RESEARCH PAPER

Smart Cardiovascular Care: Leveraging Edge Computing and IoT for Enhanced Diagnostic Capabilities

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ABSTRACT

This paper delves into the transformative impact of modern healthcare technologies, particularly edge computing, IoT, and AI, on cardiovascular diagnostics and care. As traditional cloud computing infrastructures struggle to meet evolving demands for real-time data processing and personalized patient care, the emergence of edge computing offers a promising solution. The paper highlights the advantages of edge-based solutions in terms of latency, mobility, and energy efficiency. Given the prevalence of cardiovascular disease globally, the need for innovative approaches in healthcare delivery is emphasized. The paper delves into how edge computing and IoT are utilized in smart healthcare, emphasizing their widespread adoption and indispensable utility. By conducting an extensive research, this paper delves into the complexities of the complex interactions between edge computing, IoT, and AI, and to enhance understanding of their potential to transform healthcare practices and enhance patient outcomes.

Keywords: ECG, EdgeIoT, cardiovascular diseases, IoMT, ML.

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Introduction:

The emergence of state-of-the-art healthcare technologies requires fast, energy-saving computing, improved storage, and location awareness. Traditional cloud computing infrastructures, while effective for many applications, struggle to meet these evolving demands efficiently.[1] As healthcare services increasingly rely on real-time data processing, personalized patient care, and seamless connectivity across devices, there's a growing need for innovative solutions that can deliver the computational power and responsiveness required to support these critical functions.[2]This has led to the emergence of edge computing, distributed networks, and other novel approaches tailored to the unique requirements of the healthcare industry.

Mobile cloud computing (MCC), which predates edge computing, is characterized by significant data transmission costs, extended response times, and restricted coverage.[3][4] Solutions such as cloudlets and local clouds provide a lower quality of service (QoS) for new devices., primarily due to high network traffic that increases transmission times. While cloudlet-based solutions reduce latency compared to MCC, they still struggle with mobility issues due to limited WiFi coverage. Comprehensive comparisons between cloud-based and edge-based computing demonstrate that only edge-based solutions fulfill contemporary demands for latency[5][6], mobility[7][8][9], and energy efficiency[10]. Edge computing minimizes latency for time-critical applications, such as monitoring vital signs and detecting falls in the elderly. With enhanced tracking and mobility, edge systems enable health providers to care for chronically ill patients at home using ambient and wearable sensors.[11][12] These sensors collect both indoor and outdoor data, allowing healthcare workers to monitor patients effectively. This approach personalized healthcare, tailoring it to individual needs. For optimal real-time service, edge devices need to function with low latency, energy efficiency, location awareness, and robust security.

This is particularly crucial given the prevalence of cardiovascular disease (CVD), a collective term for disorders related to the heart or blood vessels.[13] According to the OECD and the European Observatory on Health Systems and Policies,Cardiovascular disease (CVD) remains the primary cause of death and disability for women globally, and the second most common cause for men. In India, CVD has been the leading cause of morbidity and mortality, affecting both urban and rural populations and increasingly impacting younger age groups.[14] The prevalence of risk factors associated with CVD is rising rapidly, prompting numerous epidemiological studies to trace its prevalence and forecast future trends. Globally, CVDs are a dominant cause of death, with statistics from the American Heart Association in 2019 revealing that more than 17.6 million deaths occurred in 2016, a figure projected to reach 23.6 million by 2030.[15] CVDs can cause blockages and blood clots, leading to conditions like stroke and myocardial infarction. Long-term poor blood pumping by the heart can result in congestion and oxygen deprivation in all organs, causing varying degrees of damage.

The electrocardiogram (ECG) is essential in cardiovascular diagnostics, providing crucial insights into the electrical activity of the heart. Since its inception, ECG has revolutionized clinical practice, emerging as a pivotal tool for the non-invasive assessment of cardiac function and pathology. By capturing the intricate rhythm and conduction patterns of the heart, ECG aids in the identification of various cardiac abnormalities, ranging from arrhythmias to ischemic events Its widespread adoption is attributed to its simplicity, cost-effectiveness, and minimal invasiveness, rendering it indispensable in both acute and chronic cardiac care settings. In this survey paper, we provide a comprehensive survey of the intricate interplay between edge computing, IoT, and AI within the realm of modern healthcare, with a particular focus on cardiovascular diagnostics and care. As we delve deeper into the subsequent sections, we aim to provide an in-depth analysis of the advancements, challenges, and opportunities presented by these transformative technologies. By elucidating their roles in enhancing healthcare delivery and addressing critical issues such as real-time data processing, personalized patient care, and seamless connectivity, this paper seeks to offer valuable insights that contribute to the ongoing evolution of healthcare practices.

Key objective:

This survey paper explores the integration of edge IoT and AI methodologies in healthcare, focusing on advancements in cardiovascular diagnostics and care. Highlighting the role of AI and machine learning in ECG signal analysis for arrhythmia detection and atrial fibrillation screening, the paper emphasizes edge computing's capability to enhance real-time processing and remote health monitoring. It addresses challenges like edge node efficiency, data privacy, and computational demands, advocating for future research on secure frameworks and scalable AI models. Ultimately, the paper aims to drive advancements in healthcare delivery by improving diagnostic accuracy, patient outcomes, and overall system reliability through innovative technology integration.

About Sections:

The paper is structured into multiple crucial parts to offer a thorough grasp of the merging of edge computing and IoT within the healthcare sector, with a specific emphasis on ECG analysis. The first section delves into the fundamentals of ECG, explaining its significance in cardiovascular diagnostics. The second section explores the concepts of Edge IoT and computing, highlighting their roles in enhancing healthcare delivery. Following this, the literature survey presents a detailed review of existing research, summarized in two tables: one highlighting studies on edge computing, and the other focusing on papers that incorporate edge computing in ML/AI deployment. Subsequently, the survey review discusses the findings and insights from the literature, paving the way for the future direction of research in this field. The paper finally brings the key points and potential implications for future advancements.

1. Electrocardiogram (ECG) Signal

The Electrocardiogram (ECG) signal serves as a crucial tool in analyzing the electrical activity of the heart, providing insights into cardiac function and detecting potential abnormalities.[16] By measuring the electric potential changes generated by the heart during each cardiac cycle, an ECG machine captures this non-stationary physiological signal, enabling the identification of pathological patterns and assessing the regularity of heartbeats.[17] Through electrodes placed on different parts of the body tissue, the ECG signal is obtained and recorded using electrocardiographs, allowing for the diagnosis of various heart conditions, including arrhythmia, myocardial infarction, and coronary heart disease, as well as associated medical comorbidity such as diabetes and high blood pressure.

The ECG waveform, depicted by a consecutive sequence of electrical waves marked by peaks (P, Q, R, S, T, and occasionally U), provides crucial details about the duration and amplitude of electrical signals coursing through the heart muscle. Spanning a frequency range typically between 0.05 and 100 Hz, and with a dynamic range of 1–10 mV, the ECG signal enhances its diagnostic value. Accurate detection of these peaks and valleys, especially the QRS complex, alongside the T and P waves, forms the cornerstone of ECG analysis. This analysis aids in diagnosing cardiac arrhythmias, conduction issues, ventricular hypertrophy, myocardial infections, and other cardiac conditions, as illustrated in Figure 1.

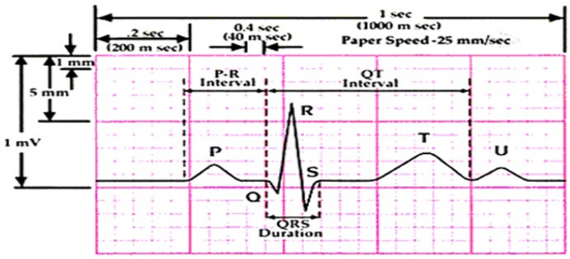

Fig. 1. A typical Cardiac Waveform [18]

The atrial activation is indicated by the P-wave in an ECG waveform, while the ventricular excitation and repolarization are represented by the QRS complex and T-wave, respectively. Automated ECG analysis relies on the detection of the QRS complex, which guides further waveform assessment to examine the rhythmic electrical depolarization and repolarization of the myocardium during atrial and ventricular contractions. Diagnosing various cardiac conditions depends on the essential duration, amplitude, and morphology of the QRS complex, typically with a normal heart rate ranging from 60 to 100 beats per minute.[20][21]

2. Edge IoT and Computing

Edge IoT and computing revolutionize traditional computing architectures by decentralizing processing power, bringing it closer to the data source. This change removes the necessity for data to be transmitted to and from centralized cloud infrastructure, thereby minimizing latency and reducing bandwidth usage. At the technical level, edge IoT and computing entail the integration of IoT devices with computational resources and software frameworks deployed at the network edge or directly on the devices themselves. These devices are equipped with CPUs, GPUs, or specialized hardware accelerators to handle processing tasks, along with connectivity protocols for communication with other devices and systems.[22]

In healthcare, edge IoT and computing play a vital role in enabling real-time monitoring and analysis of patient health data Wearable health monitoring devices, for instance, collect continuous data on vital signs such as heart rate and blood pressure. Through edge computing capabilities, these devices process the data locally, employing advanced algorithms to detect anomalies or patterns indicative of health issues. [23]This localized processing enables timely alerts to healthcare providers or automated responses, such as adjusting medication dosages, thereby improving patient outcomes.

The technical implementation of edge IoT and computing in healthcare involves the deployment of edge computing frameworks or platforms that support the development and deployment of edge applications. These frameworks provide libraries, APIs, and tools for data processing, machine learning, and analytics, as well as mechanisms for managing edge deployments. Additionally, edge IoT devices employ containerization or virtualization technologies to efficiently manage edge applications while ensuring robust security measures to protect sensitive patient data and maintain compliance with healthcare regulations.[24] Overall, edge IoT and computing empower healthcare organizations to deliver personalized care, enhance patient outcomes, and address technical challenges related to data processing, privacy, and security.

Literature Survey:

This comprehensive study [25] explores how data operations can be accelerated using edge computing, specifically focusing on encryption, transmission, authentication, classification, reduction, and prediction. By delegating these tasks to edge devices, the efficiency and speed of data processing are significantly improved. The study also identifies key limitations, noting that integrating AI into Edge IoT systems can further reduce latency, enhance privacy and security, improve reliability, and provide a more personalized and efficient user experience. Looking ahead, the design of efficient edge nodes is highlighted as a critical area for future research, as optimizing these nodes is essential for fully realizing the benefits of edge computing in healthcare applications.

This comprehensive study [26] discusses the integration of edge computing with 5G/6G networks and cloud computing, highlighting its pivotal role in both research and business domains. The paper explores how edge technology facilitates enhanced data processing capabilities by bringing computational resources closer to the data source, thereby reducing reliance on distant cloud servers. This proximity significantly lowers latency, though it is noted that edge computing still incurs higher latency compared to on-device processing, which can affect real-time applications. Future research directions are suggested, focusing on enhancing data transmission speeds, achieving real-time processing, and further minimizing latency to support increasingly demanding applications.

This comprehensive study [27] investigates the expansion of IoT in healthcare, utilizing various available databases to anlayze its growth and impact. It examines the scope of edge IoT, exploring its related terms and associated technologies. Despite its thorough analysis, the study does not address the hindrances and challenges IoT faces within the healthcare sector. Looking to the future, the integration of cutting-edge technologies with IoT holds significant promise for early diagnosis and timely remedial actions, potentially transforming healthcare delivery and outcomes.

This comprehensive study [28] synthesizes articles related to the Internet of Medical Things (IoMT) using AMSTAR and PRISMA tools to ensure methodological rigor and transparency. While the review covers a wide range of IoMT applications and their potential, it notes a key limitation: the enhancement of performance in the healthcare sector through the implementation of edge computing has not been thoroughly discussed. Future research should focus on ensuring the availability of clean data, achieving fast data processing, and selecting effective algorithms to improve healthcare systems and patient outcomes. Addressing these areas can significantly enhance the efficiency and effectiveness of IoMT in the healthcare sector.

This comprehensive study [29] examines the process of collecting body vitals and pre-processing this data before transferring it to the cloud for heavy computation, employing remote patient monitoring as its primary methodology. A key limitation discussed is that while real-time monitoring enhances system response through local data processing at the edge node, the study lacks a focus on the role and optimization of the edge gateway. In the future, the design of more sophisticated systems using state-of-the-art technologies is anticipated; further improving healthcare delivery and patient outcomes.

This comprehensive study [30] employs heat mapping and feature importance to survey the integration of AI with IoT, using AIoMT (Artificial Intelligence of Medical Things) as its core methodology. Despite its thorough exploration, the study does not examine issues related to edge IoT, leaving a gap in understanding the challenges and limitations of implementing edge computing in this context. Future research should focus on developing advanced deep learning models capable of capturing time series data to explore features for cardiovascular activities, potentially enhancing the diagnostic and monitoring capabilities of AIoMT systems in healthcare.

This comprehensive study [31] focuses on assisting doctors in diagnosing and observing medical issues regardless of the patient's location. It presents a model that automates the collection, delivery, and processing of patients' vital data using edge devices such as Raspberry Pi and Docker containers. However, a noted limitation is that the model does not solely focus on disease identification and tracking of patients and medical staff. Future work may involve enhancing security through advanced user authentication schemes and deploying the platform in actual healthcare settings to evaluate its user acceptability and performance. These enhancements could further advance the effectiveness and applicability of the proposed model in clinical settings.

The comprehensive study [32] describes a healthcare framework that integrates a promising Edge-IoT ecosystem, employing EdgeX Foundry for the telehealth application of blood pressure monitoring. However, a limitation acknowledged is the selection of the telemedicine application exclusively focused on blood pressure monitoring and forecasting, potentially limiting the scope of the framework's applicability. Future efforts should aim to scale up and down the framework to accommodate monitoring of multiple patients in real-time, thereby enhancing its versatility and utility in diverse healthcare scenarios. Additionally, integrating wireless devices into the system could further expand its capabilities and improve patient care by enabling seamless data collection and analysis from various sources.

The comprehensive study [33] employs a Systematic Literature Review (SLR) methodology to investigate the challenges associated with running machine learning (ML) and deep learning (DL) algorithms on edge devices in a distributed manner. This approach involves defining a rigorous protocol for literature search and analysis to extract information that addresses specific research questions regarding ML/DL deployment on edge computing platforms. However, a limitation highlighted in the study is that while some promising strategies for integrating ML/DL with edge computing are identified, prevailing studies in this area are still evolving and expanding. Looking to the future, there appears to be a slightly predominant tendency to utilize Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) in edge intelligence applications, suggesting potential directions for further research and development in this field.

The methodology employed in this comprehensive study [34] involves conducting a brief review encompassing the general utilization of Internet of Things (IoT) solutions in healthcare, coupled with an exploration of the most recent trends in fog/edge computing for smart health. Additionally, the study includes a review of Internet of Medical Things (IoMT) monitoring solutions, evaluating their effectiveness and suitability within healthcare contexts. Limitation highlighted in the study is the significant role played by AI and ML techniques, which often necessitate computational capacity primarily available through cloud services. Looking ahead, there is a growing need to address this limitation by enhancing the intelligence of edge devices, enabling them to fulfil the requirements of AI and machine learning applications. By shifting intelligence to the edge, future healthcare IoT solutions can potentially optimize performance, reduce latency, and enhance data privacy while meeting the demands of AI and machine learning algorithms.

This comprehensive study [35] examines the impact of AI in the field of cardiac electrophysiology, covering all aspects of this application. The methodology involves considering various cardiac devices and AI algorithms for the analysis of arrhythmias. However, the study does not mention specific types of ECG sensors, nor does it discuss the concept of edge computing or name any edge devices.

The comprehensive study [36] in these research papers reviews ML and artificial intelligence (AI) methods in the clinical practices of cardiac electrophysiology. The methodology involves a systematic discussion of AI/ML terminology and the challenges associated with the validation and deployment of algorithms in clinical settings. However, the study does not mention specific types of ECG sensors, nor does it discuss the concept of edge computing or name any edge devices.

The comprehensive study [37] in these research papers reviews ML and artificial intelligence AI methods in the clinical practices of cardiac electrophysiology, specifically using 12-lead ECG sensors. The methodology includes employing CNNs to detect the electrocardiographic signature of atrial fibrillation. However, the study does not discuss the concept of edge computing or name any edge devices.

The comprehensive study [38] in these research papers examines the applications of AI for the screening, diagnosis, and treatment of atrial fibrillation (AF) and its limitations. The methodology includes AF screening using AI with various methods such as photo plethysmography, ECG, intracardiac signals, and other means. However, the study does not mention specific types of ECG sensors, nor does it discuss the concept of edge computing or name any edge devices.

The comprehensive study [44] in these research papers focuses on applying AI to design a system that utilizes information within the ICU setting to identify sepsis in patients upon admission. The methodology involves using clinical databases to develop and compare different ML and AI models based on their AUC (Area under the Curve) and ROC (Receiver Operating Characteristic) metrics. While the study mentions the use of electrocardiogram (ECG) sensors, it does not discuss the concept of edge computing or name any edge devices.

The comprehensive study [45] introduces a method named AI-FAS (AI-based fuzzy assisted Petri net) for evaluating stress through the monitoring of heart rate (HR) and blood pressure (BP). The methodology involves the use of electrocardiogram (ECG or EKG) and photo plethysmography sensors for heart rate monitoring. Blood pressure monitoring relies on analyzing the transient time of each pulse. However, the study does not address the concept of edge computing or specify any edge devices.

The comprehensive study[49] designs a lightweight arrhythmia monitoring system for mobile health cases. The methodology involves the use of electrocardiogram (ECG) signals. To mitigate noise filtering and extensive signal processing, the study employed a single-lead ECG trace with a one-dimensional CNN using the Lightweight Arrhythmia Classification (DL-LAC) method. This method is compared with traditional approaches. However, the study does not discuss the concept of edge computing or name any edge devices.

The comprehensive study [50] aims to automatically detect arrhythmias using electrocardiogram (ECG) signals. The methodology involves the implementation of a Convolutional Neural Network (CNN) model that applies oversampling on training data. Additionally, the model is quantized to reduce computational complexity and memory usage. The performance of the model is then evaluated on three different platforms. Although the study discusses the use of edge computing and mentions testing the model on different platforms, it does not specify the names of the edge devices utilized.

The comprehensive study [53] focuses on pulse rate and body monitoring using temperature and heart rate sensors. The methodology involves health monitoring from a distance utilizing the Bluemix cloud platform. However, the study does not discuss the concept of edge computing or name any edge devices.

The comprehensive study [54] in these research papers develops a classifier for the detection of abnormalities using ECG sensors. The methodology involves partitioning a linear machine learning approach, specifically a linear Support Vector Machine (SVM), and deploying a deep learning algorithm in a distributed manner. However, the study does not discuss the concept of edge computing or name any edge devices.

The comprehensive study [51] in these research papers proposes event-driven deep learning for edge intelligence. The methodology involves collecting data from different sensors and testing them with various devices. While the study does not mention ECG sensors specifically, it discusses the concept of edge computing and mentions testing data with different devices. However, it does not provide specific names for these devices

The comprehensive study [52] in these research papers focuses on wireless health monitoring, mentioning ECG data. The methodology involves estimating blood pressure through ECG data. Additionally, the study discusses the concept of edge computing and mentions device names related to wireless health monitoring.

The comprehensive study [55] among these research papers centers on evaluating the quality of ECG signals. The methodology involves evaluating ECG signal quality through filtering using the Discrete Fourier Transform. ECG signals were obtained during various physical activities to assess their quality. However, the study does not mention specific ECG sensor types, nor does it discuss the concept of edge computing or name any edge devices.

The study [56] examines multi-sensor data classification using ECG sensors, accelerometers, and gyroscopes. It employs Random Forest and SVM models for classification and discusses edge computing with a PC server for processing, though specific edge devices are not mentioned.

Paper	Objective	Methodology	Limitations	Future scope
Hartmann, Morghan, Umair Sajid Hashmi, and Ali Imran[25]	With encryption, transmission, authentication, classification, reduction and prediction, explained how data operations can be accelerated using edge computing.	Analyze the quality of experience for Healthcare Edge Computing.	Inculcating AI into Edge IoT can achieve lower latency, enhanced privacy and security, improved reliability, and a more personalized and efficient user experience.	Design of efficient edge nodes is most prominent in Edge computing in healthcare.
Sulieman, N. A., et al. [26]	Discussed edge computing over 5G/6G and cloud computing.	Explored the role of edge technology in research and in business.	While edge computing reduces latency compared to cloud-based processing, it may still experience higher latency compared to on-device processing. Latency can affect real-time applications.	To enhance data transmission speed, real-time processing, and minimize latency.
Rejeb, Abderahman, et al. [27]	Investigated the expansion of IoT in healthcare based on different available databases.	Study Scope of edge IoT with all its related terms and with different technologies	Not discussed the hindrances of IoT in healthcare	The integration of the cutting-edge technologies with the potential of IoT can help in early diagnosis and remedial actions.

Table 1. Literature Survey Table of Edge Computing

Paper	Objective	Types of ecg Sensor	Edge computing and device name	Methodology
Feeny, Albert K., et al. [35]	Study of AI impact in the field of cardiac electrophysiology on all aspects	Not Mentioned	Not discussed	Considered cardiac dev and AI algorithms analysis of arrhythmia
Attia, Zachi I., et al.[36]	Review of ML and AI methods in clinical practices of cardiac electrophysiology	Not Mentioned	Not Mentioned	Systematic discussion terms of AI/ML, challe of validation deployment of algorith clinical practices of ca electrophysiology
Harmon, David M., et al. [37]	Using ML to identify patients with atrial fibrillation through point-of-care testing.	12-lead ECGs sensor	Not considered	CNN to detect electrocardiographic signature of atrial fibrill presence
Kilic, Arman. [38]	Study of applications of AI for the screening, diagnosis and treatment of AF (Atrial fibrillation) and limitations	Not discussed	Not discussed	AF screening using AI Photoplethysmography, with medical comorbid with ECG, with Intraca Signals And with other means
Bathilde, Johan Bhurny, et al. [44]	Detection of atrial fibrillation using wireless method	Photoplethysmography (PPG) sensor	Not discussed	This project explored feasibility of implementi migrated non-inv sensor on a microcont with Wi-Fi connectivit wireless heart monitoring.

Table 2. Incorporating Edge IoT In AI model deployment

Survey Review and Future Directions

Smart healthcare harnesses the power of digital tools and cutting-edge technologies such as AI, IoT, and wearable's to revolutionize the delivery of healthcare services. By leveraging these innovative solutions, healthcare providers can remotely monitor patients' vital signs, track health metrics in real-time, and deliver personalized care tailored to individual needs.[1] These technological advancements not only improve the efficiency and effectiveness of healthcare delivery but also empower patients to actively manage their health.

The Silent Threat - heart disease claims a life every 36 seconds worldwide. However, the rise of smart healthcare, driven by data-driven decision-making, has the potential to mitigate this impact. With vast amounts of health data at their disposal, providers can make more informed decisions, ultimately improving patient outcomes and combating the prevalence of heart disease. [2]Through sophisticated analytics algorithms, healthcare professionals can gain a deeper understanding of patients' health statuses, predict potential health issues before they arise, and devise targeted treatment plans for optimal outcomes. This approach centered around data enables proactive intervention, early detection of health risks, and more informed clinical decision-making, ultimately resulting in improved patient outcomes and enhanced quality of care.

Fig. 2. Comparison between Edge Enabled Healthcare and Legacy Healthcare.

In traditional healthcare approaches, decisions regarding patient care are typically centralized around doctors, who rely on centralized processing and storage systems (Fig. 2, right). However, the advent of edge computing marks a significant shift towards decentralized decision-making at the point of care. Edge computing brings computation closer to patients, allowing for real-time data analysis and prompt interventions without constant doctor oversight (Fig. 2, left).[4] This transition empowers edge devices to autonomously process and interpret medical data, facilitating proactive management of patient health. Moreover, edge computing not only enables autonomous decision-making but also supports doctors in making informed decisions by providing valuable insights derived from real-time data analysis.[57][49] By leveraging the information gained from edge computing, doctors can enhance their decision-making process, leading to better patient outcomes and more efficient healthcare delivery. Thus, edge computing serves as a transformative technology that not only enables decentralized decision-making but also augments the capabilities of healthcare professionals in providing optimal patient care..

Conclusion:

In conclusion, this review paper provides a comprehensive overview of the integration of edge IoT and AI methodologies in healthcare advancement and other fields such as cryptanalysis. Through an examination of various studies, the paper delves into the significant strides made in ECG signal analysis and edge computing, highlighting the potential of leveraging AI and machine learning techniques for improved cardiac health monitoring. These advancements showcase the diverse approaches employed, including convolutional neural networks for arrhythmia detection and photo plethysmography for atrial fibrillation screening, all aimed at enhancing diagnostic precision and patient outcomes. Moreover, the critical role of edge computing in reducing latency and enhancing real-time processing capabilities is underscored, emphasizing its importance in facilitating timely and accurate cardiac diagnostics.

The paper delves into how the integration of IoT and edge computing facilitates remote monitoring and early health detection by leveraging wearable and wireless sensors for continuous health surveillance and prompt data processing. It underscores the superiority of edge computing over traditional cloud-based solutions, highlighting its potential to enhance overall healthcare delivery. Several studies concentrate on deploying AI models on edge devices like NVIDIA's Jetson Nano, showcasing the feasibility and efficiency of on-device processing for real-time arrhythmia detection and health monitoring. These efforts address challenges related to signal quality assessment and lightweight classification methods, ensuring robust performance across diverse settings. The practicality of edge computing for real-time health monitoring is underscored, showcasing its potential to revolutionize healthcare delivery.

However, despite these advancements, several limitations and future directions are identified, including the need for efficient edge node design, data privacy concerns, and the computational demands of AI algorithms. Future research should focus on developing more sophisticated and secure edge computing frameworks, integrating advanced AI models, and expanding the scalability of these systems to monitor multiple patients in real-time. Additionally, advancements in advanced deep learning models for capturing time series data and exploring cardiovascular features illustrate the potential of AI in cardiac care. Enhancing security through advanced user authentication schemes and deploying these platforms in real healthcare environments are essential steps forward. These advancements can significantly improve the efficiency and reliability of healthcare systems, contributing to the betterment of public health and patient care through lower latency, enhanced privacy, improved reliability, and more personalized patient care.

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