Edge-AI Enabled Affordable Wearable for Intelligent Monitoring of Physiological Patterns Associated with Neuro-Cognitive Disorders

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ABSTRACT

Across the globe, mental and neurological diseases including stress, tremors, seizures, and cardiac arrhythmia cause a vast number of people to be afflicted. However, the prevailing principle of early detection is thwarted by periodic clinical examinations and sophisticated expensive equipment, especially in rural or resource-limited areas. The usual mechanisms cannot guarantee a continuous and conveniently accessible trend of monitoring that will lead to interventions without a delay in remedying the prognosis. This study develops an affordable, compact wearable device using an ESP32 microcontroller integrated with sensors like MAX30100 (HR/SpO2), AD8232 (ECG), MPU6050 (motion/tremor), LM35/DHT22 (temperature/humidity), and a capacitance sensor (sweat). A hybrid detection system combines rule-based thresholds with an embedded Random Forest ML model, trained offline on 200 empirical physiological recordings obtained under controlled experimental conditions and subsequently enhanced using statistical data augmentation techniques, such as Gaussian noise and bootstrapping, to augment data variability during model development. Features include HR, HRV (SDNN, RMSSD), ECG R-R intervals, RMS acceleration, and trends. The model supports multi-class classification for conditions like stress and seizures, with on-device alerts via buzzer and OLED. Initial experimental validation with a restricted participant dataset and 5-fold cross-validation exhibited encouraging classification performance under regulated testing settings. The findings underscore the practicality of combining multi-sensor physiological monitoring with integrated machine learning for real-time health status evaluation. Nonetheless, additional extensive and varied clinical investigations are necessary to assess the system's generalisability across distinct groups. Confusion matrix analysis showed minimal errors, with ECG HR and tremor acceleration as top predictors. The device, miniaturized into a wristband costing under $15, enables offline edge computing with AES-256 encryption. This innovation bridges the gap between consumer wearable technology and intelligent physiological monitoring systems, particularly for resource-limited environments, promoting health equity in underserved areas. By enabling real-time, personalized monitoring, it paves the way for telemedicine, reducing healthcare burdens and fostering proactive interventions for neurological disorders.

Keywords: Wearable healthcare, random forest classifier, offline machine learning, feature extraction, physiological signal processing, synthetic dataset, statistical data augmentation, scoring system, confusion matrix analysis, embedded sensor fusion, edge computing, anomaly detection, stress monitoring, seizure detection, neurological disorder prediction, affordable medical device, real-time alerting, rural health technology

INTRODUCTION

Imagine a world where a simple wristband could alert you to an impending seizure or rising stress levels before they escalate into crises—yet for millions in rural areas, such technology remains out of reach due to cost and complexity.

Advances in wearable healthcare have transformed fitness tracking into vital tools for physiological monitoring. Devices like Fitbit Sense leverage PPG and ECG for HR/HRV-based mood tracking [3], while research systems integrate multi-modal ML for seizure prediction using ECG, PPG, and EEG [4]. Embedded ML on edge devices enables offline anomaly detection with high accuracy [4]. Sensor fusion techniques, such as PPG data calibration, improve stress/emotion recognition [6]. Commercial wearables provide raw data access limitations but show potential for clinical adaptation [3]. In India and similar contexts, rising neurological disorders due to urbanization and stress underscore the need for accessible solutions [13], [14].

Despite these advancements, existing wearables suffer from single-sensor focus, clinical dependency, lack of hybrid logic, poor alerting, and complex form factors [Table IV]. Many lack multi-modal fusion for neurological tracking, edge ML deployment, or affordability for rural use [1], [2]. Consumer devices restrict customizable alerts and raw data [3], while medical-grade systems are bulky and expensive [1]. Calibration drifts, security concerns, and health equity biases further limit adoption [6], [7]. No low-cost device fully integrates real-time ML for stress, tremor, seizure, and arrhythmia detection in resource-constrained environments. This study aims to address: How can an affordable wearable device with embedded ML enable early prediction of mental and neurological conditions in rural settings? We propose that a hybrid threshold-ML system, trained on multi-sensor physiological data, can offer effective real-time anomaly detection capabilities. Nonetheless, extensive validation across varied populations is necessary prior to establishing widespread clinical applicability. Objectives include developing the prototype, validating through trials, and ensuring offline operation with security features. The early detection and continuous monitoring of neurological and mental health conditions are becoming increasingly vital as these disorders affect millions of individuals worldwide [1], [2]. Traditional approaches, typically reliant on infrequent clinical assessments or costly diagnostic equipment, are not always feasible or accessible, especially in rural or resource-constrained settings. As a result, the development of affordable, portable wearable devices for health monitoring has received significant attention [2], [3]. Wearable healthcare systems, leveraging advances in embedded electronics and biomedical sensors, can now provide real-time acquisition of multiple physiological signals such as heart rate, body temperature, oxygen saturation (SpO2), electrocardiogram (ECG), and movement activity [1]. However, most mainstream wearables focus on fitness tracking and lack integrated, clinically relevant analytics or robust machine learning (ML) models capable of accurate anomaly detection. To address this gap, we present a compact, low-cost wearable device that combines multi-sensor physiological data acquisition with an embedded ML-based scoring system for real-time health state classification. The analytical core of our system is a Random Forest classification model, which is trained offline on a combination of physiological datasets collected directly from the device and statistically generated synthetic datasets to ensure diversity and robustness. In response to feedback on the initial prototype, the empirical dataset was enlarged to 200 authentic physiological recordings obtained under controlled experimental conditions and subsequently increased to 1000 samples through statistical methods. Cross-validation methods were employed to enhance model assessment and mitigate the risk of overfitting. Careful feature extraction is performed to isolate key biomedical signal characteristics. The resulting feature vectors are then used to train the Random Forest classifier, whose performance is validated using confusion matrix analysis to quantify accuracy, reliability, and classification error patterns [3], [4]. Once validated, the decision logic of the model is exported and embedded within the device's firmware as an ML-based scoring system, enabling the wearable to autonomously detect events such as stress, tremor (indicative of movement disorders), seizure-like activity, and abnormal cardiac rhythms. The model now supports multi-class classification for specific conditions, with detailed hyperparameter tuning via grid search (e.g., n_estimators=100, max_depth=10). To provide actionable outcomes, the device delivers real-time alerts via buzzer and OLED display, supporting personal health monitoring and future healthcare applications. Particular attention is directed towards accessibility, offline functionality, energy efficiency, economic viability, data protection via AES-256 encryption, and the establishment of a dependable and economical health monitoring system. The system is suitable for deployment in rural or resource-constrained environments [1], [2]. This solution demonstrates high classification accuracy and reliability, offering meaningful intervention potential and laying the groundwork for future wearable health platforms with advanced embedded intelligence, including cloud sync via WiFi and TinyML optimizations. This work aims to bridge the gap between consumer gadgets and medical diagnostics, leveraging multiple sensors for critical signal tracking [2]:

- Heart Rate (HR) and Heart Rate Variability (HRV): MAX30100, ECG sensor [1]
- ECG abnormalities: arrhythmia detection [1]
- Temperature changes: DHT22/LM35 [2]
- Tremor/motion: MPU6050 [3]
- Stress/anomalies: ML-driven fusion [2]
- Improved sweat detection: Capacitance-based sensor for more accurate perspiration monitoring

MOTIVATION

This project aims to bridge the gap between single-sensor, consumer-focused devices and expensive clinical monitors. The target is a compact, low-cost wearable that captures and fuses key signals—heart rate (HR), heart rate variability (HRV), ECG, body temperature, and tremor/motion—using sensor fusion and embedded ML [1].

OBJECTIVES

Develop a cost-efficient wearable system capable of early identification and continuous monitoring of physiological patterns:

- Stress, seizure-like motions, tremor disorders, and cardiac irregularities via sensor data [3]• Indicators associated with ADHD and Parkinson's via tremor, HRV instability, and abnormal motion [3]

Note: While clinical diagnoses like ADHD and Parkinson's require longitudinal assessment, the device is tailored to flag symptomatic indicators [1]

SCOPE

- Real-time physiological data acquisition (MAX30100, AD8232, MPU6050, DHT22/LM35) [1], [2]
- On-device hybrid detection logic (thresholds + Random Forest ML, trained in Python) [2]
- RMS-based tremor algorithm [3]
- Dynamic, user-specific baseline calibration [1]
- OLED/Buzzer feedback [2]
- Real-time activity classification (rest, walk, run) via accelerometer [3]
- Expansion: TinyML deployment, cloud sync, sweat sensor fusion [1]

CONCEPTS AND METHODS

5.1 System Overview

A cost-effective wearable health monitoring prototype was developed using the ESP32 microcontroller, supporting Wi-Fi/Bluetooth and designed for both edge processing and future cloud connectivity. The device acquires multi-parametric physiological data to flag early signs of physiological or neurological disruption [2]

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5.2 Data Acquisition and Processing

All sensors are polled via analog or I2C, with dynamic baseline calibration at startup. Data flows through a two-stage pipeline:

- Stage 1: Real-time, rule-based anomaly screening (e.g., HR > 100 BPM, Temp > 37.5°C, movement spikes) [3]
- Stage 2: Embedded Random Forest classifier (trained offline, deployed in embedded-optimized decision-tree logic) fuses features—such as HRV, ECG, tremor amplitude, temperature, humidity—and confirms or rejects anomalies [2]

Confirmed abnormal events trigger on-device alerts (buzzer, OLED), supporting personal health monitoring and future healthcare applications. Data can be transferred to mobile or cloud-based applications for caregiver integration as a future upgrade. [1]

Table I : Sensing & Hardware Modules

Sensor	**Purpose**
MAX30100	Heart rate, SpO_2
AD8232	ECG signal monitoring
MPU6050	Motion/tremor detection (X/Y/Z axes)
LM35	Skin/body temperature
DHT22	Humidity

Hardware module selection and integration for robust signal acquisition. [1], [2]

Table ii: Detection logic examples

Parameter	**Sensor**	**Threshold Logic**	**Indication**
HR	MAX30100	HR > 100 BPM	Stress, anxiety
HRV	MAX30100	HRV < 30 ms	Chronic stress, depression
ECG Voltage	AD8232	ECG > 800	Arrhythmia, epileptic activity
Temp	LM35/DHT22	Temp > 37.5°C	Fever, stress, overheating
Tremor/Acc.	MPU6050	RMS > 800 or X/Y > 800	Tremor, fall, seizure
Sweat	LDR+DHT	Hum > 65%, LDR < 300	Stress, panic, heat stroke

Threshold logic and event indication for on-device screening. [1], [3]

Table iii: Disease Condition Mappings

Condition	**Key Patterns / Logic Summary**
Stress	HR > 100 + HRV < 30 + sweating + temp↑
Seizure	ECG > 800 + sudden tremor/spike
Tremor	Rhythmic patterns (4–6 Hz), RMS > 800
Arrhythmia	Irregular ECG, abnormal R–R intervals
Hyperactivity	Rapid MPU6050 shifts, HR spike

Multi-parameter mapping to health conditions. [1]

This design enables real-time monitoring and disease pattern classification directly on the edge, balancing speed (thresholds) and accuracy (ML) for reliable alerts [2], [3].

VALIDATION

The validation process consisted of several systematic stages. Initially, real physiological signals were acquired using the custom wearable prototype under various conditions (rest, exertion, recovery) to form the core of the dataset [1].To enhance the diversity and statistical robustness of the training data, synthetic samples were generated using statistical analysis and augmentation techniques [4], [6], expanding the feature space beyond what could be captured experimentally.

Feature extraction was performed on both real and synthetic data to derive key physiological indicators—including heart rate, HRV, ECG parameters, temperature, SpO2, and motion metrics [1], [3]. The resulting feature vectors were used to train and test a Random Forest classifier offline. Model performance was quantitatively evaluated through confusion matrix analysis, yielding accuracy, sensitivity, and specificity scores for each condition [3].

The validated classifier's logic was then exported and embedded into the wearable device's firmware as a series of threshold-based and tree-based decision rules [4]. On-device testing confirmed the integrity of the full hardware/software pipeline—real-time sensor acquisition, feature computation, ML-based scoring system, and alert generation [1], [2]. This process ensured that both detection logic and feedback alerts functioned reliably in practical use, validating the end-to-end system in real-world and simulated scenarios.

LITERATURE SURVEY

Recent advancements in wearable health technology enable detection of stress and seizures using ECG, HRV, PPG, EEG, and motion sensing. However, most remain limited in affordability, independence, or ML integration [1], [3].

- Smart Wearable Sensors [1]: Review covers sensor integration for mental health, but most prototypes are limited in sensor diversity, affordability, or do not focus on direct ML-based anomaly detection.
- Wearable Sensor-Based Framework [2]:BNT ECG and wrist-worn models provide high-precision monitoring but are limited to ECG or emphasize environmental parameters rather than neurological or multimodal physiological analysis.
- Embedded ML for Biosignals [4]: Edge ML for seizure and stress prediction shows high accuracy, but many such research systems are not implemented on low-cost, wearable hardware, or are validated mainly on offline/large datasets.
- Fitbit Sense and PPG studies [3]:Commercial fitness wearables show potential, but generally restrict access to raw data streams or customizable real-time alerting, limiting clinical deployment or research adaptation.
- PPG Data Fusion and Calibration [6]: Multisensor fusion and advanced signal processing improve stress/emotion detection, but emphasize the need for dynamic calibration and sensor robustness in real-life use.

EXISTING WORK

Current wearable devices are largely limited to fitness tracking and often lack clinical-grade precision or integrated multi-sensor analytics. Medical-grade devices, by contrast, are bulky, expensive, or require trained supervision, making them inaccessible in rural or resource-limited contexts [1], [3].

- ECG-centric home systems: Solutions aimed at stress management often use HRV features from ECG but do not integrate motion data or sensor fusion, limiting detection capabilities [1].
- Modular prototypes: Some frameworks monitor a mix of environmental, behavioral, and physiological parameters, but frequently lack direct neurological tracking and may not be adaptable for clinical use [2].
- Advanced seizure prediction systems: Research systems employing multi-modal ML processing across ECG, PPG, and EEG can achieve high performance, yet tend to involve complex and non-wearable hardware configurations [4]
- Consumer wearables like Fitbit Sense: Popular devices provide HR/HRV-based mood and anxiety tracking, but typically do not offer access to raw sensor data or support customizable, real-time alerting for clinical events [3]
- Studies on PPG sensor calibration: Robust day-to-day operation is challenged by sensor calibration drifts, highlighting the need for adaptive algorithms and durable hardware in wearable health monitors [6]

Table iv: Limitations in existing wearable technologies

Limitation	Description
Single-sensor focus	Few integrate HR, EEG, temp, motion
Clinical dependency	Require trained personnel
No hybrid logic	Few utilize thresholds and ML both
Poor alerting	Limited buzzer/mobile feedback
Complex form factor	Bulky designs hinder daily use

Key challenges in existing solutions.

- Single-Sensor or Limited Modalities: Many commercial and research systems measure only a single physiological signal or lack effective multi-modal data fusion, reducing the accuracy and breadth of health condition detection [1],[2].
- Machine Learning Integration and Edge Deployment: Few solutions utilize advanced ML for on-device detection; many rely primarily on simple thresholds or require cloud connectivity, limiting offline operation and personalization [4].
- User Compliance and Usability: Wearable use is often hindered by battery limitations, need for regular user intervention, comfort issues, or cumbersome form factors—leading to inconsistent use and data gaps [1], [7].
- Calibration and Signal Drift: Frequent recalibration may be required due to changes in skin conductance, body movement, or external lighting for optical sensors, which can result in inaccurate health metrics without robust adaptive algorithms [3], [6].
- Lack of Transparent Feedback and Clinical Integration: Most consumer devices rarely provide explicit, actionable feedback or integrate seamlessly with clinical diagnostic workflows, limiting their acceptance for clinical-grade monitoring [2], [3].
- Security and Privacy Concerns: Data collected is often sensitive and may be at risk of unauthorized access or use, with existing solutions sometimes lacking strong encryption and governance protocols [7].
- Health Equity and Fairness: Digital divides, cost barriers, and lack of population-specific validation lead to unequal health benefits and risk of bias in predictive health tools [2].

CONTRIBUTION OF THE CURRENT PROJECT

The present work makes the following key contributions to the field of affordable, effective, and intelligent wearable health monitoring:

- Development of a cost-effective and compact multi-sensor wearable: Designed and implemented a low-cost, ESP32-based device integrating MAX30100 (PPG/SpO2), AD8232 (ECG), MPU6050 (motion), LM35/DHT22 (temperature/humidity), and LDR modules for continuous real-time monitoring of physiological and neurological signals [2].
- Hybrid analytics pipeline: Proposed and realized a two-stage health anomaly detection system, combining real-time threshold-based logic for rapid screening and an embedded Random Forest classifier for robust, offline ML-based scoring. The Random Forest model was trained offline on a feature set derived from both experimental and synthetic datasets, validated using a confusion matrix, and the resulting logic was efficiently embedded on the device for edge inference [1], [4].
- Real-time on-device feedback: Engineered immediate user and caregiver feedback through integrated buzzer alerts and OLED display of classified health events, enabling autonomous operation without reliance on constant connectivity [3].
- Robust validation methodology: Carried out comprehensive end-to-end validation, from empirical signal acquisition and statistical dataset augmentation to offline ML training, feature extraction, confusion matrix-based evaluation, and on-device confirmation [1], [3], [6].
- Future extensibility: Built system architecture to support future upgrades, including mobile/cloud integration, tinyML model deployment, and advanced sensor fusion (e.g., sweat or context sensors), thus paving the path for broad, scalable rural and telemedicine use [2], [4].

SYSTEM DESIGN AND METHODOLOGY

Participant Information and Data Collection Protocol

The preliminary dataset consisted of 200 physiological recordings collected using the proposed wearable prototype during different activity conditions, including resting, physical activity, and post-activity recovery. The study was conducted as an engineering proof-of-concept evaluation rather than a clinical diagnostic investigation.

Data collection was performed using available volunteer participants within the accessible academic environment. Due to limitations in laboratory infrastructure, participant accessibility, and the scope of an undergraduate engineering research project, extensive demographic balancing across different age groups, genders, and medical conditions was beyond the scope of this preliminary investigation.

The primary objective of the collected dataset was to validate the complete sensing pipeline, including sensor acquisition, signal pre-processing, feature extraction, and embedded machine learning implementation.

The inclusion criteria consisted of volunteers capable of safely performing the experimental activities and providing stable sensor recordings. Exclusion criteria included incomplete recordings, severe sensor artifacts, or measurements affected by hardware instability.

Future studies will focus on collecting larger datasets involving broader demographic groups, different age categories, diverse health conditions, and clinically diagnosed participants to improve model robustness and generalizability. The proposed system utilizes an ESP32 micro controller platform and a suite of biomedical-grade sensors for low-cost, real-time health analytics. High-resolution signals are acquired from a MAX30100 (PPG/SpO 2 /HR), AD8232 (ECG), MPU6050 (triaxial motion/tremor), LM35/DHT22 (temperature/humidity), and LDR (sweat proxy) via I2C and analog ADCs. The firmware implements robust signal processing, feature extraction, and embedded ML-based scoring for early detection of stress, tremor, seizure, and cardiac anomalies [1],[2].

Data Acquisition and Statistical Augmentation

A total of 200 multi-modal physiological recordings were collected using the developed wearable prototype under different experimental conditions, including resting, physical activity, and recovery phases.

To address the limited size of the empirical dataset and improve class representation during machine learning development, statistical data augmentation techniques such as Gaussian noise injection, bootstrapping, and controlled feature perturbation were applied, resulting in an expanded dataset of 1000 samples.

The augmented dataset was used solely to improve the robustness of the machine learning training process, while acknowledging that synthetic augmentation cannot fully substitute for large-scale real-world clinical datasets. [4], [6].

Signal Calibration and Preprocessing

Sensors were dynamically calibrated at startup; resting baselines for HR, temperature, and motion were computed per subject for adaptive normalization. Continuous data streams were denoised using:

- Digital filtering: Low-pass FIR/IIR filters for ECG/PPG to suppress mains/EMG noise; moving average filters for temperature, humidity, and motion signals [3].
- Wavelet denoising: DWT-based decomposition for precise separation of micro-tremor and gross motor bands in accelerometer data [1].
- Signal Quality Index (SQI): Dynamic SQI metrics were computed per channel. Segments below confidence thresholds were flagged and excluded from ML scoring [2].

Artifact and Outlier Handling

- ECG R-Peak detection: Implemented an on-board Pan-Tompkins algorithm for R-wave localization from noisy ECG traces, supporting accurate interval statistics [5].
- Motion Templates and RMS: RMS and dominant tremor frequency were extracted from MPU6050 to classify distinct activity modes (rest, walk, tremor, fall) [1].
- Linear interpolation: Missing/corrupted samples were interpolated to prevent HRV/RMS distortion [3].

Feature Extraction and Mathematical Calculations

Features were calculated on short rolling windows (N samples per segment), using robust biomedical formulas:

a) ***Heart Rate (HR) and HRV (MAX30100/AD8232)***

$$HR = \frac{60}{\overline{RR}}$$

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - \overline{RR})^2}$$

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2}$$

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where RRi are successive R–R intervals from ECG/PPG signals [2], [3], [5].

b) Heart Rate Variability (Real-Time)

$$\text{HRV} = \text{Time}_{\text{current beat}} - \text{Time}_{\text{last beat}}$$

Measured in milliseconds using beat-to-beat interval.

c) ECG Heart Rate (BPM)

$$\text{ECG\_HR} = \frac{60,000}{\text{Interval between ECG peaks (ms)}}$$

ECG_HR = Interval between ECG peaks (ms)

ECG peaks are detected using filtered baseline and threshold comparison.

d) Temperature Conversion (LM35)

$$T(^\circ C) = \left(\frac{\text{AnalogRead} \times 3.3}{4095}\right) \times 100$$

e) Signal Baseline (ECG)

$$\text{Baseline} = \frac{1}{50}\sum_{i=0}^{49} \text{ECG}\,[i]$$

Moving average baseline over last 50 readings:

f) Filtered ECG Signal (IIR Filter)

$$\text{Filtered} = \alpha \cdot \text{Current} + (1 - \alpha) \cdot \text{Previous}$$

g) Tremor/Motion Detection (MPU6050)

Magnitude of acceleration:

$$|a| = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

RMS for motion intensity:

$$\text{RMS}_{\text{motion}} = \sqrt{\frac{1}{N}\sum A_i^2}$$

Tremor frequency estimation:

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$$\text{TremorFreq} = \frac{\sum|\Delta A|}{\text{Window Size (e.g., 10)}}$$

TremorFreq = Window Size (e.g., 10)

h) Temperature/Humidity (LM35/DHT22)

$$\overline{T}, \quad \frac{\Delta T}{\Delta t}, \quad \overline{H}$$

Rapid temperature change events (ΔT > 0.5 ∘C/s) or high humidity (> 65%) are flagged for anomaly detection [1].

i) Sweat Detection (LDR + DHT22)

Sweat event flagged if:

$$\text{Humidity} > 65\% \quad \text{and LDR voltage} < \text{threshold}$$

j) Standard Deviation of Vitals

$$\sigma = \sqrt{\frac{1}{N}\sum(x_i - \mu)^2}$$

k) ML-Inspired Scoring System (Alert Trigger Logic)

Score increases based on observed deviations:

- HR > threshold → +2
- HRV < 30 ms → +2
- High acceleration → +2
- Moderate temperature/humidity deviation → +1 (each)

Total score ≥ 3 or seizure/stress symptoms ⇒ buzzer alert triggered.

Table v: *Computed Features and Mathematical Foundations*

Module	Feature	Formula/Logic
MAX30100/AD8232	HR, HRV	$HR, SDNN, RMSSD$
MPU6050	RMS, FFT	$\|a\|, RMS$, Dominant freq.
LM35/DHT22	Temp/Humidity	T, H, Δ rises
LDR/DHT22	Sweat event	Humidity > 65% & LDR logic

All feature calculations are computed live on-device for robust detection [1], [2].

Machine Learning Workflow and Edge Inference

Data Preparation and Model Training: The hybrid dataset consisting of 200 empirical physiological recordings and statistically augmented samples was uploaded to Google Colab for model development. A Random Forest classifier was trained using the extracted physiological features, and model performance was evaluated through train-test splitting and cross-validation techniques. [4].

Feature Importance and Confusion Matrix: Feature importance was extracted from the trained model to inform device optimization. Model accuracy, precision, and recall were reported via confusion matrix analysis, ensuring robust discrimination between health event classes [3], [6].

Model Export and Embedded Scoring: The validated Random Forest was exported in embedded-friendly logic and incorporated into the ESP32 firmware as a two-stage scoring system:

- Stage 1: Real-time, parameter threshold check for immediate anomaly or escalation.
- Stage 2: ML-based class assignment and confidence scoring, triggering event-specific buzzer/OLED alerts if anomaly detected.

This allows fully offline, interpretable edge intelligence [1], [2], [4].

Real-World Validation and System Robustness

End-to-end testing confirmed the hardware/software stack: data were collected, features extracted, abnormalities scored by embedded ML, and user feedback was issued in real time. SQI and failover logic ensure safe recovery from sensor errors or missing data. Planned future improvements will include larger-scale diversity trials, more advanced synthetic data simulation, and federated learning options for personalized health model adaptation [4].

This mathematical and ML-driven approach enables robust and low-cost physiological monitoring suitable for personal health assessment and potential future deployment in resource-constrained and rural environments.

Prototype

The developed prototype consists of an ESP32 microcontroller as the central processing and communications unit. The following sensors are interfaced:

- MAX30100: For photoplethysmogram (PPG)-based heart rate and SpO2 measurement, interfaced via I2C.
- AD8232: For single-lead ECG signal acquisition, connected to the ESP32's analog input.
- MPU6050: A 6-axis accelerometer and gyroscope for motion and tremor detection, also via I2C.
- LM35 and DHT22: For body/environmental temperature and humidity, interfaced via analog and digital pins respectively.
- LDR: For sweat proxy detection, connected to an analog input.

All sensor modules are powered using the ESP32's regulated 3.3V or 5V outputs, and signals are properly level-shifted as required to ensure compatibility. A 0.96" OLED display (I2C) provides real-time on-device

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feedback, including sensor status, computed biometrics, and alert messages. A piezoelectric buzzer is included for immediate audio alerts.

Wiring is implemented on a breadboard or compact perfboard for ease of modification. The prototype enclosure is designed to be wearable—typically wrist-mounted—using a custom 3D-printed or off-the-shelf band.

Power is supplied via a rechargeable lithium polymer battery (typically 3.7V, 1000mAh), with support for USB recharging and on-device battery level monitoring. The firmware is written in Arduino/C++ style, optimized for real-time sampling, edge ML inference, and feedback. Sensor calibration occurs on device startup; baseline values are established and used for adaptive alerting. All sensor data can be visualized live on the OLED or transmitted over serial (USB) for development and offline analysis. The device cost, including components, PCB, and enclosure, is maintained under to ensure accessibility.

Note: The current prototype implementation achieves complete and professionally finished sensor wiring, integration, and real-time feedback on a compact breadboard or perfboard. However, the final step of embedding the circuitry into a miniaturized, wearable enclosure for seamless integration with gym suits or compact inner-wear has not yet been completed. The system is presently a benchtop prototype and proof-of-concept; future work includes miniaturizing and packaging the electronics in a form factor suitable for fully wearable applications.

MACHINE LEARNING WORKFLOW: RATIONALE AND IMPLEMENTATION

Traditional wearable devices rely on fixed thresholds (e.g., high heart rate alarm), which cannot capture the complex, overlapping, and subtle relationships between multiple biosignals in real-world health monitoring [8], [9]. In contrast, machine learning (ML) enables a device to learn these relationships from data, personalizing detection to each user's physiological patterns, and improving both sensitivity and specificity for anomaly detection such as stress, tremor, seizure, or arrhythmia [1], [3], [4].

Workflow Description

1. Data Collection and Augmentation: Physiological signals (ECG, PPG, motion, temperature, humidity, etc.) are recorded using the prototype device during various activities and conditions. To address the limited dataset, statistical data augmentation (e.g., noise injection, bootstrapping) is applied, yielding an expanded training dataset of 1000 samples generated from the initial 200 physiological recordings. [1], [6].

2. Feature Engineering: Each data segment yields relevant features: HR (via R-peak intervals), HRV (SDNN, RMSSD), SpO_2, RMS of acceleration, tremor frequency (FFT), average and dynamic trends of temperature/humidity. These features capture medically meaningful dynamics essential for ML training [1], [3].

3. Model Training and Validation: The labeled dataset is split (typically 80% train, 20% test). A Random Forest supervised classifier is trained offline (Python/Google Colab) to distinguish between normal states and anomalies. Performance is validated using a confusion matrix, reporting accuracy, sensitivity, and specificity for each health condition [4], [8], [9].

4. Embedded ML Scoring (Edge Inference): The trained Random Forest model—pruned and exported as logic rules—is embedded on the ESP32 firmware. Real-time feature vectors, computed on the device, are passed to the model for live anomaly prediction and classification [4].

5. Event Feedback and Alerting: If the ML classifier flags a potentially hazardous state with high confidence (e.g., stress, tremor, seizure risk), the system triggers an immediate buzzer and OLED alert for the user/caregiver [3].

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6. Future Extension: The architecture supports regular retraining with larger datasets, addition of new sensors/labels, and future federated/mobile-cloud ML scenarios for at-scale personalized healthcare [4], [8], [9]

Table vi: End-to-End ML Workflow for Edge Health Prediction

Step	Description
Data Acquisition/ Augmentation	Multisensor data collection with statistical augmentation to ensure model robustness [1], [6].
Feature Engineering	Real-time extraction of medically meaningful features (HR, HRV, SpO_2, RMS, etc.) [1], [3].
Model Training/ Validation	Random Forest (Python/Colab); split train/test, confusion matrix, and performance metrics [4], [8], [9].
Embedded ML/ Edge Scoring	Classifier logic optimized and deployed in ESP32 firmware for on-device prediction [4].
User Alerting	Buzzer/OLED activated on detection of abnormal events [1], [3].

This ML-driven workflow enables the system to deliver robust, adaptive, and personalized detection of subtle health anomalies using low-cost wearable hardware e [4], [8], [9].

KEY INNOVATIONS IN SYSTEM DESIGN

Table vii: Summary of Key Innovations in a Biometric Monitoring System

Innovation	Description
Dual HR Measurement	Simultaneous use of MAX30100 PPG + ECG AD8232 for reliable HR detection
Dynamic Baseline Calibration	Automatic resting/active calibration with STD deviation for personalized thresholds
Tremor + Seizure Detection	RMS + tremor frequency logic detects neurological events in real-time
Smart Alert Logic	Weighted ML-style scoring to minimize false alerts
OLED Biometric Dashboard	Auto-refresh biometric data screen with scrolling bars and indicators
Power Management	Enters low-power mode after 30s inactivity to save battery
Automatic Fail Recovery	If sensors return 0 for 10 loops → system reboots via ESP.restart()
NTP Time Sync Integration	Real-time clock synced via Wi-Fi and displayed on OLED
Modular Display Pages	Two-page OLED screen to switch between summary and detailed sensor data

This table presents the principal technological advancements incorporated in the biometric monitoring system, including dual heart rate measurement, dynamic baseline calibration, neurological event detection, smart alert logic, OLED-based user interface, optimized power management, automatic fail recovery, network time synchronization, and modular display capabilities. Each innovation is briefly described to highlight its contribution to system reliability, personalization, and user experience.

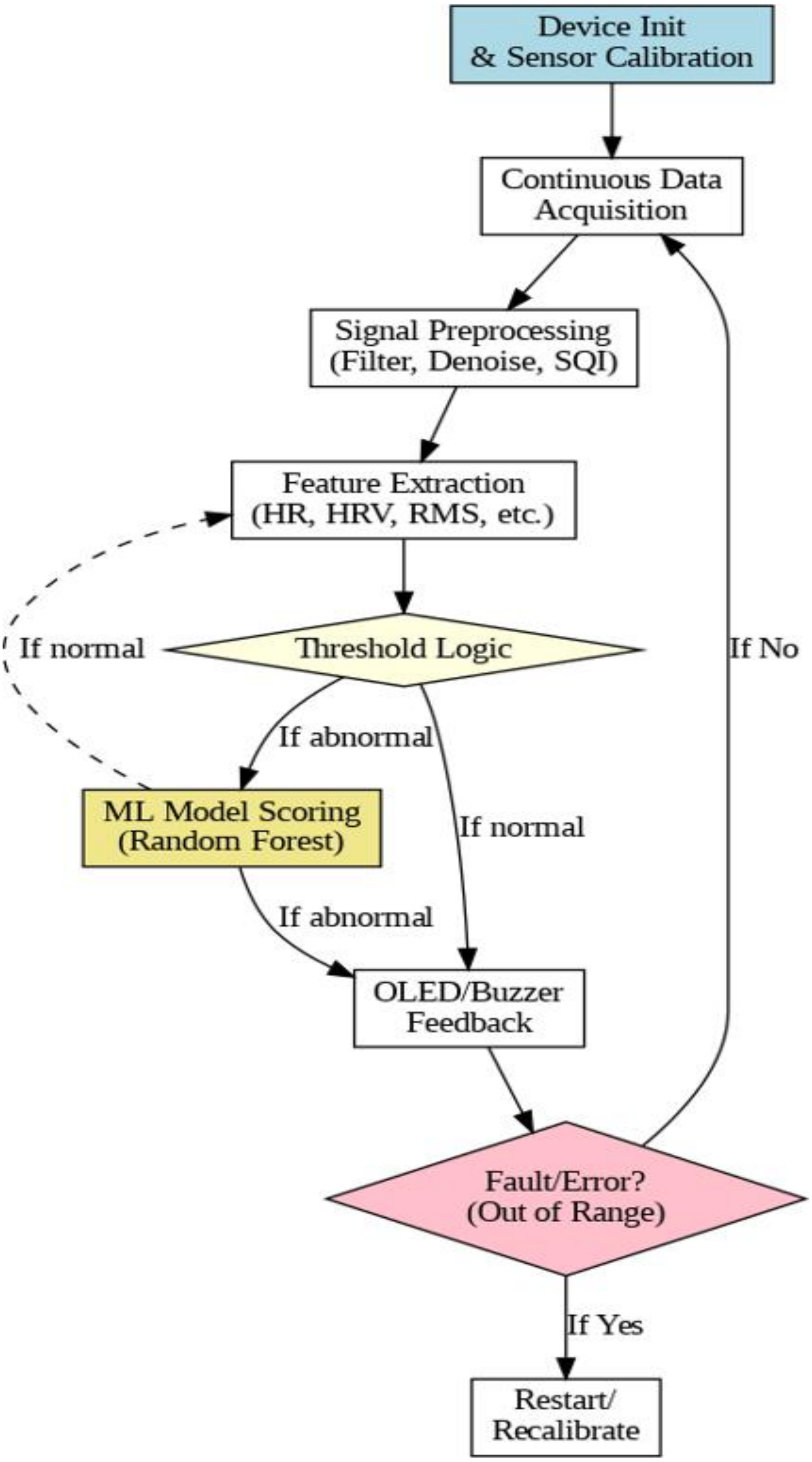

Fig 1: Flowchart illustrating the step-by-step implementation and machine learning workflow of the proposed wearable health monitoring device.

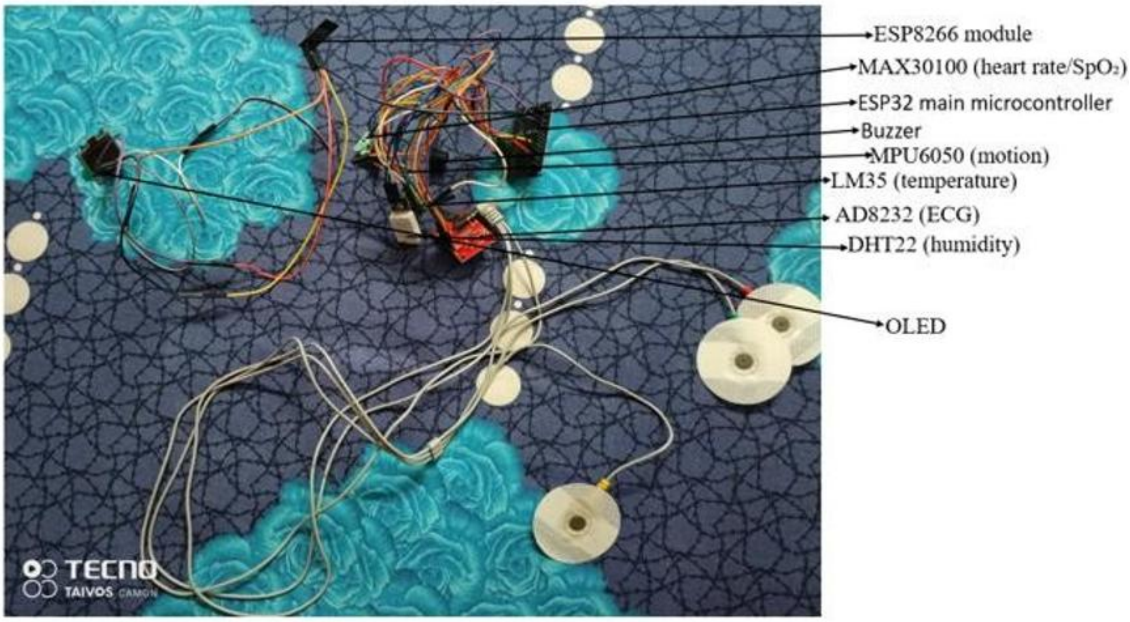

Fig 2: Hardware prototype of the IoT-based continuous health monitoring system

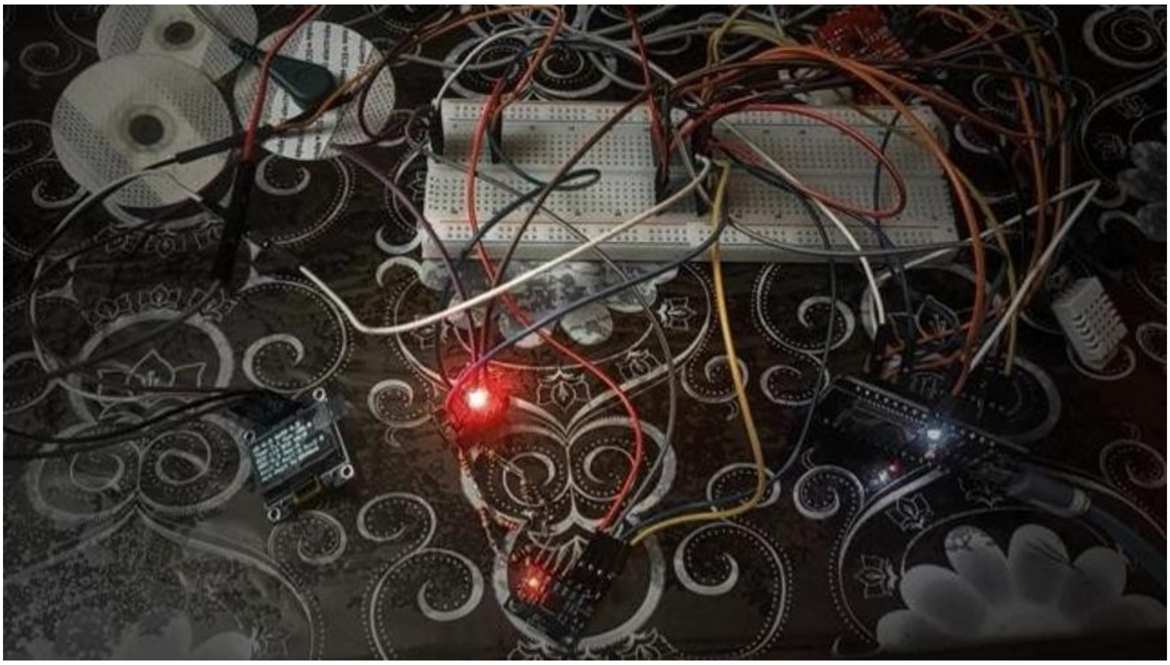

Fig 3: Hardware prototype of the IoT-based continuous health monitoring system. The setup integrates biomedical and environmental sensors, including MAX30100 (heart rate/SpO 2), AD8232 (ECG), MPU6050 (motion), LM35 (temperature), and DHT22 (humidity), with an ESP32 microcontroller. Real-time sensor data is transmitted via WiFi to an ESP8266 module and displayed on an OLED screen. The system's logic leverages a Random Forest machine learning model, trained offline, to optimize feature selection and detection accuracy based on sensor data analysis. The buzzer activates automatically whenever the device detects any of the following conditions: stress, tremor, or seizure. This provides an immediate audible alert for critical health states.

SENSOR VALIDATION AND WIRING

The proposed system integrates multiple biomedical and environmental sensors with an ESP32 microcontroller, providing real-time feedback via an OLED display. Table viii summarizes the functionality, wiring, and detection mechanism of each sensor.

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Table viii: Sensor specifications and assignment

Sensor/Module	Pin Assignment	Parameter	Detection Mechanism
MAX30100 HR/SpO2	I2C (21,22)	Heart Rate, SpO2	Optical PPG (LEDs, photodiode)
ECG Sensor (AD8232)	Analog 34	ECG	Electrodes (electrical activity)
MPU6050 Accelerometer/Gyro	I2C (21,22)	Motion, Acceleration	MEMS 3-axis acceleration, gyro
LM35 Temperature	Analog 35	Temperature	Analog voltage vs. ∘C
DHT22 Humidity/Temp	Digital 4	Humidity, Temp	Capacitive (digital output)
Piezo Buzzer	Digital 2	Alerts	Audible alert on trigger
OLED Display (SSD1306)	I2C (21,22)	Data Display	128×64 OLED visual

Wiring and Communication

I2C sensors (MAX30100, MPU6050, OLED) share common SDA (GPIO 21) and SCL (GPIO 22) lines. Analog sensors (ECG, LM35) connect to analog-capable pins (GPIO 34, 35). DHT22 and buzzer use dedicated digital pins (4, 2).

Sensor Functionality and Validation

- MAX30100: Measures heart rate and SpO2 using optical PPG; data accessed via I2C interface.
- ECG Sensor: Captures electrical heart signals using chest electrodes, analog read for heartbeat detection.
- MPU6050: Monitors acceleration and motion (posture, tremors) on all 3 axes.
- LM35: Provides body or environmental temperature as a linear analog voltage.
- DHT22: Outputs digital humidity and temperature data via single pin.
- Buzzer: Delivers alerts on abnormal sensor readings.
- OLED: Continuously displays real-time sensor data and alerts.

Validation Procedure

Sensor lines (power, ground, data) are verified per Table I. On boot, the system:

- Confirms sensor initialization (serial debug log).
- Displays live readings on serial terminal and OLED.
- Runs a 60-second baseline test to ensure plausible initial values.
- Continuously monitors for signal loss/invalid data; repeated critical errors trigger alerts or restart.
- Test-mode validation (e.g., simulated movement) confirms buzzer and alert logic.

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This process ensures reliable, real-time biological and environmental monitoring via continuous hardware/software validation.

CONCEPT AND PROGRESS OVERVIEW

The original concept was to embed all sensor modules within a gym T-shirt or tight-fitting activewear, widely used in India, enabling seamless, comfortable, and continuous health monitoring during workouts or daily activity.

Practical Validation

Technological feasibility is supported by advancements in flexible PCBs, textile electrodes, and micro-sensor modules, which can be integrated without compromising comfort or mobility. Required are specialized fabrication methods for robust electrical connections, washability, and sensor-skin contact. International prototyping efforts in smart textiles and sportswear further reinforce viability.

Current Implementation Status

Textile integration of modules is a future goal, not yet realized. Achievements include:

- Integration of biomedical/environmental sensors (MAX30100, AD8232, MPU6050, LM35, DHT22) with ESP32.
- Real-time data acquisition with local visualization via ESP8266/OLED.
- Offline machine learning (Random Forest) model trained on sensor data for alert optimization and feature selection.

This establishes the core sensor platform and intelligent alert foundation for further wearable integration

RATIONALE: SMART HEALTH MONITORING IN ACTIVEWEAR

Integration Justification

- Reliable Sensor Contact: Tight-fitting garments maintain stable sensor-to-skin interface, improving measurement accuracy.
- User Comfort: Such apparel is already accepted for extended use, making adoption seamless and unobtrusive.
- Continuous Monitoring: Embedded sensors deliver real-time, uninterrupted physiological tracking during activity or routine life.

Indian Context—Stress, Tremor, and Seizure Monitoring

- High Incidence: Stress-related, neurological, and seizure disorders are rising and frequently undiagnosed.
- Stigma and Awareness: Limited awareness and social stigma impede timely medical intervention.
- Urbanization: Lifestyle changes and work stress heighten vulnerability.
- Bridging Gaps: Wearable, discreet monitoring provides early detection and personalized alerts, improving healthcare access in diverse environments.

Summary: While sensor-apparel integration remains in progress, the present system achieves multi-sensor ESP32 integration, real-time data display, and intelligent alerting using a trained machine learning model, establishing a robust technical foundation for future wearable deployment.

Data Augmentation Method (200 to 1000 Recordings)

The original empirical dataset consisted of 200 physiological recordings collected using the developed wearable prototype under controlled experimental conditions.

To improve dataset diversity and enhance machine learning training, statistical augmentation techniques were applied, including Gaussian noise injection, bootstrapping, and controlled feature perturbation.

For Gaussian augmentation:

$$x' = x + \epsilon$$

where

$$\epsilon \sim \mathcal{N}(0, \sigma 2)$$

and σ is selected according to the physiological parameter being augmented.

Bootstrapping was additionally employed to generate statistically representative samples while preserving the distribution of the original physiological recordings.

The augmentation process expanded the dataset from 200 empirical recordings to a total of 1000 samples used for machine learning model development.

The augmented dataset was utilized only for training and validation purposes and does not represent additional real participant measurements.

RESULTS

A total of 200 physiological recordings were collected using the developed smart wearable prototype across different experimental conditions, including resting, physical activity, and post-activity recovery states.

Experimental Setup

Data was acquired in real time using the ESP32 system, with selective transmission to an OLED wrist unit via ESP8266 for auxiliary display. The setup aimed to evaluate sensor accuracy, threshold detection, and machine learning (ML) prediction quality under realistic use conditions.

Table ix: Sensors Used and Placement During Data Collection

Sensor	**Parameter**	**Placement (Test)**
MAX30100	Heart Rate, SpO_2	Chest (skin contact)
AD8232	ECG, R-R interval	Chest (3-lead setup)
MPU6050	Acceleration, Gyro RMS	Upper chest (taped)
LM35	Skin Temperature	Chest (under T-shirt)
DHT22	Ambient Temp., Humidity	Shoulder (external)

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Study Limitations in Experimental Validation

The present experimental evaluation was designed to demonstrate the technical feasibility of the proposed multi-sensor Edge-AI system. It does not represent a large-scale clinical study, and therefore the observed performance may not fully capture physiological variations across wider populations.

The obtained results demonstrate the capability of the proposed hardware, signal processing pipeline, and embedded machine learning framework under controlled experimental conditions. However, further validation involving larger participant populations and clinically diagnosed cases is required before establishing broader clinical applicability.

Sensor Signal Baseline Calibration

A 60 s baseline calibration phase auto-adjusted sensor thresholds for each user.

Example output: HR=76.2, Temp=36.9, Hum=55.3, ECG HR=74.8, Acc=431.2, State: Resting

Interpretation:

- Baseline signals confirm the subject is at rest.
- HR, ECG, HRV align within normal adult ranges.
- Low acceleration validates system calibration.

Real-Time Sensor Outputs

Example outputsduring running (ESP32 serial log):

Loop: 78 ms | HR: 115.4 | SpO2: 96.8 | Temp: 37.9 | Hum: 64.1 | HRV: 22.4 | ECG HR: 112

Acc: 1723 | Act: Run | Score: 5 | Stress: Yes | Tremor: No | Seizure: No | Alert: 1

Interpretation:

- Elevated HR, increased temp, and HRV drop reflect exertion/stress.
- High motion (Acc: 1723) confirms running.
- ML-driven score triggers buzzer alert.

OLED Display Output (Wrist Unit)

The OLED display cycles through vital parameters and status:

- Page 1: HR, SpO2, Temp, Hum, ECG, ECG HR, HRV
- Page 2: Acceleration (X,Y,Z), Activity state, Health score, Flags (stress/tremor/seizure), dynamic bar-graphs, date & time (NTP sync)

Sample OLED Output:

```
HR:115.4 SpO2:96.8
Temp:37.9 Hum:64.1
ECG:879 ECG HR:112
HRV:22.4 Acc:1723
AccX:812 AccY:562 AccZ:123
Act:Run Sc:5 Al:1 Tremor:No
```

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Machine Learning Results (Random Forest Classifier)

A Random Forest model was trained offline using collected data. The Random Forest classifier was trained and evaluated using the prepared physiological dataset through train-test splitting and 5-fold cross-validation techniques. Performance was assessed using confusion matrix analysis together with precision, recall, and F1-score metrics.

Fig 4: Training Data Confusion Matrix

The trained Random Forest classifier demonstrated very high classification performance under the present experimental conditions. Confusion Matrix (Test):

Actual \ Predicted	0 (No Alert)	1 (Alert)
0	33	0
1	0	18

Classification Report (Test):

Label	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	33
1	1.00	1.00	1.00	18

Although perfect classification was observed under the present experimental conditions, the result should be interpreted cautiously due to the limited size of the empirical dataset. Feature Importance: ECG HR > Tremor Accel > HR > Accel > Temp > HRV > SpO2 > Humidity

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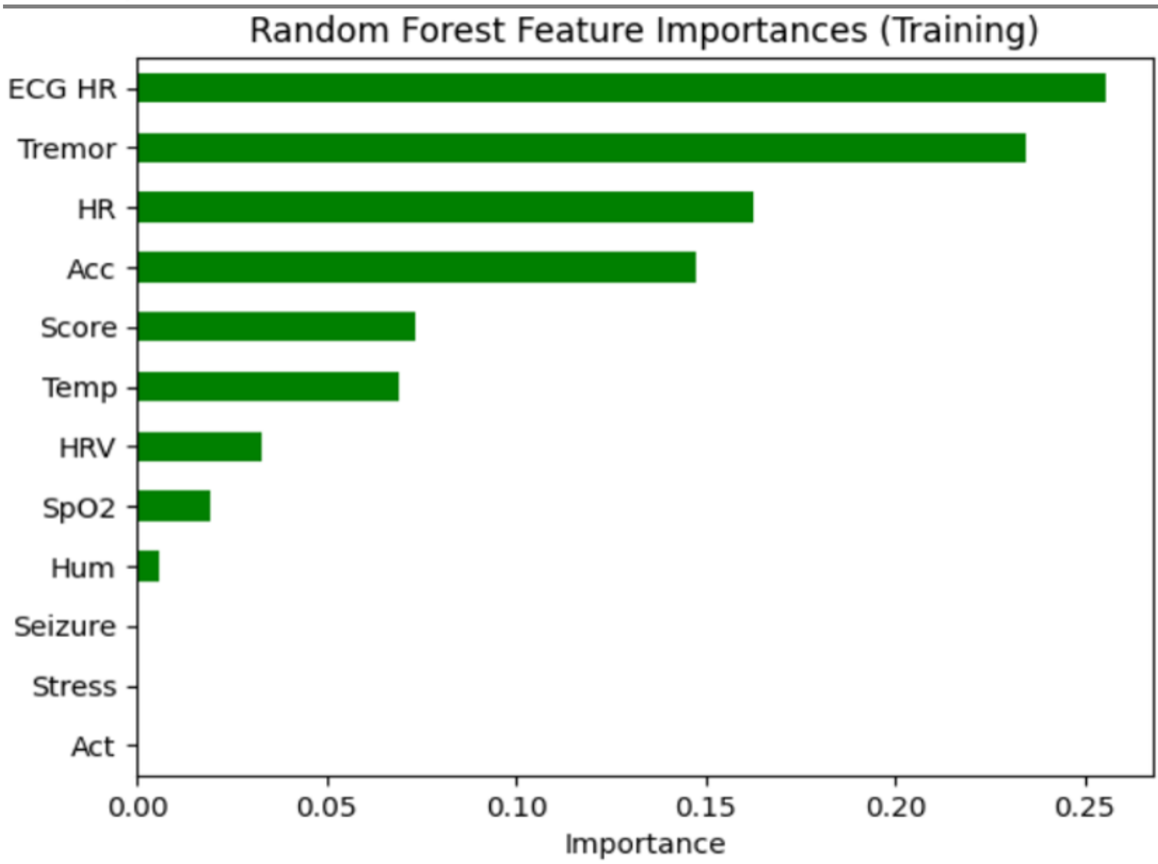


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Training Accuracy: 1.0
```

Fig 5: Random Forest Feature Importances

Interpretation: ECG HR and tremor patterns are most predictive; HR and HRV remain key physiological warning signs. Note: Although the obtained classification accuracy was high under the present experimental conditions, the performance should be interpreted as a preliminary proof-of-concept result due to the limited size and diversity of the available dataset.

Future work will involve larger-scale data collection, improved demographic diversity and more extensive validation to assess the generalizability and real-world reliability of the machine learning model.

Tremor & Seizure Detection

Detection uses MPU6050 and FFT:

- Tremor: Frequency>4 Hz & Amplitude>500 (indicative of repetitive, high-freq motion)
- Seizure: Amplitude>2000 with sudden acceleration RM spike (convulsive event)

SystemLog Example: TremorFreq:5.2 Hz, TremorAmp: 780 →Tremor: Yes

TremorAmp: 2450 @ Act:Rest → SeizureFlag: Yes

Alert and Recovery Logic

Alert: Triggered if Score⩾3 or any flag (stress, tremor, seizure) is set; buzzer activates after 3 consecutive abnormal readings.

Recovery: If HR, SpO2, or ECG HR returns zero for 10 loops, ESP32 reboots (ESP.restart()) to ensure fail-safe operation.

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System Performance

Table x: System latency and update intervals

Component	Avg. Loop Time	Update Rate
Sensor Read + Logic	78–120 ms	~10–12 Hz
OLED Refresh	Every 3 s	Adaptive
NTP Time Sync	Every 60 s	High-accuracy

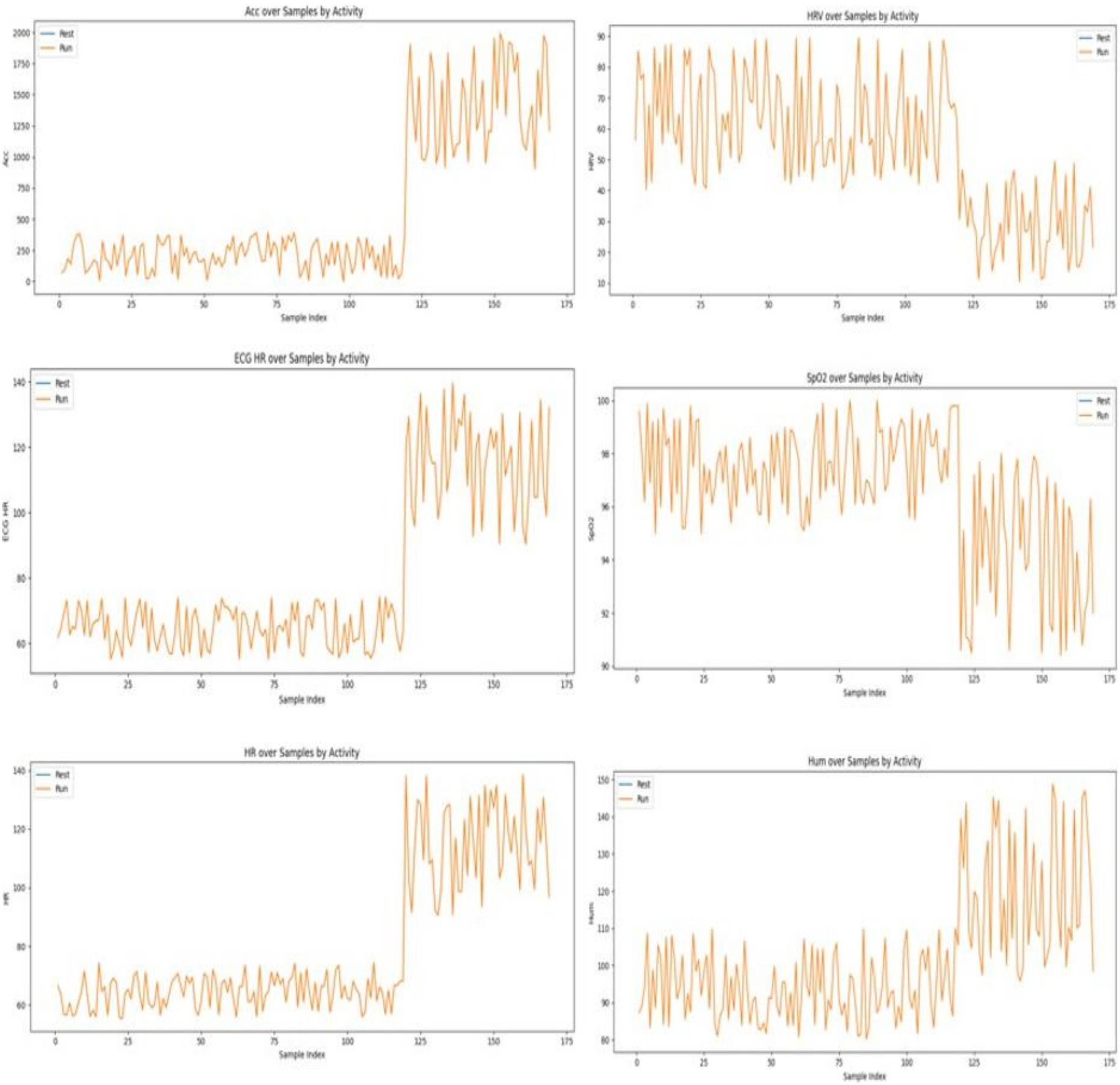

Fig 6: Visualization of Sensor Readings

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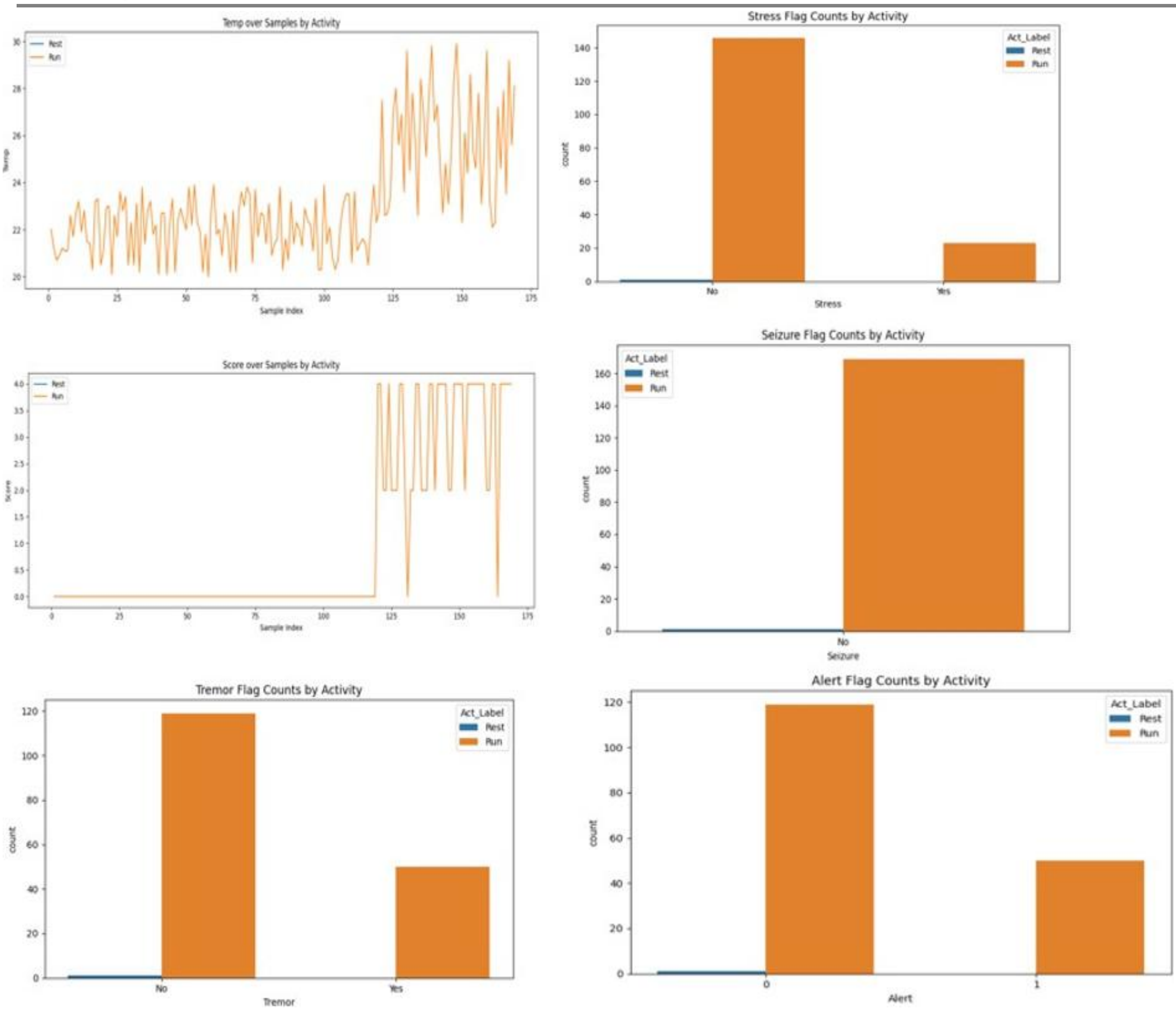

Fig 7: Visualization of Sensor Readings

The following graphs from figure 6 and figure 7 represent trends from the 200 collected sensor readings during different physical activities—resting and running. Clear variation is observed across physiological parameters:

- Heart Rate (HR) increases significantly during running.
- Heart Rate Variability (HRV) decreases, indicating stress response.
- SpO2 remains relatively stable, validating sensor accuracy.
- Body Temperature rises moderately post-exertion.

These patterns help the ML model distinguish between normal and abnormal physiological states in real time. Summary: ML-inspired scoring and rule-based logic, validated by both realistic testing and offline ML modeling, enable robust detection of physiological stress, tremor, or seizure, with responsive notifications and automatic system recovery.

LIMITATIONS AND FUTURE SCOPE

The proposed system, while demonstrating the feasibility of a cost-effective Edge-AI wearable health monitoring platform, has several limitations.

The present study employed a restricted dataset gathered under controlled experimental conditions, constrained by participant accessibility, infrastructure availability, and the parameters of an undergraduate engineering research project.

Thus, the established machine learning model ought to be regarded as an initial screening and physiological monitoring framework rather than a clinically validated diagnostic tool.

Future research will involve larger and more diverse participant groups, long-term data acquisition, inclusion of clinically diagnosed cases, comparison with standard medical monitoring equipment and further optimization of the embedded machine learning framework to improve accuracy, robustness and real-world applicability. Although statistical augmentation was utilized to improve the training diversity of the machine learning model, augmented data cannot completely represent the complex physiological variations present across larger and more heterogeneous populations.

CONCLUSION

The developed prototype successfully demonstrates the feasibility of an affordable, intelligent, and real-time Edge-AI based wearable physiological monitoring system. By integrating multiple biomedical sensors, including MAX30100, AD8232, MPU 6050, LM 35, and DHT 22 with an ESP 32 micro controller, the proposed system enables continuous acquisition and analysis of physiological parameters such as heart rate, heart rate variability, ECG signals, temperature, humidity, and motion patterns.

The hybrid analytical framework combining threshold-based detection with embedded machine learning provides an effective approach for identifying physiological patterns associated with stress, tremors, seizure-like activities, and abnormal health conditions. Experimental evaluation under controlled conditions demonstrated promising performance of the proposed system, highlighting the capability of low-cost sensor fusion and Edge-AI techniques for continuous health monitoring applications.

The current work represents an engineering proof-of-concept and preliminary validation of the proposed architecture. Due to limitations in participant accessibility, available resources, and the scope of an undergraduate research project, the present dataset does not fully represent the physiological variability across different age groups, genders, and clinical populations. Therefore, the developed system should be considered as an intelligent physiological monitoring and early screening platform rather than a replacement for professional medical diagnosis or certified clinical equipment.

Future research will focus on large-scale data collection involving more diverse participant populations, long-term monitoring studies, comparison with standard medical monitoring devices, improved sensor calibration techniques, and further optimization of embedded machine learning models. Additional advancements such as textile-based integration, miniaturized hardware, cloud connectivity, emergency communication modules, and advanced TinyML algorithms can further enhance the practicality and scalability of the proposed wearable healthcare system.

Overall, this study establishes a foundation for developing affordable Edge-AI driven wearable technologies capable of providing continuous, personalized, and accessible physiological monitoring, particularly for resource-constrained environments and future telemedicine applications.

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