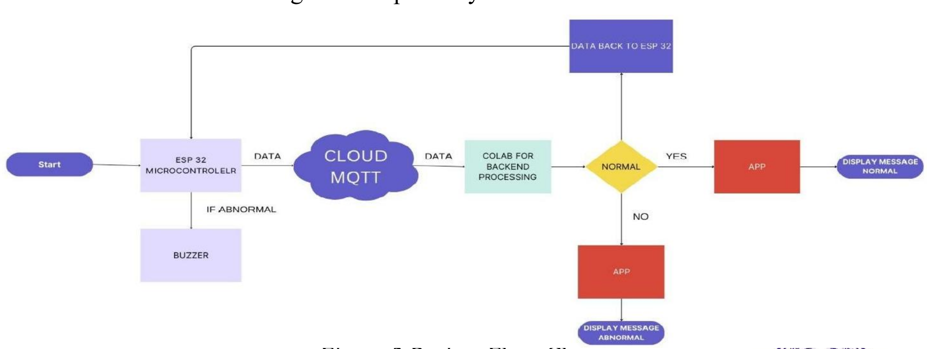

Figure 3 Project Flow Chart

The ESP32 microcontroller collects real-time sensor data and transmits it to the cloud using the MQTT protocol. This data is processed by a Colab backend, which compares it against predefined normal and abnormal datasets. If the data matches the normal criteria, a "normal" message is displayed in the user app and sent back to the ESP32. If the data is abnormal, an "abnormal" message is displayed in the app and also sent back to the ESP32. This feedback allows the ESP32 to take any necessary actions based on the status of the data, ensuring continuous monitoring and appropriate responses.

V. IMPLEMENTATION

Software Module Description:

- **Dataset Collection:** The initial phase involves collecting real-time datasets, essential for training the machine learning algorithm. The quality and quantity of data significantly impact the model's accuracy. The collection process follows three main steps: classification, regression, and ranking. These steps ensure that the data is diverse and comprehensive, covering various scenarios and conditions.
- **Dataset Pre-processing:** Before feeding the data into the machine learning model, it undergoes preprocessing to clean and format it appropriately. This step involves several operations such as normalization, feature scaling, and handling missing values. Additionally, for image data, ensuring uniform aspect ratios and image sizes is crucial. This preprocessing ensures that the data is in a suitable format for the algorithm, enhancing both accuracy and efficiency.
- **Training with Machine Learning Algorithm:** The preprocessed data trains a Random Forest algorithm, chosen for its effective classification and regression capabilities. Using ensemble learning, it combines multiple decision trees for robust predictions, achieving high accuracy and preventing overfitting, ensuring reliable performance with large datasets.
- **Validation and Evaluation:** Following training, the model undergoes validation and evaluation processes. Validation verifies the accuracy of predictions, while evaluation assesses the overall performance of the machine learning model under various conditions. These steps ensure that the model is reliable and capable of delivering accurate results consistently.
- **Prediction of Gait Instability:** The primary objective of the project is to develop a model for predicting gait instability. Utilizing he trained machine learning algorithm, the system can effectively determine the presence of gait instability in individuals. This predictive capability contributes to more efficient monitoring and management of gait- related issues, enhancing overall healthcare outcomes.
- **Mobile Application Development:** To facilitate easy access and utilization of the predictive model, a mobile application is developed. The application utilizes Flask algorithms in Python to communicate with the model backend. Users can input relevant data, such as images or other features, and receive predictions regarding gait instability. The application is developed using React Native, ensuring compatibility across both iOS and Android platforms.

Hardware Module Description:

- **Battery Power Supply:** The project incorporates a battery power supply system to ensure reliable operation, especially in scenarios where mains power may not be available. Batteries provide the necessary electrical energy for the entire system, ranging from basic handheld devices to larger industrial applications. Proper battery management, including equalization, is crucial for maintaining optimal performance and longevity.
- **Microcontroller ESP32:** The ESP32 microcontroller serves as the central processing unit for the hardware module. It offers low-cost, low-power solutions with integrated Wi-Fi and Bluetooth capabilities. The ESP32 is highly versatile, capable of functioning in industrial environments with temperature ranges from -40°C to +125°C. Its advanced features and compatibility make it ideal for IoT applications.
- **Accelerometer Sensor:** The MPU-6050 accelerometer sensor is utilized for motion tracking and sensing. It combines a 3-axis gyroscope and a 3-axis accelerometer on the same silicon die, facilitating accurate motion

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detection. The sensor incorporates Motion Fusion technology for optimal performance, making it suitable for applications in smartphones, tablets, and wearable devices.

- **Buzzer:** The piezoelectric buzzer, chosen for its compact size and low power consumption, serves as an audio signaling device in this project. It provides alerts and notifications based on system conditions, playing a crucial role in indicating various events or alarms

VI. RESULT

The dataset has been collected for the proposed work and the below figure can be seen as follows

	accel_x	accel_y	accel_z	gyro_x	gyro_y	gyro_z	time	cur_time
0	2.60	9.43	0.37	0.02	0.03	0.01	0.621	10:58:05
1	2.08	9.61	0.51	0.13	0.14	0.08	1.179	10:58:05
2	1.82	9.67	0.60	0.05	0.11	0.02	1.683	10:58:06
3	1.69	9.57	0.89	0.05	0.12	0.17	2.169	10:58:06
4	0.05	9.39	-2.10	0.56	0.20	0.00	2.718	10:58:07

Figure 4 Dataset Collection

To begin with, testing of the trained model, we can split our proposed work into modules of implementation that is done. Dataset collection involves the process of collecting from kit accelerometer and gyroscope data.

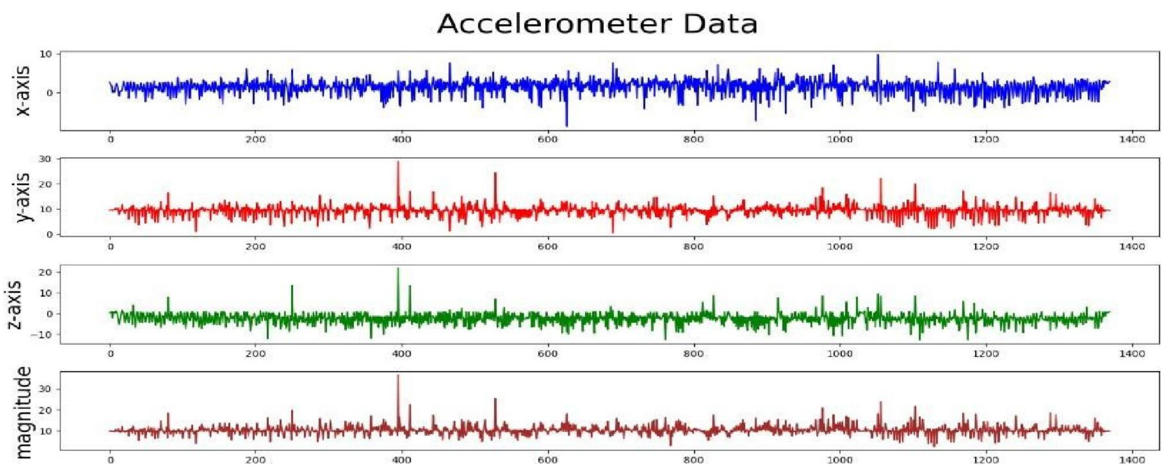

Figure 5 Accelerometer data

The graph depict accelerometer data labeled as “x-axis,” “y-axis,” “z-axis,” and “magnitude,” representing specific accelerometer data components. Color coding (blue for x-axis, red for y-axis, green for z-axis, and maroon for magnitude) aids differentiation. All graphs share a common x-scale from 0 to 1400, likely indicating time or sample points, while the y-scale varies to accurately reflect data amplitude. Such accelerometer data is essential for detecting linear acceleration, useful in applications from mobile devices to vehicle dynamics, requiring precise motion detection and analysis.

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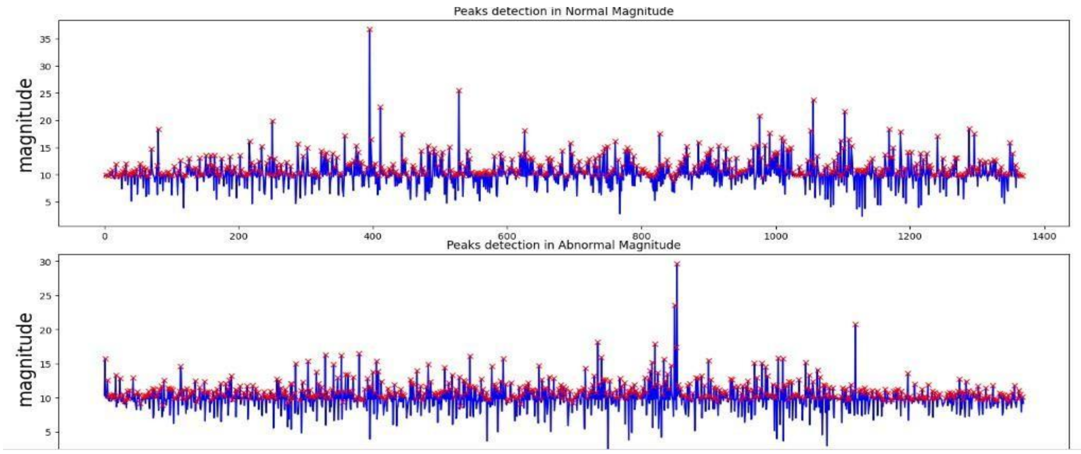

Figure 6 Peaks Detection for normal magnitude

Peaks in Normal Magnitude:
The first plot, labeled "Peaks detection in Normal Magnitude," displays a series of peaks representing normal variations in magnitude. These could indicate standard fluctuations in a given dataset.

Peaks in Abnormal Magnitude:
The second plot shows a notable peak, indicating a significant event, useful for analyzing event frequency and intensity in signal processing, vibration analysis, or health monitoring.

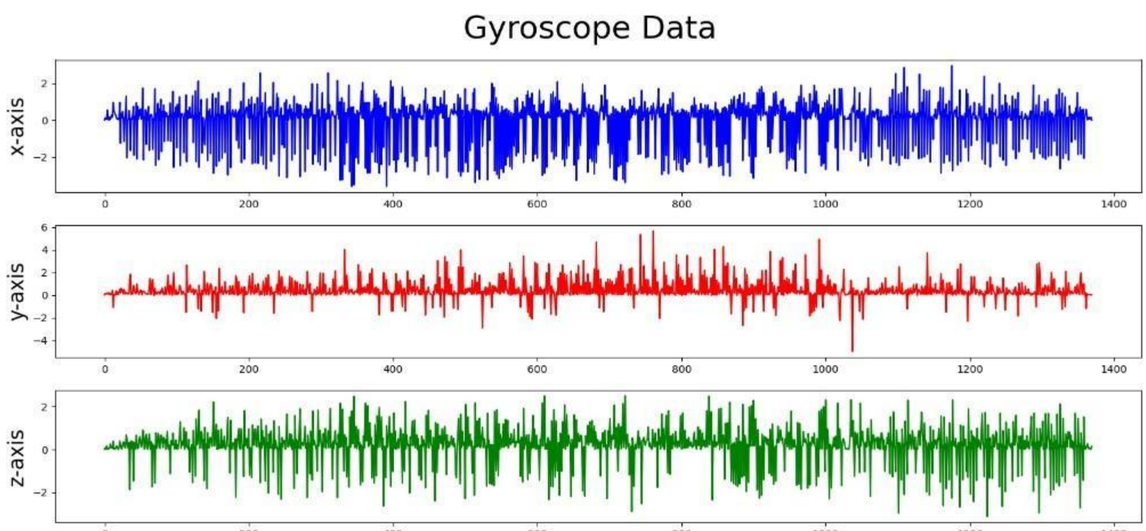

Figure 7 Gyroscope data

Graphical Representation:
The image features three line graphs, each corresponding to the gyroscope's x, y, and z axes, with distinct colors for clarity.

Data Range:
The x-axis of each graph ranges from 0 to 1400, representing time or sample points, while the y-axis scales differ; the y-axis graph ranges from -6 to 6, and the x and z axes range from -2 to 2.

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Angular Velocity:
The waveforms depict changes in angular velocity over time or per sample point, showcasing the gyroscope's sensitivity and responsiveness to movement.

	step_times	step_length	step_velocity	step_count	stride_time	stride_length	cadence	peak_prominences	peak_widths	accel_x_mean_array	accel_y_mean_array	accel_x_std_array	accel_y_std_array	class
0	3.0	4.26	1.42	3.0	0.03	0.02	20.0	0.069197	1.740100	1.186667	9.543333	0.805495	0.115854	0.0
1	3.0	4.26	1.42	3.0	0.03	0.05	20.0	0.155298	1.718256	0.250000	9.683333	0.170489	0.054365	0.0
2	4.0	5.68	1.42	4.0	0.04	0.08	15.0	0.777494	1.152246	1.827500	9.855000	0.350526	0.311006	0.0
3	2.0	2.84	1.42	2.0	0.02	0.12	30.0	1.246051	1.210002	-0.370000	9.110000	0.630000	1.260000	0.0
4	3.0	4.26	1.42	3.0	0.03	0.14	20.0	0.279859	0.752517	0.290000	9.313333	0.078740	0.249978	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
981	3.0	4.26	1.42	3.0	0.03	15.26	20.0	1.089625	1.352853	2.746667	9.720000	0.301588	0.446393	1.0
982	5.0	7.10	1.42	5.0	0.05	15.29	12.0	3.884495	1.896147	0.068000	8.596000	2.665178	1.778590	1.0
983	2.0	2.84	1.42	2.0	0.02	15.34	30.0	0.221517	0.701032	2.270000	9.395000	0.120000	0.145000	1.0
984	3.0	4.26	1.42	3.0	0.03	15.36	20.0	2.486621	4.910564	-0.830000	8.866667	1.904328	1.335224	1.0
985	4.0	5.68	1.42	4.0	0.04	15.39	15.0	0.551381	0.935413	2.025000	8.882500	1.144825	1.270637	1.0

Figure 8 Feature Extraction

Data Representation:
The table exhibits a comprehensive array of features extracted from accelerometer data across 385 rows.
Feature Categories:
It encompasses various feature categories like "step_Lines," "step_length," "step_velocity," and others.
Numerical Values:
Each row comprises numerical values under respective columns, representing different facets of the extracted features.
Purpose:
"Crucial for analyzing accelerometer data patterns for activity recognition and health monitoring."

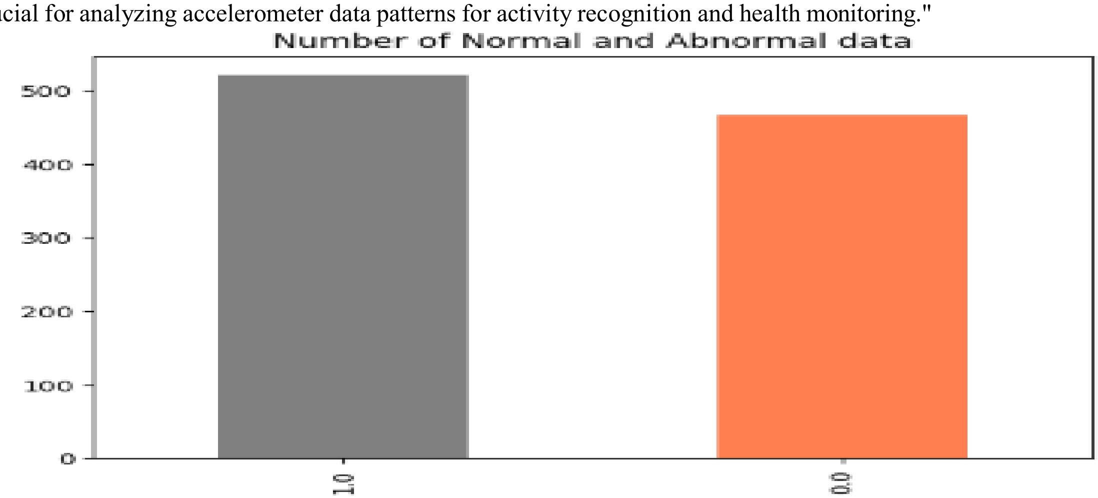

Figure 9 Number of data in a class The figure shows the amount of data in a class.

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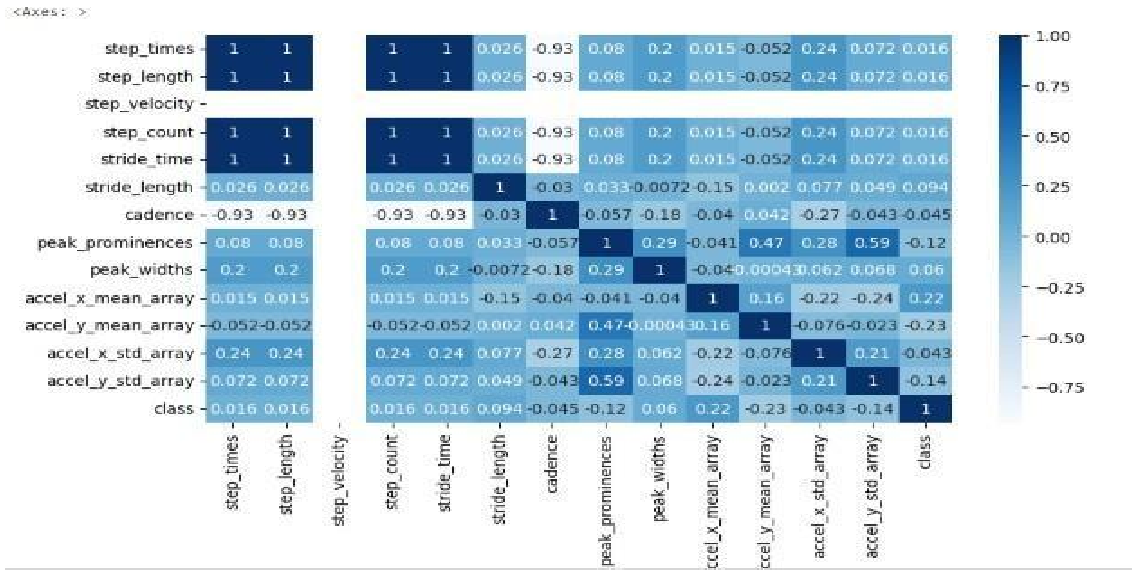

Figure 10 Heat Map

The graph depicts the correlation between each feature in the dataset. Which is represented in the range of [1, -1], here 1 and -1 is more correlation between the features. The Heat Map Shows the relationships between two variables, one plotted on each axis. By observing how cell colors change across each axis, we can observe if there are any patterns in value for one or both variables

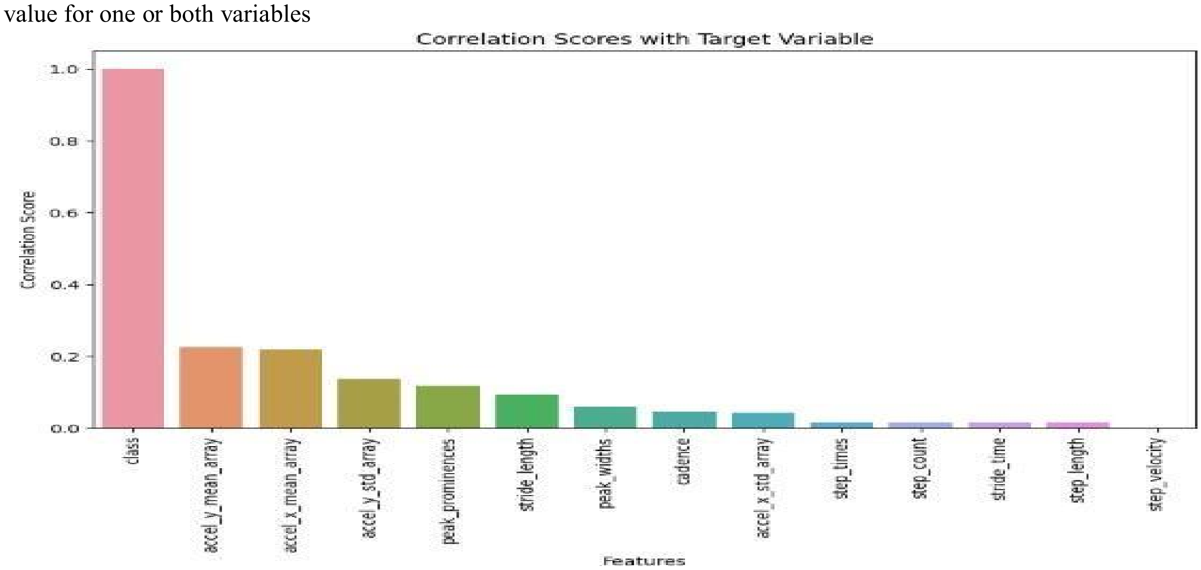

Figure 11 Correlation score

The image is a bar graph titled "Correlation Scores with Target Variable," which displays the correlation scores of various features with a target variable: High Correlation: The 'class' feature has the highest correlation score, close to 1.0, indicating a strong relationship with the target variable Color Coding: The graph uses different colors for each feature to visually distinguish the correlation scores. Analysis Utility: Such graphs are useful for feature selection in machine learning, helping to identify which features are most predictive of the target variable.

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Figure 12 Class distribution

The bar graph compares class distribution in training and testing datasets. Class 0.0 counts are similar, slightly higher in training. Class 1.0 counts are significantly higher in both, indicating larger representation. Red denotes training, teal denotes testing. This graph aids in evaluating class balance in machine learning datasets, preventing bias

Classification Report:

	precision	recall	f1-score	support
0.0	0.79	0.85	0.82	93
1.0	0.86	0.80	0.83	105
accuracy			0.82	198
macro avg	0.82	0.82	0.82	198
weighted avg	0.83	0.82	0.82	198

Figure 13 Classification Report

The Random Forest classifier model that can be seen demonstrates how well the Random Forest classifier model has been trained. This level of training is demonstrated by certain metrics such as precision, recall, and f1-score. The term "precision" refers to the proportion of times that a positive prediction is accurate. The term "recall" refers to the proportion of true positives that were correctly predicted, whereas "F1-score" refers to the average of "precision" and "recall" (2 * (precision * recall) / (precision + recall)). When precision, recall, and f1-score are taken into consideration, the Random Forest Classifier model successfully predicted each class.

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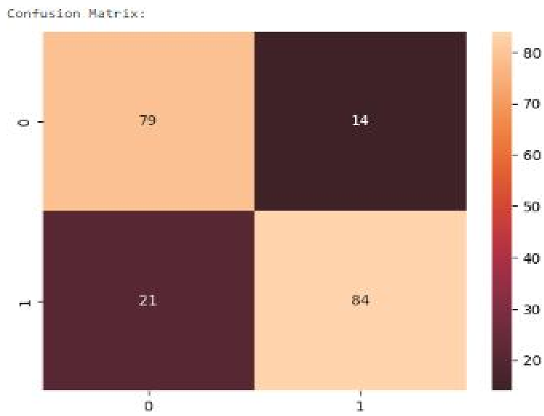

Figure 14 Confusion matrix

The Random Forest classifier model demonstrates how well the Random Forest classifier model has classified each label exactly, which is denoted by four metrics such True Positive, False Positive, False Negative and True Negative

Figure 15 Abnormal Notification

The figure depicts receiving a notification after detecting abnormal data processed by a machine learning-trained model.

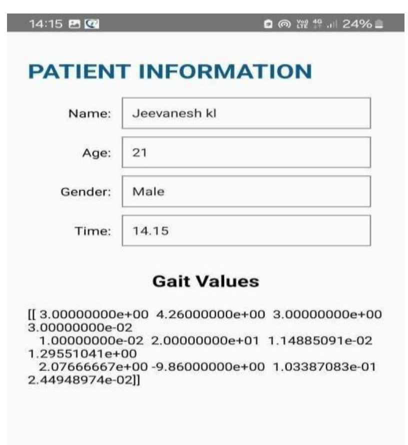

Figure 16 Abnormal Buffer Sound

The figure displays the abnormal notifications containing patient information and processed parameters derived from Accelerometer data collected along the X, Y, and Z axes. Whenever the model predicts an abnormality, a notification is sent to the mobile application using the MQTT protocol, and the buffer sound for the abnormal data is retrieved

VII. FUTURE SCOPE

In the coming future, we review the application of predict gait stability and instability in a person to determine technology in the healthcare field and it can promote the various types of diseases with more accuracy. In this field they have more chances to develop or convert this project in many ways. Thus, this project has an efficient scope in the coming future where manual prediction can be converted to computerized production in a cheap way.

VIII. APPLICATIONS

Fall Prevention: Identifying individuals at risk of falling, particularly in the elderly, to implement preventive measures.
Rehabilitation Monitoring: Assessing the progress of patients undergoing rehabilitation for conditions like stroke or orthopedic surgery.
Sports Medicine: Analyzing athletes gait to prevent injuries and enhance performance.
Parkinson's Disease Management: Monitoring gait changes to adjust treatment plans for Parkinson's patients.

IX. CONCLUSION

The project has been successfully implemented to provide a solution for predicting gait instability by capturing foot position of humans as well as integrate with sensor data to predict the gait presence in a person. The Inertial measurement sensor is utilized to fetch the change in the stability of motion while walking along with the ML based prediction. The hardware units output will get compared with the software outputs to arrive at a much stable outcome of gait monitoring. Applying machine learning algorithms such as Random Forest is used to determine gait instability. A mobile application using react native is developed in which the predicted parameters along with gait instability (yes or no) will be displayed. If the gait instability is yes, a buzzer integrated in the wearable will be switched on to alert the person. There is a lot of scope to improve the technology as the prediction of gait instability can be done in several ways.

X. ACKNOWLEDGMENT

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