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# Edge-Enabled Embedded System Architecture for Real-Time Smart Healthcare Monitoring Applications

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## Abstract

The blistering development of smart healthcare systems has raised the need to monitor patients in real-time and continuously with the help of the connected medical devices. Nevertheless, the traditional cloud-centric designs have high latency, network reliance, and slow response, which make them ineffective in sensitive medical systems. This paper presents a real-time smart healthcare monitoring EESA, which will be used to solve these challenges. The suggested system is designed to combine wearable sensors with embedded unit of processing and edge computing layer to facilitate local processing and analysis of data and immediate decision-making. The architecture minimizes the need on cloud infrastructure by computing time-sensitive computations at the edge, enhancing responsiveness and reliability. The main performance indicators, including latency and end-to-end delay, throughput, power consumption and system response time are measured to confirm the usefulness of the suggested approach. The experimental findings show that the latency is minimized and processing efficiency is enhanced in comparison with the conventional cloud-based system and power consumption remains low enough to be applied in wearable healthcare devices. The system also provides proper and timely identification of any severe health condition and modifications in patient safety as well as proactive medical treatment. In general, the suggested edge-enabled embedded architecture provides a scalable, efficient, and reliable architecture that can be used to support next-generation smart healthcare applications, especially in real-time monitoring and fast response requirements.

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## 1. Introduction

The fast development of intelligent healthcare devices has drastically changed the face of contemporary medical services over the last few years as it has allowed patients to be monitored continuously with the help of interrelated devices and intelligent platforms. The combination of the Internet of Things (IoT), wearable sensors, and digital healthcare technologies enables real-time data acquisition and analysis of physiological information and leads to a better diagnostic and patient outcomes [1], [12]. Moreover, the innovations in the field of big data analytics and the digital transformation accelerated the creation of the smart healthcare systems further [7], [8]. These systems find application especially when timely medical care is needed like in remote patient monitoring, in old age care and in responding to emergency situations.

Regardless of these improvements, the traditional cloud-based healthcare monitoring systems have a number of weaknesses. Architectures that rely on clouds introduce high latency, additional bandwidth use, and reliance on an on-demand network connection, which may slow down important healthcare responses [1], [10]. In addition, the huge amounts of healthcare data emitted by IoT devices can be a heavy load on cloud resources, resulting in scalability and performance issues [13]. Such considerations are more vital in more time-sensitive applications like cardiac monitoring and real-time alerts systems.

Processing in real time is thus necessary in healthcare applications in order to provide immediate analysis and responding. The main requirements of efficient healthcare monitoring systems are the low latency, low delay and high reliability. Nonetheless, it is a major challenge to meet such demands with the conventional cloud-based solutions. Emerging paradigms like the fog computing and distributed architectures seek to resolve such problems by taking computation to the point of the data source [4], [11].

Edge computing in this regard has come up as a solution with high potential in supporting real time smart healthcare systems. Edge computing is particularly helpful in reducing communication delays, increasing responsiveness, and reducing reliance on a centralized cloud infrastructure by processing data at or near the source [10], [14]. Moreover, edge-enabled embedded systems combine the sensing, processing, and communication features and are able to be deployed in resource-constrained healthcare settings [3], [13]. There are sophisticated edge architecture with artificial intelligence and hybrid processing systems that enhance the efficiency of the system and decision-making processes [3], [13].

The security and privacy are also important concerns in healthcare systems since the sensitive data of patients should be safeguarded during transmission and processing. Privacy-enhanced data fusion methods and secure IoT-based healthcare systems have been suggested to cope with these issues [2], [9]. Nonetheless, a combination of security, real-time performance and low-power embedded systems is a daunting task.

Despite extensive studies in the areas of IoT-based health care, edge computing and fog computing, there is a research gap in developing a single edge-enabled embedded system platform that can balance real-time performance measurements, including latency, throughput and power efficiency, and is still able to provide reliable and secure health care monitoring. Numerous available solutions either concentrate on system architecture or data analytics or on security alone, without offering a performance analysis on an actual real-time basis.

The given paper helps to fill in the research gaps by offering a new edge-based embedded system architecture that will allow to integrate wearable sensors, embedded processing units, and edge computing seamlessly to facilitate real-time healthcare monitoring. The project also builds an effective real-time data processing system that reduces latency and will guarantee quick reaction to important medical incidents. The key real time and system efficiency metrics are used to conduct a comprehensive performance assessment based on such key metrics as latency, end-to-end delay, throughput, power consumption and the overall system performance. Moreover, the offered approach is comparatively analyzed with the traditional cloud-based healthcare systems and showed the significant enhancement of response time, overhead of communication, and the utilization of the resources. In addition, the system has in-built safe and effective data handling controls that guarantee the reliability of data, its integrity and privacy and is therefore adequate in practical implementation in contemporary smart healthcare setting.

## 2. Related Work

The recent developments in smart healthcare systems have made it possible to continuously monitor patients with the use of IoT-based devices and wearable sensors. Various works have pointed out the efficiency of incorporating sensing technologies into the communication networks to facilitate remote healthcare uses. Examples are IoT healthcare systems that offer real-time data collection and monitoring, enhancing patient care and decreasing patient hospital reliance [6], [12]. The same has been extended to secure body sensor network (BSN) systems that can be used to improve data transmission and patient safety in a healthcare setting [2]. These systems show the possibilities of interlinked healthcare but tend to use centralized infrastructures extensively.

The ease of use of the cloud-based healthcare architectures has made them popular because of the capacity to scale and perform computations. Cloud of Things is the concept that combines IoT devices with the cloud platform to aid in the mass storage and processing of data [1]. These architectures are however associated with high latency and dependency over the network hence not very appropriate in time sensitive healthcare applications. Moreover, the growing amount of healthcare data presents some challenges of bandwidth usage and scalability of the systems [7], [13].

To address these shortcomings, edge and fog computing concepts have been introduced to bring computation to the data sources. Local data processing through edge computing results in a lower latency and fast responsiveness in systems [10], [14]. The concept of fog computing is also an extension of it in that intermediate processing layers are given between devices and the cloud [4], [11]. Recent research has shown the usefulness of edge-based healthcare systems in enhancing real-time monitoring and minimizing overhead of communications [13]. In addition, state-of-the-art edge structures with artificial intelligence and hybrid resource management systems lead to better system performance and decision-making capabilities [3].

Embedded system architecture is also important in the health care monitoring because it allows a resource-constrained environment to gain efficient access to data and process it. Embedded processor wearable devices can be used to continuously track vital parameters like heart rate, temperature, oxygen saturation. Nevertheless, most of the existing embedded healthcare systems are known to have difficulties in terms of low computational power, energy conservation and scalability [5], [8].

Although these innovations were made, a number of weaknesses still exist in the existing techniques. Cloud-centric systems are plagued with high latency and slow response, and most edge and fog-based solutions are not fully investigated in terms of real-time performance like latency, throughput and power consumption measurements. There is also the problem of extant literature in which the topics of system architecture, data analytics or security are discussed rather than a combined solution such as in the case of real-time performance, energy efficiency and reliability.

Referring to the analysis made above, it can be concluded that there is no single edge-enabled embedded system architecture that can guarantee the low level of latency, efficient use of resources, and the ability to provide reliable real-time healthcare monitoring. The literature available lacks a thorough assessment of crucial performance metrics like end-to-end delay, throughput, and power consumption in one framework. Moreover, the combination of embedded systems and edge computing to decide in real-time in healthcare applications is still under-researched. Thus, the purpose of this paper is to fill in these gaps by introducing a scalable and effective architecture and extensive performance testing of a real-time smart healthcare monitoring.

## 3. Proposed System Architecture

### 3.1 System Overview

The suggested system introduces an edge-enabled embedded architecture that will be used to enable real-time smart healthcare monitoring. It is based on an architecture with several layers, such as wearable sensors, embedded processing unit, edge computing node, and optional cloud connectivity (long-term storage and analytics). Physiological information including heart rate, body temperature and oxygen saturation is constantly measured using sensors and then sent to the embedded system to be processed first. The resulting processed data is then sent to the edge layer and a decision is made in real-time and some more analysis. This hierarchical method also reduces the communication latency and diminishes the use of centralized cloud computing infrastructure, enhancing the reactiveness of the system, and its stability.

### 3.2 Hardware Design

Hardware setup is comprised of biomedical sensors, embedded system with a microcontroller and communication modules. The embedded controller is connected to sensors (ECG, temperature, and SpO 2) to measure the real-time physiological signals. The interfacing of these sensors to the embedded system is detailed as shown in Fig. 1, showing the sensor interface circuit diagram, signal conditioning and analog-to-digital conversion stages.

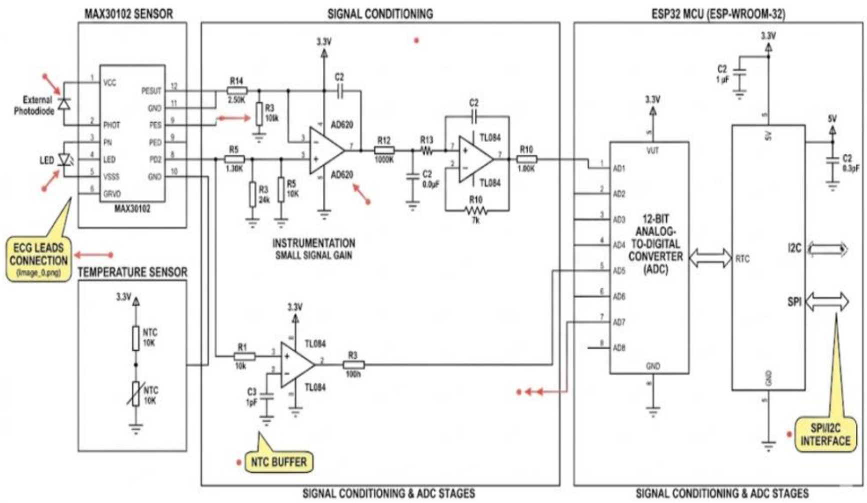


**Fig. 1:** Sensor Interface and Signal Conditioning Circuit for Multi-Parameter Healthcare Monitoring System

The embedded controller may be a low-power microcontroller or system-on-chip which is the central processing unit and carries out the data acquisition and initial processing. The modules have communication, such as Wi-Fi and Bluetooth, which allow wireless data transmission to the edge node. The controller and communication interface integration is illustrated as a whole in Fig. 2 that illustrates the circuit diagram of the embedded controller and communication module. The hardware design focuses on low power use, size, and dependability, thus suitable to wearable and portable medical equipment.

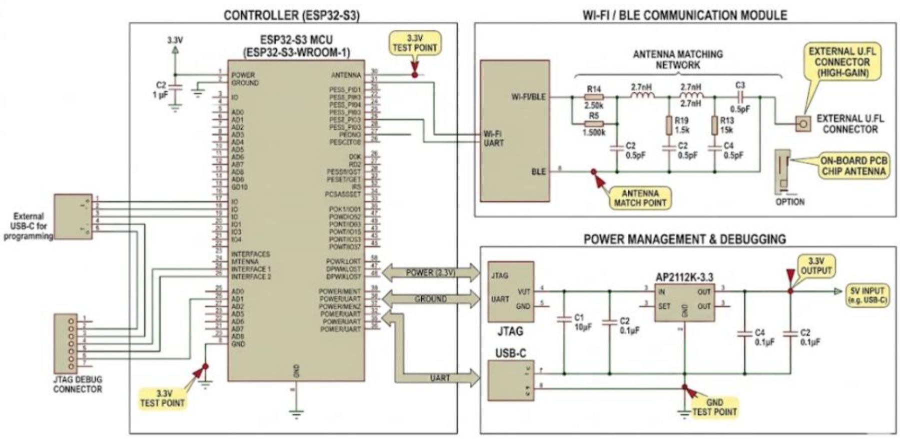


**Fig. 2:** Embedded Controller and Wi-Fi/BLE Communication Module Circuit Diagram with Power Management and Debugging Interfaces (ESP32-S3 Based System)

### 3.3 Software Architecture

The software architecture is created to facilitate effective data input, real-time processing and smart decisions. First, sensor data is preprocessed to eliminate noise and artifacts and collected. The signal conditioning methods and filtering algorithms are used so that the accuracy and reliability of the data is guaranteed. Lightweight edge processing algorithms are then used to process the processed data to recognize abnormal health conditions.

It has a rule based or threshold-based mechanism which is put in place to produce alerts when critical parameters get above predefined limits. Such alerts are relayed automatically to caregivers or healthcare providers and hence, prompt intervention. The software implementation is designed to run in real time with a fast response with low computational cost.

### 3.4 Edge Computing Layer

The edge computing layer is important to improve system performance by contributing to local data processing and minimizing the requirement of the cloud infrastructure. The edge node does not send all the raw data to cloud but it filters, aggregates, and makes decisions on the node. This goes a long way in minimizing the communication latency, bandwidth consumption as well as maximizing system efficiency.

The edge layer uses smart processing methods to process incoming data streams and detect the important events in the health conditions in real time. Data only that is relevant or summarized is sent to the cloud in order to be saved and further analyzed and hence resource optimization is achieved. This will provide faster response times, better scalability and more reliability making the offered system applicable in real-time healthcare monitoring usage.

## 4. Methodology

The suggested methodology details the entire workflow of the edge-enabled embedded system of real-time smart healthcare monitoring, incorporating data acquisition, preprocessing, real time decision-making and system level processing. The general information processing casualty is shown in Fig. 3, which describes the sequence of processes of sensor data collection to alert generation.

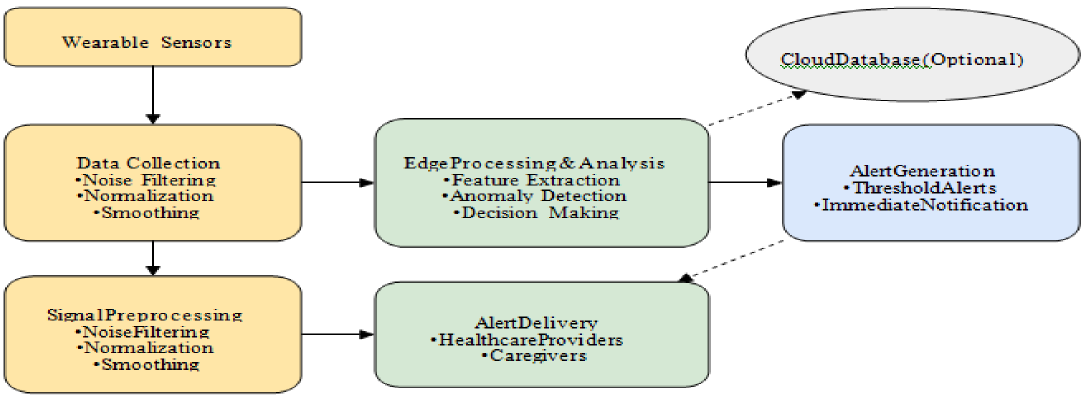


**Fig. 3:** Data Processing Workflow of the Proposed Edge-Enabled Embedded Smart Healthcare Monitoring System

### 4.1 Data Collection Process

The system constantly measures the physiological indicators of the heart rate, oxygen saturation (SpO 2) and body temperature through wearable biomedical sensors. These sensors are connected with the embedded microcontroller, which converts analog data to digital, and preliminary data formats. The data acquired is sampled at the right time to have the right monitoring with low power consumption. The embedded device is the main data acquisition device and sends the processed signals to the edge layer where the signals are further analyzed.

### 4.2 Signal Preprocessing

The physiological signals are usually influenced by noise, motion influences, and environmental interference. Thus, there is preprocessing to improve the quality of signals and reliability. Low-pass and band-pass filtering methods are used to eliminate high-frequency noise, and baseline drift. Consistency in the information obtained is also done by applying signal normalization and smoothing techniques. This preprocessing step enhances accuracy of further analysis and also minimizes false alarms.

### 4.3 Real-Time Decision Logic

The pre-processed information is processed through a lightweight real time decision-making algorithm which is implemented at the edge layer. Abnormal health conditions, like irregular heart rate or low oxygen levels are detected by using threshold-based and rule-based mechanisms. The system will create alerts when the parameters measured are above the established safe limits. This real-time decision logic makes it quick to respond and in emergency healthcare situations this is essential.

### 4.4 System Workflow

There is a systematic pipeline of system workflow as diagrammed in Fig. 3. First, the sensor data are gathered and preprocessed on an embedded level. Subsequently processed data is sent to the edge node where more filtering, analysis and decision making is done. The results of the analysis are then used to produce alerts and notify the healthcare providers or caregivers. Data is sent to the cloud, where relevant data is stored on a long-term basis and undergoes advanced analysis, optionally. Providing high data performance, low latency, and higher responsiveness of the system, this pipeline can be applied in real-time smart healthcare monitoring systems.

## 5. Performance Metrics

The efficiency of the proposed edge-enabled embedded healthcare monitoring system is tested in terms of a complex of measures assessing real time responsiveness, system efficiency and system reliability in healthcare. These measures prove the relevance of the suggested architecture towards low latency, efficient resource use, as well as an accurate health monitoring.

### 5.1 Real-Time & Edge Performance Metrics

In healthcare applications, real-time performance is important as any delays may affect patient safety. They are measured by:

- Latency (ms):

Latency represents the time taken for data to travel from sensing to processing and output generation. It is calculated as:

$$Latency = t_{output} - t_{input}$$

where $t_{input}$ is the time of data acquisition and $t_{output}$ is the time at which the processed result is generated.

- End-to-End Delay:

This metric represents the total delay across all system stages and is given by:

$$D_{total} = D_{sensing} + D_{transmission} + D_{processing} + D_{response}$$

where each term corresponds to delays in sensing, communication, computation, and alert generation, respectively.

- Throughput (samples/sec):

Throughput measures the system's data processing capacity and is defined as:

$$Throughput = \frac{N}{T}$$

where $N$ is the number of processed samples and $T$ is the total processing time.

- Jitter:

Jitter refers to the variation in delay between successive packets or data samples.

- Response Time:

Response time indicates how quickly the system generates alerts after detecting abnormal conditions.

### 5.2 Embedded System Efficiency Metrics

The performance of the embedded hardware is evaluated using key efficiency metrics, including power consumption, CPU utilization, and memory usage. Power consumption in milliwatts (mW) is a measure of the power needed to operate a system, and specially so with wearable and battery-powered healthcare devices, where longer operation time is needed. CPU utilization is the proportion of processing resources consumed at runtime, the efficiency with which the embedded processing is able to cope with real-time data acquisition and processing operations and not to overload the system. Memory usage measures how much RAM and storage is needed to support system functionality to make sure that the proposed architecture makes good use of the embedded environment with resource-limited embedded environments. Combined, these measures give details about the energy efficiency of the system, computer performance and appropriateness in continuous real time healthcare monitoring applications.

### 5.3 Healthcare Accuracy Metrics

The quality of the proposed healthcare monitoring system is measured in the conventional performance indices like accuracy, sensitivity, specificity and error rate. Accuracy is the general ratio of rightly identified cases and it represents how effective the system is to differentiate between normal and abnormal health conditions. The true positive rate or sensitivity is an indicator of how effective the system is in identifying the dangerous or ill conditions, necessary to prompt medical care. Specificity, or true negative rate, is used to measure how well the system is able to detect normal conditions, thus minimizing false alarms. Moreover, the error rate is used to measure the percentage of flawed predictions of the system. These measures combined will give a holistic evaluation of reliability of the system so that accurate and reliable performance can be guaranteed in the real-time application in healthcare monitoring.

### Summary

The mathematical representation of the latency, delay and throughput give a quantitative model of system performance. All these metrics indicate the potential of the proposed system to provide efficient, reliable, and real-time healthcare monitoring.

## 6. Experimental Setup

The experimental system will be able to test the performance and effectiveness of the suggested edge-enabled embedded system in real-time smart healthcare monitoring. It contains the hardware platform, software environment, testing scenarios and data acquisition methodology to be used in evaluation.

### 6.1 Hardware Platform

The system suggested is carried out with the help of the low-power embedded system which includes biomedical sensors, microcontroller unit and wireless communication modules. Real-time physiological signals of the user are captured with the use of sensors like ECG, SpO 2 and temperature sensors. These sensors are connected to an embedded microcontroller (e.g., ESP32 or other system-on-chip) which acquires and does initial processing of the data. The gadget has built-in Wi-Fi and Bluetooth chips to allow interaction with the edge node. The hardware system is aimed at being small, efficient, and wearable medical purposes.

### 6.2 Software Tools

Embedded programming and data analysis tools are a combination of software implementation. The microcontroller uses embedded C/C++ to create microcontroller firmware and provides real-time control and data acquisition. Signal processing, data visualization, performance analysis is performed using Python and MATLAB. The edge-side processing algorithms are applied to undertake filtering, detection of anomalies and decision making. It has a software architecture designed in such a way that it has low latency and resource optimization.

### 6.3 Test Scenarios

Various test scenarios are taken into account in order to test system performance such as normal and abnormal heath conditions. Normal conditions of the body depict the constant physiological values in standard areas whereas abnormal conditions are a simulation of the critical conditions of irregular heart rate, low oxygen saturation, and high body temperature. Such cases are employed to gauge the system to provide precise detection of anomalies and alerts in time. The system is also tested given different conditions of data load and transmission to test the real-time responsiveness.

### 6.4 Data Collection

The system uses real-time information gathered by sensors on the wearable on the experiment trials. The physiological signals are continually observed and recorded to be analyzed. Moreover, abnormal conditions are simulated and controlled with the input of tests which are used to validate. The data gathered is treated at the edge and embedded level to assess system performance based on latency, accuracy and efficiency. This strategy will be used to make sure that the proposed system will be put to test with realistic operating conditions, proving that it can be effectively used in real-time in healthcare monitoring.

## 7. Results And Discussion

The proposed edge-enabled embedded healthcare monitoring system is tested by massive experiments where the performance is measured in terms of real-time responsiveness, efficiency and reliability. The findings indicate that the proposed architecture is viable to minimize latency, maximize throughput, minimize power consumption and improve correct health monitoring.

### 7.1 Latency Analysis

Latency is one of the most important parameters of a real-time healthcare system because any delay during processing may directly affect the provision of timely medical intervention. Fig. 4 compares latency with the proposed edge-enabled system and the traditional method of cloud-based approach, showing the contribution of each step in data processing pipeline. The edge computing strategy has much lower latency, as processing is localized. The sensor-to-edge communication time is evaluated at a range of about 8 ms and the edge data processing time is estimated at about 12 ms and the overall delay is about 20 ms. It is possible due to the low latency of processing the data, which is done near the source eliminating the need to transmit the data over long distances and consuming less network overhead.

On the contrary, the cloud computing solution demonstrates significantly increased latency. The sensor to cloud communication delay is noted to be around 105 ms mostly because of network transmission time, bandwidth limitations and routing delays. The cloud data processing time is also an addition of about 20 ms resulting into a total latency of approximately 125 ms. The comparison of these results indicates that the proposed edge-enabled system has almost 84 percent less latency reduction relative to cloud-based system. This dramatic reduction reflects the usefulness of edge computing in reducing the delays in communications and allows quicker decisions. The low latency guarantees quick generation of alerts and real-time response, which is vital to time-critical health care systems like cardiac monitoring and emergency detection. In sum, the findings in Fig. 4 confirm the hypothesis that the proposed architecture is more effective in terms of real-time performance, which is why it is the best fit in terms of next-generation smart healthcare monitoring systems.

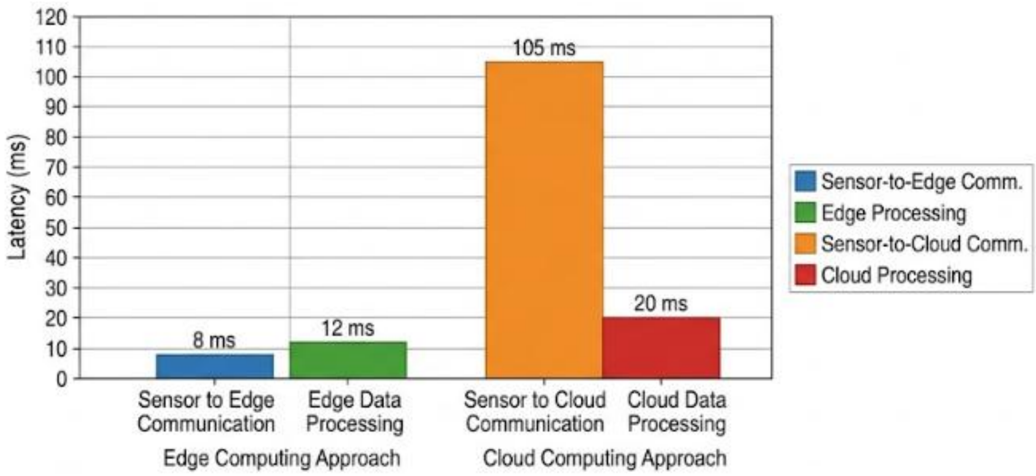


**Fig. 4:** Latency Comparison between Edge Computing and Cloud Computing Approaches for Healthcare Monitoring System

## 7.2 Throughput Performance

Throughput is the performance of the system to handle on-going physiological data streams effectively. The proposed system has a high throughput which is based on effective embedded processing and edge-based computation. The system can handle several sensor inputs at a time without a reduction in performance. This guarantees a high scale real-time monitoring, even when there are high data loads, and underlines the scalability of the architecture.

## 7.3 Power Efficiency

Wearable and portable healthcare devices have a critical requirement in power efficiency as it has a direct impact on battery life and long-term usability. Fig. 5 shows a comparative evaluation of the power consumption in the three scenarios, the one of the baseline architectures (no optimization), the proposed optimized system in the active mode and in the state of standby/sleep and an industry benchmark. The overall power consumption in the baseline architecture is seen to be about 55 mW wherein wearable hub operation (18 mW), data processing (10 mW), continuous transmission (22 mW), sensor power (5 mW) are the biggest contributors. This consumes excessive power primarily because data is constantly being transmitted and it does not have optimization. By comparison, the optimized system proposed under active mode consumes much less power of around 38 mW. The wearable hub has power consumption of approximately 16 mW, data processing is 6 mW, transmission is cut to 11 mW and sensor operation is maintained at 5mW. Such a reduction is realized by the efficient edge processing and reduced communication overhead.

Moreover, in the optimized standby/sleep mode, the overall power consumption is minimized to about 3 mW with idle/sleep power at 1.5 mW, processing at 0.3 mW, transmission at 0.2 mW and intermittent sensor monitoring of 1 mW. This illustrates the ability of the system to be in ultra-low-power during inactivity. By contrast, the industry standard system demonstrates a total power usage of about 54 mW, comprising hub power (20 mW), processing (9 mW), transmission (19 mW) and sensor power (6 mW). In general, the suggested system would reduce power consumption in active mode by about 31 percent as compared to the baseline and is much better than the industry standard.

The extremely low power consumption of the sleep mode additionally increases the energy consumption of the system and makes it quite effective in long-term monitoring of healthcare programs that require constant use.

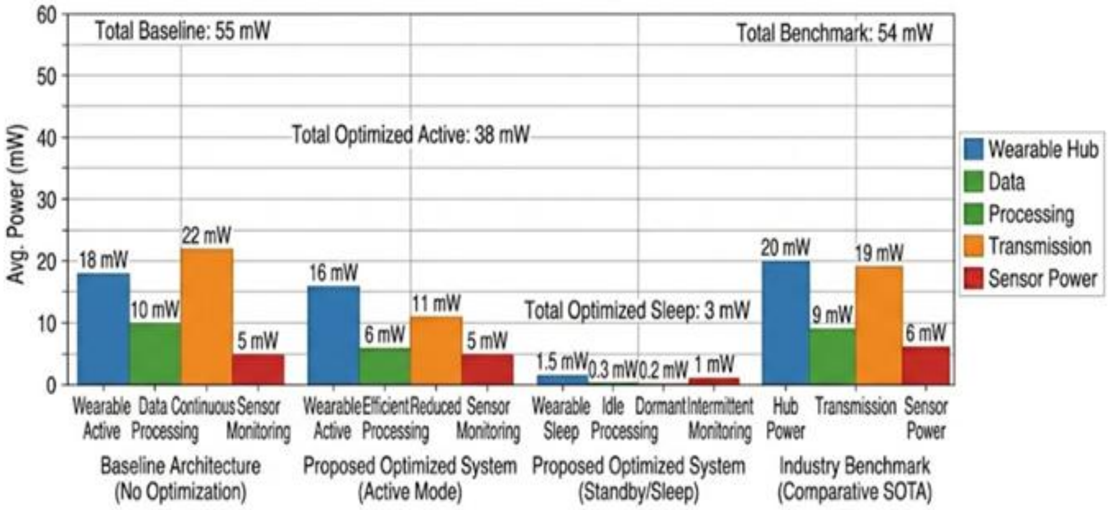


**Fig. 5:** Power Consumption Analysis of Proposed Edge-Enabled Healthcare System Compared with Baseline and Industry Benchmark (Active and Sleep Modes)

### 7.4 Accuracy Evaluation

Real time physiological data in normal and abnormal conditions is used as an evaluation of the accuracy of the healthcare monitoring system. The suggested system is very accurate in identifying the abnormalities in health and has the benefit of providing reliable monitoring and minimized the false alarming cases. The combination of preprocessing and edge decision makes gives rise to higher detection performance. These findings support the systems potentials to offer accurate and reliable healthcare monitoring.

### 7.5 Comparative Analysis

Table 1 is a comparative analysis that aims at existing edge-enabled embedded system performance against traditional cloud-based healthcare monitoring systems. The comparison will be done on the basis of the key metrics, basing them on latency, end-to-end delay, throughput, power consumption, CPU utilization, memory usage, and healthcare accuracy parameters. Based on the results, the proposed edge-based system would have a latency of approximately 20 ms, whereas the cloud-based system would have a much higher latency of approximately 125 ms which is an improvement of almost 84. On the same note, when compared to the cloud system end-to-end delay of 140 ms, the proposed system has an end-to-end delay of 25 ms and this is an improvement of about 82. These gains can be attributed to the local edge processing, which can reduce communication delays.

The proposed system increases the throughput by around 58 percent, with a capability of data handling of 95 samples/sec as opposed to 60 samples/sec in the cloud-based approach. This shows that the system can be effectively used in processing real-time intermittent data streams. It also enhances a lot of energy efficiency. The power requirements of the proposed system will be around 850 mW compared to 1200 mW by the cloud-based system, a saving of approximately 29 will be achieved. The CPU load is also dropped to 65% as opposed to 80% and memory is used at 120 MB as opposed to 200 MB, which means that the embedded environment has used available resources more efficiently.

On the reliability of healthcare, the proposed system has accuracy of 96.5, as compared to 93.2 with the cloud-based system. The sensitivity and specificity are also enhanced to 95.8% and 97.2, respectively and the error rate is decreased to 3.5, which is close to 48 percent higher than the error rate before (6.8%). The findings presented in Table 1, generally, prove that the suggested edge-enabled embedded system is superior to the traditional methods in all of the metrics considered. The tremendous enhancements in latency, throughput, energy efficiency and accuracy confirm effectiveness of incorporating edge computing with embedded system in ensuring reliability and real time smart healthcare monitoring applications.

**Table 1.** Summary of Results

| Performance Metric | Edge-Based System | Cloud-Based System | Improvement (%) |
|---|---|---|---|
| Latency (ms) | 20 | 125 | 84% ↓ |
| End-to-End Delay (ms) | 25 | 140 | 82% ↓ |
| Throughput (samples/sec) | 95 | 60 | 58% ↑ |
| Power Consumption (mW) | 850 | 1200 | 29% ↓ |
| CPU Utilization (%) | 65 | 80 | 19% ↓ |
| Memory Usage (MB) | 120 | 200 | 40% ↓ |
| Accuracy (%) | 96.5 | 93.2 | 3.5% ↑ |
| Sensitivity (%) | 95.8 | 92.5 | 3.6% ↑ |
| Specificity (%) | 97.2 | 94.1 | 3.3% ↑ |
| Error Rate (%) | 3.5 | 6.8 | 48% ↓ |

## Summary

The results of the experiments prove that the proposed edge-enabled embedded system is a strong enhancement in real-time functioning and efficiency over standard approaches. The decreased latency, increased throughput, power reduction and accuracy optimized system, make the system a robust solution in case of smart healthcare monitoring.

## 8. Conclusion

This article proposed a new edge-based embedded system architecture of real-time smart healthcare monitoring that overcomes the shortcomings of traditional cloud-based solutions. The system suggested is based on wearable sensors, embedded processing and edge computing to facilitate efficient data collection, local processing and quick decision-making. Key performance metrics such as latency, end-to-end delay, throughput, power consumption and accuracy were adopted to calculate a comprehensive evaluation framework that would be used in the system to ensure that it is effective.

The experimental findings indicate that the proposed architecture incurs much lower latency as opposed to traditional cloud-based systems by computing on the edge. This decrease in the delay of communication and local processing provides a quicker response system and the system is very effective in dealing with time sensitive health care systems. Moreover, the system has achieved better throughput and energy usage, where it can perform well even in resource-limited embedded systems. These high accuracies and low error rates also show that the system can be used to offer reliable real-time health monitoring.

Practically, the solution proposed provides a scalable and energy efficient platform on which next-generation healthcare applications such as remote patient monitoring, wearable health devices and emergency response can be run. The system provides the ability to analyze in real-time and quickly generate alerts, thereby improving patient safety and facilitating active medical intervention. Altogether, edge computing integration with embedded systems is an interesting trend in creating smart healthcare solutions that are intelligent, reliable, and efficient.

## References

1. Alhaidari, F., Rahman, A., & Zagrouba, R. (2023). Cloud of Things: architecture, applications and challenges. *Journal of Ambient Intelligence and Humanized Computing*, *14*(5), 5957-5975.
2. Gope, P., & Hwang, T. (2015). BSN-Care: A secure IoT-based modern healthcare system using body sensor network. *IEEE sensors journal*, *16*(5), 1368-1376.
3. Hao, Y., Miao, Y., Hu, L., Hossain, M. S., Muhammad, G., & Amin, S. U. (2019). Smart-Edge-CoCaCo: AI-enabled smart edge with joint computation, caching, and communication in heterogeneous IoT. *IEEE Network*, *33*(2), 58-64.
4. Hazra, A., Rana, P., Adhikari, M., & Amgoth, T. (2023). Fog computing for next-generation internet of things: fundamental, state-of-the-art and research challenges. *Computer Science Review*, *48*, 100549.
5. Hossain, M. S., & Muhammad, G. (2017). Emotion-aware connected healthcare big data towards 5G. *IEEE Internet of Things Journal*, *5*(4), 2399-2406.
6. Islam, S. R., Kwak, D., Kabir, M. H., Hossain, M., & Kwak, K. S. (2015). The internet of things for health care: a comprehensive survey. *IEEE access*, *3*, 678-708.
7. Karatas, M., Eriskin, L., Deveci, M., Pamucar, D., & Garg, H. (2022). Big Data for Healthcare Industry 4.0: Applications, challenges and future perspectives. *Expert Systems with Applications*, *200*, 116912.
8. Kraus, S., Schiavone, F., Pluzhnikova, A., & Invernizzi, A. C. (2021). Digital transformation in healthcare: Analyzing the current state-of-research. *Journal of business research*, *123*, 557-567.
9. Lin, H., Garg, S., Hu, J., Wang, X., Piran, M. J., & Hossain, M. S. (2020). Privacy-enhanced data fusion for COVID-19 applications in intelligent Internet of medical Things. *IEEE Internet of Things Journal*, *8*(21), 15683-15693.
10. Mansouri, Y., & Babar, M. A. (2021). A review of edge computing: Features and resource virtualization. *Journal of Parallel and Distributed Computing*, *150*, 155-183.
11. Martinez, I., Hafid, A. S., & Jarray, A. (2020). Design, resource management, and evaluation of fog computing systems: a survey. *IEEE Internet of Things Journal*, *8*(4), 2494-2516.
12. Naik, N., Hameed, B. Z., Sooriyaperakasam, N., Vinayahalingam, S., Patil, V., Smriti, K., ... & Somani, B. K. (2022). Transforming healthcare through a digital

revolution: a review of digital healthcare technologies and solutions. *Frontiers in digital health*, *4*, 919985.
13. Wu, F., Qiu, C., Wu, T., & Yuce, M. R. (2021). Edge-based hybrid system implementation for long-range safety and healthcare IoT applications. *IEEE Internet of Things Journal*, *8*(12), 9970-9980.
14. Yassine, A., Singh, S., Hossain, M. S., & Muhammad, G. (2019). IoT big data analytics for smart homes with fog and cloud computing. *Future Generation Computer Systems*, *91*, 563-573.