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An Energy- Efficient Iot Architecture for Remote Healthcare Monitoring and Early Risk Detection

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Abstract- Deployment of IoT technologies in healthcare has facilitated continuous monitoring and timely diagnosis of diseases without the need for clinical settings. Yet, implementation of such deployment is hindered by some important obstacles associated with energy efficiency, communication delays, and large-scale risk analytics. This paper presents an energy-efficient IoT framework that combines edge-based processing of biosensors, adaptive communication, and light-weight detection of anomalies for remote patient monitoring. The architecture uses ESP32 microcontrollers with LoRa communication technology and dynamic transmission intervals as a trade-off between power usage and monitoring promptness. Hybrid edge-cloud analytics are employed for processing of physiological signals and timely risk detection. Evaluation of the architecture shows that the solution can operate in a sustainable manner with 5-second adaptive transmission intervals, achieving robust data delivery and saving much power at the same time. Comparison of the presented architecture with conventional IoT health frameworks proves its superiority in energy efficiency and latency metrics.

Key Word: Internet of Things, Remote Patient Monitoring, Energy Efficiency, Edge Computing, Early Risk Detection, Lora Communication, Adaptive Scheduling

I. INTRODUCTION

The incorporation of Internet of Things (IoT) technologies in healthcare systems has revolutionized the way patient monitoring and disease management is done. The Internet of Medical Things (IoMT) entails a series of interconnected medical devices, wearable sensors and smart processing platforms that allow for continuous acquisition and analysis of physiological information [2][4][6]. This technology brings about a change of the previous paradigms that characterized healthcare provision especially the episodic nature of visits and the reactive nature of treatment methods. Continuous monitoring of physiological data using IoT-driven platforms provides great prospects in proactive health management, chronic disease management and personalized healthcare provision [2][4].

Remote patient monitoring (RPM) has proven to be a very innovative use of IoT technology in healthcare mainly in managing chronic diseases, post-operative care and elderly care [1][4]. In RPM, wearable and ambient sensors are used to monitor patients' vital signs such as heart rate, body temperature, blood oxygen saturation and electrocardiogram signals. The information collected by RPM is sent to healthcare practitioners for further analysis and decision making [2][6]. Through continuous monitoring, the subtle variations in physiological parameters can be detected by RPM system, which would not be possible in sporadic assessment.

However, despite the numerous benefits, the implementation of remote monitoring systems using IoT technology entails various technical challenges. Energy usage is one of the key limiting factors since remote sensors and wearable devices use batteries that have limited capacity and are expected to work for long without any maintenance needed [1][8]. The conflict between data collection and energy management is inherent due to the need for high accuracy and reliable information gathering while at the same time conserving energy resources. Moreover, the network infrastructure needed for remote monitoring should adapt to various conditions and be capable of

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functioning both in densely connected cities and rural areas lacking proper connectivity [5][8].

Such issues have led to a number of studies that attempt to solve this problem by creating architectures that would help to find the optimal combination of the performance of systems and their power consumption [1][3]. One of the solutions is Edge computing which helps to conduct all necessary computations closer to the source of information and thus reduce the need for transmissions and allows real-time analysis without a permanent connection with clouds [3][7]. It becomes possible thanks to initial processing and identifying anomalies at the edge level that results in significant decrease in the amount of data needed to be sent and thus saves energy while increasing latency of time-sensitive health incidents [7][10].

The current paper discusses energy efficient IoT architecture for remote health monitoring and risk detection which includes light edge processing, adaptive transmission scheduling and hybrid analysis. Such architecture uses ESP32 microcontrollers with integrated biosensors to collect physiological data. LoRa communication protocol is used to transmit data for a long distance with the minimum power consumption [8]. Adaptive transmission intervals are designed to change the frequency of communication according to the patient condition and risk detection [1][8].

The rest of the paper is structured in the following way. Section II describes related work in the area of architectures for IoT-based healthcare solutions, energy-efficient communication protocols and health analytics at the edge. Section III covers methodology of the solution, that is, architecture of the system, its hardware design, communication protocols used and risk detection algorithm. Section IV contains experimental evaluation results and comparison to other solutions.

II. LITERATURE SURVEY

The incorporation of IoT devices in the health care sector has raised considerable research interest, with much of the work concentrated on dealing with the energy issues associated with continuous monitoring systems [1][4][8]. This review paper highlights some of the recent developments made in various interrelated areas: efficient IoT communication architecture, edge computing for health analysis, and risk assessment techniques [3][7][10].

Energy efficiency in IoT health systems has been studied using several different angles. The basic problem is how to prolong the life span of a battery-powered node with sufficient accuracy in the process of monitoring [1][8]. Various adaptive communication techniques have been developed that vary communication parameters depending on patient's activity and clinical considerations.

The idea behind such solutions is to take into account the fact that not all the physiological information has the same importance, allowing one to transmit or reduce the frequency of sending data when it is stable. The MQTT protocol has gained wide acceptance in IoT health systems due to its light communication model and quality-of-service, although it depends very much on the frequency of the message transmission.

Selection of the communication protocol plays a significant role in determining the energy efficiency in remote sensing cases. LPWANs, specifically LoRa, have shown great promise in applications within the healthcare industry under constrained conditions due to their enhanced range and low power usage [8]. The LoRa technology is capable of sending data over ranges beyond several kilometers while using milliwatts of power, making it perfect for healthcare applications in rural areas where Wi-Fi or cellular connectivity might be problematic.

Comparisons made between various IoT communication protocols have time and again proven that LoRa and similar LPWANs are suitable for low-rate, long-range applications whereas BLE and Zigbee are perfect for short-range, high-rate applications.

Edge computing frameworks have played an indispensable role in making energy efficiency possible for IoT health monitoring systems [3][7]. This is due to the fact that by processing data at the source, i.e., at the sensor or at an adjacent gateway, the amount of data sent to the cloud server becomes less, thus saving communication energy as well as reducing latency times [7][10]. Anomaly detection based on edge computing detects crucial health events like heart arrhythmia and oxygen desaturation without

depending on any cloud connection. Studies have revealed that decision trees and other lightweight ML models work efficiently on microcontrollers and provide inference times below 200 milliseconds.

The evolution of early warning techniques in the IoT health framework has evolved through more advanced analysis. Early efforts focused on alerts that were based on thresholds and sent out when physiologic metrics reached certain limits. Although computationally efficient, such systems are not sensitive enough to detect precursors to poor health status.

The more advanced efforts have used machine learning algorithms for anomaly detection using hybrid architecture with convolutional neural network for spatial features and recurrent network for temporal features [2][6][10]. Federated learning approach is being developed to allow collaborative training of models in a decentralized manner with protection of user privacy although communication becomes an issue [10].

The final two criteria for IoT health systems include the need for secure data transmission and privacy preservation. Due to the nature of sensitive medical information, it is crucial to implement secure methods of transmission and data storage, which, at the same time, should not be very resource demanding [9][10].

There have been numerous examples of implementing lightweight cryptographic solutions for healthcare devices, such as elliptic curve cryptography and symmetric encryption. Blockchain solutions for audit trails and decentralized trust management have been proposed, although energy consumption of distributed consensus algorithms should be carefully analyzed.

Although many advances have been achieved in each of the areas mentioned above, there is still room for improvements. The combination of resource-efficient communication, edge analytics, and early risk detection within one architecture is currently lacking [1][3][8][10].

Additionally, the energy-fidelity relationship for different monitoring cases needs to be studied in order to optimize both parameters. The proposed architecture helps to fill the research gaps through the combination of these components into one solution.

III. PROPOSED METHODOLOGY

1. System Architecture Overview

Energy-saving IoT architecture for remote monitoring and healthcare surveillance is divided into four layers namely sensing and data collection layer, edge computing layer, communication layer, and cloud computing layer. The purpose of this layered approach is to distribute computation and communication tasks within the system in order to achieve efficient energy use.

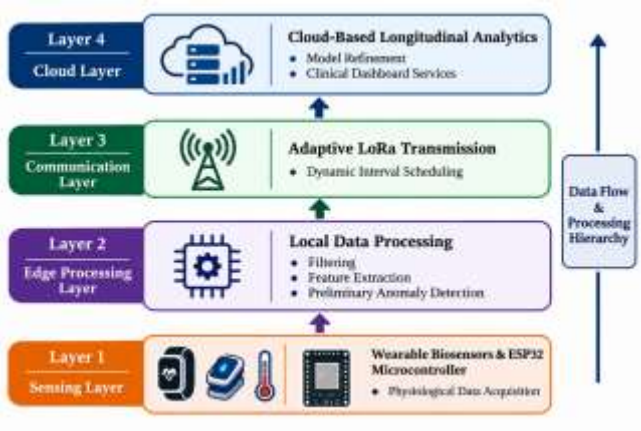


Figure 1: Proposed Four-Layer IoT Architecture for Remote Healthcare Monitoring

Figure shows the structure of the hierarchy for the architecture. The bottom layer consists of wearable sensors and the ESP32 microcontroller to collect biological signals. Edge computing layer is responsible for the processing of the biological signal data such as filtering, feature extraction, and preliminary anomaly detection. Adaptive LoRa communication with interval scheduling is used in the communication layer. The top layer stands for cloud computing with longitudinal analysis and model training services.

The sensing layer consists of a number of biosensors that are chosen for their clinical significance as well as power saving capabilities. The MAX30102 heart rate and pulse oximetry sensor is used to acquire photoplethysmography data useful in monitoring cardiovascular functions. MLX90614 infrared thermometer can measure body temperature in a non-contact manner. AD8232 ECG module detects electrical

signals from the heart and can detect any abnormal heartbeat. Other additional sensors could be a three-axis accelerometer to detect falls and activities.

2. Edge Processing And Adaptive Scheduling

The ESP32 microcontroller carries out a number of crucial roles in the proposed architecture. These include the coordination of the sampling of sensors following a customizable acquisition schedule, where the demands of signal resolution are weighed against energy use. Pre-processing of raw signals is carried out at the edge and includes digital filtering of artifacts and baselines, normalizing and compressing the signal.

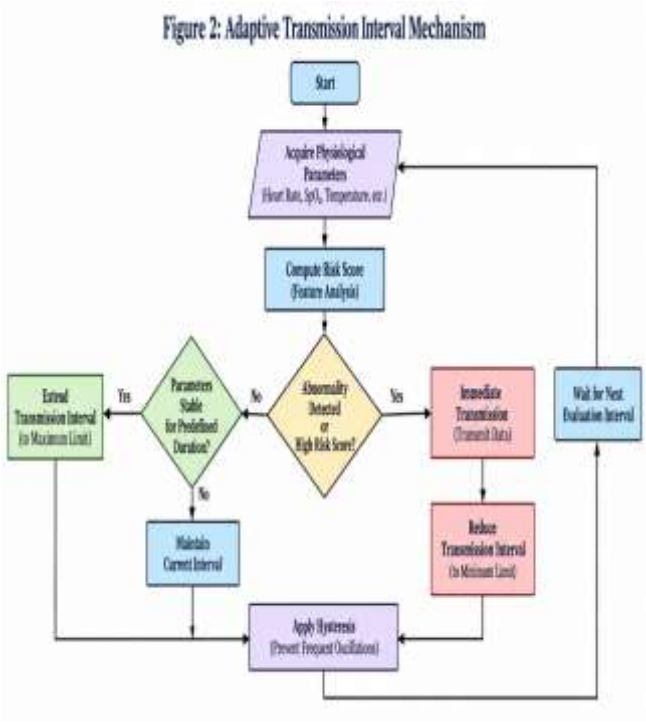


Figure 2: Adaptive Transmission Interval Mechanism

Flow chart representation of the adaptive scheduling algorithm is shown in the figure below. Stability of physiological measurements and risk levels is assessed using certain criteria. In the case of stable conditions, the transmission interval becomes longer to reduce power consumption, whereas unstable situations result in shorter intervals due to the need to transmit data immediately. The algorithm uses the concept of hysteresis.

The adaptive transmission interval is one of the most notable features of the proposed design framework. While conventional health monitoring solutions rely on fixed periodical transmissions, this framework adapts communication rates according to patient state and identified abnormalities. If the patient's physiological state remains stable, the interval between data transmissions increases in order to minimize energy consumption. In case of identified abnormalities or trends in patient state, the interval becomes smaller in order to inform clinicians faster.

3. Communication Protocol And Energy Management

The suggested system uses LoRa technology for data communication between the wearable node and the local gateway node. LoRa has many advantages for remote health monitoring due to its long-range capabilities (suitable for home or community applications), low energy consumption during the transmission, and good performance in presence of interference or lack of line-of-sight conditions. The gateway node collects data from various patient nodes and transmits collected information to cloud services using existing backhaul connectivity.

Energy management in the wearable node is based on the duty cycle principle. The ESP32 and peripherals go to deep sleep mode between the monitoring sessions and wake up at predefined moments in time to make measurements and transmit data when necessary. Energy consumption in the active state is optimized by managing the warm-up period of sensors and transmission power level. The adaptive interval affects the average energy consumption directly due to its impact on the ratio of active/sleep periods.

4. Early Risk Detection Methodology

The architecture follows a hierarchical risk detection mechanism that works in both edge and cloud tiers. In the edge tier, simple anomaly detection algorithms work to detect sharp departures from the baseline values of each patient. This is done using statistical process control techniques, which use exponentially weighted moving averages and cumulative sum analysis. Threshold alerts are used in conjunction with statistical alerts for parameters with clear clinical significance.

In the cloud tier, more complex risk analytics are performed by using longitudinal data. Machine learning algorithms are used to predict the risk of various complications such as cardiac deterioration, respiratory dysfunction, and metabolic dysfunction. The machine learning algorithms are trained on aggregate data from many patients through the use of federated learning approaches, ensuring the privacy of the data of individual patients.

Table I: Summary of Proposed Methodology Components

Component	Technology/ Algorithm	Function
Sensing	MAX30102, MLX90614, AD8232	Physiological data acquisition
Edge Processing	ESP32, digital filtering, normalization	Signal conditioning, feature extraction
Communication	LoRa, adaptive interval scheduling	Energy-efficient data transmission
Edge Analytics	EWMA, CUSUM, threshold detection	Acute anomaly identification
Cloud Analytics	Federated learning, risk modeling	Longitudinal trend analysis, model refinement

IV. ANALYSIS AND DISCUSSION

1. Experimental Configuration

Evaluations of the proposed framework were conducted by employing a combination of experiments in the lab environment and simulation of different scenarios. The wearable nodes were implemented by the use of ESP32-WROOM microcontrollers in combination with the required biosensors. Power consumption analysis was carried out for all operational states by measuring currents. Tests of the communication framework were conducted in both indoor and outdoor settings and with different node-to-gateway distances. The adaptive scheduling scheme was tested in several physiological scenarios.

2. Energy Consumption Analysis

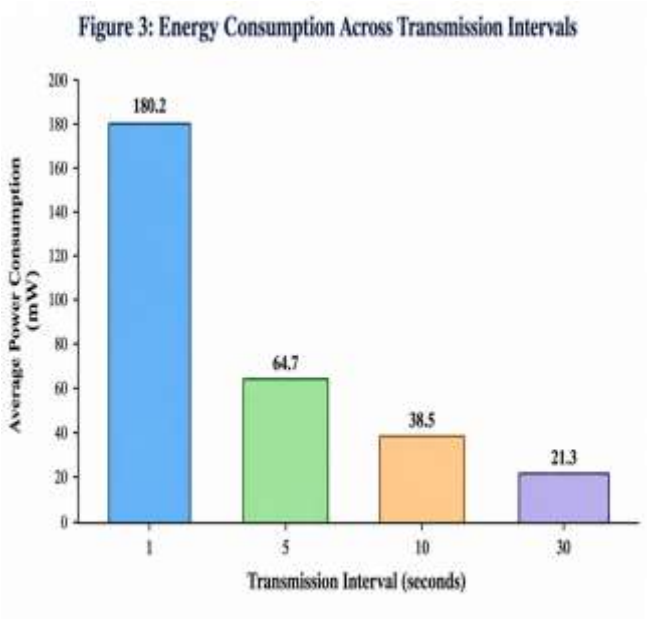


Figure 3: Energy Consumption Across Transmission Intervals

Bar graph illustrates power consumption on average for the interval time of transmission of 1 second, 5 seconds, 10 seconds, and 30 seconds. As the interval of transmission time increases, the power consumed is significantly reduced, and the highest reduction is seen between the intervals of 1 second and 5 seconds.

Experimental tests show that there is a direct correlation between the interval of transmission and the average level of energy usage. An interval of 1 second generates continuous activity, with low sleep time, leading to increased energy consumption. Intervals of 5 seconds lead to savings of energy while providing sufficient responsiveness to ensure clinical safety for most scenarios. Longer intervals, 10 seconds and 30 seconds, result in low energy savings but may affect the latency for detecting sudden events. This is in line with previous studies demonstrating that 5-second intervals provide a sustainable balance for remote monitoring of patients.

The energy advantages provided by the adaptive algorithm in addition to varying intervals based on the patient's state add more benefits in terms of energy savings compared to fixed-interval systems. During long periods of physiological stability, energy savings

are possible by extending intervals, which help build an energy budget for high-frequency monitoring during times of concern.

3. Communication Performance

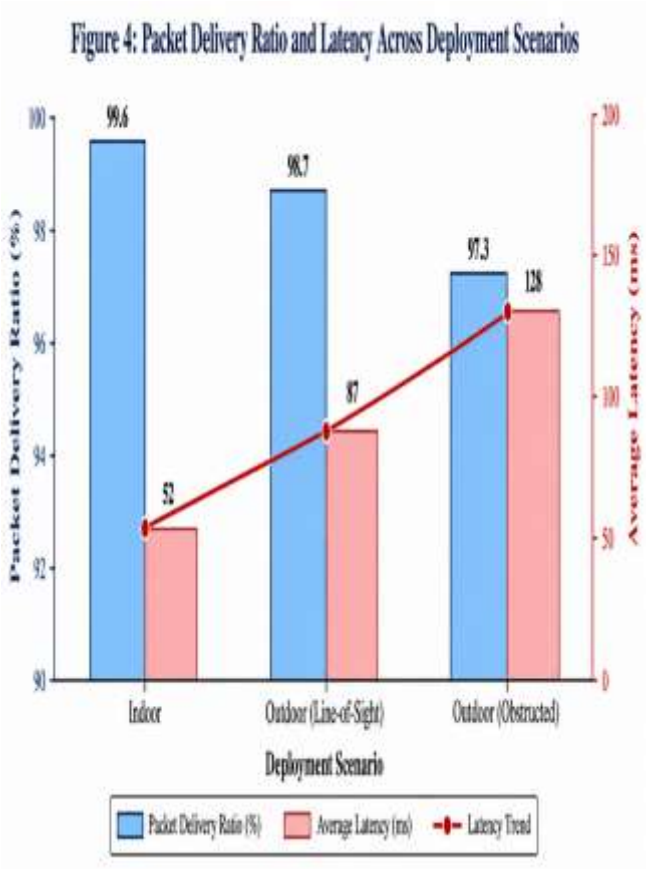


Figure 4: Packet Delivery Ratio and Latency Across Deployment Scenarios

In the chart above, delivery ratio and latency results have been provided for indoor and outdoor scenarios with line-of-sight and obstruction conditions. The delivery ratio is greater than 97% under all scenarios, whereas the latency does not exceed 150 milliseconds. The performance reduction in the case of obstruction scenarios is still acceptable for use in medical practice.

The LoRa communications showed efficient results in all the evaluated deployment scenarios. The packet delivery rate was greater than 97% in the case of indoor deployment and outdoor line of sight deployment, while the performance was affected a little bit in obstructed deployments. The average delay was less than 150 milliseconds, which is sufficient to alert the healthcare professionals about the detected abnormalities.

4. Comparative Analysis

Table II: Comparative Analysis of IoT Healthcare Architectures

Architecture	Communication	Processing	Energy Strategy	Latency
Proposed	Adaptive LoRa	Edge + Cloud	Dynamic interval scheduling	< 150 ms
Cloud-Centric	Wi-Fi/Cellular	Cloud only	Fixed intervals	> 800 ms
Traditional IoT	Zigbee/BLE	Local hub	Fixed intervals	300–500 ms
Edge-Aware	Multi-hop	On-device	Adaptive model	~210 ms
Fog-Edge Hybrid	Mixed	Fog + Edge	Task offloading	Variable
LoRa RPM	LoRa	Edge ML	Event-triggered	~118 ms

The comparative analysis will provide an assessment of the proposed architectural model in comparison with other models along the parameters that matter most. The cloud-based approach enables comprehensive analytics but is associated with high latency and energy inefficiency because of persistent connectivity needs. The traditional IoT health model that uses local hubs provides better latency but does not have such features as the suggested one. The edge-aware approach marks a big step forward, enabling low latency by means of on-device processing; however, the adaptive communication schedule adds energy efficiency to the suggested approach.



Figure 5: Multi-Dimensional Performance Comparison

The radar diagram represents the comparison between the proposed architecture and the baselines in the following five criteria: energy efficiency, latency, scalability, reliability, and analysis. The proposed architecture is strong in all five criteria; however, its strong points include energy efficiency and analytical capacity over edge-based systems.

5. Discussion

These experimental findings prove the viability of the suggested architecture in coping with the problem of trade-off between monitoring quality and energy efficiency in remote health monitoring scenarios. The idea of the adaptive interval transmission allows having an efficient mechanism of resource management, which allocates the energy for the moments when the most of it is needed. In contrast to the fixed-interval methods, which treat all the monitoring intervals equally and use the energy even in the periods when there is no need for it.

The hierarchical detection scheme uses the strengths of the edge and the cloud technologies. The edge detection allows identifying the acute episodes in a timely manner and does not require any connection to the network, which is required for emergency response situations. Cloud analysis allows detecting the gradual decline and improving the detection algorithms. The federated model learning solves the problems of privacy and allows using the data from the different patients.

Limitations that need to be acknowledged are numerous. First of all, the assessment was based on the usage of artificial physiological situations and not continuous clinical practice; secondly, long-term reliability of the system needs to be studied further. The effectiveness of the adaptive scheduling algorithm with various patients needs to be further validated.

V. CONCLUSION

In this paper, an energy-efficient architecture for remote healthcare monitoring and risk detection has been presented which provides solutions to crucial issues affecting the practicality of continuous patient monitoring systems. This architecture uses edge-based biosensor processing along with adaptive communication scheduling and hierarchical risk analysis for maximizing the trade-off between accuracy of monitoring and long-term sustainability. It has been observed through experiments that the system is able to perform sustainably with respect to energy consumption while maintaining reliability of data transmission and quick risk detection.

The main contributions of this work include: firstly, the design and validation of an adaptive transmission interval scheme where the communication rate varies adaptively according to the patient status; this helps in conserving energy effectively without any loss in monitoring sensitivity. Secondly, the development of a hierarchical risk detection scheme using lightweight edge-based analytics for immediate risk detection and cloud-based analytics for analysis of trends. Lastly, the detailed characterization of the energy-performance trade-off in different operational conditions.

This architecture is especially promising for telemedicine in environments where stable power supply and network infrastructures cannot be guaranteed. Due to the reduction of energy and communication costs, the system allows for constant monitoring with prolonged time intervals, which eliminates the need for any maintenance related to battery replacements and chargings. Edge anomaly detection guarantees timely alerting regardless of the status of the network connection.

Research questions in the future may concern clinical validation in practice by using this approach for monitoring patient cohorts and integration with electronic health records (EHR) and clinical decision support systems (CDSS). Energy harvesting techniques can provide better sustainability and increase battery capacity by harnessing ambient energy sources. Lastly,

the use of advanced machine learning methods on edge computing devices, supported by new types of neural network accelerators, which allow for reduced power usage, can improve the detection capabilities of the architecture.

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