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Multimodal Ai With Wearable And Iot Biosensors: A Review Of PPG, ECG And Temperature Fusion On ESP32 Platforms For Continuous Health Monitoring

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Abstract—Advances in artificial intelligence, the Internet of Things and wearable technology enable continuous health monitoring instead of periodic examinations that may miss physiological changes. This paper reviews multimodal AI health monitoring based on low-cost biosensors. It examines photoplethysmography for heart rate and blood oxygen saturation, single-lead electrocardiography for cardiac rhythm, and body temperature sensing, and describes how an ESP32 microcontroller acquires these signals and transmits them over Wi-Fi to a computer or cloud service. Signal processing steps including filtering, QRS detection and feature extraction are reviewed together with public physiological databases used to develop and validate algorithms. Machine learning methods such as random forest and logistic regression for classifying normal and potentially abnormal states are compared with deep learning on raw signals, and multimodal fusion strategies, early, late and hybrid, are discussed in the context of multimodal machine learning. Dashboard design for displaying live readings, history and threshold alerts is described. A five-layer architecture comprising sensing, acquisition, communication, multimodal AI and dashboard layers is proposed, along with research gaps, objectives, a comparison of sensors and challenges including motion artefacts, sensor accuracy limitations such as bias in pulse oximetry, battery life, privacy and the need for clinical validation. The review concludes that multimodal AI with wearable biosensors supports timely observation of physiological change under professional supervision.

Index Terms—Multimodal AI, wearable biosensors, IoT, ESP32, MAX30102, AD8232, PPG, ECG, sensor fusion, health monitoring

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I. INTRODUCTION

A single vital sign rarely tells the whole story. A raised heart rate may follow exercise, fever or illness; low oxygen saturation may indicate a respiratory problem or merely a poorly fitting sensor. Combining several signals gives a clearer picture. Dunn *et al.* [1] described how wearables are changing medicine by making continuous measurement possible, and Kim *et al.* [2] reviewed wearable biosensors for healthcare monitoring.

Low-cost modules make such systems accessible to students and small clinics: a pulse-oximetry module provides heart rate and SpO_2, a single-lead front-end provides an ECG, a digital sensor provides body temperature and an ESP32 microcontroller links them to a dashboard over Wi-Fi.

This paper reviews signals, processing and multimodal AI for these platforms and proposes a layered architecture.

II. THEORETICAL BACKGROUND

1. Signals And Their Information

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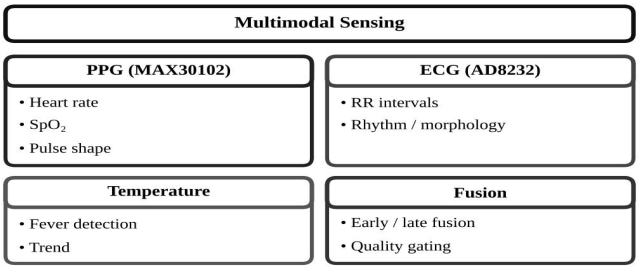


Fig. 1 maps each sensor to the physiological information it provides and the features extracted from it.

Fig. 1. Biosensors and the information they provide.

2. Multimodal Machine Learning

Baltrušaitis *et al.* [3] described the core challenges of multimodal learning, namely representation, alignment, fusion and co-learning. Fusion may be early (combining features), late (combining model outputs) or hybrid.

III. SURVEY OF EXISTING APPROACHES

Photoplethysmography. Allen [4] reviewed PPG and its clinical applications, explaining how light absorption changes with blood volume and how the ratio of red and infrared absorption yields oxygen saturation.

ECG processing. Pan and Tompkins [5] introduced a real-time QRS detection algorithm that remains a reference for heartbeat detection. The MIT-BIH arrhythmia database [6] and PhysioNet resources [7] provide annotated signals for algorithm development. Hannun *et al.* [8] trained a deep network on single-lead ambulatory ECGs achieving cardiologist-level arrhythmia classification.

Models. Random forests [9] and logistic regression are effective on extracted features and are light enough to run on a laptop or small server; deep networks on raw signals perform better but need more data.

Limitations. Sjoding *et al.* [10] reported racial bias in pulse oximetry, with occult hypoxaemia more frequent in patients with darker skin, a reminder that sensor accuracy varies across people. Perez *et al.* [11] showed in a large study that wearable rhythm notifications have reasonable positive predictive value but low overall yield. Table I summarizes these works.

Ref.	Method	Key Findings	Limitations
[5]	Real-time QRS detection	Reliable beat detection	Noise sensitivity
[7]	PhysioNet resources	Open physiological data	Research datasets
[6]	MIT-BIH database	Standard arrhythmia benchmark	Clinical recordings
[4]	PPG review	Principles and applications	Review only
[1]	Wearables in medicine	Continuous measurement potential	Perspective
[2]	Wearable biosensors review	Sensor technologies	Review only
[8]	Single-lead ECG deep model	Expert-level classification	Large dataset needed
[10]	Pulse oximetry bias	Accuracy varies by skin tone	Retrospective

TABLE I Summary of Literature Survey

1. Comparative Study

Table II compares sensors and fusion strategies by information content, artefact sensitivity and cost.

Element	Information	Artefact Sensitivity	Cost
PPG module	HR, SpO_2	High (motion)	Low
Single-lead ECG	Rhythm detail	Medium (electrodes)	Low
Temperature sensor	Fever	Low	Very low
Early fusion	Joint features	Depends on worst signal	Low

Element	Information	Artefact Sensitivity	Cost
Late fusion	Robust decisions	Lower	Low

TABLE II Comparison of Sensors and Fusion Strategies

IV. RESEARCH GAPS

- Motion artefacts corrupt PPG and ECG in daily activity.
- Low-cost modules are not medical-grade and may be inaccurate.
- Few studies fuse PPG, ECG and temperature in one low-cost system.
- Labelled data from the same hardware are scarce.
- Thresholds are often generic rather than personalized.

1. Aims And Objectives

- To review PPG, ECG and temperature sensing for wearable monitoring.
- To examine signal processing and feature extraction steps.
- To compare machine learning models and multimodal fusion strategies.
- To propose a five-layer multimodal AI monitoring architecture.
- To discuss limitations, privacy and the need for clinical validation.

V. PROPOSED ARCHITECTURE

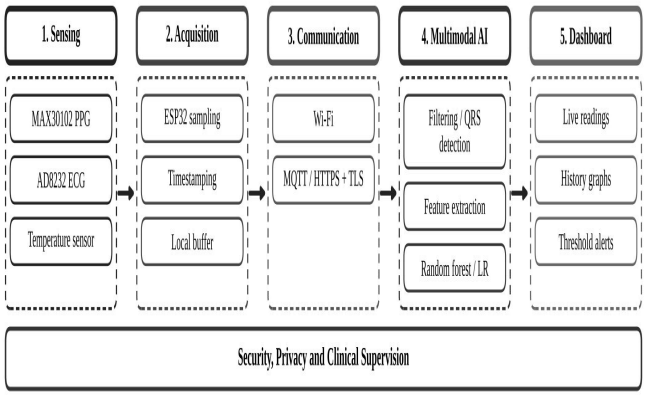


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer multimodal AI biosensor monitoring architecture.

1. Sensing Layer

A pulse-oximetry module (MAX30102) provides red and infrared PPG, a single-lead ECG front-end (AD8232) provides the cardiac waveform and a digital sensor provides body temperature.

2. Acquisition Layer

The ESP32 samples the ECG at a few hundred hertz and PPG at a lower rate, timestamps samples and buffers them to tolerate network loss.

3. Communication Layer

Data are sent over Wi-Fi using MQTT or HTTPS to a computer or cloud service, with TLS and device authentication.

4. Multimodal Ai Layer

Signals are band-pass filtered, beats are detected, features such as mean heart rate, heart-rate variability, SpO_2, ECG morphology and temperature are computed per window, and a random forest or logistic regression classifies the window as normal or needing attention; signal-quality indices gate unreliable windows.

5. Dashboard Layer

A web dashboard shows live values, historical graphs and alerts when thresholds or unusual patterns occur, with export for clinicians.

VI. PROCESS FLOW AND EVALUATION

Fig. 3 describes the workflow. Oxygen saturation is estimated from the ratio of normalized red and infrared pulsatile components,

$$R = (AC_{red}/DC_{red}) / (AC_{ir}/DC_{ir}) \quad (1)$$

with SpO_2 obtained from a calibration curve. Heart-rate variability is computed from RR intervals,

$$RMSSD = \sqrt{(1/(N-1)) \Sigma (RR_{i+1} - RR_i)^2} \quad (2)$$

Late fusion combines per-modality probabilities before the final decision.

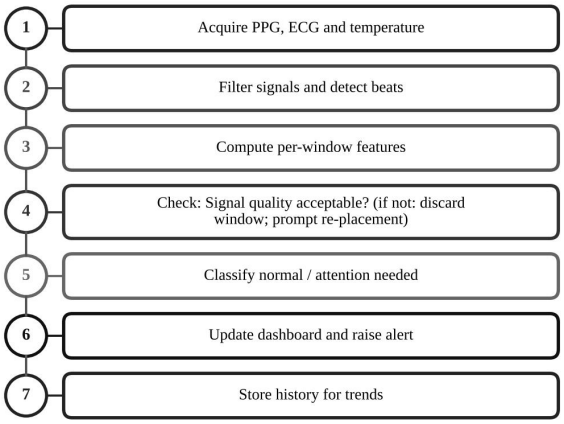


Fig. 3. Multimodal monitoring and alerting workflow.

VII. LIMITATIONS AND FUTURE SCOPE

Table III summarizes challenges. Future directions include motion-robust algorithms using accelerometers, personalized baselines, respiration estimation from PPG and ECG, and validation studies against medical-grade devices.

Challenge	Mitigation
Motion artefacts	Quality indices; accelerometer gating
Sensor accuracy and bias	Validation against medical devices
Battery life	Duty cycling; low-power modes
Data privacy	TLS; consent; minimal retention
Clinical reliability	Supervised use; no diagnosis claims

TABLE III Challenges and Mitigation

VIII. CONCLUSION

Multimodal AI combined with wearable and IoT biosensors enables continuous, personalized observation of physiological change at low cost. The reviewed literature provides established methods for PPG and ECG processing and evidence that machine learning can detect abnormal patterns, while also documenting accuracy limits and bias in consumer sensors. Reliable sensing, secure data handling and professional medical supervision are essential before such systems are used for health decisions.

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