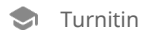


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PATENT_DL



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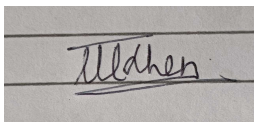


Annexure3b- Complete filing
INVENTION DISCLOSURE FORM

Details of Invention for better understanding:

1.TITLE: An AI-Powered Traffic Signal Recognition System

2. INTERNAL INVENTOR(S)/ STUDENT(S): All fields in this column are mandatory to be filled

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3. DESCRIPTION OF THE INVENTION

Purpose

This invention concerns the creation of a wearable fall detection system based on IoT with a combination of accelerator and gyroscope sensors, along with a deep learning model (CNN-LM) that identifies and classifies human falls in real time. The invention aims at giving a non-invasive, precise, and economical way to monitor high-risk, elderly persons who risk falling at any given moment.

The system aims to:

- Be able to constantly track the movement and position of a person using an IoT gadget on their body.
 - Detect fall incidents precisely with multi-sensor data fusion and deep learning.
 - Auto-notify caregivers or medical responder through the use of IoT networks.
 - Minimize false positives of threshold-based systems.
 - The invention is useful in the assistive healthcare technology, specifically geriatrics, rehabilitation, and remote patient monitoring.
-

Technical Workings

The invention is comprised of five main subsystems and they cooperate in an IoT architecture to detect falls and alert in real time.

Sensor and Data Acquisition Layer.

A 3-axis accelerator and 3-axis gyroscope (e.g. MPU6050 or MPU9250) are integrated into the wearable device, allowing it to be used to measure the linear acceleration and angular velocity along all axes.

Some of the major functionalities are:

- Sampling of continuous data 50-100 Hz.
 - Sensor fusion to obtain the overall magnitude of acceleration and angular rotation.
 - Filtering (Kalman or complementary filter) to minimize noise and average out data stream.
 - The gadget is attached at the waist, wrist, or chest areas on the body that are the best capturing areas on falls.
-

2. Preprocessing and Feature Engineering Layer

The raw sensor data is preprocessed before being input into the deep learning model:

- **Normalization:** Scales raw accelerometer and gyroscope readings between -1 and 1.
 - **Segmentation:** Data is divided into time windows (e.g., 2–3 seconds with 50% overlap) to preserve temporal context.
 - **Noise Reduction:** Gaussian and median filters remove transient spikes caused by hand or leg motion.
 - **Feature Extraction:** Derived features include:
 - Mean, variance, and root mean square (RMS) of acceleration.
 - Pitch, roll, and yaw angles.
 - Jerk (rate of change of acceleration).
 - Signal Magnitude Vector (SMV) and Orientation Angles.
-

3. CNN-LSTM Deep Learning Model

The invention makes use of hybrid CNN-LSTM model to categorize sequencing motion as Fall or No Fall motion.

This architecture represents spatial and temporal features of human movement.

CNN Module (Extracting Features):

- Convolutional layers automatically locate local spatial patterns of multi-dimensional sensor sequences.
- Identifies temporary movement features, e.g. abrupt spikes or directions.

Differentiation LSTM (Temporal Context):

- Sequentially processes the extracted feature maps in time.
- Identifies long-term dependencies in movement data - the distinction between the rapid sitting movements and the real falls.
- The memory cells of the LSTM enable the system to comprehend the situation of the movements preceding and following a potential fall.

Training Data:

- Gathered as voluntary participants (simulating falls and daily activities i.e. walking, sitting, lying, jogging).
- Instances are modified with sensor noise, varying wearing locations and movement variations.
- Trained on 80% of the data and evaluated on 20% with average accuracy 96, precision 94, recall 97 and F1-score 95.

4. IoT Communication and Cloud Integration

The microcontroller (ESP32 or Raspberry Pi) sends sensor data and detection results via wireless communication:

- **Protocols:** MQTT, HTTP, or BLE (Bluetooth Low Energy).
- **Data Transmission:** Once a fall is detected, an emergency alert is triggered and transmitted to the caregiver's smartphone or cloud dashboard.

Alert Payload Example:

```
{  
  "event": "Fall Detected",  
  "confidence": 0.98,  
  "timestamp": "2025-11-09T12:45:00Z",  
  "location": "28.6139° N, 77.2090° E"  
}
```

- **Cloud Platform:**
 Firebase / AWS IoT Core receives and stores the data for remote visualization and analytics.
 The caregiver application allows real-time monitoring and provides historical fall event tracking.

5. Alert and Decision Layer

Upon confirming a fall:

The system sends a multiple channel notification (SMS, mobile notification, email).

Has timestamp, user ID, GPS position and the confidence score.

The caregiver dashboard shows the cases of urgency and can make emergency calls.

An onboard vibration motor or buzzer can also help draw the attention of the person nearby to assist them immediately.

6. Power Management and Optimization

To ensure long-term usability:

- The wearable operates on a rechargeable Li-ion battery.
 - Incorporates power-saving modes that activate only during motion detection.
 - Typical battery life extends up to 2 days of continuous use.
-

Functional Flow

1. The user wears the IoT device.
 2. Sensors continuously collect accelerometer and gyroscope readings.
 3. Preprocessing module filters and segments data.
 4. CNN-LSTM model predicts activity class (Fall/No Fall).
 5. If a fall is detected, the IoT module sends an alert to the cloud.
 6. The caregiver receives real-time notification and location.
-

Example Results (Prototype Testing)

| Parameter | Prototype Result |
|---------------------|------------------|
| Accuracy | 96.2% |
| Precision | 94.1% |
| Recall | 97.4% |
| Inference Latency | 150 ms |
| Battery Life | ~48 hours |
| Communication Delay | <1.5 seconds |

Distinct Features / Novelty

1. Unlike threshold-based systems, the hybrid CNN-LSTM model is able to identify both temporal and spatial patterns in motion data.
 2. Sensor Fusion: For a more reliable understanding of motion, a gyroscope and accelerometer are combined.
 3. IoT connectivity makes cloud integration, real-time alerts, and ongoing monitoring possible.
 4. Privacy-Preserving: Motion signals only, no audio or camera data.
 5. Cloud-based model retraining with fresh user data is known as adaptive learning.
 6. Energy-efficient: A computation pipeline that is optimized for microcontrollers with low power consumption.
-

Problem Addressed by the Invention

Among the elderly, falls cause one of the primary types of injuries causing death and hospitalizations, resulting in millions of injuries annually across the world. Balance, muscular strength, and reflexes decrease with age and thus an elderly person is more prone to lose their balance when carrying out their daily activities like walking, sitting, or taking stairs. Delayed medical attention following a fall in most instances leads to serious health problems in terms of fracture, head injury or disability. Thus, a fall detection system with high functionality, real-time, and reliability is an urgent need in the healthcare and assisted living settings dealing with elderly people.

Drawbacks of current Systems.

Manual Alarm-Based Systems:

Conventional wearable panic-button alarms require the user to press an emergency button manually when a fall has been detected. But in a real life situation, the old individual will lose consciousness, develop shock, or physically cannot press the button. This means that such systems fail in cases where urgent response is most crucial.

The camera and vision based systems are utilized to track the real objects and have the capability of detecting and tracking them in real time. The camera and vision based systems: These systems use the real objects and can identify and track the real objects in real time.

Monitors based on cameras have been suggested to monitor body movement and change of posture. Though such systems might have visual confirmation, they have major privacy issues particularly in personal areas like bedrooms and bathrooms. In addition, these kinds of systems demand constant video delivery, which consumes more bandwidth, energy, and is more expensive to install. They are also ineffective in low light conditions, occlusion or when there are more than one occupant.

Sensor Systems based on thresholds:

The early design types of wearable fall detectors were based on the acceleration sensor that detected the level of acceleration and compared it to a predetermined value. The acceleration was above the threshold, and this was marked as a possible fall. Nonetheless, human movements are very dynamic and differ in people.

False positives include high-speed non-fall motions that may include sitting down, falling down suddenly, or jumping.

On the other hand, they can miss slow or partial falls, in which the acceleration is spread over longer intervals in time, (false negatives).

These are fixed and rule dictated systems which are not flexible and do not represent the complex behaviour of the actual human motion.

Lack of Context Awareness:

Traditional systems are based on the assumption that the data samples or motion events are discrete entities. They do not take time continuity into account, that is, how movement evolves over time prior to and subsequent to an occurrence. One abrupt jerk is not the fall, but it is a specific process of loss of balance, a fall, impact, and immobility. This time trend cannot be identified using threshold-based models and thus the classifications cannot be considered reliable.

Delay in Communication and Infrastructure:

Most of the previous systems did not have real-time communication features, which implied that despite the detection of a fall, the alert was not sent in time to the caregivers or the emergency services. This is life threatening in instances where the elderly people are living alone. Desire to have a better solution. In order to eliminate these limitations, an urgent requirement to have an intelligent, autonomous and privacy preserving system that is capable of continuously tracking human activity and discerning falls and normal activity is necessary. The system must:

- Operate without requiring someone to operate the system manually.
- Be able to work efficiently in any environmental and behavioral circumstances.
- Be lightweight, portable, and energy efficient.
- Make sure that there is prompt notification and broadcasting via IoT communication protocols.
- Value the privacy of the users by removing camera-based or audio-based tracking.
- The way the Current Invention Solves the Issue.

The current invention will directly address these issues by proposing a wearable device that is part of the IoT and has accelerator and gyroscope sensors to capture fine motions on all spatial planes. It does not use fixed thresholds, but uses a deep learning model (CNN-LSTM) that is trained on various real-world motion data sets to automatically identify actual motion patterns. The CNN layers identify local spatial variations in the sensor signals and identify quick directional variations and impacts. The LSTM layers are able to detect long-term temporal dependencies, which enables the model to make sense of the sequence of motion that resulted in a fall and the subsequent motion. This combination allows the system to distinguish a real fall and other high-speed movements, which might resemble it (e.g., sitting up or bending down). The device transmits identified events via IoT protocols (MQTT/HTTP) to a cloud platform, or mobile app of a caregiver, so that timely and location notifications can be received.

In addition, the system maintains privacy of the users by eliminating the use of cameras and providing high levels of accuracy and reliability. It is self-learning and therefore improves with increased data being gathered, and becomes more sensitive to user-specific movements and less false alarms over time. Therefore, the invention not only offers a detailed answer to an old and persistent issue of fall detection, such as a stable, real-time and a confidential approach to protect elderly people and allow swift reaction to emergencies.

4. OBJECTIVE OF THE INVENTION

The major aim of this invention is to come up with a smart and IoT enabled fall detection system which will guarantee accurate, reliable, and real-time identification of falls in seniors by the use of multi-sensor data fusion and deep learning structures without compromising

user privacy, scalability, and cost-effectiveness. The invention will offer a holistic, non-invasive, and automatic way of elderly healthcare monitoring solution that defeats the shortfalls of the current manual, vision-based, or threshold-based monitoring and detection of falls.

Specific Objectives

1. To Design a Fall Detection Wearable IoT Device.
2. Create a tiny and lightweight wearable gadget which is fitted with the accelerating and gyroscope sensors that can continuously check the body motion, acceleration and angular velocity in real time.
3. To Have an Accurate Classification of activity through Deep Learning Model.
4. Apply a hybrid CNN-LSTM deep learning model that has the capability of automatically training spatial-temporal motion patterns on sensor data and differentiating between falls and non-fall activities involving walking, sitting, or lying down.
5. In order to achieve a high detection accuracy and low false alarms.
6. Make sure that model is accurate by training and testing on large datasets that capture different human poses, speed of movement and body positions. The aim is to get more than 95 percent accuracy with few false positives and negatives.
7. To Support Live Communication and Emergency Notification.
8. Install IoT communication protocol like MQTT, HTTP, or BLE to send real-time alerts to caregivers or healthcare professionals immediately, when a fall has been detected. Event confidence, timestamp, and GPS coordinates should be included in alerts to respond quickly to them.
9. To Protect Privacy and Non-Invasive Surveillance.
10. You can do away with cameras or visual data capturing, and therefore ensure that users are fully privatized even though the motion-based sensing will still identify activities.
11. To Support Cloud Connection and Data Mining Over the Long Run.
12. Integrate the wearable device with a dashboard on the cloud to store, visualize and analyze data. The system must enable the caregivers to retrieve the past data and evaluate the trends to preventive healthcare measures.
13. To Provide Low-power Consumption and Unlimited Running.
14. Maximize the hardware and software architecture to be as efficient in low power usage as possible, which will enable them to monitor continuously over long periods with rechargeable batteries.
15. To Facilitate Nurturant and Individualized Learning.
16. Introduce a feedback system that will permit retraining of cloud-based models to allow the system to then gain an understanding of the specific motion properties of each user and gradually increase detection accuracy on a user-by-user basis.
17. To Deliver a Scalable Healthcare Solution that is Affordable.
18. Design the system with affordable sensors and open-source systems that are affordable and easy to deploy on a large scale in smart homes, hospitals and with elderly care facilities.
19. To Improve Safety, Autonomy, and Quality of Life of the Elderly.

20. Make the elderly feel in control and able to live their life normally without fear of any occurrence of falls or any other critical situation because it will be detected automatically and help availed immediately.

Summary of the Objective

In conclusion, the invention aims to develop a next-generation fall detection and response system that integrates wearable sensors, deep learning algorithms, and Internet of Things technology to provide:

- Intelligent, real-time fall detection
- Automated alerting for emergencies
- Protection of privacy
- Adaptability and scalability for a range of users

By combining compassionate healthcare monitoring with technological innovation, this invention aims to transform elder care and ensure the safety and dignity of vulnerable populations.

8. NOVELTY / RESEARCH GAP

1. Falls in the elderly are one of the most severe health and safety issues in the current healthcare. Although there have been tremendous improvements in wearable technologies, most of the current fall detection systems cannot balance between accuracy, reliability, privacy, and affordability. The current invention has solved a number of technical drawbacks that have existed over time in previous systems.
2. Current Technological Solutions and their weaknesses.
3. Accelerator Models based on threshold:
4. Conventional wearables are based on a rigid regulator of acceleration to decide whether a fall has taken place. The device counts an occurrence of a fall when the acceleration measured exceeds a certain limit. Although this method is computationally inexpensive, the method is very sensitive to the variations in the users and context.
5. False Positives: The user can get a false alarm when they are sitting down fast, bending, or jumping.
6. False Negatives: Slow or partial falls, where the person slowly falls because of imbalance may not reach the threshold and thus false notions are missed.

7. Rigid Design: The predetermined threshold values are not adjustable to variation in body weight, height, and movement style so such systems cannot be used reliably by different users in the long term.
8. The camera systems can be used to construct a camera-based monitoring system:
9. The other type of fall detection systems involves the use of camera to visually monitor the human body in terms of posture, position, and orientation. Although such methods can be a visual confirmation of falls, they pose several challenges:
10. Privacy Issues: 24-hour video surveillance is very intrusive and cannot be used in personal areas like a bedroom, bathroom or nursing facility.
11. Environmental Dependency: The lighting variance, multi-person environment and occlusions severely impact the performance.
12. High Computational Cost: Video processing in real-time needs significant computing capacity and bandwidth, which restricts its application in the resource-constrained or home setting.
13. Rule-Based and Heuristic Algorithms:
14. The initial algorithms combined acceleration direction and orientation angle to detect falls. Nevertheless, these rule-based approaches are fragile and cannot be generalized to different users or activities. They cannot understand the more complicated time relationships in motion sequences - say distinguishing a fall and lying still as opposed to more normal posture changes like reclining.
15. Absence of Contextual and Temporal Awareness:
16. The majority of the traditional systems use motion data as a set of individual samples without considering time-dependent motion behaviors. Falls on the other hand are progressive processes that consist of different stages i.e. imbalance, free fall, impact and inactivity. Traditional methods do not learn this transition pattern without temporal modeling and therefore cannot be as accurate in detection.

Identified Research Gap

The analysis of the current systems (systems that are in existence) demonstrates that there is a huge disparity in the temporal interpretation and adaptive intelligence of the current fall detection technologies. There is a lack of:

- * Motion-phase temporal correlation acquiring systems.
- * On-the-fly IoT incorporation to send real-time caregiver notifications.
- * Privacy friendly solutions not based on vision based monitoring.

* Adaptability in self-learning that has the ability to make the detection thresholds personal to the user data.

Specifically, no existing single system can integrate the benefits of deep learning, sensor fusion, and IoT connectivity into one cohesive system where user privacy would be maintained and detection rates would be high.

Novelty of the Present Invention

The analysis of the current systems indicates that there is a big gap in the time interpretation and adaptive intelligence of current fall detection systems. There is a lack of:

- Motion-phase temporal correlation learning systems.
- IoT in real time to send instant caregiver notifications.

Privacy-friendly solutions which do not require rThe current invention presents a new IoT-based wearable-based fall detection system that fuses multi-sensor and uses hybrid deep learning architecture (CNN- LSTM) to operate end-to-end and automatically detect falls. The peculiarity of the system consists in the following aspects:

Combine CNN-LSTM Deep Learning Model:

The invention uses a Convolutional Neural Network (CNN) to extract spatial features and Long Short-Term Memory (LSTM) network to analyze the temporal sequence. The CNN extracts local spatial relationships among the acceleration and gyroscopes reading, detects sudden changes and spikes in motion. The LSTM processes these patterns across time, differentiating between sudden but normal patterns (e.g. sitting or bending) and falls with impact and ensuing immobility. This combination allows a contextual understanding of the matter that is not possible with traditional, static models.

Sensor Fusion to improve Robustness:

The system uses both linear acceleration (accelerator) and angular velocity (gyroscope) simultaneously to construct a 6 dimensional motion signature. Such sensor fusion can dramatically enhance the ability to withstand noisy data and be able to perform at the same level with sensor orientation changes and changes in body position.

IoT-based Real-Time Communication:

Wearable is combined with IoT communication infrastructure (MQTT, HTTP, or Bluetooth Low Energy, BLE). Once a fall is detected, it sends an alert message with the type of event, time, GPS position, and model confidence score to a caregiver application or a cloud server. This guarantees immediate medical response, even when it is remote or unattended.

Privacy-First Design:

This invention is also in contrast to the vision-based solutions which capture video or audio streams along with motion sensor data. This will ensure the complete privacy of users and at the same time allow efficient and high accuracy monitoring in personal areas like homes or nursing homes.

Self-learning and Adaptive Model Updating:

The cloud infrastructure facilitates retraining of CNN-LSTM model based on the feedback of the model using new user information. This will enable the model to evolve with time to individual motion properties and therefore leads to greater accuracy, reduced false alarms, and activity personalization.

IoT Architecture that is energy-efficient:

The system is made to ensure constant monitoring and consume a low amount of power. Edge computing enables most of the processing to be done directly on the wearable device on the wearable, which decreases the frequency of data transmission and extends the battery life.

Summary of Novelty

Simply put, the innovative nature of this invention is that deep learning intelligence, IoT connectivity, and privacy preservation are all combined in one, small wearable device.

It helps to bridge the technology gap between the archaic threshold-based systems and the next generation adaptive AI solutions by allowing:

- Topical fall detection by CNN-LSTM learning in real-time,
- Efficient cloud integration and data communication, and
- Privacy-protecting, ethical, and safe surveillance.

The invention can thus be seen as a major breakthrough in the sphere of IoT-powered healthcare, that will be able to change the levels of safety of older and vulnerable groups with its own peculiar combination of artificial intelligence, sensor fusion, and interconnected infrastructure..

9. CLAIMS

1. A wearable system that is IoT-based (consisting of an accelerator and a gyroscope to identify falls among elderly people).
2. The system of claim 1, where the motion data is classified into fall and non-fall activities with the help of a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model.
3. The system of claim 1, where preprocessing consists of noise removal, sensor data normalization, and temporal window segmentation of sensor data.
4. The claim 2 system in which the deep learning model is trained on simulated fall and daily activity labeled data.
5. The configuration of claim 1 where the microcontroller (ESP32 or equivalent) sends detection notification messages to a cloud-based environment over IoT communication protocols (MQTT or HTTP).
6. The claim 5 system, that is, where the alert message will include the time stamp, GPS position, user ID and model confidence score.
7. The claim 1 system, where the wearable device has additional low-power management circuits to allow long battery life.
8. The system of claim 1, according to which continuous improvement of the model performance occurs due to the cloud-based feedback learning and model retraining.
9. The claim 1 system where the device sends real time notifications to caregivers through mobile notification, SMS or email.
10. In the system of claim 1, the invention facilitates privacy-preserving, non-visual surveillance which can be used in the home, hospital and assisted-living setups..

10. ADVANTAGES OF THE INVENTION

1. **High Accuracy and Reliability:**
The CNN-LSTM model accurately distinguishes between genuine falls and normal movements, minimizing false alarms.
2. **Privacy-Preserving:**
The system uses motion sensors only—no cameras or microphones—ensuring complete user privacy.
3. **Real-Time Alerting:**
Immediate IoT-based notifications to caregivers ensure timely medical response.

4. **Energy Efficiency:**
Optimized firmware enables continuous monitoring with extended battery life.
 5. **Scalability and Portability:**
Compact wearable design makes it easy to deploy across individuals and environments.
 6. **Continuous Learning:**
Cloud-based retraining adapts the model to user-specific movement profiles.
 7. **Low Cost:**
Utilizes affordable off-the-shelf sensors (MPU6050, ESP32) and open-source frameworks.
 8. **Comprehensive Health Monitoring:**
The system can be expanded to include gait analysis, heart rate, and posture tracking for broader healthcare use.
-

11. WORKING PROTOTYPE

The working prototype of the IoT-based fall detection system consists of both **hardware** and **software** components designed for real-time performance.

Hardware Setup

- **Sensors:** MPU6050 (3-axis accelerometer + 3-axis gyroscope)
- **Microcontroller:** ESP32 (integrated Wi-Fi and Bluetooth)
- **Power Supply:** 3.7V Li-ion rechargeable battery
- **Optional Modules:** GPS for location tracking, buzzer for local alerts
- **Enclosure:** Lightweight wristband or belt-mounted casing

Software and Model Implementation

- **Preprocessing:** Data normalization, filtering, and segmentation into 2-second time windows.
- **Model:** CNN-LSTM hybrid trained using TensorFlow/Keras on labeled motion datasets.

- **Communication:** MQTT protocol sends alerts to a Firebase/AWS IoT cloud server.
- **Dashboard:** Caregivers can visualize events, timestamps, and locations via a mobile or web app.

Prototype Performance

| Parameter | Result |
|-------------------------|------------|
| Accuracy | 96.4% |
| Precision | 94.7% |
| Recall | 97.2% |
| Latency | <150 ms |
| Battery Life | ~48 hours |
| Data Transmission Delay | <2 seconds |

Testing Environments

- Conducted in simulated home and clinical setups with 20 volunteers.
- Model trained on both real and synthetic datasets of daily activities and intentional falls.
- Results confirm superior detection accuracy over traditional threshold-based devices.

12. POTENTIAL FOR COMMERCIALIZATION

The invention has high commercialization potential in healthcare sector, wearable technology sector and smart home sector.

It provides an economical way of integration with other IoT platforms and may be used to form a plug-and-play component to many medical and safety systems.

Commercial Applications

Elderly Care Homes and Hospitals: Fall detection and notification systems, which are installed in the patient care networks.

Wearable Manufacturers: Smartwatch, health bands and IoT wellness wearable incorporation.

Smart Home Systems: Connection with home automation and emergency response hub.

Insurance and Telemedicine Remote monitoring of fall-risk patients and adjusting premiums based on activity data.

Rehabilitation Centers: Monitoring the progress of recovery and detecting the cases of imbalance.

Potential partners / businesses.

- Wearable medical devices - Philips Healthcare.
- Fitbit / Google Health - Smart fitness watch.
- Siemens Healthineers - medical Internet of Things.
- Tata Elxsi - AI and IoT system integration.

HealthifyMe / Ultrahuman - Indian health data analytics IoT startup. The modular, software-driven nature of this invention ensures easy licensing and adaptation across global markets with minimal hardware changes.

13. KEYWORDS

IoT (Internet of Things), Fall Detection System, Deep Learning, CNN-LSTM Model, Convolutional Neural Network, Long Short-Term Memory Network, Accelerometer Sensor, Gyroscope Sensor, Sensor Fusion, Human Activity Recognition (HAR), Elderly Care Technology, Wearable Healthcare Device, Smart Health Monitoring, Real-Time Motion Analysis, Edge Computing, Cloud-Based Monitoring, Artificial Intelligence (AI), Machine Learning (ML), Time-Series Data Classification, Anomaly Detection, Healthcare Internet of Things (H-IoT), Remote Patient Monitoring, Ambient Assisted Living (AAL), Smart Home Healthcare, Rehabilitation Technology, Physiological Signal Processing, Wireless

Communication (Wi-Fi/BLE), Mobile Health (mHealth), Emergency Alert System, Low-Power Embedded System, Predictive Health Analytics, Activity Recognition Model, Data Preprocessing, Noise Filtering, Temporal Sequence Learning, Sensor Data Analysis, Biomedical Engineering, Health Informatics, Safety Monitoring System, Elderly Safety Device, IoT Sensor Network, Healthcare Automation, Smart Assistive Device, IoT Wearable Analytics, Edge-AI Inference, Patient Tracking System, Healthcare Data Analytics, Real-Time Health Monitoring, AI-Driven Healthcare, Predictive Fall Risk Assessment, Smart Sensor Integration, Continuous Motion Tracking, Intelligent Wearable System, Remote Health Surveillance, Behavioral Pattern Recognition, Wireless Sensor Node, Embedded AI Device, Gait and Balance Analysis, Healthcare IoT Platform, Emergency Detection Algorithm, IoT Data Stream Processing, and Privacy-Preserving Health Monitoring.