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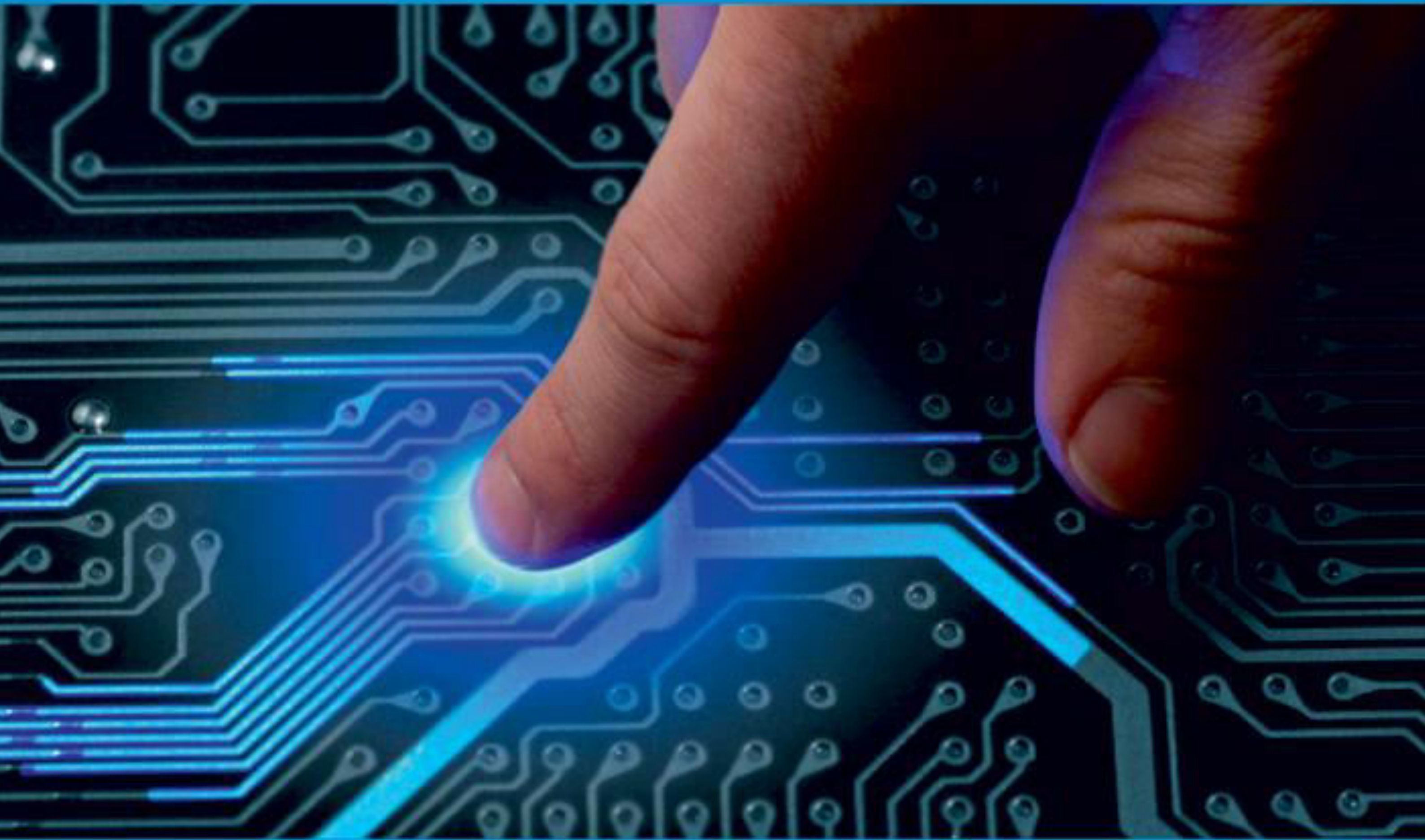

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Design and Implementation of Smart Device for Monitoring Gait Parameters using RFDT

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ABSTRACT: The pattern that people walk is Gait. Majority of the people in all age categories are suffering owing to their inability of stable walk. For this unstable walk, there may be several reasons, and it is challenging for old age people. Thus, there is a need for a gait stability evaluation and monitoring system for addressing the individual risk for falls. An implementation of the module utilizing WiFi signals for identifying human falls is proposed in this paper. A Fire Beetle ESP32 microcontroller, accelerometer, and gyroscope sensor are combined by the module in which real-time abnormal and normal conditions from the sensors were gathered and communicated to an open source known as COLAB by utilizing Message Queuing Telemetry Transport (MQTT) protocol via WiFi. Gait parameters are estimated from the gathered datasets. Then, by utilizing a Machine Learning (ML) algorithm, normalization of data is performed. Subsequently, the normalized dataset is split into training and testing parts (80% for training and 20% for testing). For training the dataset, Random Forest (RF) algorithms are utilized, and to achieve reliable higher accuracy, multiple decision trees are constructed. During abnormal conditions along with predicted parameters, the fall-down notification is sent to the mobile application and the buzzer sounds at the wearable device. Real-time gait monitoring for evaluating fall risk during walking is rendered by the proposed system.

KEYWORDS: ESP32 Microcontroller, MPU6050, machine learning, accuracy, smart phone

I. INTRODUCTION

A vital activity that people do every day in life is human gait. Age, personality, moods, and sociocultural features influence a person's gait patterns. Every person's natural walking style is uncommon. When someone has an abnormal gait, all the joints, bones, and muscles get affected in the walking process. Continuous abnormal walking results in excessive stress on joints and causes more pain. Since people get older, abnormalities in walking become more common. Approximately, 15% of folks experience walking abnormality by around 60 years old. However, more than 80% of individuals above 85 years old wind up with a walking abnormality. In old adults, the preferred speed for walking is a sensitive marking of overall health and survival.

Safety walking needed an intact cognitive and executive controller. It will be a complex biomechanical process of dynamics balance, which necessitates a person for keeping their center of gravity within their bases of supports during movements. Disorders in gait cause loss of personal freedoms, falling, and injuries. It also leads to a marked reduction of life qualities. Thus, it's great to gauge and investigate human gait. A vital bit of diagnosing several neurological discombobulations is the analysis of all components in two phases of precautions. It can also be a vital part of evaluating patient progress whilst rehabilitating and recouping from the impacts of neurologic disease, mushy and skeletal injury or disease process, and even decapitation of a low limb.

For analyzing gait, clinicians and researchers exploit many qualitative and quantitive parameters. Walking speed, cadency, and footstep/pace elongation are the most suitable parameters for gait analysis in a healthy adult population. Really, step length strongly correlates with gait speed in unperturbed overground gait. The remaining variance is negligible when variations in step length due to changes in walking speed are eliminated, thus pointing to the fact that most changes in foot placement in the sagittal plane are not utilized for controlling stability. By measuring the parameters, such as step and stride, gait analysis is performed, thus showing the difference betwixt one single step and the whole gait cycle.

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II. RELATED WORKS

Zhuo Chen [2] introduced a mobile robot-supported gait monitoring and dynamic Margin of Stability (MoS) estimation that predicted a MoS monitoring system comprising a mobile robot as well as an instrumented insoles pair, where every single insole embedded an array of pressure sensors and an IMU. Kalman filter-based approaches were developed to fuse the data from the sensors to estimate foot poses and the body CoM in the prevalence of measurement uncertainties as well as noises. H.Ohtsu [11] devised balanced tactics in the course of walking in elderly persons by predicting the balanced evaluation through GC centered on the MoS in lateral and posterior directions. F. Franchignoni [12] introduced psychometric approaches for enhancing the balance assessment system test to investigate the neurological diagnosis and disease severity of adult patients to produce a coherent balance. S. Yoshida [13] established an analysis of the balance strategy over GC centered on MoS by outlining the changes in Base Of Support (BoS) at every GC and calculating the mos at the preferred speed. L. Mademli [14] developed a low safety factor for older adults in the course of walking at preferred velocity for determination of body stability by evaluating the dynamic stability utilizing MoS as the main criterion and the ratio between MoS at WRV and MoS at PWV was computed. M. Guaitolini [15] introduced the impacts of gait speed on the MoS in young healthy adults that estimated the relation betwixt the MoS and walking speed when the subjects were on the treadmill at various speeds. F.B. Van Meulen [16] developed the ambulatory evaluation of walking balance subsequent to stroke utilizing instrumented shoes to investigate daily activities by measuring the quantitative parameters that relate to clinical assessment. F. Aprigliano [17] presented an ambulatory evaluation of the dynamic MoS utilizing an inertial sensor network, where the magneto inertial measurement unit-centric technique was used for assessing the MoS of gait and the camera-based system was used to compare the results concerning root mean square mean deviation. P.C Fino [18] introduced inertial sensor-centric centripetal acceleration as a correlate for lateral MoS in the course of walking and turning based on centripetal acceleration lateral MoS are determined by using synchronized sensors which are placed on feet and lumbar spine. J. A Albert [19] established an assessment of the pose tracking performance of the Azure Kinect and Kinect v2 for gait investigation compared with a gold standard which evaluated motion tracking performance using Kinect sensor and compared with Kinect v2 and visioned using a multi-camera motion capturing system. X. Yu [20] devised human-robot co-carrying utilizing visual and force sensing to determine framework and force sensing for cooperating with humans by enabling robots to actively reduce human efforts. M. Fahad [21] developed learning human-like motion planning utilizing gauged human trajectories in crowded spaces and proposed to use of a GAIL-based algorithm that generated maps using LIDAR as input data and output the navigation policy which results in direct human trajectories.

This paper proposes a gait monitoring system comprising an accelerometer sensor and gyroscope sensor fused with an ESP32 microcontroller. To estimate foot poses and the gait parameter value, the data from the above-mentioned sensors is sent to an ML open source through WiFi. For averaging the data with high accuracy, RF is then utilized to train and test the data. Subsequent to validation and assessment, the prediction of gait instability says whether yes or no. If yes, a notification is sent to the mobile and the buzzer gets sound.

Designing an RF algorithm grounded on a Decision Tree (DT) that predicts the result with high accuracy by averaging the dataset is the primary contribution of this work. This allows quick fall-risk evaluation of elderly people during overground walking.

The rest of the paper is organized as follows: the proposed system is described in Section III, the performance evaluation of the proposed system is presented in Section IV and lastly, the proposed system is concluded in Section V.

III. METHODOLOGY

To capture the data, wearable devices are essential while overground walking. Obtaining reliable data necessitates accelerometer sensors that are measured in meters per second squared (m/s^2), voltage of 3.3V, and weight measurement range of 2 to 250g. The gyroscope sensor measured the angular motion in degree per second (dps) and ranged between 125dps to 2000dps. Sensors are fused with an ESP32 microcontroller that sends the gathered data from the sensor via WiFi to an open-source IDE. Through the ML platform, gait instability is forecasted. ML platform facilitates data preparation, model deployment, and model monitoring of the real-time gathered data. Gathered datasets are trained with the RF algorithm after data preprocessing. RF algorithm divides the dataset as training and testing datasets. DT is generated by RF, which takes many DTs and combines them to avoid overfitting in order to estimate high accuracy. The gait estimation is notified in the mobile application and the buzzer sounds on the wearable device.

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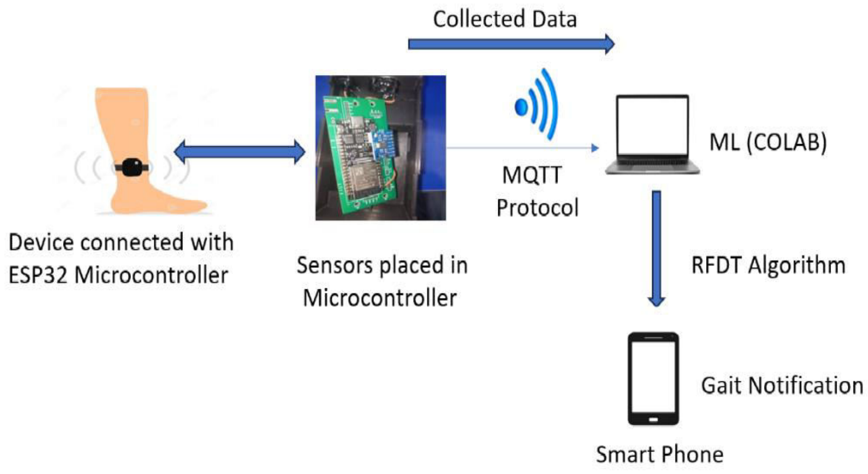

Fig.1. Hardware Description

A. System implementation scheme

1. Experimental dataset collection

Real-time datasets are gathered under overground walking from wearable devices. Subsequently, by utilizing WiFi, gathered datasets are sent to an open-source IDE via the MQTT protocol. ML opensource platform, which extracts raw data from users, performs preprocessing techniques for feature extraction. Continuous datasets were collected from the accelerometer and gyroscope sensor and fused to an ML for better accuracy performance. The sensor measures acceleration as a change in velocity for every single body motion. The sensor starts vibrating and finds the body orientation owing to body mass on the sensor. According to the body motion, the x, y, and z axis are contrasted. They are about a 6-axis gyroscope sensor, which measures a 3-axis accelerometer sensor, and the other 3-axis gyroscope sensor providing the highest stability against temperature by performing a 3-axis accelerometer taking the gyroscope axis as pitch, roll, and yaw. The gyroscope measures the orientation change in order to identify the no change in position through accelerometer rotation and changes in orientation in such cases accelerometer at the center adjusts one of its axes. Every step is measured by ranging betwixt the value of -8 to +8. It explains that if the value ranges below -8, the abnormal value is noticed; if the value ranges between -8 to +8, then the normal value is taken (refer to [1]). Continuous data were gathered in an open source through WiFi, thus performing the data preprocessing to attain data for training with the RF algorithm.

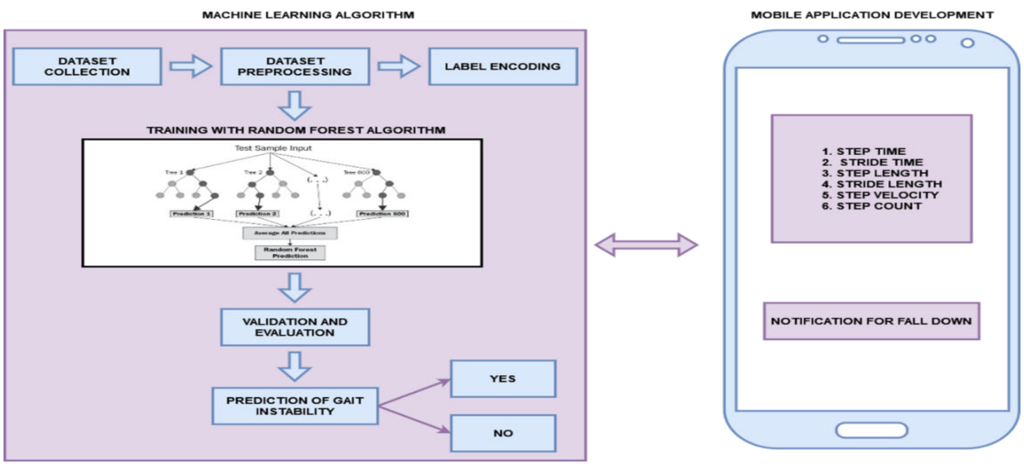

Fig.2. System Architecture Diagram

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2. Data preprocessing and feature extraction

For preparing the data, preprocessing is performed, thereby making it appropriate for ML approaches to attain higher efficiency and accuracy. By utilizing Python libraries, such as pandas and numpy, preprocessing is carried out, thus estimating mathematical operations and managing data. By importing the dataset, both the normal and abnormal datasets were gathered and executed under the Python library. During motion, sensors measure the X, Y, and Z axes and separate their values as per the range of normal and abnormal conditions. In order to identify the magnitude peak, sensors are plotted in the graph, which aids in extracting features for every single step during walking. Subsequently, by utilizing the formula [1], parameters like step time, step length, step velocity, step count, stride time, stride length, and cadence are computed, thus providing data in simple characteristics.

By measuring the magnitude of the X and Y axes, peak prominence attains peak detection via the accelerometer sensor for both normal and abnormal data. Subsequently, for every single step, the mean and standard deviation for both axes were computed. Through this, for the whole gathered data, data frames were constructed. In this, the normal condition and the abnormal condition are represented by the coral color and grey color, respectively.

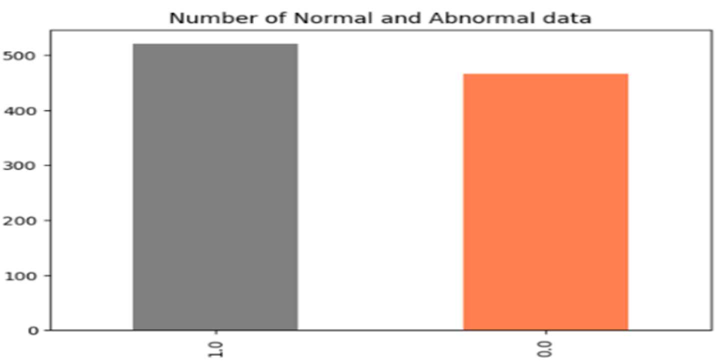

Fig.3. Representation of normal and abnormal data

Analysis is performed in the collected data through the statistical representation, which expresses the relation betwixt the correlation score and features. Through this, the peak variation betwixt every single parameter is notified, and to achieve high performance, normalization is performed to train the model.

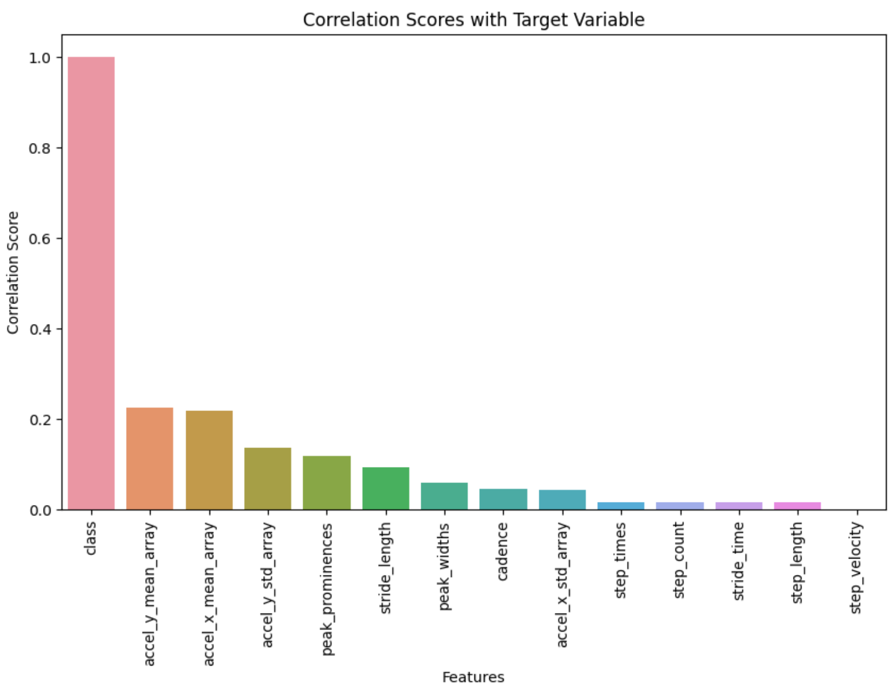

Fig.4. Graph of correlation score with target variable compared with feature extraction

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A major factor, which enhances the performance and accuracy of the model and allows data for quick linking and attainments for easier understanding, is known as data normalization. To visualize and associate the relation betwixt varying features, features on the same scale are utilized. Normalization is performed by min-max scaling, in which the range is between 0 and 1. Normalization is computed as, X normalized= X – Xmin/ Xmax- Xmin. Normalizing the dataset results in attaining a specified range value that aids in training the dataset in the algorithm and attaining more accuracy. From the feature value attained, normalization selects the minimum and maximum values. Therefore, when the X is signified as a minimum value and the numerator is zero i.e.,(Xmin- Xmin), the normalized value is 0. Also, when X is specified as the maximum value and the numerator is equal to the denominator i.e.,(Xmax- Xmin), the normalized value is 1. From this, the value 0 states that the condition is normal and the value 1 states that they are in an abnormal condition.

After normalizing, to attain a high prediction with an expected result, the dataset is split into a training dataset and a testing dataset. To fit the model and evaluate the model, training datasets and testing datasets are utilized, respectively. The subset of the original data is called the training dataset, while the unseen data of the model is called the testing dataset, and they always split the data in the ratio 70:30 80:20, or 90:10.

3. Training data under the RFDT algorithm

The data are finally trained with the RFDT(Random Forest Decision Tree) ML algorithm in order to achieve the outcome with more precision. In the course of training the dataset, they work under DT. In accordance with measuring features in every single partition, random subsets for the dataset were constructed. Grounded on the entire collected data, root nodes are split. In order to achieve the leaf node or again to split the decision node into the leaf node or terminal node, decision nodes were split from the root nodes, and the process continued till the end of class identification. The Entropy(H) and Information Gain(IG) at every single subset are computed to attain the individual outcome grounded on the target variable. They compute grounded on when an entropy with zero tends to be a leaf node. If it exits zero, then they further split into subnodes, and they are computed for one attribute as follows,

$E(T)=\sum_{i=1}^{c} -p_i \log_2 p_i$,

Where, T=current state

pi= probability of an event i of state T

Representation of multiple attributes is calculated as follows,

$E(T,X)= \sum_{c\in X} P(c)E(c)$

Here, the current state is indicated as T and the selected attribute is denoted as X. The entropy's main aim is to achieve the resultant with minimal entropy subsets.

From this, by calculating the entropy difference betwixt the previous split and the succeeding split of the dataset, IG is computed. It is signified as,

Information Gain(T,X)=Entropy(T)-Entropy(T,X)

Gini Impurity assesses the split accuracy betwixt ranked groups. Assessments are performed ranging betwixt 0 and 1. When it is 0, all examinations are under one class, and if 1 occurs then it shows a random dispersal of elements inside the classes. The score in them must be as low as possible. Therefore, the evaluation is performed in Gini Index as follows,

Gini Impurity= 1- $\sum p_i^2$

Where, the i^{th} proportional elements in the set are represented as p_i.

In order to decide the prediction performance, the majority voting for classes is performed by saying yes or no grounded on the Attribute Selection Measure (ASM). To avoid overfitting chance, the volatility among particular trees, which improves forecasting performance, is performed. By voting the consequence of all trees, the process is carried out under classification tasks. To improve prediction performance, the faint data is boosted by successively learning. Subsequently, to compute the entropy, the validation is done by utilizing the formula given below,

Entropy=-p(Yes)*log2(p(Yes))-p(No)*log2(p(No))

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Here, the proportion of “Yes” in the target variable is indicated as p(Yes).
the proportion of “No” in the target variable is specified as P(No).

From this, by predicting the target variable accuracy score in DT as 83.43, the RF algorithm concludes whether the gait is unstable or stable.

Table 1. Accuracy, precision, recall, and f1_score value

	Accuracy	precision	Recall	f1_score
Metrices	83.43	86.72	81.00	83.77

Detailed results about the normal and abnormal conditions of the gait pattern are provided in the classification report. When the condition is normal, 0 occurs, and the condition is said to be abnormal when the value is 1. These are the processes performed in the ML by implementing the device under overground walking by an elderly person. The notification is sent to the caretaker if abnormal. In the below table, the predicted values are listed.

Table 2. Classification Report of normal and abnormal data

Classification Report:

	Precision	recall	f1-score	support
0.0	0.81	0.86	0.83	94
1.0	0.87	0.82	0.84	107
accuracy			0.83	199
macro avg	0.83	0.83	0.83	199
Weighted avg	0.84	0.83	0.83	199

IV. EXPERIMENTAL RESULTS

1. Results on Mobile Application

Here, if a fall-down occurs, React Native (RN) open-source mobile applications were developed with javascript to portray the gait parameters value and notification. A community-driven technology that gets community experts' information online when caretakers face any problem is called an RN. Continuous perfect information about the person is communicated to the caretaker since RNs are more responsive. They predict whether the gait is normal or abnormal after validation. The caretaker will be notified along with parameters if an abnormal condition occurs and a person tends to fall.

Personal information and processed parameters derived from accelerometer data gathered along the X, Y, and Z axes are displayed in the figure below. When the model predicts an abnormality, a notification is sent to a mobile application by utilizing the MQTT protocol, and the buzzer sounds in the hardware.

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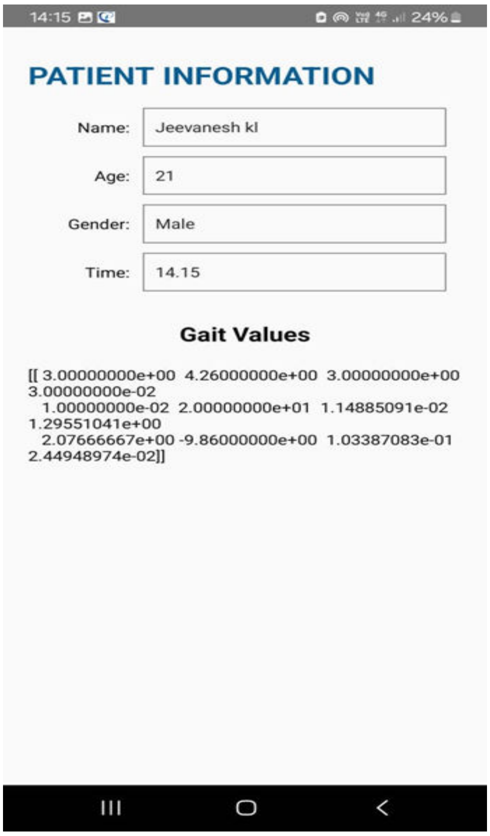

Fig 5: Information about gait parameters value

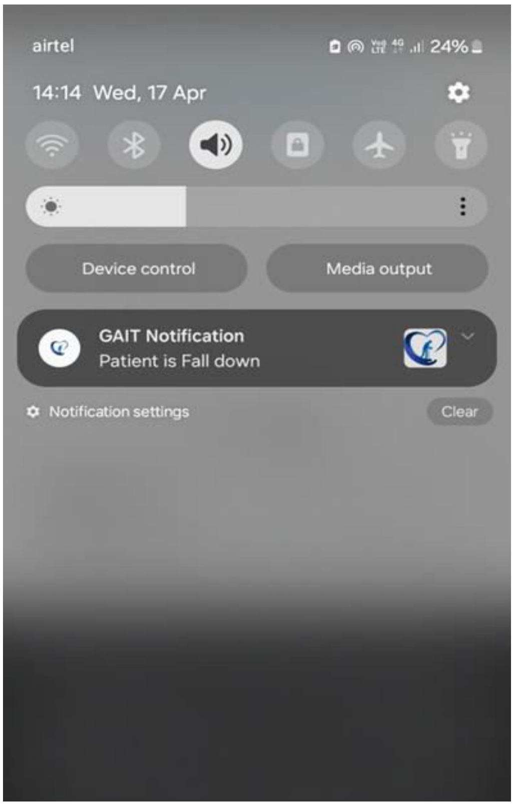

Fig 6: Abnormal notification

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The work is proposed with the ML algorithm that performs RFDT for the foot position gathered from sensors under overground walking, which acquires higher accuracy than Kalman's filter in the prevailing work. The mobile application accesses a quick fall-risk assessment for the caretaker. More data were trained under RF without any overfitting data for perfect prediction by utilizing the ML algorithm. The proposed model considered the effective determination of monitoring the real-time gait stability with high accuracy.

2. Limitation and Future Work

To determine technology in the healthcare field, the application of predicting the gait stability and instability in a person should be reviewed in the future. It can be promoted to determine the several kinds of diseases with more accuracy. They have more chance of developing or converting this project in many ways in the healthcare field. Hence, this project has an effective scope in the coming future in which manual predicting can be converted to computerized production reasonably.

V. CONCLUSION

The project has been successfully implemented to render a solution for predicting gait instability by capturing the foot position of humans and integrating it with sensor data for predicting the gait presence in a person. To fetch the change in the stability of motion while walking along with the AI-based prediction, the inertial measurement sensor was used. In order to arrive at much more stable outcomes of gait monitoring, the hardware units' output would be contrasted with the software outputs. To determine the gait instability, an ML algorithm, such as RF was used. A mobile application utilizing RN was developed, where the predicted parameters along with gait instability (yes or no) would be shown. A buzzer integrated into the wearable would be switched on to alert the person if the gait instability was yes. Since the prediction of gait instability can be performed in various means, there was a lot of scope for enhancing the technology.

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