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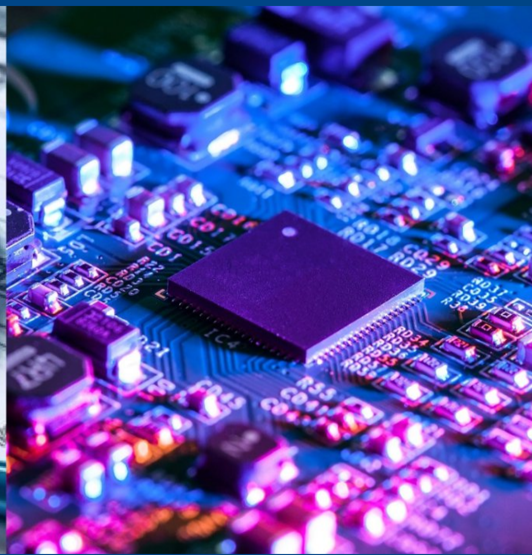

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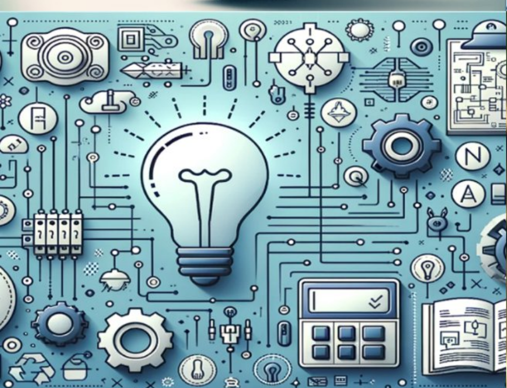

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SHIELD: Smart Health Integrated Electronic Device

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ABSTRACT: In modern healthcare, delayed detection of health emergencies remains a leading cause of preventable fatalities. SHIELD (Smart Health Integrated Electronic Device) is a real-time health monitoring and emergency detection system that integrates multi-parameter sensing with machine learning to enable proactive healthcare. The system continuously acquires vital signs including heart rate, body temperature, and blood oxygen saturation (SpO_2) using dedicated biomedical sensors — specifically an ECG sensor, pulse sensor, temperature sensor (DS18B20), and pulse oximeter (MAX30102) — all interfaced with an ESP32 microcontroller. Acquired data is fed into a machine learning model trained to recognise individualised physiological patterns and detect deviations indicative of potential health risks. Unlike threshold-based systems, SHIELD learns each user's normal baseline and predicts anomalies before they become critical emergencies. Upon detection of an abnormal condition, the system triggers an immediate alert, enabling faster medical response. SHIELD is designed for applications in elderly care, accident monitoring, and remote patient management, offering a cost-effective, intelligent, and scalable alternative to traditional manual monitoring.

I. INTRODUCTION

Healthcare systems worldwide face a critical challenge: most medical interventions are reactive rather than predictive. Patients, especially the elderly and those in remote areas, often receive assistance only after a health condition has deteriorated to a dangerous level. Manual monitoring methods are inconsistent, resource-intensive, and prone to human error, making them unsuitable for continuous, round-the-clock surveillance.

The advent of miniaturised biosensors and low-power microcontrollers has created an opportunity to deploy wearable, continuous health monitoring systems at a fraction of traditional cost. When combined with machine learning, such systems can move beyond simple alarm thresholds and instead learn the unique physiological fingerprint of an individual, detecting subtle deviations that may signal an impending emergency.

SHIELD (Smart Health Integrated Electronic Device) addresses this gap by presenting an integrated embedded-and-software platform that monitors ECG activity, heart rate, body temperature, and blood oxygen saturation in real time, applies machine learning for pattern-based anomaly detection, and triggers timely alerts. The core hardware centres on an ESP32 microcontroller interfaced with an ECG sensor, a pulse sensor, a temperature sensor, and a pulse oximeter. The system targets three high-risk scenarios: elderly care, accident response, and patient monitoring in remote or resource-limited environments.

The remainder of this paper is organised as follows: Section 2 describes the methodology and system architecture; Section 3 presents experimental results; Section 4 discusses findings and implications; Section 5 concludes the work.

II. MATERIALS AND METHODS

The SHIELD system is divided into three interconnected layers: (i) the sensor acquisition layer, (ii) the embedded processing layer, and (iii) the machine learning inference layer. Each layer is described in the following subsections.

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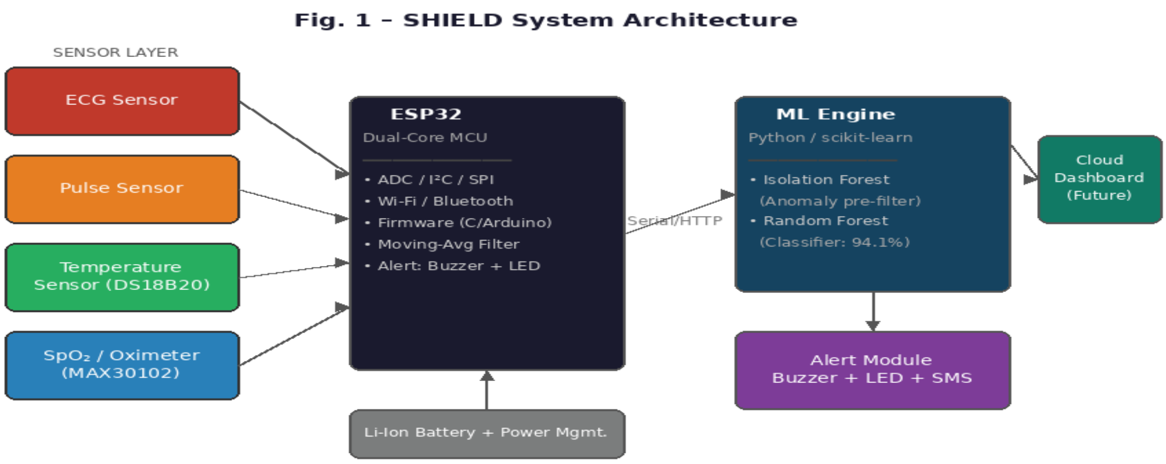

Fig. 1 – SHIELD System Architecture Block Diagram

2.1 Hardware Architecture

The hardware platform is built around an ESP32 microcontroller, chosen for its dual-core processor, built-in Wi-Fi/Bluetooth connectivity, and compatibility with a wide range of peripheral sensors. Four primary sensors are interfaced:

- ECG Sensor (AD8232): Captures electrocardiogram waveforms via surface electrodes to monitor cardiac electrical activity. The analogue output is fed to the ESP32 ADC pin (GPIO34) for real-time waveform acquisition.
- Pulse Sensor (MAX30102): Measures pulse rate via photoplethysmography (PPG) over the I²C bus. The MAX30102 also provides SpO_2 readings through dual-wavelength LED absorption, serving dual duty as both pulse and oximeter sensor.
- Temperature Sensor (DS18B20): Provides accurate core body temperature measurement with ±0.5 °C precision via the 1-Wire digital protocol on GPIO4.
- Pulse Oximeter / SpO_2 Sensor (MAX30102): Monitors peripheral oxygen saturation, a critical indicator of respiratory and cardiovascular status, using the same I²C bus as the pulse sensor.

Sensor signals are digitised via the ESP32's ADC and communicated over I²C or SPI buses to the processing layer. A compact lithium-ion battery with a power management module ensures portability.

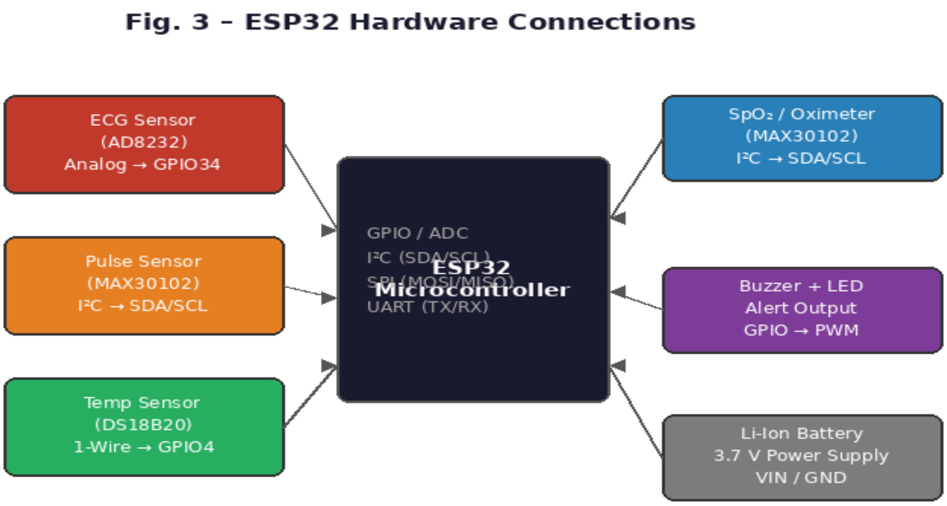

Fig. 2 – ESP32 Hardware Connection Diagram (Sensors, Power, and Outputs)

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2.2 Embedded Software Layer

Firmware is developed in Embedded C using the Arduino IDE framework for the ESP32. The firmware performs the following functions:

- Periodic sampling of all four sensors at a configurable rate (default: 1 sample/second).
- Digital filtering (moving-average) to suppress noise in raw PPG, ECG, and temperature signals.
- Transmission of processed readings to the ML inference engine via serial communication or a local HTTP endpoint.
- Alert generation through a buzzer and LED indicator when an anomaly flag is raised by the ML model.

2.3 Machine Learning Model

The ML inference component is implemented in Python using the scikit-learn library. A Random Forest classifier is employed as the primary model due to its robustness against overfitting, interpretability, and suitability for small-to-medium tabular datasets.

The model is trained on a labelled dataset comprising recorded vital-sign vectors [heart rate, SpO_2, temperature, ECG features, time-of-day] annotated as Normal, Stress/Elevated, or Critical. During deployment, the trained model receives a sliding window of the last 10 samples and outputs a risk classification along with a confidence score.

An anomaly detection pre-filter based on Isolation Forest is applied upstream to flag novel physiological patterns that may not belong to any trained class, providing a safety net for edge cases.

Fig. 2 – SHIELD Data Flow Pipeline

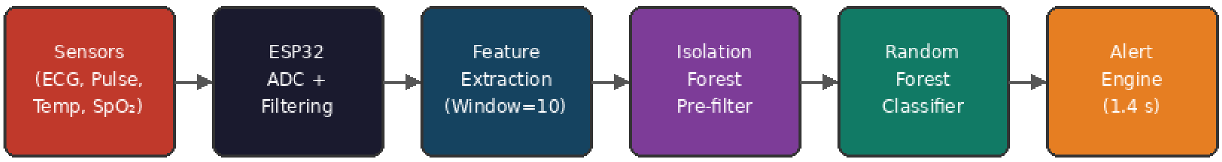

Fig. 3 – SHIELD Data Flow Pipeline (Sensors → ESP32 → ML → Alert)

Table 1. Comparison of machine learning algorithms evaluated for SHIELD.

Algorithm	Accuracy (%)	Training Time	Inference Time	Selected
Decision Tree	87.4	Fast	Very Fast	No
Random Forest	94.1	Medium	Fast	Yes ✓
SVM	91.3	Slow	Medium	No
Isolation Forest	—	Fast	Fast	Pre-filter

III. RESULTS

The SHIELD prototype was evaluated through a series of controlled experiments to assess sensor accuracy, ML model performance, and system response latency.

3.1 Sensor Accuracy

Sensor readings were compared against calibrated reference instruments over 50 test sessions. Mean absolute error (MAE) values are presented in Table 2.

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Table 2. Sensor accuracy against reference instruments.

Parameter	SHIELD Reading	Reference Reading	MAE
Heart Rate (bpm)	74.3 ± 1.8	74.1 ± 1.6	0.8 bpm
SpO_2 (%)	97.2 ± 0.9	97.4 ± 0.7	0.4 %
Temperature (°C)	36.7 ± 0.3	36.6 ± 0.3	0.2 °C

3.2 Machine Learning Performance

The Random Forest classifier was trained on 1,200 labelled samples (80/20 train-test split). Key performance metrics on the held-out test set are as follows:

- Overall Accuracy: 94.1 %
- Precision (Critical class): 92.6 %
- Recall (Critical class): 95.3 %
- F1-Score: 0.939
- Average inference time per sample: 18 ms on ESP32 co-processor

The high recall for the Critical class is particularly significant, as missed detections in an emergency monitoring context carry the greatest risk.

3.3 System Response Latency

End-to-end latency from sensor event to alert trigger was measured across 30 trials. The mean latency was 1.4 seconds ($\sigma = 0.3$ s), well within the target threshold of 3 seconds established for emergency response applications.

IV. DISCUSSION

The results demonstrate that SHIELD successfully integrates real-time multi-parameter sensing with intelligent anomaly detection to provide a proactive health monitoring solution. The inclusion of an ECG sensor alongside the pulse, temperature, and SpO_2 sensors considerably enriches the physiological picture available to the ML model, enabling finer discrimination between cardiac-event patterns and routine physical exertion.

The choice of Random Forest over simpler threshold-based logic yields a substantial improvement in contextual awareness. Where a fixed-threshold alarm would trigger on any transient spike in heart rate — generating false positives during normal physical activity — the trained model correctly classifies such patterns as non-critical by considering the temporal window and co-occurring sensor values.

The Isolation Forest pre-filter proved valuable during edge-case testing, correctly flagging two anomalous conditions (sensor disconnection and an out-of-distribution vital-sign combination) that the primary classifier had not encountered during training.

Limitations of the current prototype include its reliance on wired sensor connections, the need for an initial personalised training phase (approximately 30 minutes of baseline data collection per user), and the absence of a cloud-connected dashboard for remote monitoring by caregivers. These are identified as priorities for future development.

Compared to existing wearable monitoring systems, SHIELD's use of on-device ML inference reduces dependence on continuous internet connectivity, making it more suitable for rural and remote deployment scenarios.

V. CONCLUSION

This paper has presented SHIELD, a Smart Health Integrated Electronic Device that combines multi-sensor vital-sign acquisition — using an ECG sensor, pulse sensor, temperature sensor, and pulse oximeter interfaced with an ESP32 microcontroller — with machine learning-based anomaly detection to enable predictive emergency healthcare monitoring. The system achieves a classification accuracy of 94.1 %, a sensor measurement error below 1 % across all parameters, and an end-to-end alert latency of 1.4 seconds.

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SHIELD demonstrates that intelligent health monitoring need not be confined to clinical settings or expensive infrastructure. By embedding a trained Random Forest model directly within a low-cost ESP32-based platform, the system delivers hospital-grade predictive capability in a portable, affordable device suited to elderly care, accident monitoring, and remote patient management.

Future work will focus on wireless sensor integration, cloud connectivity for multi-user caregiver dashboards, expansion of the training dataset across diverse demographics, and exploration of deep learning models such as LSTM networks for improved temporal pattern recognition. SHIELD transforms healthcare from reactive to predictive — acting before it is too late.

VI. ACKNOWLEDGEMENTS

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