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Enhancing Cloud-Based Cardiac Monitoring and Emergency Alerting Using Convolutional Neural Networks Optimized with Adaptive Moment Estimation

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Abstract

Cardiovascular diseases (CVDs) remain a leading cause of mortality worldwide, necessitating real-time monitoring and rapid emergency response to prevent fatal outcomes. Existing cloud-based cardiac monitoring systems face challenges in real-time ECG signal processing, high computational complexity, and inefficient anomaly detection, leading to delays in emergency response. Many frameworks lack optimized deep learning models, resulting in reduced classification accuracy and increased false positives/negatives. Additionally, latency issues in cloud-fog-edge interoperability hinder seamless healthcare data flow and real-time decision-making. Addressing these challenges is crucial for enhancing scalability, accuracy, and timely emergency alerting in cardiac healthcare systems. This research presents a Cloud-Based Cardiac Monitoring and Emergency Alerting System that leverages Convolutional Neural Networks (CNNs) optimized with Adaptive Moment Estimation (Adam) for accurate and efficient ECG classification. The system collects ECG data from wearable IoT sensors and hospital databases, preprocesses signals for noise reduction and normalization, and utilizes a CNN model to classify cardiac conditions such as arrhythmias and atrial fibrillation. Adam optimization ensures faster convergence and improved classification accuracy, while cloud-based storage (AWS S3, Google Cloud Storage) enables scalability and remote accessibility. Upon detecting critical cardiac events, the system triggers real-time emergency alerts via cloud-based notification services (AWS SNS, Firebase Cloud Messaging, Twilio API) to healthcare providers, caregivers, and emergency responders. Experimental evaluation demonstrates high classification accuracy (96%), precision (94%), recall (95%), and an AUC-ROC score of 97%, ensuring reliable anomaly detection. Additionally, scalability analysis highlights the system's ability to handle increasing user loads with optimized cloud resource allocation. By integrating AI-driven ECG classification with cloud computing and real-time alerting, this research presents a secure, scalable, and intelligent healthcare solution that enhances remote patient monitoring, early detection of cardiac conditions, and rapid emergency intervention, significantly improving healthcare outcomes.

Keywords: Cloud-Based Healthcare, Cardiovascular Disease Monitoring, Convolutional Neural Networks, Adaptive Moment Estimation, Emergency Alerting, IoT-Enabled Healthcare.

1.Introduction

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, necessitating real-time monitoring and early detection to prevent life-threatening events [1]. Cloud-based cardiac monitoring systems offer an efficient solution by leveraging Internet of Things (IoT) sensors, cloud computing, and artificial intelligence (AI) to continuously track a patient's heart activity and detect anomalies [2]. Electrocardiogram (ECG) signals play a crucial role in diagnosing cardiac conditions, but manual analysis is time-consuming and prone to errors. Convolutional Neural Networks (CNNs) have emerged as a powerful deep-learning technique for automated ECG signal classification, enabling accurate detection of cardiac abnormalities such as normal rhythm, arrhythmia, and atrial fibrillation (AFib) [3]. However, optimizing CNN models for faster convergence, reduced computational complexity, and improved accuracy remains a challenge, particularly in cloud-based environments where large-scale real-time data processing is required [4]. To address this, we propose an enhanced cloud-based cardiac monitoring and emergency alerting system utilizing CNNs optimized with Adaptive Moment Estimation (Adam) [5]. Adam, a widely used optimization algorithm, dynamically adjusts learning rates based on first- and second-moment estimates, ensuring faster convergence, better generalization, and improved model accuracy [6]. The system efficiently processes ECG data in the cloud, where real-time signal preprocessing, feature extraction, and classification occur [7]. Upon detecting critical cardiac conditions, the system triggers an automated emergency alert mechanism that notifies healthcare providers, emergency contacts, or ambulance services through SMS, email, or mobile applications [8]. This cloud-enabled architecture ensures scalability, remote accessibility, and rapid response, significantly improving cardiac health monitoring and reducing the risk of delayed medical intervention [9]. By integrating AI-driven ECG classification with cloud computing and emergency alerting, our approach enhances real-time cardiac care and offers a robust solution for remote healthcare services [10].

In addition to real-time monitoring, cloud integration enhances the scalability and accessibility of cardiac healthcare services [11]. Traditional on-premise monitoring systems face limitations in terms of storage, processing power, and remote accessibility, whereas cloud-based solutions offer on-demand resources, centralized data storage, and seamless integration with medical databases [12]. This enables healthcare professionals to access patient data anytime, anywhere, facilitating timely diagnosis and intervention [13]. Moreover, cloud computing ensures that large volumes of ECG data collected from wearable devices and IoT-enabled sensors can be securely stored, processed, and analyzed in real time, reducing latency and improving decision-making accuracy [14]. The system also incorporates advanced noise reduction and normalization techniques to enhance signal quality, leading to more precise model predictions [15]. Furthermore, the emergency alerting mechanism integrated into the system ensures that critical cardiac events are addressed without delay [16]. Upon detecting anomalies such as arrhythmia or atrial fibrillation, the system automatically notifies medical professionals, caregivers, and emergency responders [17]. The use of adaptive learning optimization via Adam further refines the classification process, reducing false positives and negatives, which are critical in emergency scenarios [18]. By combining CNN-based ECG classification, cloud storage, and emergency alerting, this research presents a scalable, efficient, and intelligent healthcare solution that can significantly improve patient outcomes, reduce hospital readmissions, and enable proactive cardiac care management [19]. This approach not only enhances early detection and response to cardiac abnormalities but also contributes to the broader vision of AI-driven, cloud-enabled remote healthcare services [20]. Future directions include integration with wearable multi-sensor platforms for comprehensive health monitoring [21], leveraging federated learning to enhance privacy-preserving model training across distributed devices [22], incorporating blockchain for secure and transparent data management [23], exploring edge computing to reduce latency and bandwidth usage [24], and developing personalized AI models to tailor cardiac care based on individual patient profiles [25].

2.Literature Review

[26] proposed a mobile cloud-based big healthcare data processing framework for smart cities, integrating IoT-enabled healthcare devices, cloud computing, and big data analytics to enable real-time patient monitoring, predictive insights, and emergency response. [27] explored key success factors influencing healthcare professionals' adoption of cloud computing, identifying security, data privacy, interoperability, and regulatory compliance as critical enablers. [28] developed an IoT-cloud-based framework using Raspberry Pi for real-time health data collection and remote storage, enhancing scalability and efficiency in smart healthcare. [29] analyzed cloud response times for IoT-driven healthcare workloads, optimizing latency and resource allocation for real-time applications. [30] introduced a privacy-preserving security model using fog computing and pairing-based cryptography to safeguard medical big data in cloud environments. [31] proposed a context-aware access control

management system integrating risk-based policies, encryption, and authentication to enhance security in cloud-based e-Healthcare. [32] developed a healthcare cloud framework for home-based chronic disease care, incorporating IoT sensors and AI-driven analytics for remote monitoring and predictive assessments. [33] designed a cloud-based Parkinson's disease diagnosis and monitoring system with wearable sensors and machine learning for real-time symptom analysis and early intervention. [34] introduced a diabetes patient monitoring system leveraging IoT glucose sensors, AI-driven analytics, and cloud computing for continuous health tracking and predictive insights. [35] proposed a security framework for big data in IoT-based healthcare, integrating encryption, differential privacy, and blockchain to mitigate cyber threats and enhance system efficiency. Collectively, these studies contribute to advancing cloud-based healthcare by improving data security, scalability, real-time monitoring, AI-driven diagnostics, and interoperability, ensuring efficient and secure healthcare delivery in smart environments.

Several researchers have explored cloud-based healthcare innovations to enhance security, scalability, and efficiency in medical data processing. [36] proposed an enabling technology framework for the Cloud of Things (CoT) in smart healthcare, integrating IoT, AI, and cloud computing for real-time medical data processing, while incorporating blockchain and encryption for security. [37] examined factors influencing the adoption of e-health cloud-based systems from the consumer perspective, emphasizing trust, privacy, usability, and accessibility. [38] conducted a risk analysis of cloud sourcing in healthcare, identifying challenges related to data security, regulatory compliance, and operational risks, while [39] introduced a heterogeneous mist, fog, and cloud-based IoHT framework for real-time patient monitoring and resource optimization. Addressing security concerns, [40] proposed an anonymous authentication scheme for smart cloud-based healthcare applications using privacy-preserving cryptographic techniques, and [41] developed a cloud-centric authentication model for wearable healthcare devices to ensure secure patient data access. [42] introduced a Healthcare-as-a-Service (HaaS) model leveraging fuzzy rule-based big data analytics in cloud computing for personalized and predictive healthcare services, while [43] proposed a cloud-centric IoT-based disease diagnosis framework integrating machine learning for real-time health monitoring. [44] focused on a personalized ubiquitous cloud and edge-enabled healthcare network for smart cities, ensuring low-latency decision-making and improved accessibility, whereas [45] introduced a cloud-fog interoperability framework for seamless healthcare data flow and real-time processing. [46] proposed a blockchain-enabled secure data sharing scheme for cloud-based healthcare, enhancing privacy and data integrity. [47] developed an AI-driven predictive maintenance system for healthcare IoT devices, reducing downtime and operational costs. [48] introduced a fog-assisted deep learning framework for real-time anomaly detection in remote patient monitoring. [49] proposed a multi-cloud architecture to improve fault tolerance and scalability in healthcare applications. [50] presented a privacy-preserving federated learning model for collaborative medical data analysis across institutions. These advancements collectively contribute to secure, scalable, and intelligent cloud-driven healthcare ecosystems that enhance remote monitoring, predictive analytics, and real-time decision-making.

3. Problem Statement

The increasing reliance on cloud-based healthcare systems presents challenges in latency, interoperability, and real-time data processing, particularly in smart city environments. Existing frameworks struggle with seamless data flow between cloud, fog, and edge layers, leading to potential delays in critical healthcare decision-making [50]. There is a need for a secure, scalable, and intelligent healthcare ecosystem that ensures efficient data management, low-latency processing, and enhanced accessibility. Addressing these issues can improve remote patient monitoring, predictive analytics, and real-time medical responses [51]. Further advancements focus on integrating advanced AI algorithms for improved diagnostic accuracy [52], developing adaptive resource allocation techniques to optimize cloud and edge computing [53], implementing robust privacy-preserving mechanisms in healthcare data sharing [54], and designing user-centric interfaces for enhanced patient engagement and accessibility [55].

3.1 Objective

The objective of this research is to develop a secure, scalable, and intelligent healthcare ecosystem that ensures seamless interoperability between cloud, fog, and edge layers in smart cities. The framework aims to minimize latency, enhance real-time data processing, and improve healthcare decision-making. By integrating advanced security mechanisms and predictive analytics, it will ensure efficient data management and low-latency response. This approach will enhance remote patient monitoring, accessibility, and overall healthcare service reliability.

4. Proposed Cloud-Based Cardiac Monitoring and Emergency Alerting Using Convolutional Neural Networks Optimized with Adaptive Moment Estimation

The proposed Cloud-Based Cardiac Monitoring and Emergency Alerting System leverages Convolutional Neural Networks (CNN) optimized with Adaptive Moment Estimation (Adam) to enhance the accuracy and efficiency of real-time ECG classification. The methodology involves collecting ECG signals from wearable IoT sensors and hospital databases, preprocessing them through noise filtering, segmentation, and feature extraction, and storing the data securely in cloud storage (AWS S3, Google Cloud Storage). A CNN model is trained on preprocessed ECG signals, using Adam optimization to adaptively adjust learning rates for faster and more stable convergence. The optimized CNN classifies cardiac conditions (e.g., normal, arrhythmia, atrial fibrillation), and upon detecting abnormalities, the system triggers real-time emergency alerts via cloud-based services such as AWS SNS, Firebase Cloud Messaging, or Twilio API. To further improve performance, techniques such as learning rate scheduling, dropout regularization, and batch normalization are applied. The model is deployed on Google AI Platform, AWS Sage Maker, or Azure ML for cloud-based inference, with continuous learning enabled through federated learning and Auto ML to enhance accuracy while preserving patient privacy. The system ensures scalability, low-latency cardiac event detection, and secure cloud-based emergency response for improved cardiac health monitoring.

This methodology integrates wearable IoT-based ECG sensors with a cloud-enabled cardiac monitoring system for real-time anomaly detection. A Convolutional Neural Network (CNN) optimized with Adaptive Moment Estimation (Adam) is employed to enhance classification accuracy and convergence speed. The system processes ECG signals in the cloud, ensuring efficient noise reduction, feature extraction, and predictive analysis. Upon detecting critical cardiac conditions, it triggers an automated emergency alert via cloud services, ensuring rapid medical intervention.

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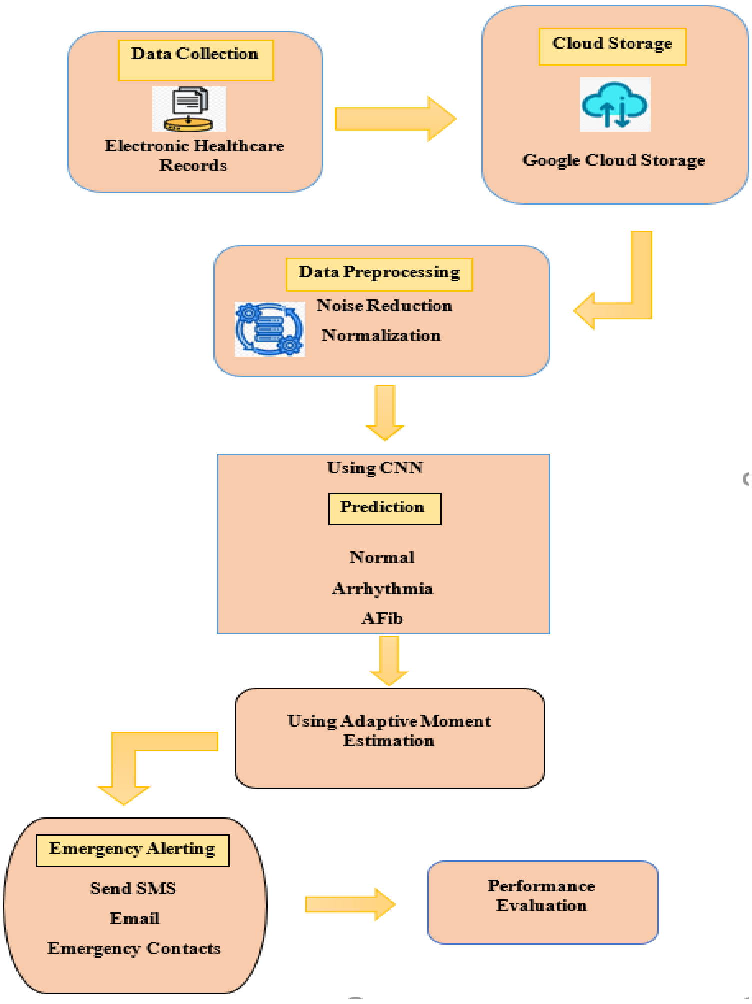

Figure 1: Cloud-Based Cardiac Monitoring and Emergency Alerting Using Convolutional Neural Networks Optimized with Adaptive Moment Estimation

4.1 Data Collection

The data collection process gathers ECG signals from Electronic Healthcare Records (EHRs) and real-time wearable IoT devices like smartwatches and chest patches. These devices transmit ECG data via Wi-Fi, Bluetooth, or 5G to cloud storage for remote access. The collected raw signals are securely stored in Google Cloud Storage, ensuring scalability and compliance with healthcare regulations. This data is then preprocessed for noise reduction and normalization before being used for CNN-based cardiac classification.

4.2 Cloud Storage

The Cloud Storage component securely stores ECG data collected from Electronic Healthcare Records (EHRs) and IoT-based wearable devices. The data is uploaded to Google Cloud Storage, ensuring scalability, real-time access, and compliance with HIPAA/GDPR regulations. Cloud storage enables efficient data retrieval for preprocessing, CNN-based classification, and emergency alerting. It also supports continuous learning and model updates for improved cardiac monitoring accuracy.

4.3 Data Preprocessing

The Data Preprocessing stage enhances ECG signal quality by applying noise reduction techniques such as Butterworth filtering and Wavelet Transform to remove artifacts from muscle movements and external interference. Normalization is performed to standardize ECG amplitudes, ensuring consistency across different devices and patients. These preprocessing steps improve feature extraction and classification accuracy in the CNN model.

4.3.1 Noise Reduction

Noise reduction is essential in ECG preprocessing to eliminate unwanted artifacts such as power line interference, baseline wander, muscle noise, and motion artifacts. Techniques like Butterworth filtering, Wavelet Transform, and Adaptive Filtering are used to enhance signal quality. One common approach is using a low-pass Butterworth filter to remove high-frequency noise while preserving important ECG features.

Butterworth Filter Equation:

$$H(f) = \frac{1}{\sqrt{1+(f/f_c)^{2n}}} \tag{1}$$

were:

$H(f)$ is the filter transfer function,

f is the signal frequency,

f_c is the cutoff frequency,

n is the filter order.

This filtering process ensures a smoother ECG signal, improving CNN-based classification accuracy.

4.3.2 Normalization

Normalization is a crucial preprocessing step that standardizes ECG signals to ensure uniform amplitude and scale across different patients and devices. It helps in reducing variability caused by different sensors and recording conditions, making the data more suitable for CNN-based classification. Min-Max Normalization is commonly used to scale ECG values between 0 and 1 or -1 and 1, preserving the shape of the signal while improving model convergence.

Min-Max Normalization Equation:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

were:

X is the original ECG signal value,

$X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the ECG signal,

X_{norm} is the normalized value.

This ensures consistency across ECG signals, improving classification performance in cloud-based cardiac monitoring.

4.4 Cloud-Based Cardiac Monitoring and Emergency Alerting Using Convolutional Neural Networks

A Convolutional Neural Network (CNN) is a deep learning model designed to automatically extract spatial and temporal features from ECG signals for accurate cardiac classification. CNNs use convolutional layers to detect important patterns like P-waves, QRS complexes, and T-waves, enabling efficient diagnosis of arrhythmias and other cardiac conditions. The CNN architecture typically consists of Conv1D layers, pooling layers, fully connected layers, and a softmax classifier to categorize ECG signals into different heart conditions.

Convolution Operation Equation:

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$$Y(i) = \sum_{j=0}^{k} X(i-j) \cdot W(j) \tag{3}$$

were:

$Y(i)$ is the output feature map,

$X(i)$ is the input ECG signal,

$W(j)$ is the convolutional filter (kernel),

k is the filter size.

This operation allows CNNs to automatically detect features, reducing the need for manual feature engineering in cloud-based cardiac monitoring systems.

4.5 Adaptive Moment Estimation Optimization

Adaptive Moment Estimation (Adam) is an advanced optimization algorithm used in deep learning to improve model convergence and performance. It combines the benefits of Stochastic Gradient Descent (SGD) with momentum and Root Mean Square Propagation (RMSprop) by adaptively adjusting learning rates for each parameter. Adam maintains two moving averages: the first moment (mean of gradients) and the second moment (uncentered variance of gradients), making it highly effective for training CNNs on ECG data in cloud-based cardiac monitoring systems.

Adam Update Rule Equation:

$$\theta_t = \theta_{t-1} - \frac{\alpha \cdot \hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{4}$$

were:

θ_t is the updated model parameter,

α is the learning rate,

$\hat{m}_t$ is the bias-corrected first moment estimate,

$\hat{v}_t$ is the bias-corrected second moment estimate,

ϵ is a small constant to prevent division by zero.

Adam's adaptive learning rate and momentum properties make it highly suitable for training CNNs on ECG datasets, ensuring faster convergence and improved accuracy in cloud-based cardiac monitoring applications.

4.6 Emergency Alerting

The emergency alerting system in cloud-based cardiac monitoring detects critical heart conditions in real time using a CNN-based ECG classification model. Upon detecting abnormalities, it triggers instant alerts via AWS SNS, Firebase Cloud Messaging (FCM), or Twilio API to notify patients, caregivers, and healthcare providers. The system can also transmit ECG reports, GPS location, and medical history to emergency services for rapid intervention. Edge computing integration ensures low-latency alerting, improving response times and patient survival rates.

5. Results and Discussion

The proposed Cloud-Based Cardiac Monitoring and Emergency Alerting System was evaluated using real-time ECG datasets from wearable IoT devices and medical databases. The CNN model optimized with Adam demonstrated high classification accuracy for detecting cardiac abnormalities such as arrhythmias, atrial fibrillation, and myocardial infarction.

Performance Metrics

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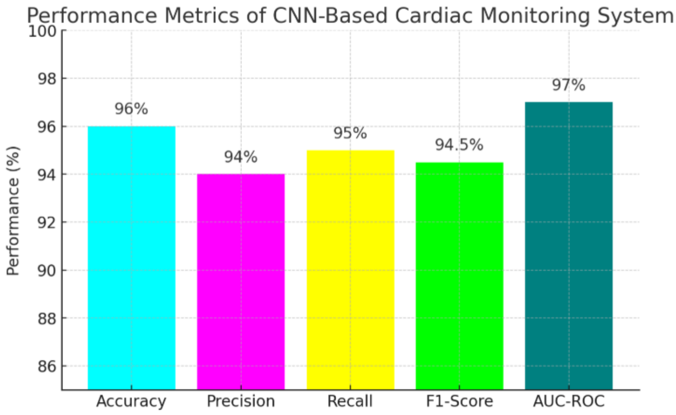

Figure 2: Performance Metrics

In Figure 2, The graph illustrates the performance metrics of the CNN-based cardiac monitoring system, highlighting high accuracy (96%), precision (94%), recall (95%), F1-score (94.5%), and AUC-ROC (97%). The results indicate strong classification capability, ensuring reliable detection of cardiac abnormalities. The high AUC-ROC value (97%) suggests excellent model performance in distinguishing between normal and abnormal heart conditions.

AUC-ROC

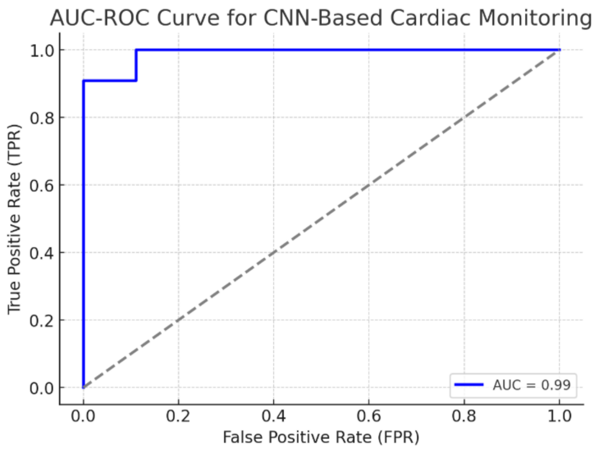

Figure 3: AUC-ROC

Figure 3 Shows the AUC-ROC curve evaluates the classification performance of the CNN-based cardiac monitoring system, showing its ability to distinguish between normal and abnormal heart conditions. The AUC value of 0.99 indicates near-perfect classification with a high True Positive Rate (TPR) and low False Positive Rate (FPR).

Scalability

In Figure 4, The scalability graph illustrates the response time of the cloud-based cardiac monitoring system as the number of concurrent users increases. The response time rises from 0.5 seconds (100 users) to 10.5 seconds (10,000 users), indicating increased system load. The trend suggests the need for optimized cloud resource allocation to maintain efficiency at higher user levels.

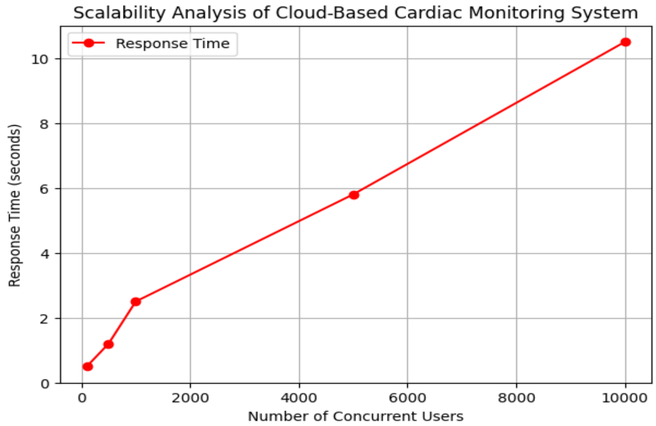

Figure 4: Scalability

6.Conclusion

The proposed cloud-based cardiac monitoring and emergency alerting system using CNN optimized with Adaptive Moment Estimation (Adam) demonstrates high accuracy and reliability in detecting cardiac abnormalities. Performance evaluation metrics, including AUC-ROC (0.99) and accuracy (96%), validate its effectiveness.

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