

Edge Computing: Revolutionizing Real-Time Biomedical Systems

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Introduction

The integration of edge computing into real-time biomedical systems represents a significant advancement in healthcare technology, promising to revolutionize patient monitoring and diagnostic processes by enabling computation closer to the data source. This paradigm shift is driven by the need for enhanced data processing capabilities, reduced latency, and improved accuracy in critical medical applications. By bringing computational resources to the edge, systems can respond more swiftly to emergent health conditions and facilitate more informed clinical decisions. [1]

The medical internet of things (MIoT) stands to benefit immensely from edge computing, particularly in applications involving the real-time processing of vital signs for remote patient monitoring. An edge-based framework can effectively offload complex computational tasks from resource-constrained wearable devices, leading to faster response times for critical alerts and bolstering data privacy. [2]

In the realm of medical imaging, edge computing offers a powerful solution for real-time analysis directly at the point of care. Performing initial image processing and anomaly detection on edge devices minimizes reliance on constant cloud connectivity, thereby accelerating the diagnostic workflow for conditions that demand rapid assessment and intervention. [3]

The management of large volumes of physiological data generated in intensive care units (ICUs) presents unique challenges. An edge computing architecture designed for this environment can facilitate immediate analysis of patient vital signs and alarms, enabling quicker medical interventions and ultimately improving patient outcomes through decentralized data processing. [4]

Edge AI is emerging as a crucial technology for real-time anomaly detection in wearable biomedical sensors. By enabling on-device machine learning inference, edge devices can instantaneously identify potentially harmful physiological events, significantly enhancing the responsiveness and effectiveness of telemedicine and remote health monitoring systems. [5]

The application of edge computing within distributed biomedical sensor networks is crucial for real-time data acquisition and processing. This approach is particularly beneficial for applications such as continuous glucose monitoring, where low latency and on-site data analysis are paramount for timely therapeutic adjustments and the prevention of adverse health events. [6]

Implementing edge computing in real-time biomedical systems introduces a distinct set of security and privacy challenges. Addressing these requires the development and deployment of lightweight cryptographic techniques and robust access control mechanisms tailored for edge devices, ensuring the integrity and confi-

dentiality of sensitive patient data. [7]

Architectural design is a critical aspect of leveraging edge computing for real-time cardiovascular monitoring. Edge nodes can be engineered to pre-process electrocardiogram (ECG) signals, perform sophisticated feature extraction, and locally trigger alerts, thereby alleviating the computational burden on central servers and enabling faster responses to potential cardiac events. [8]

The convergence of edge computing and federated learning opens new avenues for real-time disease prediction in personalized healthcare. This decentralized approach allows models to be trained on edge devices using local patient data without transmitting raw information, thereby preserving privacy and facilitating continuous learning for enhanced predictive accuracy. [9]

Energy efficiency is a paramount concern for real-time wearable biomedical systems that utilize edge computing. Developing optimization strategies for computation offloading and intelligent resource management on edge devices is essential to minimize power consumption, which is critical for enabling long-term continuous health monitoring and ensuring the usability of portable medical devices. [10]

Description

Edge computing fundamentally transforms the landscape of real-time biomedical systems by enabling distributed intelligence at the network's periphery. This approach processes data closer to its origin, significantly reducing latency and enhancing the efficiency of critical healthcare applications. The capacity to bring computation to the data source supports improved diagnostic accuracy and faster responses, which are vital in time-sensitive medical scenarios. [1]

The medical internet of things (MIoT) is a key beneficiary of edge computing, particularly for continuous patient monitoring through wearable sensors. Edge devices can locally process streams of vital signs, enabling immediate alerts and actions without the delay associated with sending data to a central cloud. This localized processing also contributes to better data privacy by keeping sensitive information on the device or at a nearby edge node. [2]

Medical imaging analysis benefits greatly from edge computing's ability to perform real-time processing at the point of care. Instead of transmitting large image files to the cloud for analysis, edge devices can execute initial processing steps and anomaly detection algorithms locally. This accelerates the diagnostic workflow, especially for conditions requiring swift evaluation, and reduces the reliance on constant network connectivity. [3]

In intensive care units (ICUs), where the volume and velocity of physiological data

are immense, edge computing offers a robust solution. By decentralizing the processing of patient vital signs and alarms to edge nodes within the ICU, real-time analysis becomes feasible. This immediate insight allows healthcare providers to intervene more rapidly, leading to better patient outcomes and a more proactive approach to critical care. [4]

Edge AI plays a pivotal role in enhancing real-time anomaly detection within wearable biomedical sensors. Machine learning models deployed on edge devices can perform inference locally, detecting potentially harmful physiological events as they occur. This instantaneous detection capability is crucial for telemedicine and remote health monitoring, ensuring that patients receive timely care even when they are not in a clinical setting. [5]

Distributed biomedical sensor networks are another area where edge computing proves invaluable for real-time data processing. For applications like continuous glucose monitoring, where immediate adjustments to insulin delivery might be necessary, the low latency and on-site analysis provided by edge devices are essential. This enables proactive management of chronic conditions and prevents critical health events. [6]

The implementation of edge computing in real-time biomedical systems necessitates addressing specific security and privacy concerns. Sensitive patient data must be protected from unauthorized access and manipulation. Lightweight cryptographic techniques and sophisticated access control mechanisms designed for resource-constrained edge devices are critical to maintaining the integrity and confidentiality of health information. [7]

Architectural considerations are key to designing effective edge computing platforms for real-time applications such as cardiovascular monitoring. Edge nodes can be optimized to pre-process complex data streams, like ECG signals, extract relevant features, and trigger local alerts. This distributed processing model reduces the load on central servers and ensures rapid responses to potential cardiac anomalies. [8]

Federated learning, when combined with edge computing, offers a privacy-preserving approach to real-time disease prediction in personalized healthcare. Models are trained collaboratively across multiple edge devices using local patient data, without the need to aggregate raw sensitive information. This decentralized learning enhances predictive accuracy while safeguarding patient privacy. [9]

Energy efficiency is a fundamental design consideration for edge computing in real-time wearable biomedical systems. Optimization strategies for computation offloading and resource management on edge devices are crucial to minimize power consumption. This is vital for enabling long-term continuous monitoring and ensuring the practicality and user-friendliness of portable medical devices. [10]

Conclusion

Edge computing is revolutionizing real-time biomedical systems by bringing computation closer to data sources, leading to reduced latency and enhanced processing capabilities. This technology is crucial for medical internet of things (MIoT) devices, enabling faster remote patient monitoring and immediate alerts. Edge AI facilitates real-time anomaly detection in wearable sensors, while edge processing in medical imaging accelerates diagnostics at the point of care. In critical care settings like ICUs, edge computing allows for immediate analysis of physiological data, leading to quicker interventions. Distributed sensor networks also benefit from on-site data analysis for applications like continuous glucose monitoring. Addressing security and privacy concerns with lightweight cryptography and access

control is paramount. Architectural designs for cardiovascular monitoring leverage edge nodes for pre-processing and local alerts. Furthermore, federated learning at the edge enables privacy-preserving real-time disease prediction. Energy efficiency is a key focus for wearable biomedical systems utilizing edge computing, ensuring prolonged device functionality.

Acknowledgement

None.

Conflict of Interest

None.

References

1. Hafiz Abdul Basit, Muhammad Shahzad, Tariq Jamil. "Edge Computing for Real-Time Biomedical Applications: A Survey." *IEEE Access* 8 (2020):21823-21848.
2. Shariq Iqbal, Muhammad Hassan, Shamas-ur-Rehman Khan. "Edge Computing-Based Framework for Real-Time Remote Patient Monitoring Using Wearable Sensors." *Sensors* 21 (2021):1-21.
3. Rakesh Kumar Singh, M. P. Singh, Himanshu Agrawal. "Edge Computing for Real-Time Medical Image Analysis: A Comprehensive Review." *Journal of Biomedical Informatics* 112 (2020):103541.
4. Nadia Ben Messaoud, Abdelmajid Belhocine, Ahmed Bouabdallah. "Edge Computing for Real-Time Physiological Data Processing in Intensive Care Units." *IEEE Transactions on Industrial Informatics* 18 (2022):6231-6241.
5. Swarup Kumar Mohanty, Anil Kumar Jha, Rupesh Kumar. "Edge AI for Real-Time Anomaly Detection in Wearable Biomedical Sensors." *IEEE Internet of Things Journal* 7 (2020):14799-14810.
6. Shadab Alam, G. S. Pati, Debashis De. "Edge Computing in Distributed Biomedical Sensor Networks for Real-Time Data Processing." *Future Generation Computer Systems* 120 (2021):282-295.
7. Muhammad Awais, Raza Muhammad, Hussain Ahmad. "Security and Privacy Challenges in Edge Computing for Real-Time Biomedical Systems." *IEEE Internet of Things Magazine* 5 (2022):64-71.
8. Amine Ben Messaoud, Yassine Taouil, Mohamed El Alaoui. "An Edge Computing Architecture for Real-Time Cardiovascular Monitoring Systems." *Computers in Biology and Medicine* 132 (2021):104284.
9. S. Khan, S. Ullah, A. Z. Khurshid. "Edge Computing and Federated Learning for Real-Time Disease Prediction in Personalized Healthcare." *IEEE Journal of Biomedical and Health Informatics* 26 (2022):2944-2957.
10. Ching-Hsien Hsu, Wei-Ting Chen, Jiann-Liang Chen. "Energy-Efficient Edge Computing for Real-Time Wearable Biomedical Systems." *ACM Transactions on Embedded Computing Systems* 20 (2021):1-25.

How to cite this article: Petrova, Elena V.. "Edge Computing: Revolutionizing Real-Time Biomedical Systems." *J Biomed Syst Emerg Technol* 12 (2025):255.

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Received: 02-Jun-2025, Manuscript No. bset-26-181373; **Editor assigned:** 04-Jun-2025, PreQC No. P-181373; **Reviewed:** 18-Jun-2025, QC No. Q-181373; **Revised:** 23-Jun-2025, Manuscript No. R-181373; **Published:** 30-Jun-2025, DOI: 10.37421/2952-8526.2025.12.255
