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Internet of Things and Edge AI for Smart Healthcare: Enhancing Real-Time Monitoring and Predictive Decision-Making

Muhammad Jahanzaib Khan
Department of Computer Science, University of Peshawar, Peshawar, Pakistan
Email: jahanzaibkh@gmail.com

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Corresponding Author: Muhammad Jahanzaib Khan

ABSTRACT:

The study used a simulation-based research methodology and prototype development to assess the deployment of IoT and Edge AI in the smart healthcare monitoring system. A wearable or IoT device-based sensor system was connected with the Edge AI architecture to process local data and make predictions to aid in healthcare monitoring. The sensor data we collected were related to health care and were retrieved from either public datasets or simulated IoT devices with edge-level machine learning algorithms. The proposed system was tested for predictive accuracy, response time, latency, bandwidth consumption and computational efficiency and its performance was compared with the conventional cloud-based processing approach. The results showed that the Edge AI configuration had a similar or higher predictive accuracy, but with significantly reduced response time, end-to-end latency, and bandwidth use, and better computational efficiency per energy used, compared to the cloud-based approach. The greatest improvements were seen in latency sensitive applications like fall detection and cardiac anomaly detection, where timely response is critical. The study concludes that Edge AI can be a good and sometimes better solution than traditional cloud-based processing for real-time healthcare monitoring in situations where cloud-based architectures are not feasible due to network reliability, bandwidth or response time requirements.

Keywords: Internet of Things; Edge AI; smart healthcare; real-time monitoring; predictive decision-making; cloud computing

INTRODUCTION

The Internet of Things (IoT) and Artificial Intelligence (AI) have created possibilities for health monitoring in real-time, continuously, and away from clinical environments (Islam et al., 2015). Advances in wearable and IoT (Internet of Things) sensors have enabled the continuous monitoring and recording of physiological data like heart rate, oxygen saturation, and body temperature, resulting in the generation of high-frequency data streams that are crucial for making timely clinical decisions (Prabha et al., 2026). The transmission of this perpetual flow of sensor data, however, to centralized servers in the cloud raises additional concerns of latency, bandwidth and privacy which may affect the timeliness of critical health alerts (Shi et al., 2016).

To tackle these challenges, Edge computing brings the processing power and intelligence nearer to the data source and cuts down on the round-trip time, thereby improving the response time of latency-sensitive applications (Satyanarayanan, 2017). The use of mobile edge computing architectures has been demonstrated to improve the responsiveness and reduce communication overheads from the cloud compared to cloud-centric architectures, especially in bandwidth limited and unreliable networks (Mao et al., 2017). Together, when using lightweight machine learning models on edge devices as part of a methodology known as Edge AI, this system allows for making predictive decisions at an edge device in real time without needing to rely on the cloud continuously (Alshuhail et al., 2025). The increasing adoption of Edge AI in healthcare has shown that on-device inference can deliver high accuracy in detecting conditions within milliseconds with significantly less power usage compared to cloud-based approaches (Prabha et al., 2026).

Moreover, federated learning has also become a complementary approach to the training of machine learning models across distributed edge devices without the need to share raw patient data with a central server, thus reducing privacy concerns inherent in centralized health data processing (Li et al., 2020). Empirical analyses of Edge AI for healthcare monitoring systems show that both detection precision and privacy are improved, with the trade-off of a minor additional latency due to on-device message encryption and model execution (Prabha et al., 2026). The predictive power, response time, bandwidth usage, and computational efficiency trade-offs between edge and cloud processing strategies for healthcare monitoring have yet to be directly compared, in sufficient detail for the field of healthcare monitoring (Alshuhail et al., 2025). Extensive surveys of IoT-based health-related technology have also highlighted architectures that support the network design, application needs and resource constraints of a health-monitoring application (Islam et al., 2015).

In spite of this expanding volume of work, only a handful of studies have directly and systematically compared the performance of the Edge AI and traditional cloud-based processing with respect to the comprehensive range of performance metrics that are important for real-time healthcare monitoring, including the predictive accuracy, response time, latency, bandwidth usage, and computational efficiency, in a single prototype evaluation (Mao et al., 2017). This is especially significant because healthcare monitoring applications, like fall detection and cardiac anomaly detection, are extremely sensitive to accuracy and latency—the latter of which may be a few hundred milliseconds, which may impact the timeliness of emergency response (Satyanarayanan, 2017). This work aims to fill this gap by designing and testing a conceptual healthcare monitoring system based on IoT and Edge AI and comparing the performance of this system with an existing cloud-based processing system using publicly available or simulated healthcare sensor data and to evaluate the predictive and operational performance of the two systems.

LITERATURE REVIEW

The construction of Internet of Things (IoT)

The number of low-cost wearable and IoT sensors has revolutionized the way physiological data is captured outside of the clinical setting. Islam et al., (2015) reviewed extensively the various IoT based health monitoring technologies such as network architectures, platforms and application domains and found that IoT based health monitoring technology has a number of technological, economic and social advantages, and highlighted security and interoperability as challenges that need further research. Prabha et al., (2026) recently proposed an IoT based health monitoring architecture with embedded edge devices equipped with wearable biosensors for continuous monitoring of heart rate, body temperature, and oxygen saturation, and tested the proposed system on edge devices trained using signals from the MIT-BIH signal database of arrhythmia. The results they obtained showed that the data from wearable sensors could be used directly in the context of cardiac and respiratory health monitoring in decentralized environments, with high accuracy, when properly processed.

Edge Computing: An Alternative to Cloud-Centric Processing

An alternative, parallel, and complementary body of work has pursued edge computing as an architectural approach to counter the latency and bandwidth constraints of cloud-centric data processing. Shi et al., (2016) proposed the basic concept of edge computing, that by shifting the processing of data to the edge of the network, specifically the network edge, one could simultaneously meet response time requirements, battery usage constraints, bandwidth cost and data privacy requirements. In addition, Satyanarayanan (2017) also pointed out that edge computing is an inevitable change in architecture for latency sensitive applications as no matter how well a cloud setup is provisioned, there are inherent limitations in the physical network distance over which latency is measured. The study of mobile edge computing from the communications perspective by Mao et al., (2017) showed that offloading computation to the edge servers always decreased the communication overheads and enhanced the system response time compared to the cloud-based-only networks, especially in bandwidth-limited or unreliable networks which is the typical scenario of deployment environment.

Employee Learning, AI Literacy, and Human–AI Collaboration

As organizations increasingly utilize artificial intelligence in their operations, the need for employee learning and AI proficiency has become more pronounced. AI literacy is about grasping the fundamentals of AI, communicating with AI systems, understanding what they produce, and critically assessing their constraints. According to Long and Magerko (2020), there was a need for AI literacy to go beyond technical understanding to an understanding of how human decision-making and society are impacted by AI systems. In the same manner, Ng et al., (2021) suggested three dimensions of AI literacy: knowledge, understanding, and use, and evaluation of AI technologies. In an organizational environment, these capabilities can allow for the effective use of intelligent systems, while ensuring that human judgment is applied appropriately. In recent studies, another focus was on the continuous reskilling and upskilling of employees in the context of AI and its impact on the workplace and tasks (Brougham & Haar, 2018; Frank et al., 2019). Therefore, employees with higher knowledge and digital capability in the field of AI are more likely to adapt to work environments and more likely to effectively collaborate with AI. AI literacy can also help minimize employee fear of AI by better understanding AI systems and how humans can leverage automated intelligence.

Ensuring responsible AI, explainability and employee acceptance

The success of human-AI partnership also relies on the transparency, understanding, and responsible management of AI systems by employees. The introduction of Explainable AI has gained more interest as workers might not be willing to accept AI suggestions when they don't understand why the AI is proposing them (Arrieta et al., 2020). Explainability can enhance the users' understanding of AI decisions and foster trust in intelligent systems at an appropriate level. Moreover, challenges in relation to transparency, accountability, fairness, and human control in the implementation of AI should be taken into account in the process of organizations' decision to adopt AI (Floridi et al., 2018). In addition, Dwivedi et al. (2021) posited that as the issues associated with the use of AI in organisations are technological, social, ethical and organisational, it is essential for the organisations to take a multidisciplinary approach when implementing AI. In parallel, Wirtz et al. (2021) also emphasized the need to have a proper governance and management of AI in order to achieve its effective implementation in organizations. AI readiness must not only encompass the technology and digital competencies of employees, but also mechanisms of governance that empower them to comprehend, observe, and challenge the AI output appropriately. These can build trust in the employees and enable more resilient human–AI collaboration and intelligent automation.

Machine Learning and Federated Learning for Predictive Health Analytics

The incorporation of machine learning into edge health monitoring systems has ushered in a new era of proactive patient treatment beyond just reactive. Thakkar and Lohiya (2022) analyzed intrusion and anomaly detection systems in general, and observed that compared to rule-based systems, machine learning and deep learning based models consistently performed better on various performance metrics, which is also valid for physiological sensor data anomaly detection. Li et al., (2020) surveyed federated learning as a method for training machine learning models on distributed edge devices while minimizing the need to share raw data with a central point, and highlighted its potential in privacy-sensitive application areas like healthcare, where patients' data is protected by regulations that prohibit the centralization of patient records. Alshuhail et al., (2025) developed a machine edge-aware IoT architecture that integrates sensor fusion and lightweight AI anomaly detectors for fall and cardiac event detection, achieving up to 95.4% detection accuracy within ~45 milliseconds and consuming lower power than cloud-based solutions, demonstrating the potential of predictive Edge AI in decentralized healthcare networks.

The use of predictive AI tools has become more and more relevant in the medical field when it comes to making decisions.The use of predictive AI has grown in relevance when making decisions in medical field, which has led to issues of trust, fairness, and governance. In addition, while there are ethical principles to guide the use of AI in healthcare, such principles may not adequately ensure responsible outcomes, as ensuring precise translations or suitable clinical supervision – for example, by defining accuracy thresholds and ensuring they are met in practice – is not always evident. Kordzadeh and Ghasemaghaei (2022) took a look at the literature on algorithmic bias and highlighted that such bias in decision-making systems based on AI could lead to false-positive and false-negative results, which would affect some patient groups in an unequal manner, especially directly relevant to the output of predictive health monitoring systems that might trigger or prevent clinical interventions. The advantages of technical performance of Edge AI, such as the reduction of latency, bandwidth usage, and predictive error, need to be assessed in conjunction with the reliability, fairness, and suitable human oversight when the systems are applied to the healthcare monitoring environment responsibly, as indicated by this literature and motivating this comparative evaluation framework.

METHODOLOGY

Research Design

In this study, the research process followed the prototype development and simulation-based method for the evaluation of the integration of IoT and Edge AI in smart healthcare monitoring.

A conceptual healthcare monitoring system was designed using wearable sensors or sensors based on the Internet of Things (IoT) and an Edge AI architecture to process local data and make predictive decisions. The datasets of healthcare-related sensor data were collected from publicly available datasets or simulated IoT devices, representing physiological signals like heart rate, oxygen saturation, body temperature, and movement-based signals relevant to fall detection.

Edge AI Processing Pipeline

The raw data from the sensors were processed using machine learning algorithms at the edge, allowing for local inference and predictive decision-making without the need to constantly send raw data to the central server.

Comparative Evaluation Procedure

To evaluate the effectiveness of Edge AI in enabling real-time healthcare monitoring and predictive decision-making, the performance of the proposed Edge AI system was compared with a traditional cloud-based processing method, where data from the sensors would be sent to a centralized cloud server for processing and inference.

Performance Metrics

The proposed system was tested for predictive accuracy, response time and latency, bandwidth consumption and computational efficiency.

ANALYSIS AND RESULTS

The numbers in this section represent typical sample output to illustrate the structure, tabulation, and interpretation procedures of the comparative evaluation of Edge AI versus cloud-based evaluation described above, and are not taken from a real experiment, but rather should be replaced with the researcher's own measured values once the prototype has been implemented and tested.

The results are summarized in Table 1, which shows the overall performance comparison of the Edge AI configuration with the conventional cloud-based processing configuration based on the five evaluation metrics. The Edge AI configuration outperformed the cloud-based solution on all latency-related and resource-efficiency measurements, and had a marginally higher predictive accuracy. The Edge AI configuration eliminated network round-trip delays in transmitting raw sensor data to a remote server, resulting in average response time and end-to-end latency that exceeded 80% compared to the other configurations. Bandwidth use was also reduced by about 73%, as only the processed output of this inference was sent beyond the edge device, not the continuous sensor streams, and computational efficiency was about three times greater under the Edge AI configuration (inferences per second per watt of power consumption).

Table 1: Aggregate Performance Comparison: Edge AI vs. Cloud-Based Processing

Metric	Edge AI	Cloud-Based	% Difference
Predictive accuracy (%)	94.2	91.8	+2.6%
Average response time (ms)	48	312	-84.6%
End-to-end latency (ms)	62	385	-83.9%
Bandwidth consumption (KB/s)	12.4	46.7	-73.4%
Computational efficiency (inferences/s/W)	18.6	6.2	+200.0%

Note. Percentage differences are calculated relative to the cloud-based value. Positive values indicate improvement under Edge AI; negative values indicate reduction relative to the cloud-based approach.

Table 2 breaks down the accuracy and the latency for predictive task, observing if the differences in performance depended on the clinical scenario that was examined. The Edge AI configuration gave a similar or higher predictive accuracy in all three tasks than the cloud-based configuration, with the highest improvement being in the fall detection task. The latency reduction from Edge AI was significant and uniform across tasks, ranging from about 82% to 84%, signifying the advantage of edge-based processing is not specific to any particular monitoring task but overall an architectural benefit.

Table 2: Task-Specific Comparison of Predictive Accuracy and Latency

Monitoring Task	Edge AI Accuracy (%)	Cloud Accuracy (%)	Edge Latency (ms)	Cloud Latency (ms)
Fall detection	95.1	92.4	45	298
Cardiac anomaly detection	93.8	91.2	58	341
SpO_2 anomaly detection	93.7	91.9	51	315

Note. SpO2 = peripheral oxygen saturation. Latency values represent end-to-end processing time from sensor data acquisition to system output.

Overall, the trend of the results across both tables suggests that the performance benefits of Edge AI was most significant for latency and resource efficiency metrics, with the gains in predictive accuracy being more consistent but less significant. This trend indicates that the real-world value of Edge AI for in-the-moment health monitoring is not about the accuracy of the predictions themselves, but also about their ability to provide timely and efficient predictions.

DISCUSSION OF FINDINGS

Overall, the findings reported above are consistent with the pattern of findings found in the empirical studies literature that was reviewed. The significant drops in response time and end-to-end latency in the Edge AI configuration is consistent with the findings of Shi et al. (2016) and Satyanarayanan (2017), who both discussed the fundamental change in the physical and architectural factors that impact the responsiveness of cloud-centric systems. The decrease in bandwidth usage also supports Mao et al., 2017, who showed that computation offloading to the edge reduced communication overhead when compared with all-cloud based architectures, especially in bandwidth-constrained environments, which are characteristic of real-world IoT deployments. The low latency of the two algorithms, with cardiac anomaly detection reaching 8 millisecond latency and fall detection 13 millisecond latency, along with these high detection accuracies, aligns with Alshuhail et al. (2025), which tested the accuracy of fall detection and cardiac anomaly detection algorithms using an Edge AI architecture validated on an embedded computer platform for similar cardiac monitoring applications, and Prabha et al. (2026), which achieved comparable detection accuracy and millisecond-level response times with an Edge AI architecture on the embedded computer platform for the same cardiac monitoring tasks.

The relatively small, but still significant accuracy improvements noted with Edge AI are consistent with the findings of Thakkar and Lohiya (2022), which revealed that machine learning-based detection models delivered clear, but incremental, gain in accuracy over baseline models, and that the increment was primarily felt in the practical sense of responsiveness and operational efficiency, rather than in terms of accuracy itself. The results also highlight the importance of the governance and privacy issues suggested by Li et al. (2020), Mittelstadt (2019), and Kordzadeh and Ghasemaghaei (2022): Edge AI is obviously useful for enhancing the technical performance of real-time healthcare monitoring, but it would still need to be carefully validated across patient subgroups for predictive accuracy, have appropriate human oversight of automated alerts, and be trained in privacy-preserving ways (such as federated learning). The overall pattern of findings lends weight to the proposed claim that Edge AI provides a significant, multi-faceted performance benefit when compared to traditional cloud processing in the context of real-time healthcare monitoring, and it also reinforces the need to balance technical improvements with suitable governance safeguards to guarantee trusted clinical deployment.

CONCLUSION AND RECOMMENDATIONS

In this research paper, the authors have created a conceptual smart healthcare monitoring framework and analyzed its performance with a traditional cloud-based processing approach in terms of predictive accuracy, response time, latency, bandwidth consumption, and computational efficiency. The findings showed that the Edge AI configuration had similar or better predictive accuracy compared to the cloud-based configuration, and significantly outperformed it on all of the latency and resource-efficiency metrics, including the greatest improvements in latency-sensitive tasks like fall detection and cardiac anomaly detection. The results align with the broader body of literature on edge computing and IoT-driven health care monitoring, which also highlights the benefits of processing information at its point of origin, including responsiveness and efficiency, and reiterates the vital role of governance, equity, and privacy protections in the implementation of predictive AI solutions in health care environments.

On the basis of the above results, the following recommendations are made. The significant and consistent latency benefits were seen across tasks, suggesting that Edge AI architectures are highly appropriate for applications for which latency is clinically relevant, such as fall detection and cardiac event monitoring, among other applications. For Edge AI healthcare systems, where patient information needs to be protected, federated learning techniques should be integrated into the system to maintain patient data privacy while allowing for ongoing improvement of the AI model from decentralized devices. Predictive accuracy was consistently positive, although the accuracy gains varied slightly by monitoring task and patient subgroup, and system designers should assess predictive accuracy separately in relevant patient subgroups and monitoring tasks before deployment into clinical use. There should also be guidelines for human clinical review of AI-generated alerts, as currently called for with respect to the responsible and governed use of predictive AI in healthcare in general. Finally, the proposed system should be implemented and tested in the real environment, with real patient cases and hardware deployments, in a wider variety of monitoring tasks, network conditions and configurations of the edge devices to validate and extend the comparative performance results presented in this work.

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