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Privacy-Preserving Edge-Based Wearable System for Real-Time Detection of Hand Tremors and Seizure-Like Movement Events

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Abstract: Epileptic seizures and pathological tremors can seriously affect a person's safety and daily life, which is why wearable systems that monitor continuously and raise timely alerts are so valuable. Many existing wearables depend on cloud connectivity, rely on a single sensor, or stream data nonstop. This adds communication overhead, drains energy, and often leads to false alarms.

In this paper, we propose an edge-processed, multimodal wearable system for real-time monitoring of pathological tremors and seizure-related events, built into a low-cost smart glove. The glove combines surface electromyography (sEMG) and inertial measurement unit (IMU) sensors, so it can capture both muscle activity and movement patterns. All signals are processed locally on an ESP32 -based embedded platform, where signal-processing techniques and a lightweight, quantized machine-learning model are intended to classify movement patterns as they happen. An OLED display and a buzzer give immediate local alerts, while Bluetooth Low Energy (BLE) offers optional wireless communication, so the device never needs a constant internet connection.

Keywords: Epileptic seizure monitoring, pathological tremor, wearable system, multimodal sensors, edge computing, TinyML, ESP32, sEMG, IMU, Bluetooth Low Energy.

I. INTRODUCTION

Epilepsy and pathological tremors are neurological conditions that can take a real toll on a person's daily routine, independence, and quality of life. Seizures can involve abnormal movements and changes in muscle activity, while pathological tremors show up as involuntary, rhythmic shaking. Catching these events early matters, because a delayed response raises the risk of injury and makes it harder for caregivers to step in with the right help. Clinical monitoring is useful, but it isn't always practical for everyday life. That's why wearable technologies are increasingly being explored as a way to track physiological and movement signals outside the hospital.

Advances in wearable sensors and embedded systems have made it possible to collect motion and physiological data for seizure-related event detection. Accelerometers and gyro scopes are the usual choice for picking up the movement patterns of convulsive seizures and tremors. The catch is that systems relying on motion data alone can mistake ordinary daily activities for abnormal ones, which leads to false alarms. To get around this, researchers have looked at multimodal systems that combine several types of sensing, such as accelerometry, electrodermal activity, photoplethysmography, and electrocardiography. The base paper by Ben Dhiab et al. shows the promise of multimodal

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sensing and edge-based machine learning for real-time seizure detection, but it also points out limits in sensing capability and the need for continuous data transmission.

II. EXISTING SYSTEM

Most wearable systems for seizure detection today rely on a handful of sensors: accelerometers, gyroscopes, surface electromyography (sEMG), heart-rate sensorsand electrodermal activity sensors. They recorddata continuously andlook for abnormal movement or physiological changes. Signal processing or machine learning then flags possible seizure events. Some systems also send alerts to caregivers through a connected mobile app or a wireless link.

Motion-based systems mainly depend on accelerometer and gyroscope readings to spot unusual movement. This works for certain motor seizures, but everyday activities like walking, writing, eating or exercising can produce similar movement patterns and trigger false alarms. A system that relies on movement alone may also miss events that don't cause much visible movement.

Multimodal wearables try to fix this by combiningmovement data with physiological signals such as sEMG or heart rate. The extra information makes it easier to tell abnormal events from routine activity. The trade -off is that more sensors make signal processing, feature extraction and model development more complex. Wearables also have to cope with limited battery life, limited computing power, noisy sensor signals and a lack of validation in real -world conditions.

III. OBJECTIVES

The main aim of this research is to propose a low-cost wearable system that monitors and classifies pathological tremor and seizure-related activity in real time, using edge computing and Tiny Machine Learning (TinyML).

The specific objectives are:

1. **Multimodal sensor integration:** Combine surface electromyography (sEMG) with a six-axis inertial measurement unit (IMU), so the system captures both muscle activity and movement.

2. **Real-time signal processing:** Clean up the incoming sensor signals and extract useful features. This includes using the Fast Fourier Transform (FFT) to analyse the frequencies that matter for tremor.

3. **On-device classification:** Build a TinyML classifier that runs on the wearable itself and can tell normal activity, pathological tremor and seizure-related activity apart.

4. **Low-latency processing:** Aim for fast, real-time inference with as little computational load as possible on resource-limited embedded hardware.

5. **False-alarm reduction:** Test whether usingsEMG and IMU data together gives fewer false alarmsthanmotion-only detection.

6. **Offline operation:** Make sure the core functions of sensing, classification and local alerting work without a constant internet connection or any cloud processing.

7. **Alerts and notifications:** Give local alerts through a buzzer, a vibration motor and an OLED display, with optional Bluetooth Low Energy (BLE) notifications to caregivers.

8. **Low-cost, energy-efficient design:** Keep the device affordable, compact and efficient enough for long periods of monitoring.

9. **System evaluation:** Measure how well the system performs through experiments, looking at classification performance, inference latency, false-alarm rate, sampling reliability and power consumption.The methodology has the following stages.

IV. LITERATURE SURVEY

Wearable technologies for epileptic seizure detection have drawn a lot of attention, mainly because people need continuous monitoring, timely alerts, and less dependence on hospital equipment. Earlier studies have looked at accelerometers, gyroscopes, electromyography, electrodermal activity, and cardiovascular signals as ways to spot

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seizure-related events. More recent work combines multiple sensors, machine learning, and edge computing to improve detection and make real-time operation possible. This survey goes through the relevant studies and what each one contributes to the proposed system.

1. Multimodal Wearable Seizure Detection

The wider literature suggests that physiological signals can fill in what motion data misses and help separate seizure related events from routine activity. Still, wearable systems have to strike a balance between sensor accuracy, comfort, power use, and computing demands.So the benefit of sensor fusion has to be tested experimentally to see whether it really beats a single-sensor setup.

2. Physiological Signals for Seizure Monitoring

Chen et al. [2] publisheda scopingreview of seizure detection usingmultimodal signals. It covered non-invasive physiological measurements and machine-learning methods. The review points to the promise of combining signal types, but also notes that detection performance varies widely between studies. It also stresses that sensitivity and false alarm rate should be evaluated, not just classification accuracy.

3. Machine Learning and TinyML for Wearable Devices

Machine learninghas been widelyusedto classify sensor data andfindpatternslinkedto seizure-related activity. The literature reviewedby Chen et al. [2] covers approaches suchas Support Vector Machines, Random Forests, and threshold-based algorithms. These methods can work well, but how they perform in practice depends on input data quality, feature extraction, model complexity, and how carefully they are validated.

4. Existing Multimodal Wearable Framework

The base paper by Ben Dhiab et al. [1], An IoT-Based Multimodal Wearable Framework for Real-Time Epileptic Seizures Detection Using TinyML, presents a wearable framework that aims to improve seizure monitoring through multimodal sensing and edge-based processing. Its existing data-collection platform uses an STM32F4 microcontroller with accelerometer, gyroscope, and temperature sensors. The data can be sent over Bluetooth to a mobile app and a cloud-based monitoring platform.

The paper itself points out several limitations of this framework: the sensor types are limited, the original system has no integrated real-time inference, and continuous data collection and communication use more energy. Its proposed improvements add more physiological sensors and edge-based TinyML processing. This gives a solid starting point for wearables that combine several sensing modalities with local event classification. That said, the proposed improvements and early sensor tests shouldn’t be taken as proof of validated clinical performance.

V. RESEARCH GAP

Researchers have already tried a range of approaches to wearable seizure detection, including motion sensors, physiological signal monitoring, multimodal sensing and machine-learning classification. But it is still hard to build a compact, low-cost wearable that monitors continuously and runs real-time inference directly on resource-limited hardware.

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VI. METHODOLOGY

1 System Requirements

TABLE I HARDWARE REQUIREMENTS

Sr. No.	Hardware component	Specification / requirement	Purpose
1	Microcontroller	ESP32 development board	Runs signal processing and TinyML inferenceon the device and controls the system
2	sEMG sensor module	Surface electromyography sensor with suitable signal conditioning	Picks up the electrical activity of the muscles
3	IMU sensor	6-axis accelerometer and gyroscope	Measures hand movement and tremor-related motion
4	OLED display	Small OLED display module	Shows monitoring status, detection results and system warnings
5	Buzzer	Low-voltage active buzzer	Gives an audible alert
6	Vibration motor	Compact low-voltage vibration motor	Gives the wearer a tactile alert
7	BLE communication	ESP32 built-in Bluetooth Low Energy	Sends optional event notifications to a paired caregiver device
8	Battery	Rechargeable low-voltage battery	Powers the wearable while it is in use on the go
9	Power-management circuit	Suitable voltage regulation and battery monitoring	Keeps the power supply stable and supports low-battery warnings
10	Connecting hardware	Wires, connectors and a prototype PCB or breadboard	Links the sensors, controller and output modules
11	Wearable enclosure	Lightweight glove or wearable casing	Holds the electronics securely and keeps the device comfortable to wear

TABLE II SOFTWARE REQUIREMENTS

Sr. No.	Software requirement	Purpose / description
1	Embedded development environment	Used to write, compile and upload firmware to the ESP32 board
2	ESP32-compatible firmware framework	Controls the sensors, processes the signals, runs inference and manages the output devices
3	Sensor acquisition software	Reads data from the sEMG sensor and the six-axis IMU
4	Signal-processing algorithms	Clean up the sensor signals and extract useful features, including FFT-based analysis of the 4–8 Hz tremor band
5	TinyML model	Sorts input patterns into the proposed categories: normal/routine movement, pathological tremor and seizure-aura-related patterns

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Sr. No.	Software requirement	Purpose / description
6	Model quantization support	Supports an INT8-quantized model to cut memory and computation needs on the microcontroller
7	OLED display-control software	Shows the system status and classification or alert information
8	Buzzer and vibration-control software	Triggers the local alerts according to the programmed decision rules
9	Bluetooth Low Energy (BLE) software	Supports optional wireless notifications to a paired caregiver device, without needing Wi-Fi or cloud processing
10	Power-management firmware	Manages operating states and helps avoid unnecessary power use
11	Testing and evaluation tools	Used to evaluate classification performance, latency, false alarms, resource usage and battery life
12	Version control and documentation tools	Keep track of the source code and changes, and document the implementation and testing

2 Sensor Data Acquisition

The first stage is collecting data from the wearable device, using two sensing modalities: Surface electromyography (sEMG): Measures the electrical activity of muscle contraction and shows how the muscles are activating. Inertial measurement unit (IMU): Uses accelerometer and gyroscope readings to capture hand movement, orientation, and intensity of motion. The two sensors complement each other, which can help tell routine hand movements apart from abnormal ones. The SRS sets a target sampling rate of 50 Hz, and the readings are grouped into analysis windows for the next stages. The sEMG acquisition andconditioningstage needsa suitable signal-conditioningcircuit and samplingsetup. The exact raw sEMG sampling rate and any envelope-processing step will be fixed once the hardware is selected, before implementation begins.

3 Signal Preprocessing

Next, the sensor data is cleaned up to improve signal quality and limit the effects of noise and motion artifacts. This stage checks incoming samples, flags missing or saturated data, and arranges the valid readings into fixed -length windows. Preprocessinggets the data ready for feature extraction and classification. Any invalid window is left out of classification so the model doesn't produce unreliable predictions. The whole pipeline runs locally on the ESP32 and doesn't need a continuous cloud connection.

4 Feature Extraction Using FFT

Feature extraction turnsraw sensorreadings intoa compactform that suits embedded classification. For the accelerometer and gyroscope channels, the Fast Fourier Transform (FFT) is used to look at the frequency content of the motion signals. The SRS identifies the 4–8 Hz bandas the target region for pathological tremor analysis. The system is meant to calculate three features:Signal power within the 4–8 Hz band.Dominant frequency within that band.Ratio of power in the band to total signal power

5 TinyML Model Development and Classification

We propose a lightweight neural network to classify the extracted features. It is trained on labelled sensor data for the three classes defined in the project requirements: normal or routine movement, pathological tremor, and seizure-aura related activity. Model development covers preparing the dataset, extracting the chosen features, training the classifier, and testing it on independent data.

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The trained model is then quantized to INT8 to shrink its memory footprint and make it suitable for the embedded platform. The quantized model is meant to run on the ESP32 and return a predictedclass and a confidence value for every analysis window. How well it performs depends on having representative, correctly labelled data. Seizure-aura classificationin particular needs data that truly reflects the pre-event condition, sincedetectingseizure-related movement on its own does not prove the system can predict anything.

6 Event Confirmation and Alert Generation

To avoid unnecessary alerts from one-off movement blips, the system includes an event-confirmation step. Instead of alerting on a single classification, it checks whether the relevant class shows up across a set number of consecutive analysis windows. Once an event is confirmed, the system triggers its outputs: the OLED display shows the detected event category or system status, the buzzer gives an audible alert to the wearer or people nearby, and an optional BLE notification is sent to a paired device. The exact number of consecutive windows needed for confirmation will be chosen during testing. Since the alerting is designed to work locally, the core alert function doesn't depend on an internet connection.

A single odd movement shouldn't set off an alarm, so the system doesn't react to just one classification. Instead, it waits to see whether the same class keeps showing up across several analysis windows in a row, and only then treats it as a real event. Once that happens, the glove lets the wearer and the people around them know in three ways: the OLED display shows what was detected or thecurrent system status, the buzzer sounds an audiblealert, and an optional BLE notification can be sent to a paired device. How many consecutive windows are needed before an event counts as confirmed isn't fixed yet; we'll settle on that number during testing. And because the alerting happens on the device itself, the core alert function keeps working even when there's no internet connection
. Fig 1. Hardware block dig

7 Embedded Implementation and Offline Operation

Sensor acquisition, preprocessing, FFT feature extraction, classification, and alert generation are all built into the ESP32 firmware. The software is split into separate modules, which makes testing, debugging, and maintenance easier. The quantized model and its working buffers have to fit within the microcontroller's available memory. BLE is used only for optional notifications, and raw sensor data is not meant to be stored permanently or transmitted by default. This supports offline operation and cuts down on unnecessary wireless communication.The system is also meant to keep an eye on sensor and battery status, so that a hardware failure or low battery is never mistaken for "no event detected."

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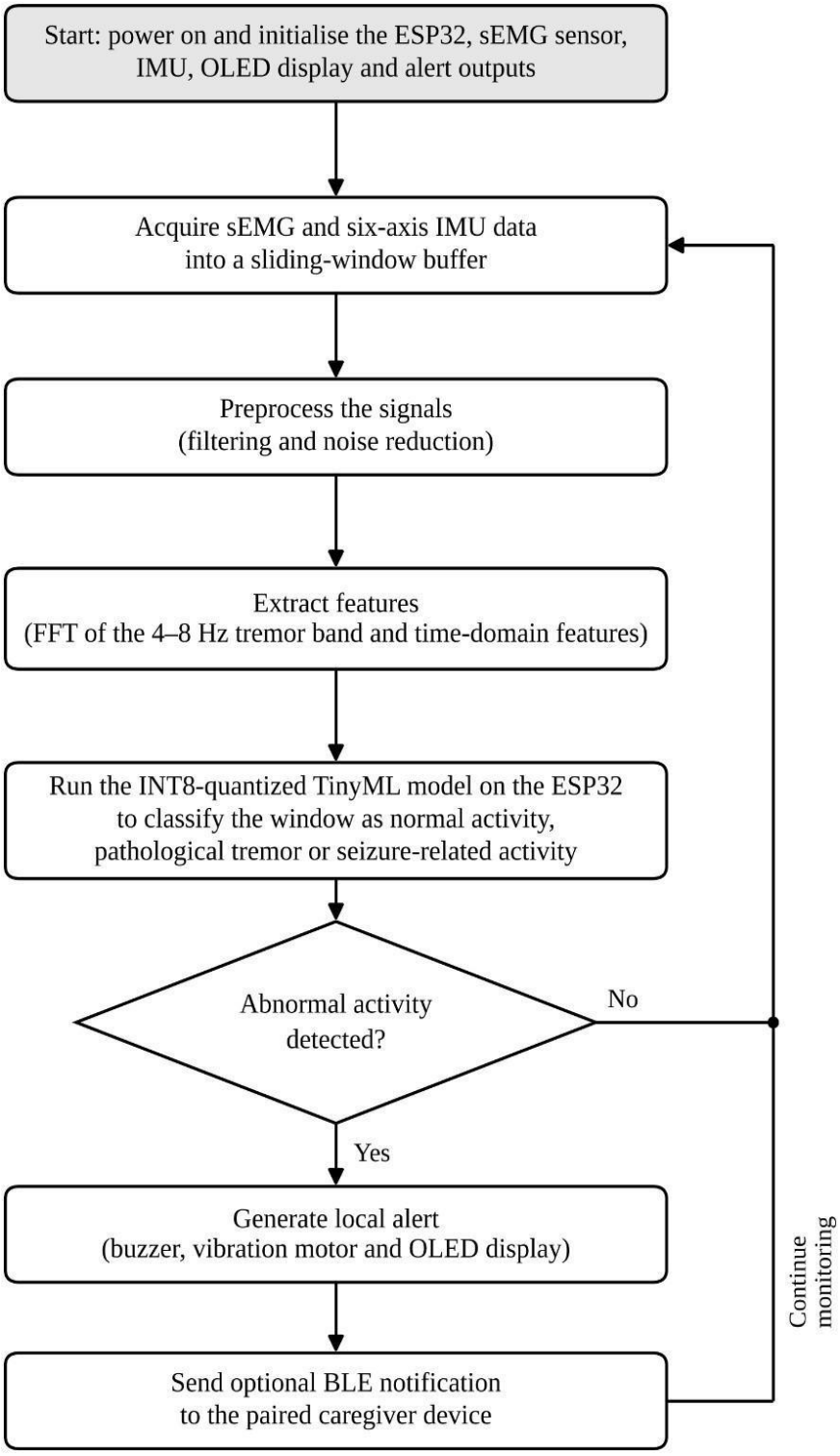


Fig. 1. Flowchart of tremor and Seizure Detection System

9 Safety and Limitations

The device is an academic research prototype and is not meant to replace clinical diagnosis, medical monitoring, or professional care. Missed detections and false alarms are still possible. How well the system identifies pathological tremors and seizure-related events depends on sensor quality, model training, and experimental validation. Any claim of seizure-aura prediction would need separate evidence showing that detection happens before an event begins.

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VII. SYSTEM ARCHITECTURE

The proposed system architecture is organized into three main layers: the sensinglayer, edge processinglayer, and output and alert layer. These layers work together to collect physiological and movement data, analyze it locally, and notify the wearer when a potentially abnormal pattern is detected. The system is designed to perform its primary processing on the ESP32 microcontroller, reducing its dependence on internet connectivity and cloud -based services.

1. Sensing Layer

The sensing layer consists of an sEMG sensor module and a six-axis inertial measurement unit (IMU). The sEMG sensor measures electrical activity produced by the muscles, while the IMU uses its accelerometerand gyroscope to capture movement-related information. The two sensors provide complementary data that can help distinguish ordinary hand movements from patterns associated with pathological tremors. The collected signals are passed to the ESP32 for further processing.

2. Edge Processing Layer

The ESP32 acts as the central processing unit of the proposed system. It receives the sensor readings and performs the mainprocessingand classification tasks directly on the device. This layer contains the following functional modules:

a. Data acquisition: Collects sEMG and IMU readings andorganizesthem into a sliding-window buffer for continuous analysis.
b. Signal preprocessing: Applies filtering and noise-reduction techniques to improve the quality of the acquired signals before feature extraction.
c. Feature extraction: Calculates relevant signal characteristics, including FFT-based features from the 4–8 Hz tremor frequency band and selected time-domain features.
d. On-device TinyML inference: Uses an INT8-quantized machine-learning model to classify the extracted features. Quantization is intended to reduce the model's memory and computational requirements, making it more suitable for a resource-constrained microcontroller.
e. Decisionlogic andalert control: Evaluates the model's output anddetermines whetherthe configured conditions for generating an alert have been met. Confirmation rules can be used to help prevent unnecessary alerts caused by isolated or unreliable classifications.

Processing these stages locally is intended to support timely responses while reducing the need to transmit raw sensor data to external servers.

3. Output and Alert Layer

The output andalert layer communicatesthe system's status and classification results to thewearer. It includes an OLED display, a buzzer, a vibration motor, and an optional Bluetooth Low Energy (BLE) communication module.The OLED display presents status information and warnings, while the buzzer and vibration motor provide audibleandtactilealerts. These outputs allow the wearer to receive notifications without continuously looking at the device. The BLE module can optionally transmit alerts to a paired caregiver device, providing an additional notification channel when the paired device is within communication range.

4. Power Management

The system is powered by a rechargeable battery connected to a power-management circuit. This circuit regulates the supply voltage and supports battery-level monitoring. Its role is to provide suitable power to the ESP32, sensors, and output components while supporting the portable operation of the wearable device.

5. Overall Working

The system begins by acquiring muscle activity and movement data from the two sensors. The ESP32 processes the incoming signals, extracts relevant features, and passes them to the TinyML model for classification. The decision logic then determines whether an alert is required. If the configured alert conditions are satisfied, the system activates the local output devices and may send a BLE notification to a paired caregiver device. The sensing and processing cycle continues as new data becomes available.

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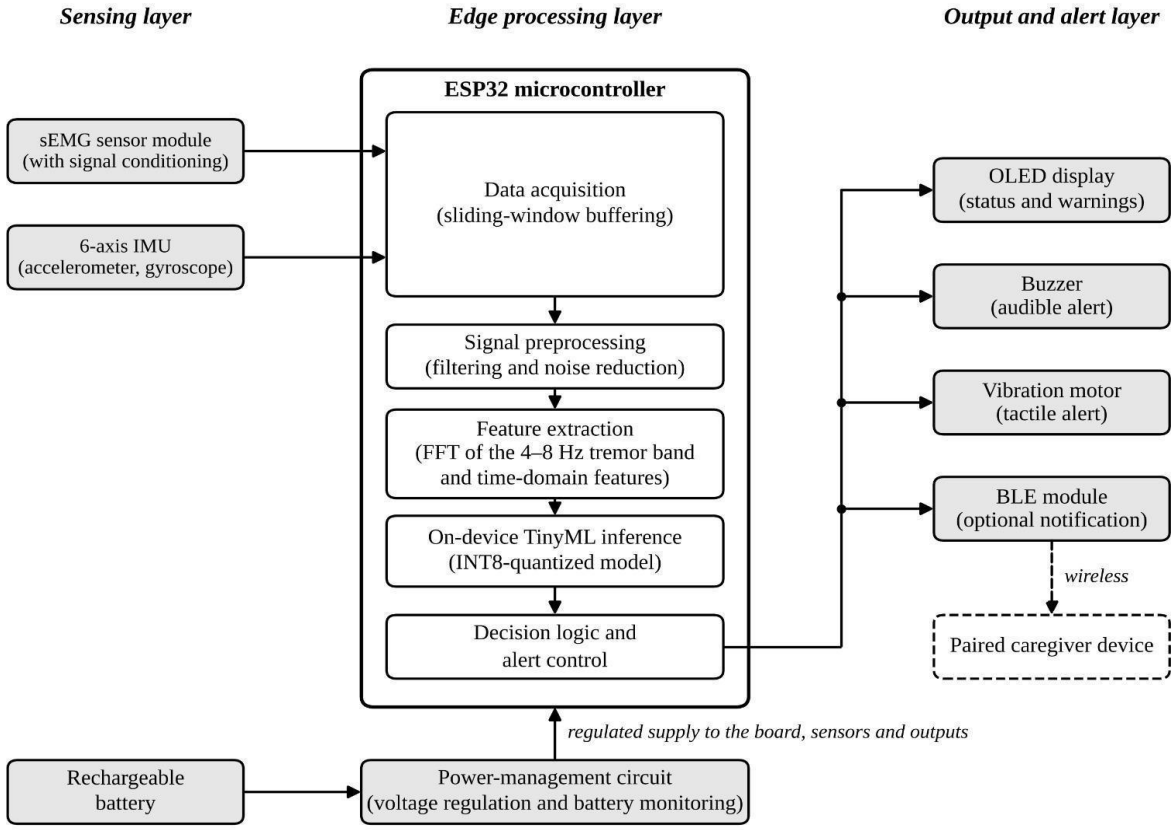


Fig 2. System Architecture

VIII. CONCLUSION AND FUTURE SCOPE

This research proposes an edge-processed, multimodal wearable system for real-time monitoring of pathological tremors and seizure-related events, built into a low-cost smart glove. The glove combines surface electromyography (sEMG) and inertial measurement unit (IMU) sensors to capture both muscle activity and movement patterns. An ESP32 -based platform is intended to handle local signal preprocessing, FFT-based feature extraction, and classification with an INT8-quantized TinyML model. Alerts comethrough an OLED displayand buzzer, with optional Bluetooth Low Energy (BLE) notifications, and the system doesn't need a continuous internet connection to do its job.

B . Future Scope

The system can be taken further in several directions to make it more reliable, usable, and practical.

1. Dateset expansion: Collect and evaluate more diverse, properly labelled recordings covering normal activities, pathological tremors, and seizure-related events. Subject independent testingwould show how well the model generalizes to new users.
2. Model optimization: Try other lightweight machine learning architectures, quantization techniques, and feature selection methods to improve classification while using less memory and power.
3. Improved seizure prediction: Look into validated pre event signal patterns and suitable labelled datasets to find out whether reliable early warning is actually possible. Prediction should be evaluated separately from detecting movements during an ongoing event.
4. Power optimization: Fine-tune sensor sampling, processor activity, display use, and BLE communication to extend battery life for longer continuous monitoring.
5. Personalized classification: Explore controlled user specific calibration or adaptive models that account for differences in movement patterns, sensor placement, and individual physiology.
6. Enhanced connectivity: Build an optional mobile app to show notifications, system status, and event summaries, while keeping the core monitoring and alerting fully offline.
7. Robustness and usability testing: Check sensor placement, motion artifacts, hardware reliability, wearing comfort, and alert effectiveness under controlled conditions and during realistic daily activities.
8. Clinical and regulatory validation: Run properly supervised studies with expert involvement, ethical approval, and informed participant consent before any clinical use is considered. Any medical application would also need

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regulatory assessment and solid evidence of safety and effectiveness.

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