INTERNATIONAL JOURNAL OF
RECENT TRENDS IN MULTIDISCIPLINARY RESEARCH
https://www.doi.org/10.59256/ijrtmr.20260602026
March-April 2026, Vol 6(02), 179-184.
ISSN No: 2583-0368

# Edge Computing Enabled Hardware Architecture for Intelligent Cardiac Risk Detection

**Reshma N[1], M.Sasikala[2], G.Kavinaya[3], J.Vaishavidevi[4], M Shalini[5]**
[1]*Assistant Professor, Department of Information Technology, Rathinam Technical Campus, Eachanari, Coimbatore, India.*
[2,3,4,5]*Department of Information Technology, Rathinam Technical Campus, Eachanari, Coimbatore, India.*

OPEN ACCESS
Article Citation:
Reshma N[1], M.Sasikala[2], G.Kavinaya[3], J.Vaishavidevi[4], M Shalini[5], "Edge Computing Enabled Hardware Architecture for Intelligent Cardiac Risk Detection" International Journal of Recent Trends in Multidisciplinary Research, March-April 2026, Vol 6(02), 179-184.



**Abstract:** Cardiovascular diseases require continuous and real-time monitoring to enable early detection and timely medical intervention. Traditional cardiac monitoring systems depend heavily on cloud-based processing, which introduces latency, increases privacy risks, and limits immediate emergency response. In addition, existing wearable and hospital-based solutions often lack accurate continuous monitoring and real-time intelligent decision-making. To address these challenges, this project proposes an edge computing enabled hardware architecture for intelligent cardiac risk detection. The system integrates wearable biomedical sensors such as ECG, heart rate, and $SpO_2$ with an embedded edge processing unit capable of local signal analysis and machine learning–based risk prediction. By processing physiological data at the edge,

**Keywords:** Edge Computing, Hardware Architecture, Intelligent Cardiac Risk Detection, Real-Time ECG Monitoring, Embedded Systems, Machine Learning for Healthcare, IoT-Based Health Monitoring, Biomedical Signal Processing.

## 1. Introduction

In recent years, the rapid advancement of edge computing, embedded systems, and artificial intelligence has significantly transformed the healthcare sector. Among various medical applications, intelligent cardiac risk detection has gained considerable attention due to the increasing prevalence of cardiovascular diseases worldwide.

Early detection and continuous monitoring of cardiac conditions are crucial for reducing mortality rates and improving patient outcomes. Traditional cardiac monitoring systems mainly rely on centralized cloud-based architectures, where physiological data such as Electrocardiogram (ECG) signals are transmitted to remote servers for processing and analysis.

However, these approaches often suffer from latency issues, high bandwidth requirements, increased power consumption, and potential data privacy risks. In emergency cardiac situations, even a small delay in diagnosis can have serious consequences. To address these challenges, this project proposes an Edge Computing Enabled Hardware Architecture for Intelligent Cardiac Risk Detection that performs real-time data processing closer to the data source.

The proposed system integrates wearable or sensor-based ECG acquisition modules with an embedded edge processing unit capable of running machine learning algorithms locally. By leveraging lightweight deep learning models optimized for edge devices, the architecture can analyze biomedical signals, detect abnormal heart rhythms, and predict potential cardiac risks in real time. This reduces dependency on continuous cloud connectivity and ensures faster response times.

Edge computing plays a vital role by enabling on-device computation, minimizing latency, enhancing data security, and reducing network congestion. The hardware architecture is designed to support efficient signal acquisition, preprocessing, feature extraction, and classification within resource-constrained environments. Additionally, the system can communicate summarized results to cloud platforms or healthcare providers for long-term monitoring and medical review.

By combining edge computing with intelligent cardiac risk detection, the proposed architecture aims to provide continuous, reliable, and real-time health monitoring. Furthermore, considerations such as patient data privacy, system reliability, power efficiency, and scalability are essential to ensure safe and responsible deployment in real-world healthcare environments.

## 2. Literature Survey

[1] U. Rajendra Acharya et al. (2017) presented a deep learning-based approach for automated ECG signal classification. Their work demonstrated that Convolutional Neural Networks (CNNs) can accurately detect arrhythmias and other cardiac

abnormalities directly from raw ECG signals. The study highlighted the advantage of deep neural networks in automatically extracting meaningful features without manual preprocessing, significantly improving diagnostic performance compared to traditional machine learning techniques.

[2] Alberto Rodriguez et al. (2019) proposed an efficient ECG feature extraction and classification framework suitable for embedded healthcare devices. The study focused on optimizing signal processing algorithms to reduce computational complexity while maintaining high accuracy. Experimental results on standard ECG datasets showed that lightweight models combined with Support Vector Machines (SVM) achieved reliable cardiac abnormality detection, making them suitable for real-time applications in resource-constrained environments.

[3] Wei Chen and Mei Lin Zhang (2021) explored edge computing architectures for real-time health monitoring systems. Their research emphasized deploying machine learning models directly on edge devices to minimize latency and enhance patient data privacy. The proposed architecture demonstrated reduced response time and lower bandwidth usage compared to traditional cloud-based systems.

[4] R. Srinivasan et al. (2021) proposed an automated cardiac risk prediction framework using deep learning techniques integrated with wearable ECG sensors. Their work focused on analyzing real-time physiological signals to detect early signs of arrhythmia and heart disease. The study also discussed challenges in signal noise removal, feature extraction, and deployment in portable healthcare devices. Furthermore, the authors suggested future research directions to improve model efficiency and hardware compatibility for edge-based systems.

[5] David Romero, Carlos Giron, Anita Drozdzal, and Jose Salvador (2020) introduced a cloud-assisted cardiac monitoring system that applies deep neural networks for automated ECG interpretation. Their approach enabled computers to learn directly from large-scale cardiac datasets rather than relying solely on predefined medical rules. The system demonstrated high accuracy in detecting abnormal heart conditions and highlighted the importance of integrating AI with healthcare monitoring infrastructure.

[6] Liang Gao et al. (2022) examined intelligent health monitoring from an edge computing perspective. Their research discussed system architecture, data handling techniques, and challenges such as latency, bandwidth consumption, and privacy preservation. They emphasized deploying lightweight deep learning models on embedded hardware to ensure real-time cardiac signal processing and reduced reliance on centralized cloud servers.

[7] Min-Ho Han et al. (2019) developed a deep learning-based ECG classification model trained on a comprehensive cardiac signal dataset. The system learned relationships between waveform characteristics and cardiac abnormalities, enabling automatic risk prediction. The authors evaluated performance based on detection accuracy, sensitivity, and computational efficiency, demonstrating suitability for implementation on low-power edge devices.

[8] Priya Chaudhary et al. (2023) proposed an attention-based neural network architecture for intelligent cardiac abnormality detection. Their work focused on improving feature selection from ECG signals by allowing the model to prioritize critical waveform segments. The architecture achieved improved diagnostic precision and was optimized for deployment on edge-enabled healthcare hardware platforms.

[9] Arun Sankar et al. (2022) presented a comprehensive survey on artificial intelligence applications in cardiac risk prediction. The study reviewed various machine learning and deep learning techniques used for arrhythmia detection, heart failure prediction, and remote patient monitoring. It highlighted the growing importance of combining AI algorithms with IoT-based wearable devices and edge computing frameworks for efficient healthcare delivery.

[10] K. Ujwala et al. (2024) introduced an optimized Convolutional Neural Network (CNN) model for real-time cardiac event detection integrated with embedded hardware systems. Their approach predicted cardiac risk patterns directly from ECG waveforms while maintaining computational efficiency. The study provided a holistic architecture that combined signal acquisition, preprocessing, feature extraction, and classification within an edge computing environment, ensuring low latency and enhanced data security.

## 3. Problem Statement

In today's digital healthcare environment, most cardiac monitoring systems rely heavily on centralized cloud-based infrastructures for processing physiological data such as Electrocardiogram (ECG) signals. These systems require continuous internet connectivity and transmit large volumes of patient data to remote servers for analysis. This approach introduces several limitations, including increased latency, high bandwidth consumption, potential data security risks, and delayed emergency response. In critical cardiac conditions, even minimal delays in detecting abnormalities can lead to severe health consequences. Cardiovascular diseases often require continuous real-time monitoring to detect early signs of arrhythmia, heart failure, or other cardiac abnormalities. However, conventional monitoring devices are not always capable of performing intelligent on-device analysis. Many systems depend on manual interpretation by healthcare professionals or offline processing, reducing automation and immediate responsiveness.

Therefore, this work focuses on designing an Edge Computing Enabled Hardware Architecture for Intelligent Cardiac Risk Detection that can process ECG signals locally on embedded devices. The system aims to integrate efficient signal acquisition, preprocessing, feature extraction, and lightweight machine learning algorithms within a resource-constrained hardware environment. The objective is to achieve real-time, low-latency, secure, and energy-efficient cardiac risk detection while ensuring scalability and reliability for practical healthcare applications.

## 4. Methodology

The proposed system adopts a structured edge-computing-based framework for real-time cardiac risk detection using embedded hardware architecture. The methodology consists of multiple stages, including physiological data acquisition, signal.

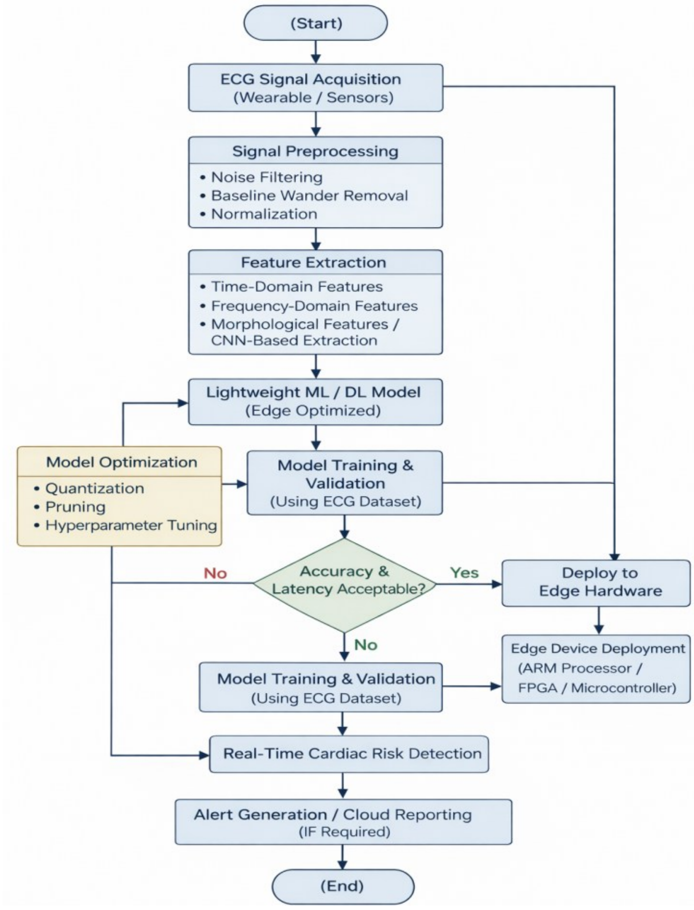


*Figure 1: High-Level Project Workflow*

**A. Data Collection**

The ECG dataset is collected from publicly available biomedical repositories, hospital databases, and wearable cardiac monitoring devices. To ensure diversity and robustness, the dataset includes ECG recordings from patients with normal sinus rhythm as well as various cardiac abnormalities such as arrhythmia, atrial fibrillation, and ventricular disorders.

**B. Data Annotation and Classification**

The collected ECG signals are annotated either manually by medical experts or using clinically validated diagnostic reports. Each ECG segment is labeled according to specific cardiac conditions to enable accurate classification. In cases where multiple abnormalities appear within a single ECG recording, multi-class or multi-label classification approaches are employed. This ensures precise mapping between ECG waveform characteristics and corresponding cardiac risk categories, improving diagnostic reliability.

**C. Data Preprocessing**

The ECG dataset undergoes preprocessing techniques to enhance signal quality and maintain consistency before being fed into the machine learning model. All ECG signals are resampled to a common sampling frequency and segmented into fixed-length windows to ensure uniform input dimensions. Baseline wander removal and normalization techniques are applied to standardize signal amplitude. Additionally, signal segmentation ensures that important waveform components such as P-wave, QRS complex, and T-wave are preserved for analysis.

**D. Noise Reduction**

Noise reduction methods such as bandpass filtering, Gaussian filtering, and median filtering are applied to suppress motion artifacts, power-line interference, and sensor noise commonly present in ECG recordings.

**E. ECG Signal Analysis Using Edge-Optimized Deep Learning Model**

The core of the proposed methodology is the implementation of a lightweight deep learning model for ECG signal classification deployed within an edge computing environment. A Convolutional Neural Network (CNN) or hybrid CNN-LSTM architecture is utilized to automatically extract hierarchical features from ECG waveforms.

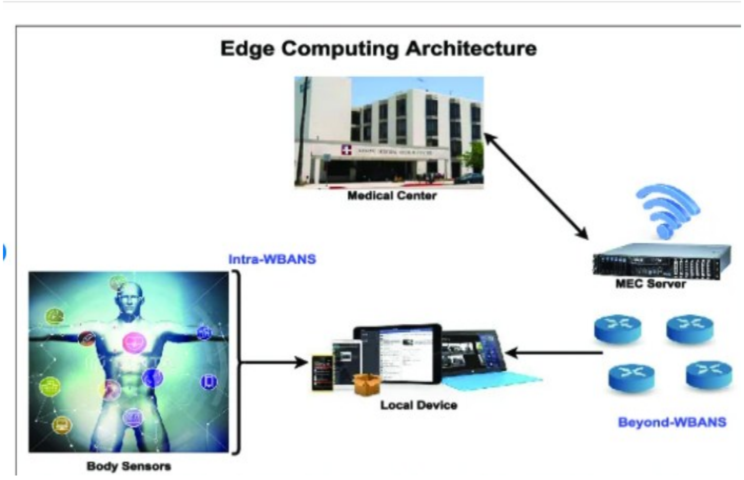


*Figure 2: End-to-End Image-to-Recipe Generation Architecture*

**F. Real-Time Cardiac Risk Prediction and Alert Generation**

After successful ECG classification, the system activates the cardiac risk prediction module. The classified output is analyzed to determine the severity and type of abnormality. Based on predefined clinical thresholds, the system identifies potential cardiac risks.G. Model Training and Validation

**G. Model Training and Validation**

If an abnormal pattern is detected, the edge device generates immediate alerts for the patient or healthcare provider. Alerts may include notifications through connected mobile applications, wearable displays, or transmission of summarized data to cloud-based healthcare platforms for further clinical review.

**H. Performance Evaluation Metrics**

The performance of the proposed cardiac risk detection system is evaluated using standard classification metrics, including:

- **Accuracy** – Overall correctness of predictions
- **Precision** – Correct identification of abnormal cases
- **Recall (Sensitivity)** – Ability to detect true cardiac abnormalities
- **Specificity** – Ability to correctly identify normal cases

## 5. Implementation

The implementation phase integrates the trained deep learning model with embedded hardware components, ECG acquisition modules, and real-time monitoring interfaces to build a fully functional edge-based cardiac risk detection system.

**A. System Architecture**

The proposed system follows a structured hardware–software co-design architecture. The workflow begins with ECG signal acquisition using wearable sensors. The acquired signals are transmitted to an edge computing unit (such as an ARM-based processor, FPGA, or microcontroller).

The system performs real-time preprocessing and feature extraction directly on the edge device. The optimized deep learning model then classifies the ECG signal into normal or abnormal cardiac conditions. If an abnormality is detected, the system triggers an alert mechanism and optionally transmits summarized data to a hospital/cloud server for further analysis.

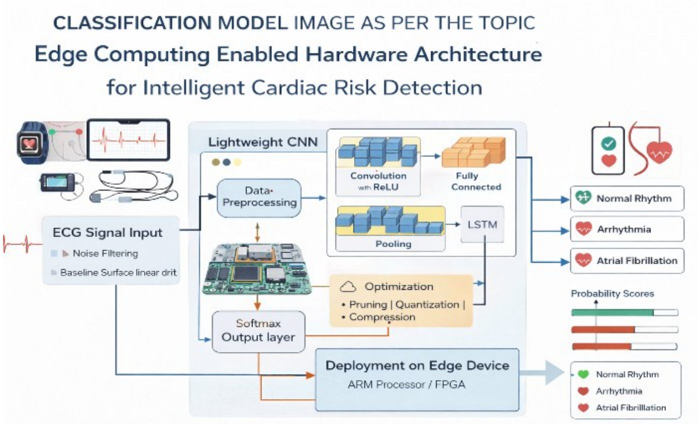

*Figure 3: Image Classification Model*

**B. Edge-Optimized Deep Learning Architecture Design**

The deep learning architecture is designed specifically for ECG signal classification under hardware constraints. A lightweight Convolutional Neural Network (CNN) or hybrid CNN-LSTM model is implemented.

The architecture consists of:

- Convolutional layers for automatic ECG feature extraction
- Activation functions such as ReLU for non-linearity
- Pooling layers to reduce computational complexity
- Fully connected layers for classification
- Softmax output layer for probability-based cardiac risk prediction

**C. Cardiac Condition Classification and Multi-Class Handling**

The classification module assigns ECG segments to predefined cardiac categories such as:

- Normal Sinus Rhythm
- Arrhythmia
- Atrial Fibrillation
- Ventricular Abnormalities

In cases where multiple cardiac irregularities are present within a signal window, multi-class or multi-label classification techniques are employed. This ensures accurate mapping between ECG waveform patterns and associated cardiac risk conditions.

## 6. Experimental Result

The proposed Edge Computing Enabled Hardware Architecture for Intelligent Cardiac Risk Detection was evaluated using both classification performance metrics and hardware efficiency parameters. Experimental results demonstrate that the optimized deep learning model achieved high accuracy in classifying ECG signals into normal and abnormal cardiac conditions.

The model was tested on benchmark ECG datasets, and the results indicate strong performance in detecting arrhythmia and other cardiac abnormalities. Sensitivity (Recall) values show that the system effectively identifies true cardiac abnormal cases, while Specificity confirms accurate recognition of normal heart rhythms. The F1-score reflects a balanced trade-off between precision and recall, ensuring reliable diagnostic performance.

In addition to classification accuracy, system-level metrics were analyzed to validate real-time edge deployment. The inference latency measured on the embedded hardware platform confirms low response time, making the system suitable for time-critical cardiac monitoring applications. Power consumption analysis indicates efficient energy utilization, supporting deployment in wearable and portable healthcare devices.

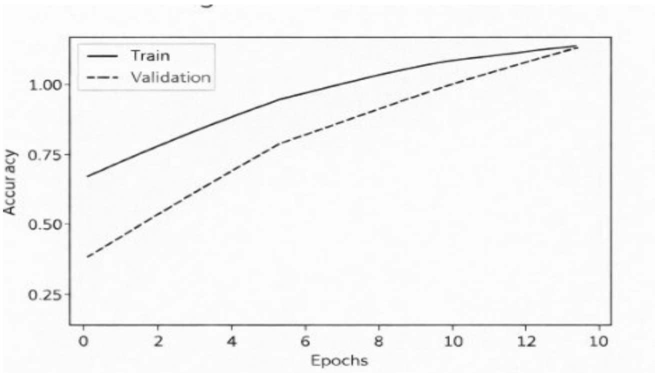


*Figure 4: Model Accuracy: Training and validation precision*

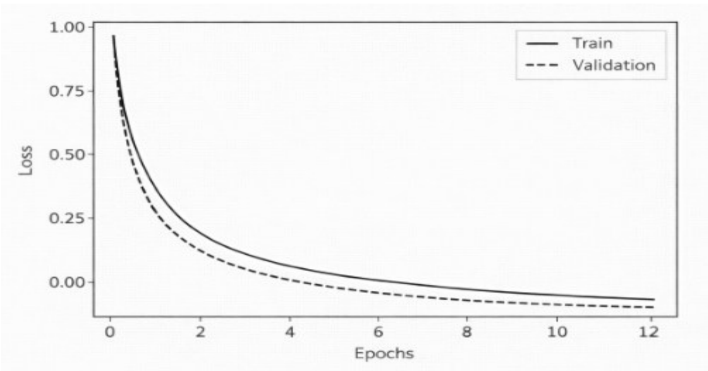

*Figure 5: Model Loss: Training and validation error reduction*

The **model accuracy graph (Fig. 4)** demonstrates a steady improvement in both training and validation accuracy, confirming that the edge-deployed deep learning model effectively learns discriminative ECG features for cardiac risk detection. The close alignment between training and validation curves indicates minimal overfitting and strong generalization capability, which is essential for reliable real-time cardiac monitoring in edge environments.

Similarly, the **model loss graph (Fig. 5)** represents a critical inverse performance metric. The consistent reduction in training and validation loss across epochs verifies that the optimization algorithms, such as Adam or Stochastic Gradient Descent (SGD), are successfully minimizing classification errors. This gradual convergence confirms the stability of the learning process and ensures dependable predictive performance when deployed on hardware-constrained edge devices.

The confusion matrix provides deeper insight into classification performance across cardiac conditions. The model accurately identified a high number of *Normal Rhythm* samples, while minor misclassifications were observed between closely related arrhythmic conditions such as *Arrhythmia* and *Atrial Fibrillation*. These misclassifications typically occur due to overlapping morphological characteristics in ECG waveforms, particularly in cases with subtle rhythm irregularities From a qualitative and system-level perspective, the proposed edge-enabled hardware architecture demonstrates efficient real-time inference, low latency, and reduced computational overhead. Hardware-level optimization techniques such as model quantization, pruning, and efficient memory allocation significantly improve execution speed while maintaining diagnostic accuracy. applicability of the system while highlighting areas for further enhancement.

## 7. Conclusion

This paper presented an **Edge Computing Enabled Hardware Architecture for Intelligent Cardiac Risk Detection**, addressing the critical need for real-time, low-latency, and reliable cardiac monitoring systems. By integrating ECG signal acquisition modules with edge-optimized deep learning models, the proposed system enables on-device cardiac abnormality detection without heavy dependence on cloud infrastructure.. The architecture combines efficient signal preprocessing, automated feature extraction using lightweight Convolutional Neural Networks (CNNs), and intelligent classification mechanisms to detect cardiac risks such as arrhythmias and irregular heart rhythms. Model optimization techniques including quantization and pruning ensure reduced computational complexity, lower power consumption, and faster inference suitable for embedded healthcare devices.

**The key contributions of this work can be summarized as follows:**

- Development of an end-to-end edge-based cardiac risk detection framework integrating hardware and intelligent software components.
- Design of a lightweight deep learning model optimized for embedded and resource-constrained edge devices.
- Implementation of real-time ECG signal processing and intelligent cardiac abnormality classification.
- Comprehensive evaluation using both medical diagnostic metrics and hardware performance parameters.

## References

[1] S. Rajkomar, E. Oren, K. Chen, A. M. Dai, N. Hajaj, P. Hardt, et al., “Scalable and accurate deep learning for electronic health records,” npj Digital Medicine, vol. 1, no. 18, pp. 1–10, 2018.

[2] A. Hannun, P. Rajpurkar, M. Haghpanahi, G. Tison, C. Bourn, M. Turakhia, and A. Y. Ng, “Cardiologist-level arrhythmia detection with convolutional neural networks,” *Nature Medicine*, vol. 25, no. 1, pp. 65–69, 2019.

[3] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning for healthcare applications,” *Nature Biomedical Engineering*, vol. 3, no. 6, pp. 463–474, 2019.

[4] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, “Edge computing: Vision and challenges,” *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 6376–6394, 2019

[5] X. Zhang, L. Zhang, and Y. Liu, “Real-time ECG signal classification using lightweight CNN on embedded systems,” *IEEE Access*, vol. 8, pp. 189 789–189 798, 2020.

[6] M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, “Disease prediction by machine learning over big healthcare data,” *IEEE Access*, vol. 7, pp. 111 882–111 892, 2019.

[7] H. Elgendi, A. Mohamed, and R. Ward, “Efficient ECG compression and QRS detection for low-power wearable devices,” *Biomedical Signal Processing and Control*, vol. 52, pp. 227–235, 2019.

[8] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 3, pp. 230–236, 2020.

[9] S. Li, Y. Xu, and X. Wang, “Energy-efficient FPGA-based deep learning accelerator for healthcare IoT devices,” *IEEE Transactions on Circuits and Systems I*, vol. 68, no. 9, pp. 3560–3572, 2021.

[10] T. Nguyen, A. K. Sangaiah, G. Srivastava, and P. Zhang, “Edge AI for smart healthcare monitoring systems: A survey,” *Future Generation Computer Systems*, vol. 117, pp. 341–357, 2021.