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Lightweight Deep Learning-Based Anomaly Detection for Resource-Constrained Embedded Systems

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Abstract - Continuous health monitoring has become increasingly important for preventive healthcare, remote patient observation, elderly care, and personal wellness applications. Conventional health monitoring architectures frequently depend on continuous communication with cloud platforms, which can introduce communication overhead, latency, privacy concerns, and increased energy consumption. This paper presents a low-power embedded system architecture for real-time health monitoring using edge intelligence. The proposed system integrates physiological sensors with a resource-constrained embedded controller to acquire vital parameters including heart rate, blood oxygen saturation, body temperature, and electrocardiogram signals. Local preprocessing is performed at the embedded device to remove noise and prepare the acquired signals for analysis. A lightweight edge intelligence module performs health-status classification and anomaly detection locally, thereby reducing dependence on cloud-based processing. The system incorporates an energy-aware operating mechanism based on adaptive sensing, duty cycling, and low-power processor operation. Wireless communication is used primarily for transmitting processed information, alerts, and selected health summaries rather than continuously transmitting raw physiological signals. The proposed architecture provides a unified framework combining physiological sensing, local signal processing, edge intelligence, wireless communication, and energy management. The architecture is suitable for wearable and portable health monitoring applications where low latency, reduced energy consumption, privacy, and continuous operation are important requirements.

Keywords - Edge Intelligence, Embedded System, Health Monitoring, TinyML, IoT, Wearable Healthcare, Low-Power System, Real-Time Monitoring, ESP32.

I. INTRODUCTION

The increasing adoption of wearable and portable healthcare technologies has created new opportunities for continuous monitoring of physiological parameters outside conventional clinical environments. Real-time monitoring of parameters such as heart rate, oxygen saturation, body temperature, and electrocardiogram signals can provide useful information for preventive healthcare and remote observation. Embedded controllers with wireless connectivity have enabled the development of compact health monitoring devices capable of acquiring physiological information and transmitting it to remote platforms [1].

IoT-enabled embedded systems provide a practical approach for collecting and remotely accessing health information. The integration of physiological sensors with microcontrollers and wireless communication allows health parameters to be monitored through mobile or cloud-based interfaces [2]. However, continuous transmission of raw physiological data can increase communication activity and energy consumption, particularly in battery-operated wearable systems.

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MQTT and similar lightweight communication protocols have been adopted in healthcare IoT systems to support real-time transmission of vital-sign information. Such communication architectures enable remote monitoring while reducing the communication complexity associated with conventional protocols [3].

Although cloud computing provides substantial computational resources, cloud-dependent health monitoring can introduce additional latency and communication requirements. Edge computing addresses this limitation by moving data processing closer to the sensing device. Edge intelligence enables preprocessing, feature extraction, anomaly detection, and lightweight machine learning inference to be performed locally [4].

Tiny machine learning provides a mechanism for deploying compact machine learning models on resource-constrained embedded devices. Lightweight models can perform health-related classification and anomaly detection without requiring continuous transmission of raw data to a remote server. This approach is particularly relevant to cardiovascular and wearable health applications where rapid local decision-making is desirable [5].

Low-power machine learning techniques can further improve the practicality of continuous health monitoring. Quantization, compact neural networks, efficient feature extraction, and event-driven processing can reduce the computational requirements of embedded inference. Such approaches enable health-related intelligence to be incorporated into devices with limited processing capability and battery capacity [6].

The main contributions of the proposed architecture are as follows:

1. Development of a low-power embedded architecture for continuous physiological monitoring.
2. Integration of multiple physiological sensors within a compact embedded platform.
3. Implementation of local signal preprocessing to reduce noise and unnecessary data transmission.
4. Integration of lightweight edge intelligence for real-time health-status and anomaly analysis.
5. Development of an energy-aware sensing and processing mechanism using duty cycling and low-power operation.
6. Integration of wireless communication for remote transmission of processed health information and alerts.

The remainder of this paper is organized as follows. Section II presents the literature survey. Section III describes the proposed low-power embedded architecture and edge intelligence methodology. Section IV discusses the performance evaluation framework and system-level analysis. Section V concludes the paper.

II. LITERATURE SURVEY

Recent research in wearable healthcare has investigated distributed sensing and edge intelligence as mechanisms for improving the responsiveness and efficiency of health monitoring systems. Distributed wearable architectures can process health information closer to the user while reducing the dependence on centralized processing [7].

Embedded wearable platforms have also demonstrated the feasibility of performing computationally intensive physiological signal processing locally. Multi-sensor wearable architectures can acquire ECG, PPG, inertial, and other physiological signals while performing selected processing tasks directly on embedded hardware [8].

IoT-based health monitoring systems have further incorporated machine learning to provide preliminary health assessment and decision support. Such systems demonstrate that physiological parameters can be acquired through compact embedded platforms and processed using machine learning before selected information is transmitted to remote healthcare services [9].

Advanced edge-intelligence architectures have been developed for continuous cardiovascular monitoring by combining physiological sensors, embedded processing, and lightweight deep learning models. Local inference can reduce the dependency on cloud processing and provide faster analysis of health signals [10].

Resource-aware TinyML deployment is particularly important when health monitoring models are executed on microcontrollers. The selection of an appropriate model requires consideration of predictive performance, memory usage, inference latency, throughput, and energy consumption. These factors must be jointly considered when deploying machine learning models on resource-constrained embedded hardware [11].

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Recent embedded health-monitoring research has also investigated dedicated low-power processing architectures that combine physiological signal acquisition with lightweight machine learning. Such architectures demonstrate the potential for integrating edge intelligence directly into low-power healthcare devices [12].

Despite these developments, several challenges remain. Continuous physiological sensing can increase energy consumption, while continuous wireless transmission can further reduce battery life. Cloud-dependent processing may also introduce communication latency and expose sensitive health information to external infrastructure. Therefore, an integrated architecture that combines local physiological signal processing, edge intelligence, energy-aware operation, and selective wireless communication is required.

The proposed architecture addresses these challenges by placing the principal real-time processing functions at the embedded edge node while using wireless communication primarily for processed information, health summaries, and abnormal-event notifications.

III. PROPOSED METHODOLOGY

A. Overall System Architecture

The proposed system consists of five major layers: physiological sensing, signal preprocessing, edge intelligence, wireless communication, and energy management.

The physiological sensing layer acquires the required health parameters from sensors. The embedded processing layer performs signal validation, filtering, feature extraction, and data preparation. The edge intelligence layer analyzes the processed information and identifies normal or abnormal health conditions.

The communication layer transmits selected health information to a remote monitoring platform. The energy-management layer controls sensing, processing, and communication activities according to the operating condition of the system.

The overall architecture of the proposed system is shown in Fig. 1.

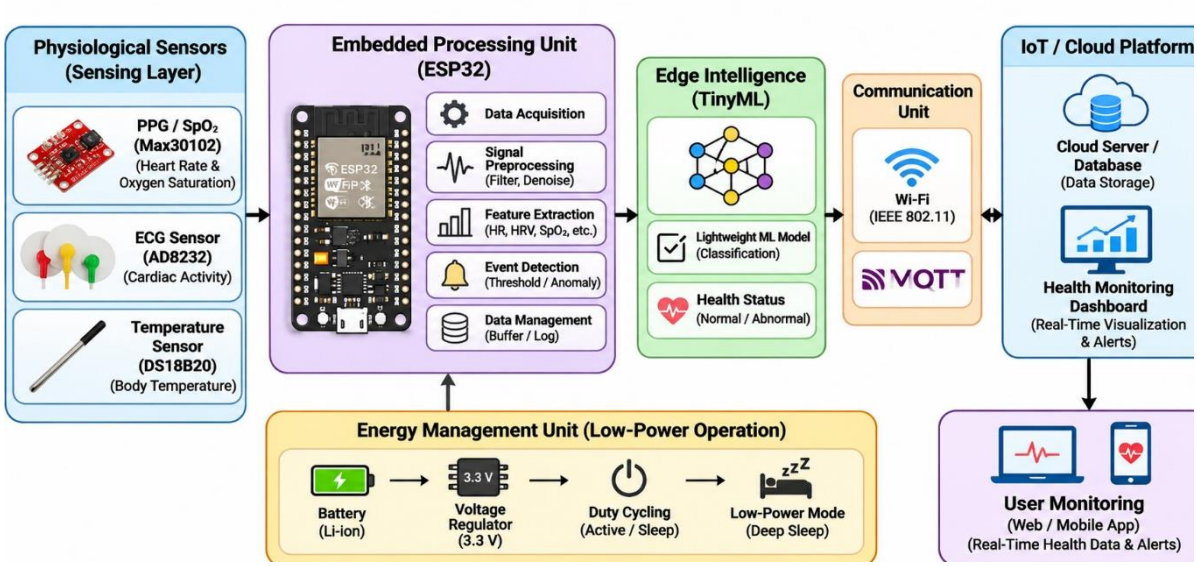


Fig. 1. Architecture of the proposed low-power embedded system for real-time health monitoring using edge intelligence.

B. Physiological Sensing Layer

The sensing layer consists of physiological sensors required for continuous health monitoring. A photoplethysmography sensor can be used to acquire pulse-related information and estimate heart rate and oxygen saturation. A temperature sensor can be used to monitor body temperature.

An ECG sensor can also be incorporated when cardiac electrical activity needs to be monitored. The modular structure allows additional sensors to be included according to the requirements of the application.

The sensors provide raw physiological measurements to the embedded controller at predefined sampling rates.

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C. Embedded Processing Unit

The embedded controller acts as the central processing unit of the proposed system. An ESP32-class microcontroller can be used because it provides sufficient processing capability, memory, wireless connectivity, and low-power operating modes within a compact platform.

The controller coordinates sensor acquisition, signal preprocessing, feature extraction, edge inference, alert generation, and wireless communication.

The embedded processing unit is designed to minimize unnecessary computation and communication. Only relevant information is forwarded to the remote monitoring platform.

D. Physiological Signal Preprocessing

Raw physiological signals can contain motion artifacts, electrical interference, baseline fluctuations, and other unwanted variations. Therefore, preprocessing is performed before edge intelligence is applied.

The preprocessing stage includes signal validation, filtering, normalization, and segmentation. For ECG signals, the preprocessing stage can identify suitable signal segments for feature extraction. For PPG signals, filtering can be used to reduce high-frequency disturbances and improve the quality of pulse-related measurements.

The processed signals are converted into suitable representations for the edge intelligence module.

E. Feature Extraction

The proposed architecture extracts compact features from the processed physiological signals to reduce computational requirements.

For heart-rate monitoring, pulse intervals and related temporal characteristics can be obtained from PPG or ECG signals. For ECG analysis, features associated with waveform morphology and RR intervals can be extracted.

For multi-parameter monitoring, the extracted features can be combined with temperature, SpO_2, and other physiological measurements to construct an input feature vector for the edge intelligence module.

F. Edge Intelligence Module

The edge intelligence layer performs health-status analysis directly on the embedded device. A lightweight machine learning model is selected so that inference can be executed within the available memory and computational resources.

Possible lightweight models include decision trees, support vector machines, compact neural networks, and quantized neural networks. The final model can be selected according to the available computational resources and the requirements of the health-monitoring application.

The edge model classifies the processed health information into predefined states such as normal, warning, or abnormal.

The local inference mechanism reduces the requirement to continuously transmit raw physiological signals to the cloud.

G. Anomaly Detection and Alert Generation

The proposed system combines physiological measurements and edge inference to identify abnormal conditions.

When the estimated health status crosses a predefined decision boundary, the embedded controller generates an alert event. The event can contain the detected condition, relevant physiological measurements, timestamp information, and device status.

Critical events are prioritized for immediate transmission, while routine measurements can be transmitted periodically.

This mechanism allows the system to provide rapid local responses while reducing unnecessary wireless communication.

H. Wireless Communication

Wireless communication is used to transfer processed health information from the embedded device to the remote monitoring platform.

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Wi-Fi or Bluetooth Low Energy can be selected according to the application requirements. MQTT can be used when communication with an IoT server or cloud platform is required.

The proposed communication strategy does not require continuous transmission of raw physiological signals. Instead, processed measurements, health-status information, and alerts are transmitted according to the configured communication policy.

This reduces communication overhead and supports energy-efficient operation.

I. Energy Management

Energy management is an essential component of the proposed architecture because wearable and portable health monitoring devices are generally battery operated.

The proposed system uses duty cycling to control sensing, processing, and wireless communication activities. The controller remains in an active state when measurements or inference are required and enters a low-power state during inactive periods.

The communication module can also be activated only when a data packet or alert needs to be transmitted.

The sensing interval can be adapted according to the health-monitoring requirement. More frequent sampling can be used for high-priority physiological signals, while less frequent sampling can be used for slowly changing parameters.

J. End-to-End Processing Flow

The complete processing sequence begins with physiological signal acquisition. The embedded controller collects measurements from the connected sensors and performs signal validation.

The valid signals are filtered and segmented before relevant features are extracted. The resulting features are passed to the lightweight edge intelligence model.

The model generates a health-status classification or anomaly decision. If the condition is normal, the processed information can be stored locally or transmitted according to the configured monitoring interval.

If an abnormal condition is detected, an alert is generated and transmitted immediately through the wireless communication interface.

After completion of the processing and communication tasks, the embedded controller enters a low-power state until the next monitoring cycle.

IV. RESULTS AND DISCUSSION

A. Performance Evaluation

The proposed architecture is evaluated using system-level parameters covering sensing, processing, edge inference, communication, and energy consumption.

The important evaluation parameters are presented in Table I.

TABLE I: PERFORMANCE EVALUATION PARAMETERS OF THE PROPOSED SYSTEM

Parameter	Evaluation Criterion
Heart-rate measurement	Comparison with reference measurement
SpO_2 measurement	Comparison with reference pulse-oximeter
Temperature measurement	Comparison with reference thermometer
ECG acquisition	Signal quality and waveform consistency
Edge inference latency	Time required for local classification

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Model memory footprint	Flash and RAM utilization
Communication latency	Sensor-to-dashboard transmission delay
Alert response	Time from anomaly detection to notification
Energy consumption	Current/power during active and sleep modes
Battery endurance	Operating duration under selected duty cycle

The table provides a structured evaluation framework for validating the proposed architecture. The final numerical values should be obtained from prototype measurements using the selected sensors, embedded controller, machine learning model, and battery configuration.

B. Edge Intelligence Performance

The principal advantage of the proposed architecture is that health-related inference is performed close to the sensing source. Instead of transmitting every raw physiological signal to a remote server, the embedded controller performs preprocessing and feature extraction locally.

This reduces the amount of information requiring wireless transmission. It also allows the system to generate preliminary health-status decisions without waiting for a cloud response.

The performance of the edge intelligence module should be evaluated using inference latency, classification accuracy, memory consumption, and computational load.

C. Low-Power Operation

Energy consumption depends on the sensing frequency, processor activity, wireless communication, and machine learning workload.

The proposed architecture reduces energy consumption through controlled activation of the sensing and communication modules. The controller can enter a low-power state after completing a measurement and inference cycle.

Wireless transmission is also minimized by transmitting processed information instead of continuously transmitting raw physiological signals.

The effectiveness of the energy-management mechanism should be determined by measuring current consumption during active sensing, edge inference, communication, and sleep operation.

D. Real-Time Health Monitoring

The proposed system supports real-time monitoring by performing the primary processing tasks locally.

The sensing module continuously acquires physiological information according to the selected sampling configuration. The preprocessing module prepares the signals, while the edge intelligence module performs local health-status analysis.

When an abnormal condition is detected, an alert can be generated without requiring continuous cloud-based inference.

This architecture is particularly useful for applications where rapid detection is more important than continuous transmission of raw physiological data.

E. Communication Performance

The communication subsystem provides connectivity between the embedded health-monitoring device and the remote monitoring platform.

The proposed system prioritizes health alerts and important processed information. Routine measurements can be transmitted at a lower frequency to reduce communication activity.

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MQTT can provide an efficient publish-subscribe mechanism for transmitting health information to an IoT platform. The communication performance can be evaluated using packet delivery, transmission latency, connection stability, and data synchronization.

F. Privacy and Data Reduction

Physiological information is sensitive, and unnecessary transmission of raw signals can increase privacy risks. The proposed architecture reduces this dependency by performing initial processing and inference locally.

Only selected measurements, health-status information, and alerts need to be transmitted to the remote platform.

This edge-oriented architecture therefore provides a mechanism for reducing the volume of sensitive physiological data leaving the embedded device.

G. Overall Discussion

The proposed low-power architecture integrates physiological sensing, embedded processing, edge intelligence, wireless communication, and energy management into a single system.

The architecture provides three major advantages. First, local processing reduces dependence on cloud-based computation. Second, lightweight edge intelligence enables real-time health-status analysis. Third, duty cycling and selective communication reduce unnecessary energy consumption.

The modular structure also allows the system to be adapted to different health-monitoring applications by changing the sensor configuration and edge intelligence model.

For a practical implementation, the final system should be evaluated using reference medical devices and representative physiological datasets or controlled measurements. In particular, measurement accuracy, edge inference performance, power consumption, battery endurance, and communication reliability should be experimentally measured before clinical or real-world deployment.

V. CONCLUSION

This paper presented a low-power embedded system architecture for real-time health monitoring using edge intelligence. The proposed system integrates physiological sensors with a resource-constrained embedded controller to acquire health parameters such as heart rate, oxygen saturation, body temperature, and ECG signals.

The architecture performs signal preprocessing, feature extraction, and lightweight machine learning inference locally at the edge. This reduces dependence on continuous cloud processing and enables rapid identification of abnormal health conditions.

An energy-aware operating mechanism based on duty cycling, selective communication, and low-power processor operation is incorporated to support long-duration operation. Wireless communication is used primarily for transmitting processed health information, alerts, and selected monitoring data.

The proposed architecture provides a flexible foundation for wearable and portable healthcare applications. Future implementation can focus on optimizing the edge intelligence model, reducing memory and computational requirements, improving energy efficiency, and experimentally validating the system against reference medical devices and real-world physiological datasets.

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