EdgeAI driven Wearable Device for Fall Predicition and Heath Monetering

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***Abstract*—Falls are a significant concern for the elderly and individuals with mobility impairments, often leading to severe injuries and increased healthcare costs. This research presents a novel approach for fall detection and simultaneous health monitoring using an integrated system that leverages an Inertial Measurement Unit (IMU), Galvanic Skin Response (GSR) sensor, and heartbeat sensor. The proposed system collects real-time data on body movements, physiological responses, and heart activity, which are transmitted to IoT platforms such as Thing Speak for cloud-based analysis. Additionally, Edge Impulse is utilized to train machine learning models on the gathered data, enabling accurate fall prediction through advanced anomaly detection techniques. The system's architecture is designed for scalability and responsiveness, providing caregivers and healthcare professionals with timely alerts and insights into the monitored individual's health status. Initial findings demonstrate the efficacy of this approach in reducing false positives and enhancing the reliability of fall detection. This research not only contributes to improving personal safety for vulnerable populations but also showcases the potential of integrating IoT and edge AI in health monitoring applications.**

Keywords—Galvanic Skin Response : GSR, Daily Normal Activities : DNA

I. INTRODUCTION

A. Motivation

Falls are a common incident with elderly people and anyone with long-term illness, and they form a high number of accidents. Such occurrences result in extensive physical harm, long hospital stays, disability, or worse still fatality. Since activity reduces at older ages, maintaining mobility is important and falls are a significant concern for those who are frail and elderly. Therefore, there is a need to reduce these incidences by developing Health safety measures. However, current wearable technology systems offered in the current market lack enhanced capabilities. Instead, they tend to address only one type: a fall or a health issue, without integrating the other, thus providing disjointed data about the wearer's status. Furthermore, most devices are passive; they only get triggered by a fall and do not attempt to monitor other aspects of the wearer's health, including irregular pulse rates, high stress levels, or pre-and post-fall situations.

The other drawback is that these systems do not function as real-time management response tools. As such, even when a fall is identified, there is usually a long time before caregivers, or a doctor is informed. These devices also cannot forecast a fall or future health problems other than because of existing patterns detected. This puts the users at the mercy of one or many events that might have been averted at an earlier time. Therefore, there is an increasing demand for a multi-parameter continuously supervising integrated system for both fall recognition and overall health monitoring with speedy interventions and improved treatment.

B. Literature Survey

Mathematical Model for Fall Detection Predication in Elderly People -This paper seeks to create a mathematical prediction model of fall detection in the elderly using a single triaxial accelerometer along with quaternions to describe the rotation of the three joints (thoracic, hip, and knee). Given human body kinematics, the model can predict the likelihood of fall occurrence and implemented both online and offline in real time. The research goals aim to assess the performance of the proposed model against a logistic regression and compare its accuracy, precision, recall, specificity, and execution time latency with existing techniques.

Fall Detection by Ambient Sensors on Years-Long Simulation Data-This paper endeavors to construct a long-term fall monitoring system at a house scale within a virtual smart home with ceiling infrared motion sensors. For realism, the system simulates falls as a behavior that can happen during daily activities. The system is tested for nine years where 26 falls happen for the virtual resident with cognitive function declines over time. The primary objective of the thesis is to evaluate the effectiveness of the decision tree with Non-parametric Rule Discovery (NRD) method in the detection of falls as different from other classification techniques.

Smart Walker: an IMU-Based Device for Patient Activity Logging and Fall Detection-In this paper constructs a low cost, smart sensor device using an inertial measurement unit attached to a walker and combine it with another IMU to detect real time falls of elderly patients. Research objectives include gathering and labeling data for walking, falling and standing, training a Convolutional Neural Network (CNN) trained for multi class classification, and obtaining high accuracy for fall detection.

Fall Detection System for Elderly People using IoT and Machine Learning technology -A budget friendly, portable fall detection device for the Arduino MKR1010 microcontroller and a 3 axis gyroscope/accelerometer is proposed. Data is continuously gathered by the device, transmitted to a cloud architecture to organize events and notify the affected family in the event of a fall. It is comfortable and fast, the risk of major harm or death is reduced. In addition, it reviews related work on fall detection systems, including wearable, non wearable, and hybrid systems. The proposed solution is an integration of wearable and IoT based devices that adopts a machine learning model for more accurate fall detection and presence of real time data. The architecture is made of an edge layer for data acquisition and a cloud layer for the prediction and data analysis. Data processing and communication takes a place via HTTP connection, MQTT protocol, Spark Streaming service, which provides data security and scalability.

Fall Detection for Elderly People Using Machine Learning-This paper attempts to document sensor network and Internet of Things (IoT) based fall detection systems including data collection, transmission, sensor fusion, analysis, data security and privacy issues. Additionally, we are also looking at the performance of the machine learning algorithms fall detection, specifically Support Vector Machines (SVM) and Decision Trees, and comparing their accuracy, sensitivity, specificity, prediction time.

Smart Wearable System For Fall Detection In Elderly People Using Internet of Things Platform- The specific objective of the paper is to provide a cost effective and efficient fall detection system in elderly persons living alone by use of IoT technology like mobile phones and wireless sensor networks. The system is provided with advanced sensors, including an accelerometer, heart rate sensor, and temperature sensor, to detect falls and monitor post fall condition. The goals of the research are improving the precision of the fall detection, as well as improving the overall functionality of the system adding other sensors and integrate the system to IoT technology, for real time alerts and storage of data.

Fall Monitoring for the Elderly Using Wearable Inertial Measurement Sensors on Eyeglasses-The fall detection system based on IMU sensors embedded in eyeglasses is presented in the study. Sudden head movement changes and vertical acceleration are used by the system to identify falls. The angular data are further improved by a complementary filter, and false alarms are minimized by a threshold based algorithm. Testing with five participants yielded a high accuracy rate of 95.44% in identifying falls or non falls. The results indicate the proposed system is an acceptable solution for fall detection of elderly individuals.

C. Research Gap

In order to overcome the shortcomings of current systems, we put forward an all-encompassing wearable device far beyond basic fall detection. It features both continuous health monitoring and fall detection and provides real time feedback of vital signs, e.g. heart rate or stress. The dual functionality of the device guarantees that not only will the device precisely identify a certain fall, but also constantly monitor the wearer’s general state of health to offer a much more holistic understanding of what its well being. The device, which mixes motion with physiological metrics, provides an earlier intervention in cases of high stress or abnormal heart rates that could cause fainting or other medical emergencies.

Until now, current wearable solutions are limited in their ability to deliver real time health insights as well as reliable fall detection, with the majority of current wearable solutions resulting in false alarms. But our system is much more advanced, since it uses a suite of the latest sensors to track many different kinds of data points, from mechanical movements to internal physiological changes. This approach allows the device to distinguish between patterns pertaining to normal activities (walking, jogging or standing) and abnormal events (i.e. having a falls). The device captures the data with granular detail on body movement and physiological status thus enabling users, caregivers, and healthcare providers to understand trends in health more thoroughly and act proactively when necessary.

Powered by cutting edge machine learning models such as Spectral Analysis and Classification, high precision fall detection is achieved in the system. They are these algorithms that will process the motion pattern in real time such that the device can be able to predict and detect falls more accurately and responsively. Such machine learning models gain even more value if they are fine tuned to the user's unique motion profile, as this not only decreases false alarm likelihood, but also increases their ability to immediately recognize and report an incident if it is legitimate. For high risk individuals, this level of precision is important, because it reduces the chance of false alarms washing out real threats, and aids in accompaniment during real emergencies.

Additionally, our healthy monitoring component is more robust as well; tracking vitals like heart rate and stress consistently. In these cases, real time monitoring allows alerts to be issued before events such as fainting, when stress and irregular heart rates are often first signs of a more serious event. This capability allows the wearer to rest easy, that the device will alert them and caregivers if the wearer's health may begin to deteriorate. In addition, these insights will let users know, identify and minimize health risk factors overtime so that users will be able to adapt to lifestyle changes or seek medical advice on time.

D. Objective/Flowchart

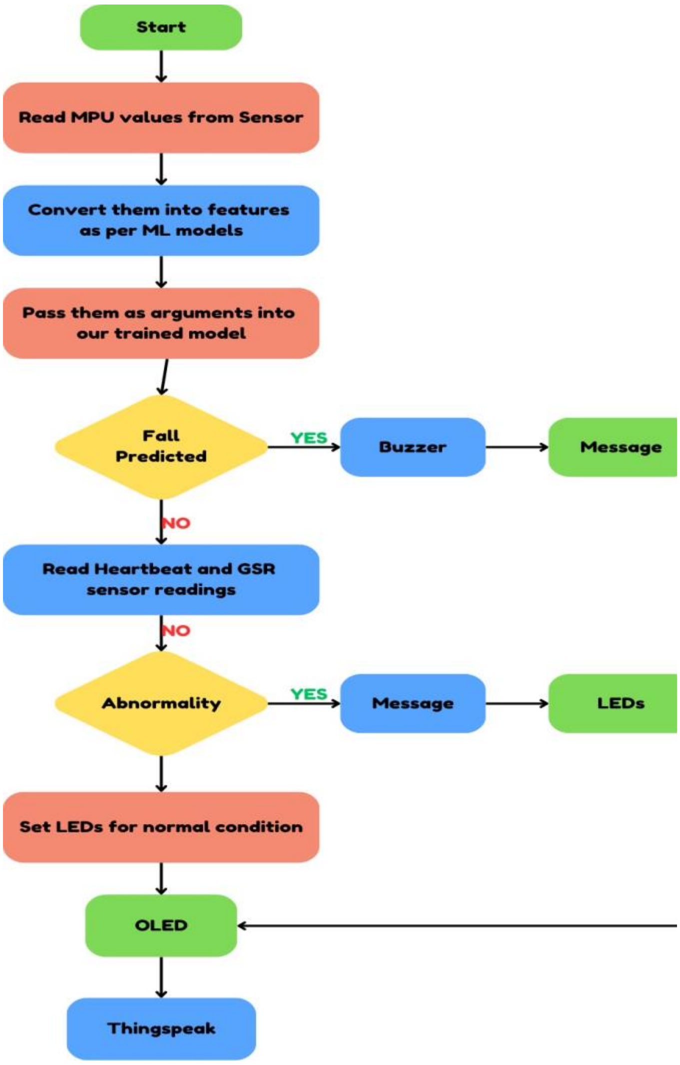


Fig1 System Flowchart

This flowchart outlines a very robust way to monitor user motion as well simultaneously monitor health parameters, thereby increasing user safety through continuous monitoring. A wearable device provides real-time fall detection with low false alarm rate and proactive health monitoring, in particular, for users at risk of medical emergency such as fainting or cardiac event. Using motion and physiological monitoring along with this, the device, the device should provide a comprehensive health profile — enabling timely intervention and fostering prevention.

Due to this dual functionality, our proposed system is not just useful for fall risk management, but also for more general health applications. Machine learning models for pattern recognition and anomaly detection allow the device to integrate with user profiles, and facilitate accurate and reliable results. Additionally, the presence of a cloud connectivity, as provided through Thing speak, permits remote monitoring, which enables caregivers see and understand the user's health and safety status far away.

Finally, wearing the proposed wearable device makes it a practical and advanced solution for fall detection and health monitoring that simultaneously fills the gaps existing systems encountered to provide all the comprehensive, real time data processing and alert capabilities. In addition to improving the safety and quality of life for users, this scope of work broadens the scope of applications for wearable health technology in healthcare monitoring and intervention.

II. METHODOLOGY

A. Data Collection Process

Software/Hardware requirements for data collection includes:

- MPU-6050 Sensor- It fuses 3-axis accelerometer and 3-axis gyroscope module used to study person's motion and rotation.
- Raspberry Pi Pico W- Used as an Edge device for running ML models locally and detect falls.
- Edge Impulse – It's a widely used software to train ML/ Deep Learning Models for Edge devices.

For collection of data MPU6050 was connected to Raspberry Pi Pico W and the data was sent to Edge impulse application via serial manner. MPU6050 readings were renewed at approximately 73Hz rate. The sampling window upon which further analysis were carried out is set to 3000ms.Our ultimate objective is to detect "Fall". In order to achieve this goal we have collected data on "Daily Normal Activities". We train our model on DNA and if the test data shows deviation, model regards that sample as anomaly and predicts Fall. To understand how this works lets first classify various DNAs.

<u>Daily Normal Activities</u>	<u>Description</u>
Jogging	It captures motion of a person in jogging state.
Walking	It captures motion of a person in walking state

Chill_OnPhone	It captures motion of a person at rest or using his/her phone.
Exercise	It captures motion of a person doing stretching exercise.
Eating	It captures motion of a person Eating.

When a person, especially elderly is outside the above classified are most common activities that they are likely to perform. Sleeping, as an activity is intentionally not included as this system is specifically designed to be used outside ones house. Before we move forward with our discussion on “Daily Normal Activities” vs “Fall” ,lets first understand what categorizes as a Fall? A “Fall” is sudden shift from any “normal” activity which is preceded by sharp/instantaneous change in axis readings of IMU .
Analyze the following images,

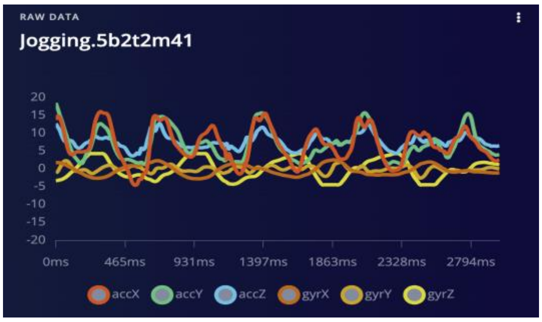


Fig 2 Jogging Sample

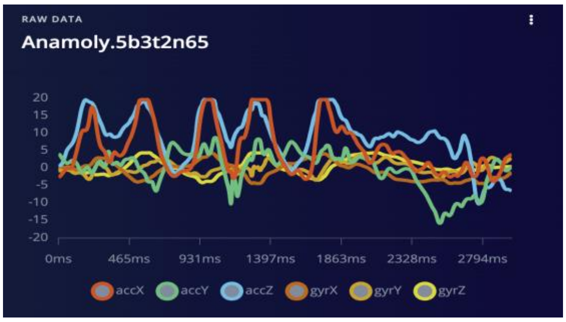


Fig 3 Jogging to Fall

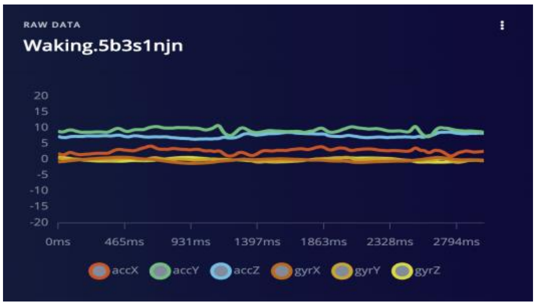


Fig 4 Waking Sample

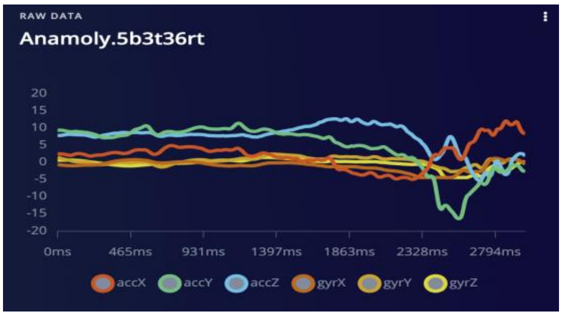


Fig5 Waking to Fall

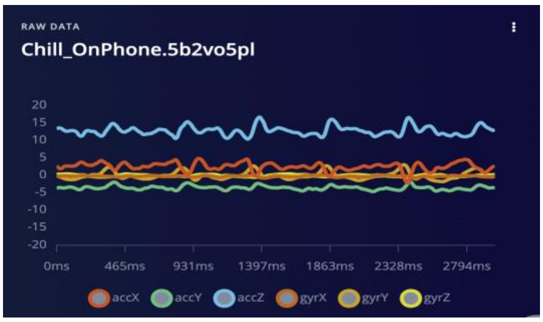


Fig6 Chill_OnPhone Sample

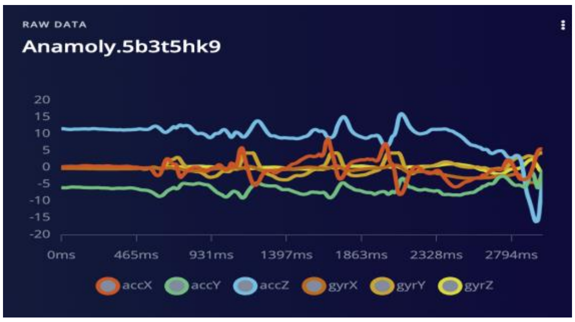
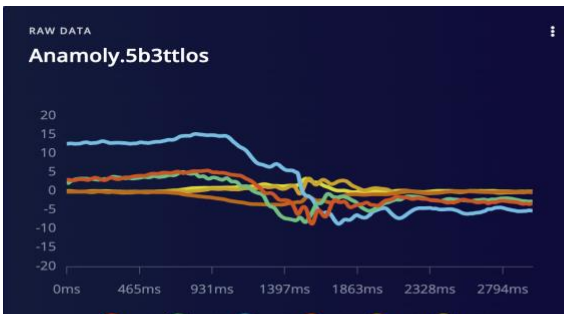


Fig7 Chill to Fall



Left images/Even numbered images correspond to "Normal activities", whereas right ones/odd numbered corresponds to sudden fall while performing normal activities. As we can observe that the IMU readings change abruptly upon encountering a fall. This "abruptness" i.e., instantaneous change along the accelerometer/gyroscope axis helps us predict a " fall". This setting helps us predict a fall without sampling fall data as "fall" is regarded as sudden deviation from normal activity. All the data used for training is model is collected on our own. No secondary data /public datasets are used. The data collected was even split in standard ration of 80-20 before proceeding with data processing or classification. Compare and check Fig2vsFig3, Fig4vsFig5, Fig6vsFig7 etc.. one can visually identify. Normal vs anomaly. Furthermore, data from GSR (Galvanic Skin Response) and MAX30102 is also used to detect heath anomalies .However it is important to note that the data from these sensors is not used for Machine Learning.

B. Process Flow for Fall Detection

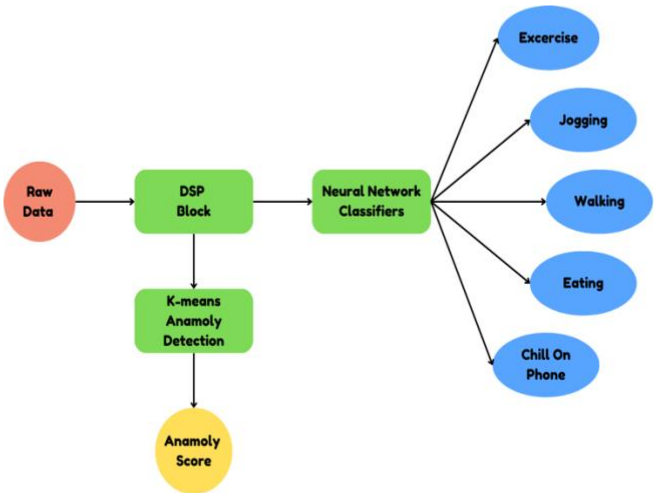


Fig9 Process Flow Diagram

DSP Block **:** This block consists of spectral feature analysis to extract crucial information such as frequency ,power and other characterizes of the signal. Before processing the data we have not used any filter . This is because our fall prediction approach is frequency sensitive. Furthermore , we have used "Fast Fourier Transform" to analyze repetitive patterns in our signal. This method is widely used in signal processing .Finally, using this technique we compute two main type of features per axis- Statistical and Spectral. Statistical features include RMS values along axis, Skewness etc. Statistical features summarize the amplitude characteristics and distribution shape of the signal in the time domain. Spectral features highlight key frequency components, indicating patterns or periodic behaviors in the signal. The output of this block gives processed features along with importance of each feature. This data is quintessential for anomaly detection. According to our analysis the best features include along following axis in decreasing order acceleration X RMS ,acceleration Y RMS, acceleration Z RMS, Gyroscope Y Spectral Power 34-38Hz.

*Classifier***:** This block takes processed features as input and gives a probability score that indicates how likely it is that the input data belongs to a particular class. Our classifier is based on "Neural Networks approach". Neural networks are built from simple processing units called "neurons" or "nodes" arranged in 3 layers: Input Layer-The first layer, where the network receives raw data. Hidden Layers-Intermediate layers where computations occur. Each hidden layer consists of neurons that apply transformations to the data, typically with weights and activation functions. Output Layer -The final layer that provides the network's prediction or classification result. The architecture of Neural Network is influenced by the following functions; "Activation Function", "Loss Function", "Optimizer". Additionally, Eon tuner compiler was used for deployment on Rpi Pico W . Our NN classifier architecture l uses "SoftMax function" and in addition to that "Categorical Loss Entropy" Loss function. This helps us draw precise inferences for multi-class classification.

Anomaly Detection: "K-means clustering method" is used to evaluate anomaly .Technically , X numbers of clusters are created for our training dataset . We store center and size of each cluster .If the test data is outside the perimeter of this cluster then it is considered as an anomaly . A threshold on Anomaly Score could be used to correctly identify a fall.

III. Results

A. Classification Output

Fig10 Classification Report

From this classifier output we can observe that almost all the samples are correctly identify. Have a look at validation set results to mathematically understand results.

B. *Anomaly Detection resut*

Fig11 Anomaly Detection 1

Fig12 Anomaly Detection2

As we can observe that, the test data goes out of the cluster . This is an indication of anomoly (fall) in our case. Also notice the axis chosen for K-means clustering . These are the same axsis along which we get best features. These samples in Test data were intentionally added to identify fall. Its worth noting that out all the fall samples given to this detection block we got correct results for 87% of time . For Others ,there was uncertainity in our output.

C. *Validation set reults*

Model	Accuracy	Area Under ROC	Average Precision	Average Recall	Loss	F1 Score
NN Classifier	0.97	1.00	0.98	0.98	0.19	0.98

	CHILL_ONPH	EATING	EXCERCISE	JOC
CHILL_ONPHON	100%	0%	0%	
EATING	5%	90%	5%	
EXCERCISE	0%	0%	100%	
JOGGING	0%	0%	0%	1
WALKING	0%	0%	0%	
F1 SCORE	0.98	0.95	0.96	

Fig13 Confusion Matrix for Training Set

D. Computational Matrix

Maximum Time Taken For Computation	238ms
Ram Usage	5.3KB
Flash USage	16.9KB

The edge device that we are using RPI PICO W has 240KB of RAM and 2MB of Flash Memory available. Thus ,this model is possible to be uploaded on RPI Pico W .

E. Test dataset results

Model	Accuracy	Area Under ROC	Average Precision	Average Recall	Loss	F1 Score
NN classifier	0.91	1.00	0.97	0.97	0	0.97

	CHILL_OI	EATING	EXCERCIS	JOGGING	WALKIN
CHILL_ONPI	93.3%	0%	0%	0%	0%
EATING	0%	75%	0%	0%	0%
EXCERCISE	0%	0%	95.2%	0%	0%
JOGGING	0%	0%	0%	100%	0%
WALKING	0%	0%	0%	0%	83.3%
ANOMALY	-	-	-	-	-
F1 SCORE	0.97	0.86	0.98	1.00	0.91

Fig14 Confusion Matrix for Test Set

The performance of test dataset helps us understand how will the model perform on edge device. Though our accuracy decreases in comparison to validation set resuts but we still have high precision ,recall levels thus indicating that our system is sensitive to falls .This is extremely pivotal in our case . Thereby ,this model seems acceptable.

The link for my project dashboard could be found [1].

IV. SYSTEM INTEGRATION

A. Hardware Integration

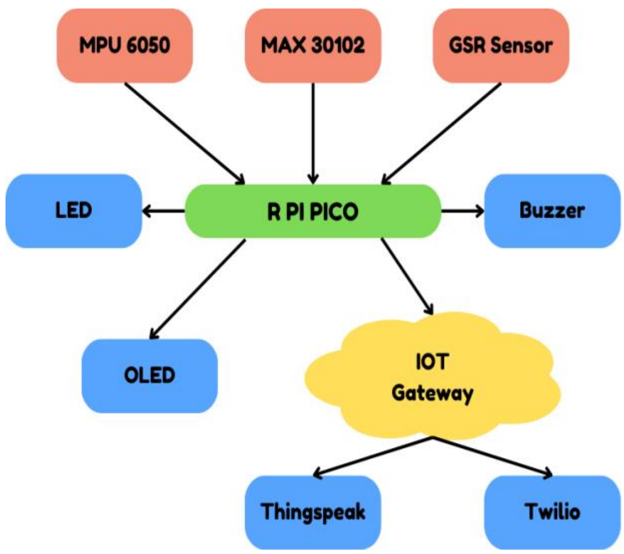


Fig15 Block Diagram of overall System

At the centre of the architecture is the Raspberry Pi Pico (R PI PICO) microcontroller as the main processing unit that interfaces with all sensors and output devices. At the top, we have the Input Sensors, which include the MPU6050, a motion sensor that integrates both an accelerometer for detecting acceleration and falls, and a gyroscope for measuring orientation and angular velocity. The MAX30102 heart rate sensor monitors the user's pulse rate, while the GSR sensor measures skin conductance to assess stress levels. On the left and centre, the Output Devices consist of an LED that provides visual indicators for different states and alerts, an OLED display screen that shows real-time vital signs and system status, and a buzzer that produces audible alerts when falls are detected.

To the right, the Communication section features an IoT Gateway that manages external communications. This includes connectivity to Thing Speak, a cloud platform for data visualization, health trend analysis, and remote monitoring. Additionally, it connects to Twilio, a communication service that sends SMS alerts to caregivers and notifies emergency contacts when falls are detected or vital signs are abnormal.

The diagram illustrates how data flows from the sensors through the Pico for processing, then displays information locally via the OLED and LEDs, triggers the buzzer for immediate alerts, and sends data to cloud services through the IoT Gateway for monitoring and notifications. This architecture creates a comprehensive system that combines real-time monitoring, local alerts, and remote notification capabilities, effectively enhancing health and safety monitoring.

B. Software Integration

a. Data Processing Pipeline

Raw Sensor Data Collection**:** The system implements a unified data collection approach, maintaining a synchronized sampling frequency across all sensors to generate predictions every 3 seconds. This setup includes an MPU6050 sensor, which provides integrated 6-axis motion sensing through accelerometer and gyroscope measurements along the X, Y, and Z axes, capturing precise motion and orientation data. Additionally, the MAX30103 sensor records heart rate data, enabling real-time heart monitoring. A GSR (Galvanic Skin Response) sensor further contributes by measuring raw analog values to assess skin conductance, offering insights into physiological responses.

All raw sensor readings are stored in CSV format, allowing for easy data manipulation and analysis. This structured method supports systematic data collection and efficient processing of sensor outputs, making it suitable for robust data analysis and predictive modelling.

Signal Processing and Conditioning**:** The system utilizes a minimalist approach to signal processing, intentionally avoiding excessive filtering techniques that could potentially obscure fall signatures in motion data. This design choice stems from the observation that over-filtering may impair the system's ability to detect the sudden movements typically associated with falls.

Key processing elements include calibration of the GSR sensor to ensure accurate skin conductance measurements, enhancing the reliability of physiological data. Additionally, a robust data validation protocol identifies and re-records any corrupted or invalid sensor readings, maintaining data integrity throughout the collection process. Finally, raw analog values from the GSR sensor are preserved to retain maximum signal fidelity, ensuring that essential signal characteristics are unaltered for analysis.

Feature Extraction: The feature extraction process is customized to address each sensor's unique function within the system.

For Motion Analysis, primary features are derived from the MPU6050 sensor, including accelerometer readings and gyroscopic measurements across the X, Y, and Z axes. Additionally, frequency domain analysis is applied to improve motion pattern recognition, enhancing the system's ability to identify significant movement patterns.

In Physiological Monitoring, heart rate data is extracted from the MAX30102 sensor, providing real-time insights into heart health. Meanwhile, raw GSR conductance values are preserved to indicate stress levels, offering a non-invasive measure of physiological responses to various stimuli.

Data Integration and Analysis**:** The system employs a specialized approach to data handling and analysis, designed to efficiently process diverse sensor inputs. Data is managed through independent processing streams, with motion data from the accelerometer and gyroscope dedicated to fall detection, while physiological data—such as heart rate and GSR readings—is processed separately for health monitoring. Fall detection relies exclusively on IMU data (accelerometer and gyroscope) and utilizes anomaly detection to identify deviations from normal activity patterns, focusing on sudden changes that differ from established baseline activities like walking, eating, exercising, or resting.

Health monitoring operates in parallel, processing heart rate and GSR data independently to analyse physiological parameters. This pipeline architecture supports the efficient handling of multiple data streams, allowing for real-time anomaly detection in fall identification and continuous monitoring of health parameters. The design ensures robust system performance through streamlined data handling, prioritizing real-time processing capabilities and reliability by focusing analysis on relevant parameters for each monitoring function.

b. Cloud Platform Integration

The system implements a cloud-based monitoring and alert infrastructure utilizing Thing Speak for data visualization and Twilio for emergency notifications. This architecture enables remote health monitoring capabilities while maintaining real-time alert functionality.

Thing Speak Integration**:** The system incorporates a structured data upload mechanism, facilitating efficient management and transmission of sensor data. Key specifications include an upload frequency of every 5 seconds, during which the system transmits GSR (Galvanic Skin Response) measurements and heart rate readings. Data is communicated through an HTTP-based protocol, with authentication handled via direct API key integration within the system's firmware.

The Visualization Implementation employs a real-time line graph framework to represent temporal data, providing separate data streams for GSR and heart rate monitoring. Data is plotted continuously with 5-second update intervals, allowing for near real-time visualization of physiological parameters.

System Reliability is ensured through basic reliability measures, including system reset functionality for network connectivity issues, a sequential data upload mechanism, and a design that proceeds to the next sample after any failed upload attempt. Operationally, the system requires continuous internet connectivity, an active Thing Speak channel configuration, and valid API key authentication to ensure uninterrupted data transmission and visualization.

<u>System Architecture Considerations</u>**:** The system architecture is designed with specific Network Dependencies, operating under constraints that require constant internet connectivity and direct HTTP communication with Thing Speak servers. This setup enables real-time data transmission to ensure timely and accurate data updates.
For Data Flow Management, the data pipeline is structured to collect sensor readings (GSR and heart rate), format the data for cloud transmission, and upload it to Thing Speak at 5-second intervals. This setup ensures seamless data flow and automatic updates to visualization graphs.
Error Handling is supported through basic error management features, including automatic continuation after upload failures, a system reset function to address major connectivity issues, and a wait-and-retry mechanism for failed transmissions. These measures promote data reliability and maintain smooth operation under various conditions.

Fig16:ThingSpeak Data Visualization Interface

The real-time data visualization implementation through ThingSpeak demonstrates the system's capability for continuous health monitoring and data analysis.
The GSR Monitoring Graph features a time-series plot that displays GSR variations over a specific period, from 06:50 to 07:00. The Y-axis scale ranges from approximately 500 to 900 units, allowing for a clear representation of stress level fluctuations over time. This setup offers a temporal resolution that effectively captures real-time data updates, ensuring that users can monitor changes in stress levels as they occur.
Additionally, the Alert System Integration provides a visual indicator system for status monitoring. It employs color-coded alerts to signify different threshold levels, facilitating quick identification of critical situations. Timestamp information is included for event logging, allowing for accurate tracking of when specific events occur. Furthermore, the system is integrated with an emergency response framework, ensuring that alerts can prompt timely actions if necessary. This comprehensive visualization interface enhances the overall functionality of the wearable fall detection and health monitoring system by providing users with immediate insights into their health status.

```
Starting inferencing in 2 seconds...
Sampling...
INFO: HW RFFT failed, falling back to SWINFO: HW RFFT failed, falling back to S
Predictions:
  Chill_OnPhone: 0.00000
  Eating: 0.94922
  Excercise: 0.00391
  Jogging: 0.05078
  Walking: 0.00000
Anomaly prediction: 1.039
```

Fig17 Machine Learning Model Performance on Serial Monitor of Arduino IDE

The Edge Impulse inference results demonstrate the system's real-time classification capabilities and anomaly detection performance, showcasing the effectiveness of the integrated machine learning algorithms.
In terms of Activity Classification, the system monitors multiple activity states, including Chill_OnPhone, which detects sedentary phone usage; Eating, recognizing nutrition intake activities; Exercise, for physical activity monitoring; Jogging, capturing dynamic movement detection; and Walking, classifying normal ambulatory motion. This comprehensive range of monitored activities allows for a nuanced understanding of user behaviour.
Regarding Inference Metrics, the system operates with a sampling frequency of 2-second intervals, providing timely data for analysis. Confidence scores are generated for each activity class, alongside anomaly prediction scores that range from -0.02 to 50 These metrics not only validate the real-time inference capability of the system but also enable continuous monitoring of user activities.
The overall System Performance is characterized by a continuous sampling mechanism and hardware RFFT (Real Fast Fourier Transform) implementation, ensuring efficient processing of sensor data. Robust fallback mechanisms are in place to maintain reliable operation, and clear classification boundaries between activities enhance the accuracy of the system.
These implementation results signify the successful integration of hardware sensors, machine learning algorithms, and cloud-based monitoring systems. The combination of real-time processing capabilities, accurate activity classification, and effective anomaly detection validates the system's effectiveness in fall detection and health monitoring applications, offering promising advancements in user safety and health awareness

Fig18 :Physical Implementation of the Wearable System

The prototype implementation showcases the practical realization of our proposed fall detection and health monitoring system. At its core is a Raspberry Pi Pico W microcontroller mounted on a breadboard, serving as the central processing unit. The integration includes several key elements.

First, the Hardware Configuration features a 128x64 OLED display module that provides real-time visual feedback of sensor data and system status. The GSR (Galvanic Skin Response) electrodes are attached to two fingers using conductive fabric patches, ensuring effective measurement of skin conductance. The integrated circuitry is arranged in a wearable configuration on the dorsal aspect of the hand, with power and data connections implemented using standard gauge wiring. The overall design emphasizes a compact form factor, optimizing wearability and user comfort.

Second, the Sensor Placement is carefully considered, with strategic positioning of the GSR electrodes to ensure consistent skin contact. The MPU6050 sensor is oriented optimally for accurate motion detection, while the ergonomic arrangement of components minimizes interference with natural movement. This thoughtful design enhances the functionality and usability of the wearable system, making it suitable for continuous monitoring in everyday scenarios.

V. CONCLUSION

This research presents a novel integrated approach to wearable health monitoring through the development of a comprehensive fall detection and vital sign monitoring system. The implementation successfully demonstrates the feasibility of combining multiple sensing modalities with machine learning algorithms to create a robust health monitoring solution. By integrating MPU6050 for motion detection, MAX30102 for heart rate monitoring, and GSR sensors for stress level assessment, our system achieves both fall detection and physiological monitoring capabilities within a single wearable device. The unique features of this paper include : Multi-Modal Sensing Architecture, Real-Time Processing Framework, Cloud Integration and Alert System, Machine Learning Implementation.

The experimental results demonstrate the system's capability of the system is designed to accurately detect falls with minimal false positives, enhancing user safety and reliability. It continuously monitors heart rate and stress levels in real-time, providing valuable insights into the user's physiological state. During critical events, the system immediately sends alerts to designated contacts, ensuring timely intervention when needed. Built for robustness, the system maintains consistent performance across various operating conditions, adapting to different environments and user activities. This combination of precision, responsiveness, and durability makes the system suitable for continuous, dependable health monitoring, catering to diverse needs across age groups and health scenarios.

The developed system is versatile, with potential applications in elderly care facilities for enhanced safety, remote patient monitoring for continuous health oversight, personal health tracking for daily wellness, rehabilitation monitoring to aid recovery, and athletic performance assessment to optimize training and prevent injuries.

The success of this project demonstrates the potential for integrated wearable devices to improve healthcare monitoring and emergency response systems, particularly for vulnerable populations. The findings and implementation strategies presented here contribute to the growing field of wearable healthcare technology and provide a foundation for future developments in this domain.

VI. REFERENCES

[1] https://studio.edgeimpulse.com/studio/543496

[2] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9099035p.jsp?tp=&arnumber=10255626

[3] https://www.ijraset.com/best-journal/fall-detection-for-elderly-people-using-machine-learning-398

[4] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10255626

[5] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10014869

[6] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10651854

[7] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8250644

[8] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1025218

[9] https://www.sciencedirect.com/science/article/pii/S0263224124000708

[10] https://typeset.io/papers/smart-application-for-fall-detection-using-wearable-ecg-2bl7u2wu

[11] https://www.sciencedirect.com/science/article/pii/S1877050918304721

[12] https://ieeexplore.ieee.org/document/6814018

[13] https://docs.edgeimpulse.com/docs/edge-impulse-studio/processing-blocks/spectral-features

[14] https://docs.edgeimpulse.com/docs/edge-impulse-studio/learning-blocks/anomaly-detection

[15]

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[19]

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