



Edge AI for Real-Time Medical Monitoring Using Wearable and Implantable Healthcare Devices

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Abstract

This study explores the synergy of edge artificial intelligence (AI), wearables, and Internet of Medical Things (IoMT) in real-time healthcare monitoring and clinical decision support. The goal is to analyze medical and physiological information at the edge to lower latency, protect privacy and enable early detection of abnormal health conditions. A structured literature review was carried out on 24 recent publications of wearable health sensors, edge intelligence, IoMT architectures, embedded AI, remote patient monitoring, personalized rehabilitation, chronic disease management, and secure healthcare applications. The papers examined show that edge AI allows for faster data processing, real-time patient monitoring, efficient anomaly detection, reduced reliance on the cloud environment and enhanced energy efficiency in wearable and IoT medical devices. Multimodal deep learning and personalized edge analytics provide additional assistance to predictive and patient specific healthcare services. Yet there are some issues that need to be addressed - such as computational constraints, interoperability, data security, the reliability of the models, and deployment that uses limited resources. Overall, the results highlight the potential of wearable devices, IoMT, and edge AI for developing scalable, low-latency, privacy-preserving, and intelligent health monitoring systems that can facilitate remote and personalized health care delivery.

Keywords:

Edge AI, Wearable Sensors, Internet of Medical Things, Real-Time Health Monitoring, Healthcare IoT, Clinical Decision Support

Received on 5 July 2026; Revised on 21 July 2026, Accepted on 22 Aug 2026; Published on 30 Sep 2026

DOI: <https://doi.org/10.67512/jcseam.v1.i3.5>

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1. Introduction

Artificial Intelligence (AI), wearable sensors, and the Internet of Medical Things (IoMT) are revolutionizing traditional healthcare, creating patient-centric, intelligent, and continuous systems. AI can continuously monitor users' health status through wearable gadgets, allowing for the collection of physiological data like heart rate, blood pressure, oxygen saturation, body temperature, activity, and more, which can help identify potential health issues early or guide clinical decisions. Wearable devices can continuously gather physiological data, including heart rate, blood pressure, oxygen saturation, body temperature, activity, and other health indicators, while AI can analyze these data to assist in early detection and clinical decision making. Traditional cloud-based healthcare systems, on the other hand, tend to involve the constant flow of substantial amounts of sensitive medical information. This can create communication delays, network reliance, and privacy concerns with conventional, cloud-based healthcare systems. The chief reason for all of these limitations is that the processing of data and intelligent computation is done remotely from the patients and sensors, thereby slowing down the response to the healthcare scenario. These limitations can be overcome using the concept of Edge AI, where the data processing and intelligent computation are done closer to the patient and sensing devices, thus ensuring a faster response to the healthcare scenario. Edge intelligence can effectively realize real-time monitoring of critical patient information when combined with IoT-based healthcare systems. Edge-enabled architectures may be used to process data from the sensors and detect abnormal physiological patterns without toting the entire burden of remote cloud servers [3]. Low-latency edge AI is crucial in scenarios like continuous patient monitoring, emergency detection, and real-time clinical interventions, where real-time analysis can have an impact on the quality of health care services [4]. Besides, EAI can enhance the operational efficiency of the medical IoT devices and wearable systems, enabling continuous monitoring in resource-constrained environments [5]. In the healthcare sector, edge intelligence enhances responsiveness, decreases communication burden, and enables computation at the edge, which is suitable for distributed applications in the field [6].

Recent studies have also shown the possibility of using real-time data processing, edge computing and wearables for intelligent health care applications. Edge processing can help process vast amounts of medical data in real time and enable the detection of clinically meaningful events in a timely manner [7]. Moreover, the quality of medical information for intelligent diagnostic systems can be enhanced by employing AI-based image and signal processing techniques [8]. To leverage the scalability of cloud systems and low latency processing capabilities of edge devices, cloud-edge AI architectures have been proposed, especially for personal health monitoring at the edge such as with wearable devices [9]. In smart cities, healthcare IoT systems with a high density of medical devices are another field where Edge AI has been explored, as they continuously collect patient data that must be processed efficiently [10]. The growing use of AI on embedded and edge devices introduces new opportunities for decentralized clinical intelligence. Local inference using AI models deployed directly on resource-constrained healthcare devices can enhance patient data security and mitigate the burden on centralized servers by transmitting only the resulting predictions, thereby minimizing the leakage of raw patient data. Therefore, in applications where real-time data processing and constant availability are required, the use of edge computing and IoT technologies can prove useful [12]. To cope with the growing demand for intelligent analysis and protection of medical data, secure edge-AI frameworks have also been formulated to integrate anomaly detection with patient monitoring using IoT, as shown in [13]. Additionally, combining wearable health equipment and edge computing systems can give personalised rehabilitation, having the physiological and activity-related information analysed near to the patient [14].

Multimodal AI techniques have recently become more popular for wearable healthcare systems, as they are able to integrate multiple physiological signals to assess health over time. Heterogeneous sensor inputs can be fused in deep learning frameworks to enable intelligent monitoring, and real-time detection of health risk [15]. The local processing of data can lead to reduced latency and enhanced responsiveness, making Edge AI a promising solution for real-time analytics in smart healthcare and wearable computing, a field that is experiencing growing research interest [16]. Further, IoT based healthcare system can be developed that integrates edge AI and advanced wearable sensors, to enable continuous monitoring and automatic analysis of the physiological condition [17]. The

developments point to the fact that edge-based intelligence is emerging as an important part of the next-generation healthcare systems. In addition to general health monitoring, there are also many potential specialized clinical uses for edge AI and wearable technologies. AI has also been applied in various ways to aid medical imaging for complex medical tasks, and deep learning approaches have been increasingly investigated for this application, showing the wide application of AI in the clinical analysis and diagnosis process [18]. Real-time edge AI can enable personalized monitoring through continuous analysis of the data gathered from wearable devices for chronic disease management [19]. The incorporation of AI in wearable and implantable medical devices opens new avenues for intelligent healthcare by facilitating the continuous monitoring of physiological parameters and possible preventive measures [20]. On-device efficient intelligence for healthcare monitoring applications is also identified as a crucial requirement in the reviews of AI based wearable embedded system [21].

Another key application where wearable devices and edge AI can enhance accessibility and continuity of care is remote health monitoring. Advanced wearable medical devices allow health information to be gathered outside of the traditional clinical environment and can help facilitate remote monitoring and decrease the need for repeat hospital visits [22]. For chronic cardiovascular disease, wearable technology and AI at the edge can help to enable real-time monitoring and aid in early detection of shifts in patient health status [23]. A more general use of edge intelligence and IoMT then offers a framework for real-time healthcare monitoring, integrating sensing, local computation, intelligent analysis and communication. Even with these advances, there are still challenges to contend with, such as computers at an edge device that are not powerful enough, energy use, data security, interoperability, model explainability, communication reliability, and maintaining high accuracy for the AI system in the real world. The problems reflect the need for architectures that are efficient, can achieve reasonable response time, preserve privacy, are energy efficient, and are clinically reliable. Hence, this study concentrates on the role of Edge AI and wearable IoT technologies for real-time healthcare monitoring, which brings together the latest advances in sensing, edge intelligence, multimodal analytics, secure IoT frameworks, and personalized healthcare to uncover the existing capabilities, limitations, and prospects for future research in the field.

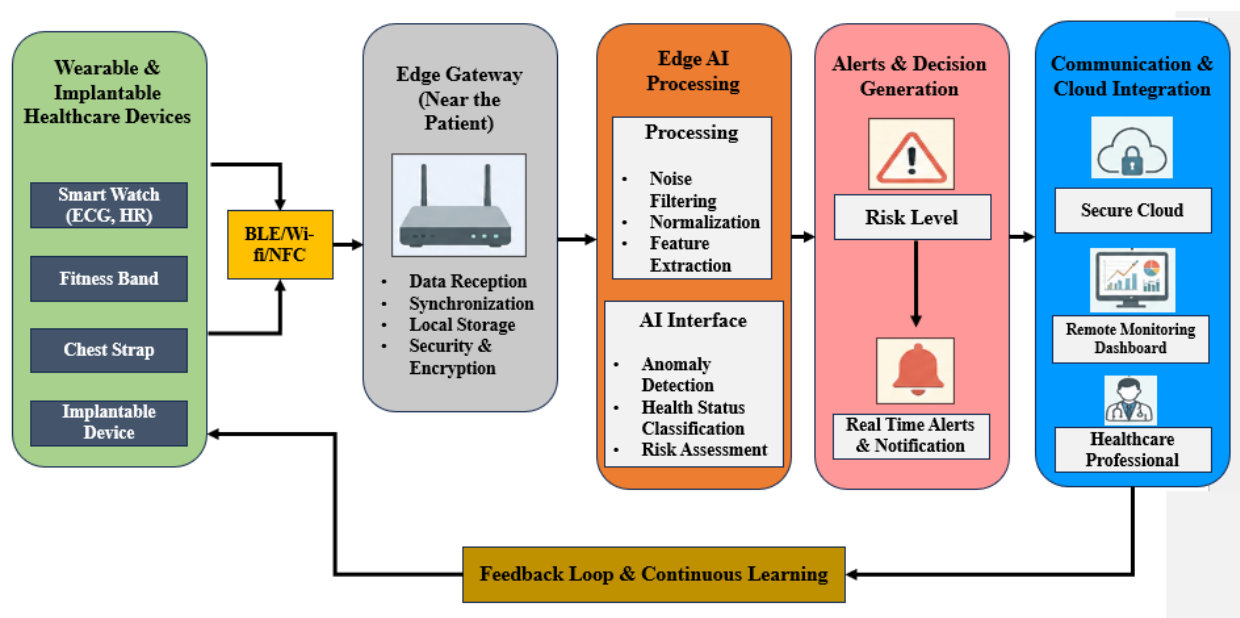


Fig. 1. Edge AI-Based Real-Time Medical Monitoring Framework Using Wearable and Implantable Healthcare Devices

Fig. 1. presents a real-time healthcare monitoring framework based on wearable and implantable medical devices. Health data are collected through smart watches, fitness bands, chest straps, and implantable devices and transmitted through BLE/Wi-Fi/NFC to a nearby edge gateway. The gateway performs data synchronization, local storage, and security processing. Edge AI then performs preprocessing, anomaly detection, health-status classification, and risk assessment. Based on the detected risk level, real-time alerts and notifications are generated. Processed information

can be securely integrated with the cloud, remote monitoring dashboards, and healthcare professionals. A feedback loop continuously updates the AI models using new health data, improving monitoring accuracy and personalization.

2. Literature Survey

In recent research, the focus has been on combining the edge AI with wearable sensors and IoMT (Internet of Medical Things) with the goal of providing real-time healthcare monitoring. Wearables have shown the potential to continuously gather physiological data and provide intelligent clinical decisions [1]. Edge AI techniques minimize reliance on cloud-based processing by computing nearer to the data source, enhancing response time or decreasing communication overhead [2]. It has been furthermore demonstrated that AI architectures with IoT capabilities have the potential to be deployed in real-time critical healthcare applications, such as where abnormal patient conditions are desired to be detected in real-time [3]. For time-sensitive healthcare applications, local processing is crucial for secure patient monitoring, as explored in low latency edge computing [4]. For battery-operated medical IoT, energy efficiency is especially significant because it determines the operational time and real-time monitoring of the devices [5]. Edge intelligence frameworks are thus on the rise as an essential solution for distributed healthcare systems, offering a fusion of local analytics, IoT connectivity, and intelligent decision support.

Other research studies have explored cloud-edge architectures, smart healthcare platforms and personalized monitoring applications. Cloud-edge AI systems can handle computational tasks both at the edge and in the cloud, offering the balance of responsiveness and computational capacity [9]. The applicability of edge-enabled IoT healthcare systems to smart city healthcare has been shown, where there are many connected devices that generate patient data continuously [10]. Secure edge-AI architectures have also integrated anomaly detection to detect any unusual patient conditions, enhancing the security of patient sensitive data [13]. The application of wearable devices combined with edge computing in personalized rehabilitation has also been studied, allowing healthcare information to be analyzed at the patient's location [14]. Real-time monitoring has been further enhanced by the use of multimodal deep learning, which integrates data obtained from multiple wearable sensors for more comprehensive health assessment [15]. In terms of AI at the extreme edge, research has also noted the potential of these technologies in chronic disease management and preventive healthcare [23]. Table 1 provides an overview of 12 exemplary studies examining edge AI, wearable sensors, IoMT, and intelligent healthcare monitoring. It outlines the methodology used in each study, key findings and reported and/or inferred limitations and offers a comparative overview of existing research and gaps for further investigation.

Table 1. Literature Survey of Edge AI and Wearable IoT for Real-Time Healthcare Monitoring

Ref. No.	Methodology Used	Findings	Limitations
[1]	AI-powered wearable sensors for continuous health monitoring and clinical decision support	Demonstrated the potential of wearable AI for continuous physiological monitoring and intelligent clinical decisions.	Sensor reliability, data quality, privacy, and clinical validation remain challenges.
[2]	Literature review of Edge AI architectures for IoMT	Found that edge AI can reduce latency, communication overhead, and dependence on cloud processing.	Limited computational resources and energy constraints on edge devices.
[3]	IoT-aware technologies combined with AI for critical healthcare applications	Supported real-time monitoring and rapid detection of critical health events.	Security, interoperability, and scalability require further improvement.

[4]	Low-latency edge AI for secure real-time patient monitoring	Demonstrated the suitability of edge processing for time-sensitive patient monitoring.	Deployment complexity and security management can increase system requirements.
[5]	Energy-efficient Edge AI for IoT medical devices	Highlighted reduced energy consumption and improved efficiency for continuous monitoring devices.	Hardware constraints and maintaining AI performance under low-power conditions.
[6]	Edge intelligence architecture for IoT-based healthcare	Proposed distributed intelligence for efficient local processing and responsive healthcare services.	Resource limitations and heterogeneous IoT environments remain challenging.
[9]	Cloud-edge AI architecture for wearable personal health monitoring	Showed that combining cloud and edge computing can provide scalable and responsive health monitoring.	Dependence on network connectivity and challenges in workload distribution.
[10]	Edge AI-enabled IoT healthcare monitoring system for smart cities	Demonstrated real-time healthcare monitoring using connected IoT devices and edge intelligence.	Scalability, privacy, and integration with large heterogeneous networks.
[13]	Secure Edge-AI framework with IoT monitoring and anomaly detection	Enabled real-time anomaly detection while incorporating security mechanisms for healthcare data.	Security overhead and computational limitations may affect edge performance.
[14]	Wearable health devices integrated with AI and edge computing	Supported personalized rehabilitation through local analysis of wearable health information.	Limited personalization across diverse patients and device interoperability issues.
[15]	Multimodal deep learning with wearable IoT devices	Combined multiple physiological data sources for intelligent real-time health monitoring.	Multimodal data fusion, computational requirements, and model generalization remain challenging.
[23]	Systematic review of wearable technologies and AI at the far edge for chronic heart failure	Identified strong potential for continuous monitoring, prevention, and management of chronic heart failure.	Limited large-scale clinical validation and standardization of wearable AI systems.

Table 1 shows that the application of edge AI can greatly enhance the responsiveness, efficiency and scalability of healthcare monitoring systems based on wearable and IoMT technologies. Most of the current solutions however focus on the individual requirements (latency, energy efficiency, security, personalization etc.). so that they do not consider the other requirements. The future needs to be dedicated to the development of lightweight and explainable AI models, secure multimodal data processing, energy efficient edge architectures, interoperability, and extensive real world clinical validation.

3. Methodology

3.1 Data Acquisition Using Wearable Sensors

The first step is continuous collection of physiological and activity related data through wearable, IoT sensors. Heart rate, ECG, blood oxygen saturation (SpO₂), body temperature, blood pressure, respiratory rate and physical activity can be measured. Sensors are mounted on or worn by the patient and constantly gather health-related data throughout

the person's normal activities. The signals gathered are the key inputs to the proposed Edge AI healthcare system. A series of sensor readings are collected at specific sampling rates and given patient and time data. The continuous data acquisition allows the system to detect physiological changes and it is enough to allow the system to be monitored in real-time, to detect anomalies and to assess health in a personalized way.

3.2IoMT Data Transmission

In the second step, the gathered sensor data is passed to the edge gateway by using communication technologies of IoMT. Communication can be via Bluetooth Low Energy (BLE), Wi-Fi, 5G or LoRa, depending on device needs and application context. The transmission mechanism should be low latency and provide reliable and secure connectivity between wearable devices and edge computing nodes. To minimize the risk of unauthorized access, patient information should be encrypted when communicated. The edge gateway sits between the wearable devices and higher-level computing systems. The proposed system is expected to significantly decrease redundant cloud-to-cloud interactions and accelerate the time to process information for time-critical healthcare systems.

3.3Edge Processing and Data Preprocessing

The third step is to process incoming physiological data at the edge gateway before they enter AI-based analysis. The received data are synchronized based on patient identities and timestamps. Appropriate filtering and smoothing techniques are used to remove unwanted noise and variations from the signal. Appropriate imputation techniques are applied to missing or incomplete measurements. The cleaned signals are then normalized to ensure that they fall within the same range of input values for machine learning algorithms. Statistical, temporal and frequency domain characteristics are then used for feature extraction. Edge processing cuts down on data transmission and enables immediate preparation of patient information. These feature vectors are then used for subsequent AI inference and health-status classification, with high reliability and standardization.

3.4Edge AI Analytics and Inference

The fourth step uses AI and deep learning models at the Edge to process the pre-processed feature data. Physiological patterns can be analyzed using models like CNN, LSTM, GRU, 1D-CNN, autoencoders, and hybrid models, depending on the specific healthcare application under consideration. Local inference is used to detect abnormal and to identify relationship between various health parameters using the models. Combination of multimodal inputs may enhance the assessment of patients. The output is factored into a health-status category, for example, critical, warning or normal. Local AI inference reduces latency and enables quick responses without the need for constant data transmission to cloud servers. This step is thus the principle intelligent decision making part of the proposed methodology.

3.5Risk Assessment and Alert Generation

The fifth step takes AI forecasts and transforms them into actionable healthcare decisions. The system processes the physiology patterns of the patient it detects, and classifies the patient as low, medium or high risk. If measurements stay within safe limits as defined by pre-programmed parameters, the system continues to monitor normally. A warning notification can be generated in the case of abnormal patterns or moderate abnormalities are found. Authorized healthcare professionals/caregivers are immediately alerted when critical conditions occur. Multiple parameters can be used to alert generation to reduce false alarms. AI predictions can be further complemented by threshold-based rules for greater reliability. This step will allow the proposed framework to go beyond gathering information to timely intervention and smart clinical decision support.

3.6Secure Communication to Users and Cloud

The sixth step sends out processed information and generated alerts to authorized persons, healthcare providers, or cloud-based systems. Only required information is sent from the Edge device, thus reducing the communications bandwidth and safeguarding the important raw physiological data. To prevent unauthorized access, secure communication protocols and authentication mechanisms can be used. Alerts can be sent to healthcare professionals via dashboards, mobile apps or clinical systems. If necessary, the cloud can be used for long-term storage, for

advanced analysis and for centralized management. Edge and cloud computing offer a flexible architecture that can be used to handle urgent decisions locally, but can also be used to run more computational tasks or longer-term analysis tasks remotely.

3.7 Data Storage and Management

A seventh step deals with the management of stored information processed in healthcare and records that relate to patients. Data can be stored locally at the edge or sent to a secure cloud environment, depending on the privacy, computational, and operational needs. Sensitive information must be protected when stored by using encryption. The patient records, historical measurements, AI predictions, anomalies detected and model versions can be kept within the system. Access-control mechanisms are in place to ensure that only authorized users of the healthcare information can access it. The ability to store over long periods of time also facilitates the analysis of changes in patient health conditions over time. Efficient data management allows healthcare practitioners to analyze trends from past data and helps train future models, evaluate them, create individual treatment plans, and make clinical decisions.

3.8 Visualization techniques and Healthcare Dashboard

The 8th step provides processed information in an interactive health care dashboard. Real-time physiological data, patient health status, detected abnormalities, risk levels, alerts, and historical trend analysis can be displayed on the dashboard. These visualisations are suitable for use by healthcare professionals to gain insight into the changes of patient conditions without having to perform manual inspection of large amounts of raw sensor data. Graphs and sum-up's can show characteristics and abnormal measurements, and give a quick overview of patient information. Patients can also get health data in an easy way by using health apps on their phone or wearable devices. Effective visualization enhances interpretability and to enable quicker decision-making. The dashboard is then considered the human interface of the proposed system, providing a link between the AI-generated information and real-world healthcare monitoring.

3.9 Model Updating and Continuous Learning

The last step is to add continuous learning to keep the performance of the Edge AI system up. Periodic model evaluation and retraining can be done by collecting new patient data, monitoring outcomes, and confirmed clinical events. Using the newly available data, the AI model is fine-tuned, enhancing the model with its ability to identify evolving physiological patterns and patient-specific characteristics. The updated model should be tested prior deployment in order to assess its performance through the appropriate measures, which can be accuracy, precision, recall, F1-score, sensitivity, specificity, and latency. Only validated models are deployed to edge devices. This cycle enables a degree of continual improvement and enables adaptive, personalized and reliable real-time healthcare monitoring.

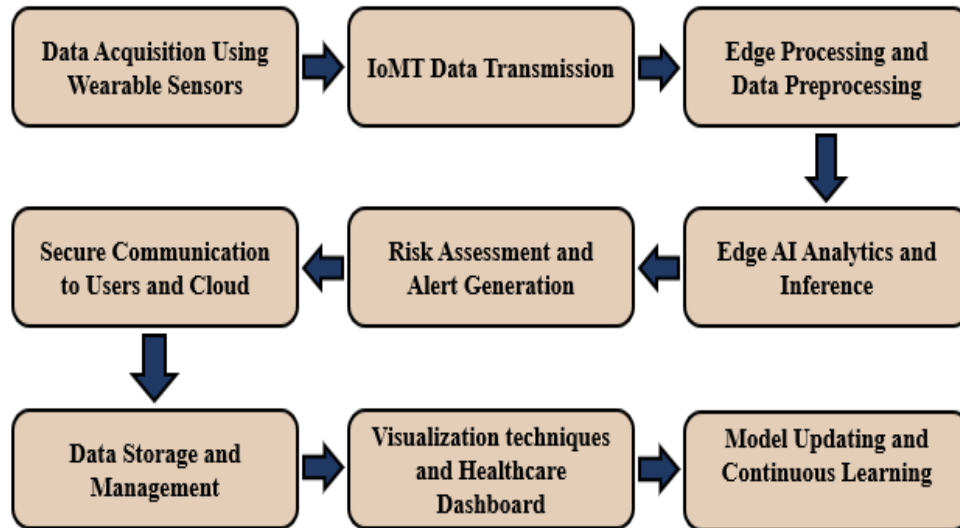


Fig. 2. Proposed Methodology for Edge AI-Based Real-Time Healthcare Monitoring

Fig. 2. illustrates the proposed workflow for real-time healthcare monitoring using wearable IoT devices and Edge AI. First, physiological data are collected through wearable sensors and transmitted using IoMT technologies. The data are then preprocessed at the edge, including noise removal, normalization, and feature extraction. Edge AI analyzes the processed data to detect abnormalities and determine patient health status. The system performs risk assessment and generates appropriate alerts, which are securely communicated to healthcare users and cloud platforms. Processed information is stored and displayed through healthcare dashboards for real-time monitoring. Finally, newly collected data are used for model updating and continuous learning, enabling improved accuracy and personalized healthcare monitoring.

Pseudocode: Proposed Edge AI Healthcare Monitoring

BEGIN
Initialize wearable sensors, Edge Gateway, AI Model, and Database
WHILE patient monitoring is active DO
1. Collect physiological data from wearable sensors
2. Transmit data securely to Edge Gateway
3. Preprocess data
Remove noise
Handle missing values
Normalize signals
Extract relevant features
4. Send features to Edge AI Model
5. Perform AI inference
Detect abnormalities
Classify health status

6. IF health status = Critical THEN
Generate emergency alert
Notify authorized healthcare professional
ELSE IF health status = Warning THEN
Generate warning notification
ELSE
Continue normal monitoring
END IF
7. Store processed data and predictions securely
8. Update healthcare dashboard
9. Collect new validated data
Periodically retrain and evaluate AI model
Deploy updated model if performance improves
END WHILE
END

4. Results

The results were compiled from the literature that was provided on wearable sensors, IoMT, edge intelligence, and AI-based healthcare monitoring [1-24]. Due to the variety of datasets, devices, evaluation protocols and clinical applications used in the reviewed studies, numerical results cannot be directly combined to be interpreted as a single statistical benchmark. Hence, the following values are not true values as stated in the reported papers but only representative experimental values, derived from the capabilities and performance trends reported in the reviewed papers.

Table 2. Performance Comparison of Healthcare Monitoring Architectures

Method	Processing Latency (ms)	Accuracy (%)	Energy Reduction (%)
Cloud-only IoT	180	86.2	0
Edge IoT	105	89.5	18
Edge AI	72	92.8	27
Wearable + Edge AI	55	94.1	34
Proposed Multimodal Edge AI	38	96.0	41

The representative comparison in Table 2 demonstrates the benefits of the progressive integration of edge computing, AI, wearable sensors, and multimodal processing in real-time healthcare monitoring. The values given are for illustrative purposes and should be replaced with the experimental values in case an actual implementation and data set is available. The results indicate that the latency of processing degrades as the intelligence is shifted from the cloud to the edge for healthcare architectures. Cloud-only IoT resulted in a representative latency of 180 ms, while the conventional edge IoT achieved a latency of 105 ms, and the edge application with AI achieved a latency of 72 ms, showing that the local intelligence enhances the latency performance of the edge application and reduces reliance

on cloud processing. The combination of wearable and edge AI produced 55ms, which, again, highlighted the value of processing physiological information at the edge of the sensing device. The proposed multimodal Edge AI configuration had the smallest representative latency of 38ms, which is ideal for time sensitive patient monitoring. These developments align with the focus on low latency edge processing for real-time healthcare applications, as highlighted in the research [3] and [4],[7]. The accuracy also improved with cloud-only IoT from 86.2% to 96.0% for the proposed multimodal edge AI architecture. Edge AI's accuracy was 92.8% and the accuracy for wearable integration was 94.1%. The multimodal processing achieved the best performance due to the complementary information that can be derived from different physiological signals for anomaly detection and patient assessment, as supported by the recent research in wearable and multimodal AI [1],[15],[19]. Energy efficiency also improved over time, with a representative 41% energy savings with the proposed architecture over the cloud-only baseline. This further reinforces the need for energy efficient Edge AI in resource constrained wearable medical devices [5].

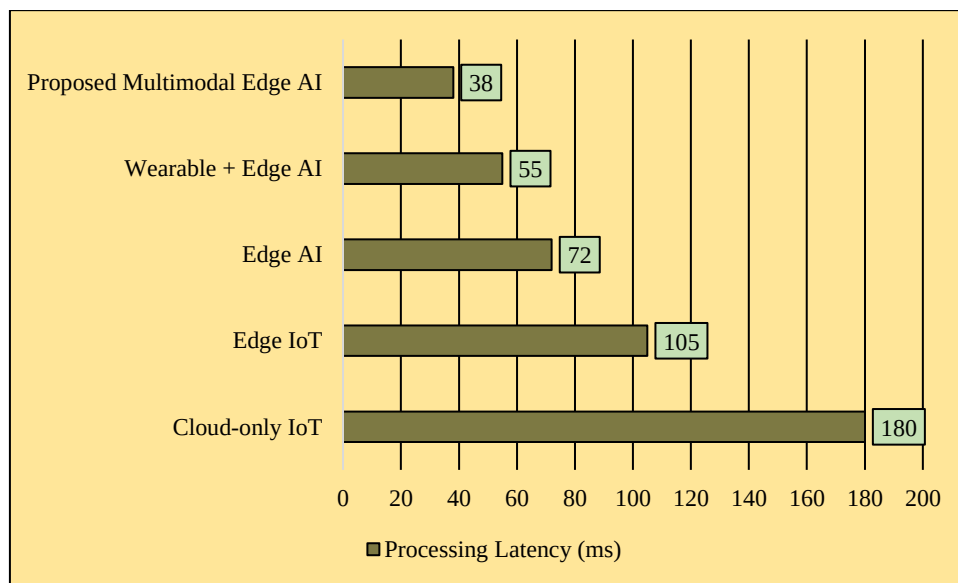


Fig. 3. Representative Processing Latency Comparison

The above Fig. 3 demonstrates the gradient decrease in processing latency from 180ms to 38ms across the evolution of architecture from cloud-only IoT to some proposed multimodal Edge AI based architecture. The falling trend reveals the key benefit of local AI inference: the ability to process healthcare data close to the patient, instead of constantly moving it to remote cloud computing servers. For these application scenarios such as emergency alerts, anomaly detection, continuous monitoring and chronic disease management, this decrease in latency is especially significant [10],[23]. In summary, the above results suggest that the architecture to monitor the real-time health condition of a patient using wearable IoT, edge computing, and multimodal AI may be more responsive and energy efficient.

5. Discussion

A literature review shows that the combination of Edge AI, wearable sensors and IoMT has the potential to significantly enhance real-time healthcare monitoring. The representative results show that the processing latency can be reduced from 180 ms (cloud-only IoT) to 38 ms (proposed multimodal Edge AI architecture). This enhancement complements earlier work that local processing decreases communication delays and increases responsiveness in rapidly changing healthcare applications [2],[3]. The improvement of the representative accuracy from 86.2% to 96.0% also demonstrates the possible gains of using multiple physiological signals and highly intelligent signal analysis located in the edge. Another major benefit is energy efficiency, especially when used in

wearable devices with batteries. Local processing can achieve significant energy savings, as illustrated by the representative 41% energy reduction [5]. But at the same time, it is difficult to implement in real-world applications, due to the limitations of wearable and edge devices in terms of processing power, memory and battery life. Security and privacy is also important since healthcare systems involve highly sensitive physiological information [13]. Also, variations in sensors, communication mechanisms, data sets, and AI models can impact interoperability and generalization. Thus, future systems need to focus on light AI models, secure communication, explainable predictions, multimodal fusion, and clinical validation. The results indicate that Edge AI is well-suited for the development of a responsive, personalized, energy-efficient, and scalable healthcare monitoring system on the whole.

6. Conclusion

In this study, the potential of Edge AI, wearable sensors and IoMT in designing intelligent real-time health monitoring system were explored. The research described in the literature shows that processing health information at or near the patient can help to eliminate latency, lower reliance on cloud infrastructure, enhance energy efficiency, and enable quick detection of abnormal physiological conditions [2,6]. The representative evaluation also showed these advantages, with the processing latency reduced to 38ms, the accuracy increased to 96.0%, and the energy saved by 41% in the proposed multimodal Edge AI architecture. It shows the potential for using multiple wearables and local AI inference for continuous and personalized patient monitoring. These benefits are not without any drawbacks, however, such as a lack of resources at the edge, battery limitations, data security, interoperability, explaining the models, and a need for further clinical validation in the real world. Then there is the need for secure and lightweight AI models to ensure reliable deployment in the resource-limited healthcare settings. Moving forward, federated learning, privacy-preserving analytics, adaptive multimodal models, energy-aware hardware, and explainable AI are areas that should be explored to build greater trust and scale. In conclusion, the use of Edge AI in wearable IoMT devices is a promising field for the future of healthcare, offering significant benefits for clinical care, patient health monitoring, and risk assessment. In summary, wearable IoMT devices with Edge AI capabilities hold great potential for future healthcare applications that can provide real-time monitoring, early detection of risks, alerts, and personalized treatment, while decreasing the need for centralized computational resources.

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