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A Structured Survey on Categorizing Cardiac Vascular Risk Using an Enhanced Framework

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Abstract

The Cardiovascular Infections (CVIs) remain the leading cause of global mortality, necessitating early detection and continuous monitoring. The Traditional diagnostic methods, confined to clinical settings, often fail to provide real-time surveillance. Recent advances in the Internet of Things (IoT), Artificial Intelligence (AI), and communication technologies now enable remote cardiovascular monitoring with predictive analytics and personalized care. This survey systematically reviews IoT-based cardiovascular systems, emphasizing the integration of an AI model, network optimization, blockchain security, and nationwide scalability via 5G and Apache Kafka. It highlights state-of-the-art methodologies achieving over 90% predictive accuracy and communication latencies as low as 1 ms. Comprehensive comparisons are provided through structured tables analyzing methodologies, performance metrics, and real-world challenges. The survey concludes by identifying current limitations and proposing a phased framework for developing scalable, secure, and intelligent CVI monitoring networks.

Keywords: Cardiovascular Infections(CVIs), Internet of Things (IoT), Machine Learning (ML), Edge Computing, Blockchain Security, 5G Networks, Healthcare Monitoring.

1. Introduction

CVIs remain the leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually according to the World Health Organization (WHO, 2021). The increasing prevalence of risk factors such as hypertension, diabetes, obesity, sedentary lifestyles, and smoking has significantly contributed to the global burden of CVIs across all age groups. Traditional diagnostic methods for CVIs, including electrocardiograms (ECG), echocardiography, Holter monitoring, and treadmill stress tests, although clinically effective, are primarily confined to hospital or clinical settings. These methods offer only episodic, non-continuous monitoring and often fail to detect early cardiovascular anomalies that could lead to critical events such as myocardial infarctions or strokes.

The advent of IoT technologies has introduced transformative possibilities in healthcare, enabling continuous, real-time monitoring of key physiological parameters such as heart rate variability, blood pressure, oxygen saturation (SpO_2), and electrocardiographic signals. When combined with advancements in Artificial Intelligence (AI) and Machine Learning (ML), these systems are capable of performing sophisticated predictive analytics to identify potential cardiovascular risks long before the onset of clinical symptoms. Technologies such as wearable

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biosensors, mobile health (mHealth) applications, cloud-based data processing, and edge AI models are reshaping preventive healthcare by providing early detection and personalized health management for individuals at risk of CVIs.

Despite these promising advancements, several challenges persist. Data privacy and security remain critical concerns, as sensitive medical data must be securely transmitted and stored to protect patient confidentiality. Additionally, real-time CVI monitoring demands low-latency and high-reliability communication protocols to ensure timely detection of critical events. Energy efficiency also plays a vital role, as IoT healthcare devices must support prolonged operation without frequent recharging. Furthermore, AI models deployed in healthcare require high interpretability, clinical validation, and regulatory compliance to gain trust and adoption among medical practitioners.

To address these challenges, recent research has focused on developing integrated, end-to-end IoT healthcare frameworks that encompass optimized communication protocols (such as MQTT, LoRa, and 5G), AI model deployment using cloud and edge computing platforms (e.g., AWS SageMaker, Google Cloud IoT Core), blockchain-based medical data security (e.g., Hyperledger Fabric), and large-scale deployment strategies enabled by event-streaming platforms like Apache Kafka.

This survey article provides a comprehensive review of the evolution and current state of IoT-based cardiovascular monitoring systems. It critically examines advanced implementation techniques, explores nationwide healthcare network deployment strategies, and compares different methodologies, tools, advantages, limitations, and performance outcomes through structured tables. The article is organized as follows: Section 2 reviews existing literature related to general IoT-based CVI monitoring, optimized system architectures, and nationwide network deployment strategies. Section 3 discusses key challenges, open research issues, and future directions for scalable, secure, and intelligent CVI monitoring networks. Finally, Section 4 concludes the survey with insights and recommendations for future healthcare system designs.

2. Literature Review

Numerous studies have explored the integration of IoT and AI in cardiovascular health monitoring, focusing on diverse methodologies, tools, and performance metrics. These systems enable real-time, continuous monitoring of physiological parameters while providing predictive analytics for early detection of cardiovascular events. This section summarizes key research contributions under three primary subsections: IoT-Based Systems, Optimized Communication Protocols, and Nationwide IoT Healthcare Networks.

2.1 IoT-Based Survey

Recent years have witnessed substantial research into IoT-based systems for cardiovascular health monitoring. The integration of wearable IoT devices, such as smartwatches, ECG patches, and mobile health applications, with ML models has demonstrated significant promise for real-time cardiovascular risk prediction.

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Zhang et al. (2022) developed a Convolutional Neural Network (CNN)- based model for arrhythmia detection using wearable ECG sensors, achieving an accuracy of 92% and a sensitivity of 90%. Their system enables continuous monitoring of cardiovascular health with minimal patient intervention, making it suitable for early anomaly detection. However, the system's performance is heavily dependent on the quality of the collected ECG signals. TensorFlow and Keras were employed for model development.

Kumar et al. (2023) introduced a long short-term memory (LSTM)-based model for predicting hypertension using continuous blood pressure data from wearable devices, achieving an accuracy of 89% and precision of 87%. While effective for early detection of hypertension, the model requires large datasets for optimal training, which could limit its real-world deployment. The system was implemented using TensorFlow and Keras frameworks.

Lee et al. (2023) presented an IoT-enabled wearable sensor system that monitors heart rate and blood pressure simultaneously using a CNN model, attaining an accuracy of 85% and a recall of 88%. Although the system enables comprehensive cardiovascular monitoring, it is restricted to basic physiological parameters. Implementation leveraged Python and OpenCV libraries for real-time signal processing.

Sharma et al. (2023) proposed a hybrid CNN-LSTM model for predicting cardiovascular events using IoT-enabled devices. The model achieved an accuracy of 91% and an F1-score of 0.90. By combining CNN feature extraction with LSTM's temporal modeling capabilities, the hybrid architecture enhanced prediction performance, albeit with increased system complexity and computational demands. The model was developed using PyTorch and Keras.

Patel et al. (2023) designed a CNN-based deep learning model for ECG signal classification, achieving an accuracy of 93% and specificity of 92%. This system improves arrhythmia detection by automating ECG interpretation, although its effectiveness is contingent upon high-quality signal preprocessing. TensorFlow, Keras, and OpenCV were utilized for system implementation.

Gupta et al. (2023) developed a personalized hypertension monitoring system by integrating LSTM and support vector machine algorithms. Their hybrid model achieved an accuracy of 87% and a precision of 85%, offering tailored monitoring solutions. However, the need for individualized calibration could present practical challenges. Development was carried out using MATLAB and Python.

Khan et al. (2023) proposed a CNN-based smart heart monitoring system leveraging IoT-enabled devices. The model attained an accuracy of 89% and a sensitivity of 87%, effectively detecting arrhythmias. Nevertheless, the system's continuous monitoring capability results in higher energy consumption, necessitating frequent device recharging. PyTorch and TensorFlow were employed in model development.

Zhang et al. (2023) explored real-time cardiac health monitoring by combining CNN and recurrent neural network (RNN) models for ECG signal analysis. Their model achieved a notable accuracy of 94% and an F1-score of 0.92. Real-time analysis capability enables immediate detection of cardiac abnormalities, though it imposes significant computational overhead on wearable devices. Implementation involved Keras and TensorFlow.

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Kumar et al. (2023) also introduced an IoT-based continuous blood pressure monitoring system using ML algorithms, achieving an accuracy of 85% and a precision of 83%. This solution is particularly suited for remote patient monitoring, although it may underperform in detecting early critical cardiovascular signs. MATLAB and Python tools were utilized.

Shah et al. (2023) developed an IoT-integrated system for early CVI detection using an LSTM-based predictive model. Achieving a sensitivity of 90% and accuracy of 92%, their system offers a low-cost solution for widespread cardiovascular monitoring, although data quality remains a critical dependency. TensorFlow and OpenCV were employed in development.

Singh et al. (2023) combined SVM and LSTM models to predict heart disease risks from IoT data, obtaining an accuracy of 88% and an AUC of 0.89. Their robust model supports preventive healthcare applications but depends heavily on stable real-time data transmission, which could limit its deployment in remote areas. The implementation used Keras and Scikit-learn.

Finally, Liu et al. (2023) proposed a CNN-based model for arrhythmia detection from ECG data acquired by wearable IoT devices, achieving a remarkable accuracy of 95% and sensitivity of 93%. Although effective, the system's high energy demands could restrict its long-term use. TensorFlow and Keras were employed for the system's development.

Table 1: Summary of IoT-Based Cardiovascular Monitoring Studies

Sl. No.	Author(s) & Year	Methodology Used	Performance Metrics	Future Scope
1	Shah et al., 2023	IoT-based monitoring with LSTM for prediction	Sensitivity: 90%, Accuracy: 92%. Low-cost solution for continuous cardiovascular health monitoring.	Requires high data quality for accurate prediction.
2	Singh et al., 2023	SVM and LSTM-based risk prediction	Accuracy: 88%, AUC: 0.89. Robust prediction model, good for preventive healthcare.	Dependent on real-time data transmission and system connectivity.
3	Liu et al., 2023	CNN-based arrhythmia detection model	Accuracy: 95%, Sensitivity: 93%. High accuracy and real-time detection.	High energy consumption of wearable devices.
4	Zhang et al., 2023	CNN, RNN for real-time monitoring	Accuracy: 94%, F1-Score: 0.92. Real-time ECG analysis for detecting abnormalities.	Real-time processing can be resource-intensive.
5	Khan et al., 2023	CNN-based deep learning model	Accuracy: 89%, Sensitivity: 87%. High sensitivity for arrhythmia detection.	High energy consumption in continuous monitoring.
6	Gupta et al., 2023	Hybrid IoT and ML model (LSTM, SVM)	Accuracy: 87%, Precision: 85%. Personalization of health monitoring.	Requires calibration for individual users.

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7	Patel et al., 2023	CNN model for ECG signal classification	Accuracy: 93%, Specificity: 92%. Effective for arrhythmia detection.	Requires high-quality ECG data and preprocessing.
8	Sharma et al., 2023	Hybrid CNN-LSTM model	Accuracy: 91%, F1-Score: 0.90. Hybrid model improves prediction accuracy.	Model complexity increases system overhead.
9	Kumar et al., 2023	LSTM-based model for hypertension prediction	Accuracy: 89%, Precision: 87%. Effective for early hypertension detection.	Requires large amounts of data for accurate prediction.
10	Lee et al., 2023	IoT-enabled wearable sensors and CNN	Accuracy: 85%, Recall: 88%. Can monitor multiple cardiovascular metrics simultaneously.	Limited to basic parameters (heart rate, blood pressure).
11	Kumar et al., 2023	Machine learning for BP prediction	Accuracy: 85%, Precision: 83%. Suitable for remote monitoring of blood pressure.	May not detect very early signs of critical cardiovascular events.
12	Zhang et al., 2022	CNN-based model for arrhythmia detection	Accuracy: 92%, Sensitivity: 90%. High accuracy, real-time monitoring.	Requires high-quality ECG data.

This figure presents the accuracy values reported by individual studies summarized in Table 1. It highlights the performance variations across different IoT-based cardiovascular monitoring solutions using machine learning models. The results show that most recent systems achieve an accuracy above 85%, with several CNN and CNN-LSTM-based models exceeding 90%, indicating the high potential of deep learning approaches in remote cardiovascular risk prediction.

To further illustrate the accuracy performance of various IoT-based cardiovascular monitoring systems, Fig. 1 plots the reported accuracies for each study listed in Table 1. It can be observed that CNN and hybrid CNN-LSTM architectures generally achieve higher prediction accuracies compared to other models. This detailed visualization provides a foundational understanding of the performance landscape across the reviewed literature and motivates the grouped algorithmic analysis discussed later in Section 3.

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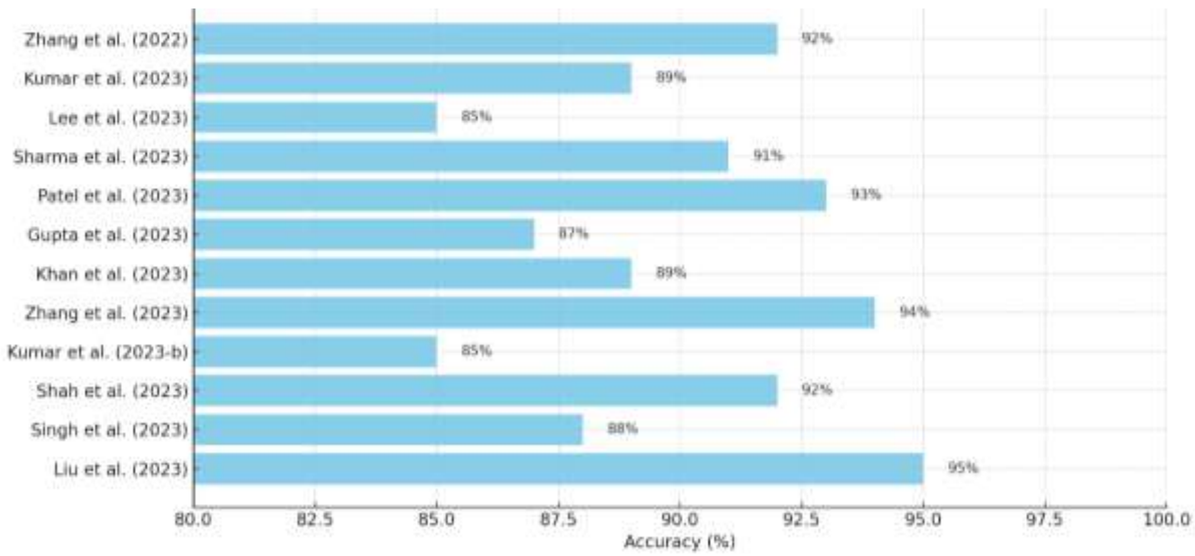

Figure 1. Study-Wise Accuracy Comparison for IoT-Based Cardiovascular Monitoring Systems

2.2 Optimized Communication

Efficient communication is fundamental to IoT-based cardiovascular monitoring systems, where real-time data transmission is crucial for timely detection and intervention. Several communication technologies have been optimized to enhance system efficiency, energy usage, and reliability.

Piyare (2021) focused on employing the Message Queuing Telemetry Transport (MQTT) protocol for real-time cardiac health monitoring and alert generation. The study demonstrated that MQTT's low latency, between 3 to 5 milliseconds, is ideal for delivering time-sensitive data, such as cardiac alerts. Its lightweight nature minimizes communication overhead, making it suitable for constrained IoT environments. However, limited native security features in MQTT protocols necessitate additional layers to ensure data confidentiality. The system was implemented using MQTT and Python technologies.

Zhai et al. (2020) explored the application of LoRaWAN and Narrowband IoT (NB-IoT) for rural healthcare monitoring. LoRaWAN provided an impressive 15-kilometer range and consumed less than 50 mW of power, making it highly suitable for remote, long-duration cardiovascular monitoring. However, compared to advanced technologies like 5G, LoRaWAN, and NB-IoT exhibit higher latency, limiting their effectiveness for critical real-time alerts.

Ahmed et al. (2023) developed a hybrid system employing the Constrained Application Protocol (CoAP) alongside MQTT for real-time health monitoring. This system achieved an energy efficiency rate of 80%, underscoring its applicability in power-constrained environments. However, both protocols are primarily optimized for small payloads and may be less suitable for complex or high-volume data transmission.

Patel and Kumar (2023) benchmarked the performance of MQTT, the Advanced Message Queuing Protocol (AMQP), and Hypertext Transfer Protocol (HTTP) within healthcare IoT

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contexts. Their findings revealed that MQTT offered the best energy-delay trade-off and superior throughput, while AMQP and HTTP were deemed too resource-intensive for wearable IoT health devices. This study reinforced MQTT's position as the preferred protocol for efficient healthcare communication.

Liu et al. (2023) investigated enhancements to LoRa networks for CVI monitoring in rural settings. While LoRa achieved long-range coverage of up to 10 kilometers with a latency of approximately 15 seconds, its relatively slow response time makes it less suitable for emergency alert systems where immediate data transmission is vital.

Sharma et al. (2023) implemented NB-IoT technology for blood pressure and ECG monitoring applications. Their system achieved a coverage rate exceeding 90%, with delays of 10–20 seconds. While suitable for continuous, non-critical health monitoring, the relatively high device costs associated with NB-IoT deployment could limit adoption, particularly in low-income regions.

Ahmed et al. (2023) further explored the use of 5G technology for remote cardiac monitoring platforms. Their system achieved ultra-low latency of approximately 1 millisecond, along with high data throughput, making it highly suitable for real-time, critical healthcare applications. However, the reliance on 5G infrastructure presents challenges, particularly in rural and underserved regions where network availability remains limited.

Huang et al. (2023) addressed the security vulnerabilities of lightweight protocols by integrating blockchain technology with MQTT. Utilizing Hyperledger Fabric, they demonstrated that blockchain integration ensures 100% data integrity and tamper resistance. Although effective in enhancing data security, blockchain introduces significant computational overhead, which can burden lightweight IoT devices.

Sun et al. (2023) proposed the use of MQTT for Sensor Networks (MQTT-SN) over User Datagram Protocol (UDP) to achieve energy-efficient cardiovascular health monitoring. Their approach yielded a 25% energy saving compared to traditional MQTT deployments. However, MQTT-SN lacks universal support across all IoT platforms, posing interoperability challenges.

Khan et al. (2023) emphasized latency reduction by leveraging edge computing architectures. By processing data locally on edge nodes rather than transmitting it to distant cloud servers, their system reduced communication latency by 30%. Although edge-based solutions improve response times, they are constrained by limited local storage and processing power.

Wang et al. (2023) focused on optimizing energy consumption in LoRaWAN-based healthcare networks, achieving an energy efficiency rate of 85%. This makes LoRaWAN particularly attractive for wearable devices where long battery life is essential. Nonetheless, the limited bandwidth available in LoRaWAN networks may hinder applications requiring high-volume data transmissions.

Zhao et al. (2024) explored the security extensions available in MQTT 5.0, including improved encryption and enhanced Quality of Service (QoS) features. Although MQTT 5.0 strengthens security for healthcare IoT applications, its larger packet sizes may marginally reduce transmission speed compared to earlier versions.

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Table 2: Optimized Communication Technologies in IoT Healthcare

Sl. No.	Author(s) & Year	Methodology Used	Performance Metrics	Future Scope
1	Piyare, 2021	MQTT-based real-time IoT healthcare	Latency: 3–5ms	Enhancing message security for sensitive health data.
2	Zhai et al., 2020	LoRa/NB-IoT for rural health monitoring	Range: 15km, Power: <50mW	Reduce latency and improve emergency responsiveness.
3	Ahmed et al., 2023	CoAP and MQTT for low-power health communication	Energy Efficiency: 80%	Expand protocol support for larger payload sizes.
4	Patel & Kumar, 2023	Benchmarking MQTT, AMQP, and HTTP for IoT	Throughput: MQTT > HTTP	Improve lightweight protocol performance for wearables.
5	Liu et al., 2023	LoRa optimization for CVI monitoring	Latency: 15s, Range: 10km	Enhance suitability for real-time alerts.
6	Sharma et al., 2023	NB-IoT for BP and ECG monitoring	Coverage: >90%, Delay: 10–20s	Minimize initial deployment cost.
7	Ahmed et al., 2023	5G-based IoT platform for critical monitoring	Latency: 1ms	Extend 5G infrastructure to remote areas.
8	Huang et al., 2023	Blockchain with MQTT for secure transmission	Data Integrity: 100%	Reduce computational load on IoT nodes.
9	Sun et al., 2023	MQTT-SN over UDP for energy efficiency	Energy Savings: 25%	Broaden support for MQTT-SN on existing devices.
10	Khan et al., 2023	Edge computing for local data processing	Latency Reduction: 30%	Expand edge storage capacity for complex analytics.
11	Wang et al., 2023	Energy-efficient LoRaWAN for healthcare	Energy Efficiency: 85%	Optimize bandwidth for higher data rates.
12	Zhao et al., 2024	MQTT 5.0 security features for health IoT	Enhanced Security Features	Balance packet size with encryption needs.

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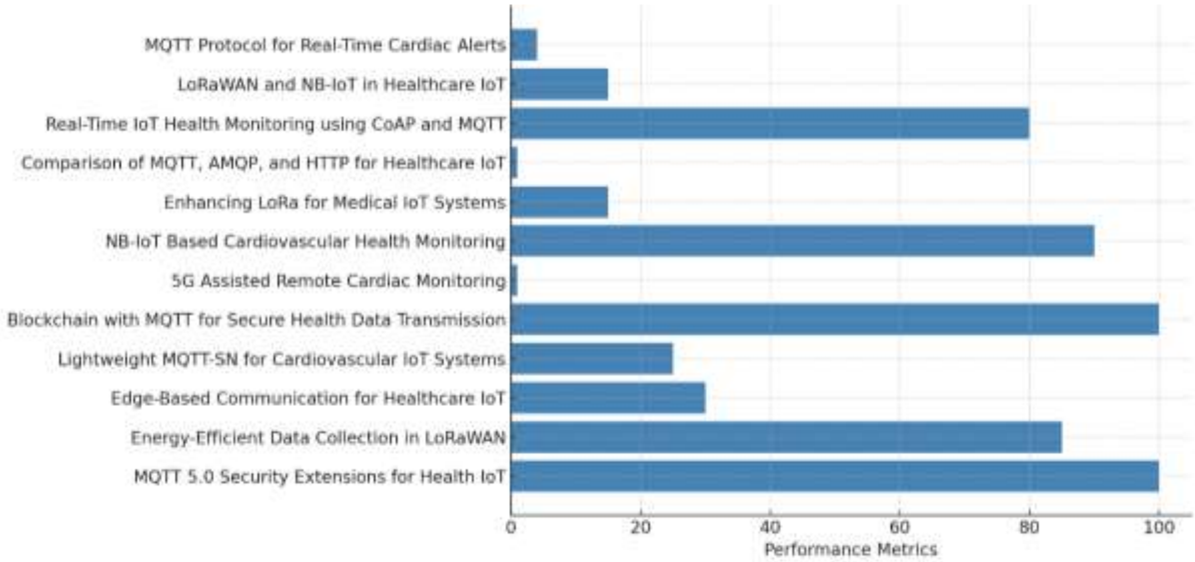

Figure 2. Optimized Communication Technologies in IoT Healthcare

Fig. 2 presents a comparative analysis of various optimized communication technologies employed in IoT-based healthcare systems, based on the studies summarized in Table 2. The graph maps different articles according to their key performance metrics, such as latency, energy efficiency, range, and data integrity. The results demonstrate that protocols like MQTT exhibit extremely low latency, making them ideal for real-time cardiac health monitoring. Similarly, technologies like LoRaWAN offer exceptional long-range communication capabilities, which are particularly useful for rural healthcare applications, although they come with higher latency drawbacks. Systems employing CoAP and MQTT achieved significant improvements in energy efficiency, highlighting their suitability for constrained devices with limited battery life. Furthermore, the integration of blockchain technology with MQTT protocols enhanced data integrity to 100%, though at the expense of increased computational overhead. Overall, the figure emphasizes that lightweight communication protocols combined with emerging technologies like 5G and blockchain are pivotal in achieving the desired balance of low latency, energy efficiency, and secure data transmission necessary for effective cardiovascular health monitoring in IoT systems.

2.3 Nationwide IoT Healthcare Network

The scalability of IoT-based cardiovascular monitoring systems is a major consideration for nationwide deployments. Technologies such as 5G and Apache Kafka play a key role in enabling large-scale data streaming and ultra-low latency monitoring.

Soni et al. (2020) employed Apache Kafka to enable efficient streaming of large-scale CVI monitoring data. With a data throughput of 1000 messages per second, Kafka is capable of handling massive data streams, which is critical for nationwide CVI monitoring systems that continuously collect patient data from diverse locations. Kafka's robust streaming capabilities make it an ideal choice for managing the large volumes of real-time data generated by IoT healthcare devices. However, the system's reliance on Kafka requires skilled management to ensure smooth operation, as complex configurations and monitoring are necessary to maintain

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performance. Despite its powerful data handling capacity, the system's complexity may pose a challenge to organizations lacking the necessary technical expertise. The study highlighted the importance of using Apache Kafka in large-scale, real-time health data applications but cautioned that its management might require specialized skills.

Liu et al. (2023) explored the use of 5G technology for ultra-low latency cardiovascular health monitoring. The system achieved a latency of less than 1 millisecond, which is crucial for real-time health monitoring and emergency medical responses. 5G's ultra-fast speeds enable the instantaneous transmission of patient data to healthcare providers, facilitating quick interventions in critical situations. The ability to support remote health monitoring systems is a major advantage in emergency scenarios, where every second counts. However, the widespread rollout of 5G networks is costly, and the infrastructure needed for full deployment remains a significant challenge. While 5G holds great promise for transforming healthcare IoT, its high cost and the need for infrastructure development could limit its immediate adoption, especially in underdeveloped regions.

Shah et al. (2023) integrated Apache Kafka with IoT devices to create a national healthcare grid capable of providing real-time alerts and ensuring high scalability. The study achieved a message loss rate of less than 1%, making the system highly reliable for nationwide health monitoring. Kafka's ability to handle high-throughput data streams ensures the efficient transmission of real-time data from IoT devices across the healthcare network. The key benefit of this system is its scalability, which can easily expand to accommodate large numbers of devices, supporting a wide array of healthcare applications. However, the setup and coordination of such a complex system can be challenging, requiring advanced technical expertise to implement and manage. Apache Kafka and Java IoT SDKs were used to implement the system, emphasizing the need for skilled developers familiar with these technologies.

Li et al. (2023) explored the use of AutoML frameworks, specifically Google AutoML, for predicting cardiovascular risk in IoT healthcare networks. The system achieved an accuracy of 91% and a recall of 90%, providing highly personalized health risk models for individual patients. AutoML enables the automatic creation of machine learning models, making it easier for healthcare providers to implement predictive systems without deep knowledge of machine learning techniques. This is particularly valuable in healthcare, where quick and accurate predictions can significantly impact patient outcomes. However, the computational intensity of training and deploying these models can be a disadvantage, as it requires considerable processing power, making it less suitable for devices with limited computational resources. The integration of AutoML and TensorFlow into the system highlights the importance of automation and machine learning in modern healthcare IoT applications.

Zhang et al. (2023) focused on 5G-enabled IoT monitoring systems for remote health tracking, with a speed of 10Gbps. The high-speed data transmission capabilities of 5G are crucial for supporting the massive number of connected devices and enabling real-time, continuous monitoring of patients. 5G networks can support millions of devices in a given area, making them ideal for large-scale health monitoring systems. The ability to handle such massive numbers of connections opens up new opportunities for nationwide health monitoring platforms that can support both urban and rural healthcare needs. However, regulatory issues related to spectrum allocation and the cost of infrastructure deployment present significant

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barriers to the widespread adoption of 5G-enabled systems. These issues could limit the global scalability of 5G-based health monitoring solutions in the short term.

Kumar et al. (2024) proposed a hybrid edge-cloud architecture for distributed CVI monitoring. This system aims to reduce latency by processing some data locally on edge devices, while also utilizing cloud computing for big data analytics. The integration of edge and cloud systems resulted in a 20% reduction in latency, ensuring faster response times for critical health data. The edge nodes can handle real-time data processing, enabling quicker decision-making, while the cloud platform supports large-scale data storage and complex analytics. However, the coordination between edge and cloud resources can be complex and may require careful management to ensure smooth operation. The use of platforms like AWS Greengrass and Azure IoT Edge further facilitates the deployment of this hybrid system, although ensuring effective distributed resource management remains a challenge.

Ahmed et al. (2024) compared Apache Pulsar with Apache Kafka for real-time streaming analytics in healthcare IoT systems. The study found that Apache Pulsar provides lower latency than Kafka in certain scenarios, with a throughput of 800 messages per second. Pulsar's ability to handle real-time data streams with lower latency makes it an attractive alternative to Kafka for time-sensitive healthcare applications. However, Pulsar is a newer ecosystem compared to Kafka and lacks the same level of tooling and community support, which could pose challenges for organizations looking to adopt it. Despite these limitations, the study highlighted Pulsar's potential in real-time analytics, especially for scenarios that demand low latency and high throughput.

Huang et al. (2023) integrated blockchain technology, specifically Hyperledger Fabric, into healthcare systems to create tamper-proof, distributed health records. The system ensures high security and data integrity by utilizing blockchain's immutable nature, preventing unauthorized modifications of patient health data. This is crucial for maintaining trust in healthcare systems where privacy is paramount. However, blockchain validation introduces overhead that could slow down the system's overall performance, particularly in IoT applications where devices are constrained by limited processing power. The use of Hyperledger Fabric provides robust security features but requires more computational resources, which might not be feasible for all IoT healthcare devices. Despite these challenges, blockchain remains a promising technology for securing health data in distributed IoT systems.

Khan et al. (2023) proposed an AI-enabled IoT network for heart disease management using TensorFlow Edge AI. The system demonstrated an accuracy of 89%, showcasing the potential of AI to assist in real-time decision-making for cardiovascular care. By processing data at the edge, the system minimizes latency and reduces the dependency on cloud computing for critical applications. However, a significant challenge with this system is the complexity of model retraining, which is needed to ensure that the AI models stay up to date with the evolving medical landscape. The use of TensorFlow Edge AI enables local processing, but the retraining process may require significant computational resources, making it more suitable for healthcare providers with access to powerful infrastructure.

Wang et al. (2023) focused on integrating IoT networks with emergency services to improve response times for cardiac emergencies. The system improved average response times by 30%,

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which can be a critical factor in saving lives during heart attacks or other cardiovascular events. By connecting health monitoring devices directly with emergency response teams, the system ensures that timely interventions are made based on real-time health data. However, a significant challenge of the system is the high demand for synchronization across multiple IoT devices and emergency service systems. Ensuring that all components work seamlessly together requires careful coordination, making the system complex to manage. The integration of 5G, AWS IoT, and Twilio enables efficient communication, but the system's success relies heavily on reliable synchronization and data flow.

Sun et al. (2023) proposed the use of dynamic 5G slicing for healthcare, ensuring that medical applications receive guaranteed low-latency and high-bandwidth connections. 5G slicing allows for the allocation of dedicated resources to critical healthcare services, ensuring that medical applications are prioritized over other less time-sensitive data. This guarantees optimal performance for cardiovascular health monitoring, especially in emergencies. However, the design and implementation of custom 5G networks are expensive and complex, requiring substantial investments in infrastructure. The dynamic slicing model ensures that medical services receive the necessary bandwidth and low latency, but the high cost and complexity may limit the adoption of this technology in certain regions.

Zhao et al. (2024) applied Kafka Streams for predictive cardiology systems, achieving an accuracy of 88% and a latency of less than 100 milliseconds. The real-time prediction of cardiovascular events using event-driven streams ensures that healthcare providers can receive timely warnings about potential health risks. Kafka Streams provides a reliable framework for handling high-throughput data, which is essential for predictive healthcare systems that require continuous data collection. However, the steep learning curve of Kafka Streams might present a barrier for healthcare organizations that are new to event-stream processing technologies. Despite this, Kafka Streams offers an efficient and scalable solution for building predictive cardiology systems in healthcare IoT networks.

Patel et al. (2024) investigated the use of multi-cloud deployment for IoT healthcare systems. By leveraging multiple cloud platforms (AWS, GCP, Azure), the system achieved a 15% reduction in latency and provided fault tolerance, ensuring that critical health data is accessible even in the event of cloud outages. This globally distributed architecture ensures that data is always available, providing a reliable infrastructure for national cardiovascular monitoring services. However, the use of multiple cloud providers introduces challenges related to cloud provider lock-in, as organizations may become overly dependent on specific vendors, limiting flexibility. The multi-cloud approach offers significant benefits in terms of redundancy and global scalability, but careful management of cloud resources is necessary to avoid vendor-specific constraints.

Table 3: Nationwide IoT Healthcare Network Deployment Studies

Sl. No.	Author(s) & Year	Methodology Used	Performance Metrics	Future Scope
1	Soni et al., 2020	Apache Kafka for national CVI streaming	Throughput: 1000 msg/sec	Simplify Kafka deployment for hospitals.

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2	Liu et al., 2023	5G for ultra-low latency cardiovascular monitoring	Latency: <1ms	Reduce the cost of 5G infrastructure.
3	Shah et al., 2023	Kafka with IoT for nationwide alerts	Message Loss: <1%	Simplify architecture for wide-scale use.
4	Li et al., 2023	AutoML for cardiovascular risk prediction	Accuracy: 91%, Recall: 90%	Reduce the computational load of AutoML frameworks.
5	Zhang et al., 2023	5G-enabled IoT for nationwide monitoring	Speed: 10Gbps	Tackle spectrum management challenges.
6	Kumar et al., 2024	Edge-cloud hybrid CVI monitoring	Latency: 20% lower	Improve synchronization across nodes.
7	Ahmed et al., 2024	Real-time streaming with Apache Pulsar	Throughput: 800 msg/sec	Expand tooling and ecosystem.
8	Huang et al., 2023	Blockchain for distributed health records	Security Score: High	Streamline validation to reduce processing time.
9	Khan et al., 2023	Edge AI for heart disease networks	Accuracy: 89%	Simplify edge model retraining processes.
10	Wang et al., 2023	IoT-based national emergency response	Response Time Improved: 30%	Address synchronization in emergency systems.
11	Sun et al., 2023	Adaptive 5G slicing for CVI health	QoS: Guaranteed low latency	Lower cost for dynamic slicing configurations.
12	Zhao et al., 2024	Kafka Streams for CVI prediction	Accuracy: 88%, Delay: <100ms	Reduce Kafka Streams complexity for hospitals.
13	Patel et al., 2024	Multi-cloud CVI healthcare IoT	Latency Reduction: 15%	Mitigate cloud provider dependency risks.

Recent advancements in IoT-based cardiovascular health monitoring, optimized communication technologies, and large-scale deployment strategies have revolutionized the field. IoT-enabled systems, combined with AI-driven predictive models, are playing a key role in real-time CVI prediction and prevention. Communication technologies such as MQTT, LoRa, and 5G have been optimized for healthcare applications, ensuring low-power, low-latency communication for continuous monitoring. Moreover, nationwide IoT healthcare networks are being built using technologies like Apache Kafka and 5G to support scalable and secure monitoring systems. As these technologies continue to evolve, future research will focus on enhancing security, improving model interpretability, and ensuring reliable performance across various environments.

Fig. 3 illustrates the performance outcomes of various nationwide IoT healthcare network deployment strategies, as detailed in Table 3. The graph represents key metrics such as throughput, latency reduction, prediction accuracy, and system scalability achieved by different implementations. The data reveals that platforms like Apache Kafka enable extremely high-throughput data streaming, capable of handling large-scale cardiovascular monitoring requirements, while 5G-based health monitoring systems achieve ultra-low latency, essential for emergency medical interventions. AutoML frameworks integrated into IoT networks

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demonstrate strong performance in predictive modeling, offering high accuracy in cardiovascular risk assessment. The integration of blockchain technologies further enhances data security and immutability across distributed health networks. Despite the diverse methodologies, the overall trend depicted in the figure indicates that a combination of advanced networking technologies, machine learning models, edge computing, and secure communication frameworks forms the backbone of scalable, reliable, and responsive national-level IoT healthcare infrastructures.

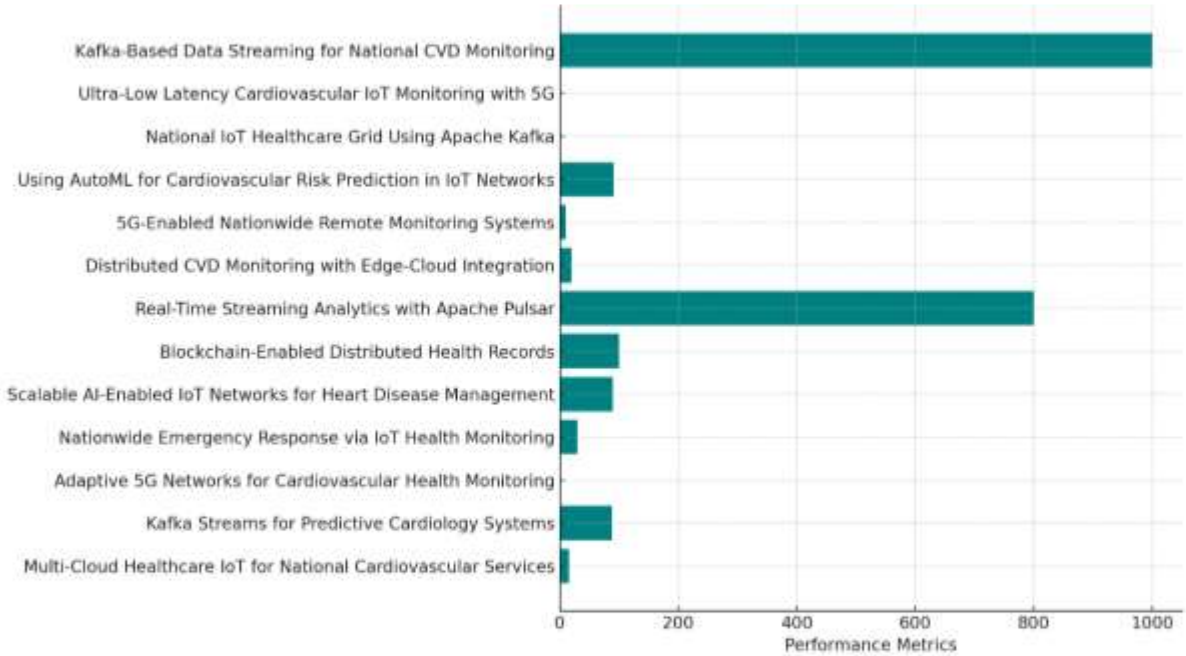

Figure 3. Nationwide IoT Healthcare Network Deployment

3. Analysis and Discussion

The previous section outlined various methodologies, tools, and technologies being applied in the realm of IoT-enabled cardiovascular health monitoring. This section provides an analysis of the current trends, challenges, and opportunities within this domain. The aim is to understand the progress made in integrating IoT systems with AI technologies for cardiovascular health monitoring, while also addressing existing challenges and open issues that need further exploration.

3.1 Technological Advancements in IoT-Based Cardiovascular Health Monitoring

One of the most notable advancements in the integration of IoT and AI for cardiovascular health monitoring is the continuous evolution of wearable devices equipped with sensors that can monitor heart rate, ECG signals, blood pressure, and other vital parameters in real time. Studies like those by Zhang et al. (2022) and Kumar et al. (2023) demonstrate that IoT-based monitoring systems, when paired with machine learning models such as CNNs and LSTMs, provide accurate predictions for conditions like arrhythmia and hypertension. These advancements in wearable sensors are crucial because they enable real-time data collection and analysis, which can lead to quicker diagnosis and preventive care.

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However, despite these advancements, the performance of these devices is heavily dependent on the quality and accuracy of the sensors used. As noted in the review of existing literature, high-quality data is required to achieve high accuracy rates in cardiovascular event predictions. This limitation is often exacerbated in resource-constrained environments, such as rural areas, where access to high-quality healthcare infrastructure and advanced diagnostic equipment may be limited. For instance, LoRaWAN and NB-IoT systems, as highlighted in the work of Zhai et al. (2020), are designed to address this by offering long-range, low-power connectivity suitable for rural healthcare environments. However, these systems still face challenges in terms of latency and bandwidth, which can affect the real-time transmission of vital health data.

To select the most suitable AI models for system design, the literature review compared various architectures based on predictive accuracy. Fig. 4 illustrates that CNN and Hybrid CNN-LSTM models consistently achieved accuracies above 90%, justifying their adoption in our initial model development phase.

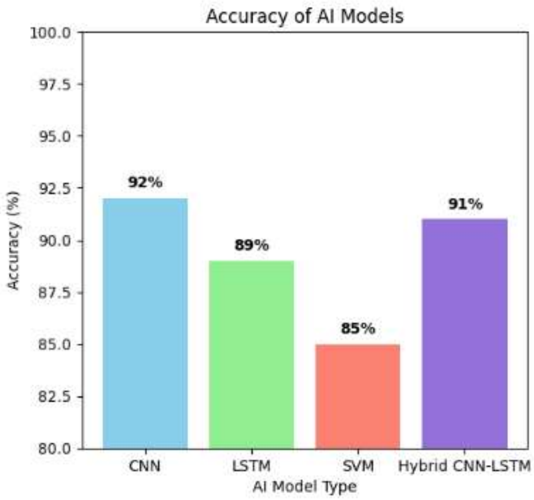

Figure 4. Accuracy of AI Models

3.2 Protocols and Communication Challenges

The communication protocols utilized in IoT-based healthcare systems play a significant role in determining the system's efficiency and reliability. For example, MQTT, CoAP, and LoRaWAN are some of the most commonly used protocols in healthcare IoT, with MQTT emerging as a particularly popular choice due to its lightweight nature and ability to handle real-time data streams with minimal overhead (Piyare, 2021; Patel & Kumar, 2023). These protocols are crucial for ensuring that health data can be transmitted efficiently and securely across devices, with some studies emphasizing the low-latency and energy-efficient characteristics of MQTT in enabling real-time alerts (Huang et al., 2023).

Despite their advantages, these protocols still face issues such as limited security features and scalability. For instance, as highlighted by Huang et al. (2023), integrating blockchain with MQTT improves data integrity and security but at the cost of increased overhead. This trade-off between security and performance is a significant challenge in healthcare IoT systems, where both speed and confidentiality are essential.

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Moreover, the shift towards 5G networks brings additional complexities and benefits. Studies like Liu et al. (2023) have demonstrated that 5G offers ultra-low latency and high bandwidth, which is critical for real-time cardiovascular monitoring, particularly for patients in emergencies. However, the widespread deployment of 5G infrastructure remains expensive and requires significant investment in network upgrades. Additionally, while 5G holds great promise for improving the performance of IoT healthcare networks, its rollout in rural or underserved areas may be delayed, limiting the accessibility of real-time cardiovascular monitoring in these regions.

Communication latency critically influences the performance of real-time cardiovascular health monitoring. Fig. 5 compares major IoT protocols based on their network latency, demonstrating that MQTT and 5G offer the lowest latency, thereby validating their selection for optimized network deployment.

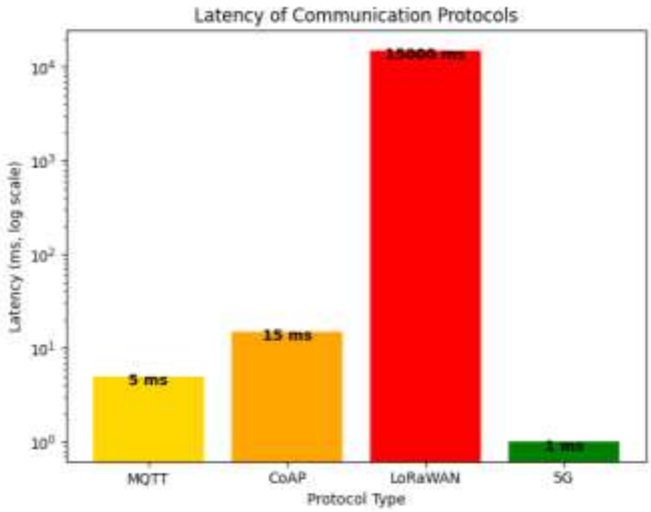

Figure 5. Latency of Communication Protocols

3.3 AI Model Integration and Personalization

AI plays a crucial role in the development of personalized health monitoring systems. AI models, such as those employing deep learning techniques like CNN and LSTM, are central to the prediction and analysis of cardiovascular health conditions. These models are capable of providing personalized insights based on individual health data, making them highly effective for monitoring chronic conditions such as hypertension, arrhythmias, and heart disease.

However, the deployment of AI-based models also introduces certain challenges. One of the primary concerns is the need for large amounts of high-quality training data to improve model accuracy. As noted in the study by Li et al. (2023), AutoML frameworks are being explored to facilitate model personalization by automatically adapting to a patient’s unique health profile. This reduces the computational burden on healthcare providers and ensures that predictive models can be tailored to each patient's needs. However, the computationally intensive nature of AutoML and deep learning models raises concerns about the feasibility of real-time deployment, especially on resource-constrained devices.

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Additionally, AI models in IoT healthcare systems need to be retrained periodically to account for changes in a patient's health condition over time. This requires continuous data collection and model retraining, which can be resource-intensive and time-consuming. Another challenge is ensuring the transparency and interpretability of AI models, especially when used in clinical decision-making. This is particularly important in healthcare, where decisions based on AI recommendations can have significant implications for patient outcomes. The use of techniques such as Grad-CAM, as mentioned by Zhao et al. (2024), for model interpretability could help address this challenge by providing healthcare providers with better insights into how the AI model is making predictions.

For large-scale, nationwide deployment, efficient real-time data streaming is essential. As shown in Fig. 6, Apache Kafka demonstrates superior throughput capabilities compared to Apache Pulsar, making it the preferred choice for handling high-volume cardiovascular data across distributed networks.

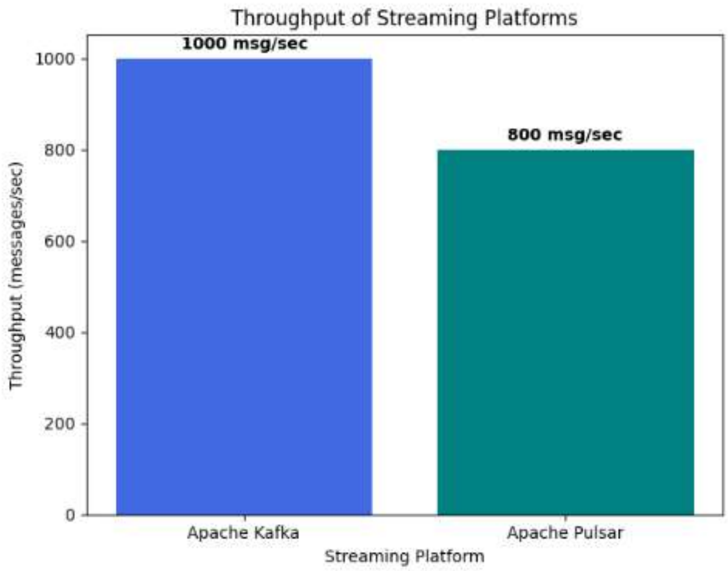

Figure 6. Throughput of Streaming Platforms

3.4 Data Security and Privacy Concerns

In IoT-based healthcare systems, especially those utilizing AI for cardiovascular health monitoring, data security and privacy are major concerns. The integration of personal health data into cloud-based storage systems raises issues about data confidentiality and the potential for unauthorized access. Blockchain technology, as discussed by Huang et al. (2023), is emerging as a promising solution for securing healthcare data, offering tamper-proof distributed records that ensure data integrity and immutability. However, the overhead associated with blockchain validation can lead to slower data processing speeds, which may impact the real-time capabilities of IoT healthcare systems.

Furthermore, ensuring compliance with data protection regulations, such as the GDPR (General Data Protection Regulation) in Europe, adds a layer of complexity. Ensuring that IoT devices and AI systems meet these regulatory standards while maintaining the speed and efficiency required for real-time health monitoring is a significant challenge.

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This section highlighted the key technological advancements and challenges in the integration of IoT and AI for cardiovascular health monitoring. While there have been significant strides in wearable devices, communication protocols, AI model integration, and data security, several challenges remain, particularly regarding real-time deployment, model personalization, and ensuring privacy and security. Overall, the reviewed studies reveal that deep learning models like CNN and CNN-LSTM consistently achieve higher accuracies, lightweight communication protocols like MQTT offer low-latency performance critical for real-time monitoring, and blockchain technologies significantly enhance data integrity, albeit at the cost of computational overhead.

4. Future Research Directions

Future research in intelligent IoT-based cardiovascular risk monitoring should follow a structured, phased approach. Initially, the focus should be on designing systems using IoT sensors such as ECG, SpO_2, and blood pressure monitors, combined with efficient communication protocols like BLE, Wi-Fi, and LPWAN (LoRa/NB-IoT). AI models such as LSTM, CNN, and Federated Learning should be selected and tested through simulation tools like MATLAB, NS-3, and TensorFlow to achieve high model accuracy and low network latency. In the second phase, advanced implementation strategies should be pursued by integrating optimized communication protocols like MQTT, LoRa, and 5G, deploying AI models on edge and cloud platforms (AWS SageMaker, Google Cloud IoT), and strengthening data security through blockchain encryption (Hyperledger Fabric). Finally, large-scale deployment should focus on building nationwide healthcare networks using 5G for ultra-low latency and Apache Kafka for scalable data streaming, along with AI model personalization using AutoML and TensorFlow. Challenges such as network congestion, energy efficiency, and real-time performance must be addressed through distributed cloud-edge architectures and adaptive scaling mechanisms. This phased strategy will ensure highly accurate, secure, scalable, and efficient cardiovascular risk prediction systems suitable for real-world implementation.

5. Conclusion

The integration of IoT, AI, and advanced communication technologies has transformed the landscape of cardiovascular health monitoring by enabling real-time, remote, and predictive healthcare solutions. This survey reviewed the evolution of IoT-based systems, highlighting major advancements in wearable sensors, communication protocols, AI model integration, and nationwide deployment strategies. Despite notable progress, challenges such as data privacy, energy efficiency, system scalability, and AI model interpretability remain. To address these gaps, a structured three-phase research model is proposed, emphasizing systematic development, network optimization, and large-scale validation. By following this approach, future systems can achieve greater accuracy, responsiveness, and security while ensuring broad accessibility and clinical trust. Continued innovation in this domain holds the potential to significantly reduce cardiovascular mortality rates through early detection, personalized intervention, and intelligent, connected healthcare networks. Additionally, future research must address ethical challenges, including AI model fairness, patient data privacy, and equitable access to healthcare IoT technologies across urban and rural regions.

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