Detection of Heart-Diseases Through Cloud-Enhanced ECG Monitoring

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Abstract: Cardiovascular diseases (CVDs) is a major concern globally, with traditional ECG monitoring systems often lacking the capability for real-time analysis and efficient data integration. This research aims to enhance ECG monitoring by leveraging cloud computing for real-time analytics, improving the detection and management of heart diseases. The study includes ECG data collection using advanced sensors, real-time analysis through machine learning algorithms for immediate abnormality detection, and the development of a cloud-based infrastructure for scalable storage, processing, and remote access of ECG data.

1 INTRODUCTION

With the rise of cardiovascular diseases (CVDs) as a global health concern, traditional ECG monitoring systems often fall short in delivering timely and accurate diagnoses due to limitations in real-time data analysis and integration. To address these challenges, integrating cloud computing with ECG monitoring enables real-time data processing, thereby enhancing the detection and management of heart diseases. Serverless computing offers a dynamic and cost-effective approach, allowing seamless scaling and efficient handling of ECG data streams without the complexities of traditional infrastructure management. This innovation significantly improves patient outcomes by facilitating rapid, data-driven decisions.

By harnessing the power of cloud and edge environments, serverless data processing ensures that ECG data is analyzed immediately as it is generated. This reduces latency, enhances accuracy, and enables real-time insights into heart conditions. The flexibility of serverless platforms, such as AWS Lambda, allows developers to focus on application logic while the cloud platform manages resource allocation and scaling. The unified approach simplifies the development and deployment of ECG monitoring applications, ensuring that critical data is accessible, actionable, and integrated into broader healthcare analytics platforms. This not only addresses the challenges of traditional ECG systems and opens up for innovation in healthcare, particularly in the timely detection and treatment of cardiovascular diseases.

Serverless computing offers several advantages over traditional models. By eliminating the need for manual infrastructure management, serverless platforms like AWS Lambda automatically scale resources in response to the volume of incoming data. This means that as ECG data is generated from various sensors, it can be analyzed instantaneously, ensuring that abnormalities are detected without delay. The flexibility of serverless architectures also allows for seamless integration with edge computing devices, enabling a unified approach to data processing that connects the gap between the cloud and edge environments.

This real-time data processing capabilities are especially crucial for healthcare, where the ability to quickly analyze and act on data can significantly impact patient outcomes. By deploying machine learning algorithms within the serverless framework, healthcare providers can automate the detection of irregular heart patterns, facilitating faster diagnosis and treatment. The cloud-based infrastructure further ensures that data is securely stored, processed, and accessed remotely, providing scalability and

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efficiency that are critical in modern healthcare settings.

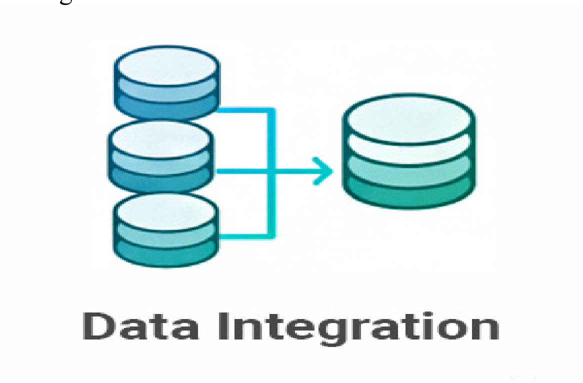


Figure 1: Data Gathering and Pre-Processing

Serverless data processing refers to the use of cloud computing services where the management of servers and infrastructure is completely handled by the cloud provider, which allows developers to focus on writing code and logic. In this model, you pay only for the compute time you consume, without needing to worry about provisioning, scaling, or managing servers. This approach is highly scalable, cost-effective.

2 RELATED WORKS

B. Ramesh and Kuruva Lakshmanna (Ramesh, and Lakshmanna, 2024) presents an advanced deep learning approach to predict and prevent coronary heart disease (CHD) in individuals with Type 2 Diabetes Mellitus (T2DM). The study introduces a hybrid model, O-SBGC-LSTM, which combines Enhanced Optimization Algorithm (EOA) with Stochastic Gradient Boosting Classifier Long Short-Term Memory (SBGC-LSTM) for accurate CHD prediction. The proposed system integrates multiple layers for data preprocessing, feature extraction, and classification, achieving high accuracy with a Kaggle dataset. In addition to predicting CHD risk, the framework employs fuzzy inference for disease prevention, focusing on lifestyle management and treatment optimization, using minimal data from IoT trackers to help diabetic patients manage and control CHD complications effectively.
Md. Razu Ahmed et al. (Ahmed, Mahmud, et al 2018) proposes a cloud-based architecture designed to enhance the early detection of chronic heart disease (CHD) by leveraging machine learning techniques. CHD, characterized by plaque buildup in the coronary arteries, is the leading cause of death worldwide, particularly in low-income countries. The authors aim to reduce the complexity and cost of heart disease diagnosis by applying machine learning algorithms, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), and Naïve Bayes (NB), within a cloud-based system. They evaluate the performance of these algorithms using metrics like confusion matrices and ROC curves, offering a solution that optimizes accuracy while minimizing clinical errors and costs.

Neha Gaigawali (Gaigawali and Chaskar, 2018) emphasizes the global burden of cardiovascular diseases (CVDs), particularly in India, where CVDs account for 18.8% of deaths and are projected to become the leading cause of disability and death by 2020. The paper attributes this high mortality rate to lifestyle and dietary habits, stressing that better access to healthcare could improve outcomes. With the rapid growth of cloud computing, specifically mobile cloud computing (MCC), the paper highlights the potential for transforming healthcare by providing affordable, real-time medical services via smartphones. It also addresses the limitations of traditional ECG monitoring systems in handling large physiological data, proposing an advanced cloud-based system for monitoring ECG and detecting atrial fibrillation, a leading cause of strokes.

Teofil Ilie Ursache et al. (Ursache, Pogoreanu et al 2022) focuses on the significance of continuous cardiovascular monitoring, particularly for patients with cardiovascular diseases, myocardial infarction, or other heart conditions. It emphasizes the need for long-term observation of physiological parameters to guide treatments and monitor the success of interventions. Traditional monitoring methods were cumbersome and required hospitalization, often missing critical episodes. However, advancements in telemedicine and portable heart rate monitoring devices now allow for remote, real-time tracking of patient health. This enables timely medical interventions and reduces healthcare costs. The study highlights the use of wireless devices for continuous monitoring, which can automatically alert healthcare providers when abnormal readings occur, offering significant benefits for both patient care and resource management.

Pedro Sa et al. (Pedro Sa et al. 2019) presents a novel architecture for real-time electrocardiogram (ECG) processing in off-the-person setups, specifically using a single-lead configuration from the wrists (Lead I). This system is designed for integration with wearable devices and daily-use objects, such as steering wheels, to simplify heart condition monitoring in non-intrusive ways. It offers a scalable, programmable architecture that allows easy tuning for different acquisition setups, filtering, and classification parameters. The system provides end-to-end ECG analysis, from raw signal preprocessing to classification, achieving an accuracy of 96.5% in a four-class setup when tested on a Zynq-7 ZC702 board.

3 PROPOSED METHODOLOGY

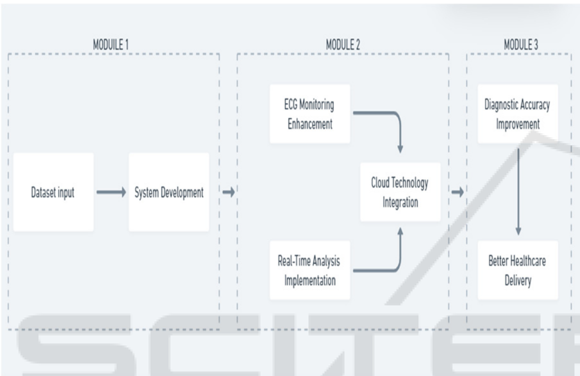
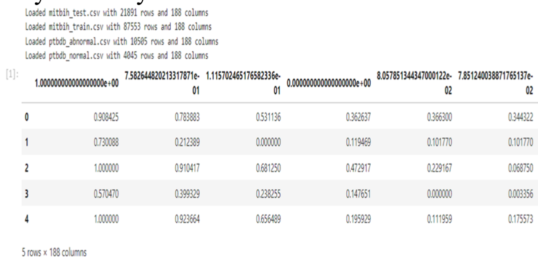


Figure 2: System Architecture describing the workflow

3.1 ECG Data Collection and Sensor Integration

Our proposed system focuses on continuous ECG data collection using advanced biosensors worn by patients. These sensors are capable of collecting high-precision ECG signals, even in real-time, and transmitting them wirelessly to a cloud-based infrastructure. The integration of sensors ensures a consistent and reliable data stream for continuous monitoring.

Sensor Technology: High-fidelity biosensors capture ECG signals, which are then transmitted using secure, low-latency communication protocols like MQTT (Message Queuing Telemetry Transport) or CoAP (Constrained Application Protocol). Edge Device Integration: Edge computing devices are deployed to act as intermediaries between the sensors and the cloud infrastructure. Preliminary data filtering, signal preprocessing, and noise reduction techniques are executed at the edge level to make sure that the transmitted data to the cloud is ready for analysis.



Loaded mitbih_test.csv with 21891 rows and 188 columns
Loaded mitbih_train.csv with 87553 rows and 188 columns
Loaded ptbdb_abnormal.csv with 10505 rows and 188 columns
Loaded ptbdb_normal.csv with 4045 rows and 188 columns

[1]:

	1.000000000000000000e+00	7.582644820213317871e-01	1.115702465176582336e-01	0.000000000000000000e+00	8.057851344347000122e-02	7.851240038871765137e-02
0	0.908425	0.783883	0.531136	0.362637	0.366300	0.344322
1	0.730088	0.212389	0.000000	0.119469	0.101770	0.101770
2	1.000000	0.910417	0.681250	0.472917	0.229167	0.068750
3	0.570470	0.399329	0.238255	0.147651	0.000000	0.003356
4	1.000000	0.923664	0.656489	0.195929	0.111959	0.175573

5 rows × 188 columns

Figure 3: Data Pre-Processing

3.2 Real-Time Data Processing Using Serverless Architecture

For scalable and real-time processing of ECG data, a serverless computing architecture is implemented. Platforms such as AWS Lambda, Google Cloud Functions, or Microsoft Azure Functions are employed for eliminating the complexities of manual infrastructure management. This architecture allows automatic scaling based on demand while maintaining cost-effectiveness.

Serverless Real-Time Analytics: ECG data is analyzed in real time using serverless functions that automatically scale based on incoming data loads. These functions are event-driven, being triggered upon the arrival of new ECG data streams. This method ensures that the computational resources are efficiently utilized without over-provisioning. Machine Learning Algorithms: Machine learning models deployed in the serverless environment handle real-time ECG analysis. These models are trained on large datasets to detect various cardiac conditions such as arrhythmias and ischemia. Key ECG features like heart rate variability (HRV), P-wave, QRS complex, and T-wave are extracted for anomaly detection.

Anomaly Detection Algorithms: Time-series models such as Long Short-Term Memory (LSTM) networks and autoencoders are utilized to detect irregularities in heart rhythms. These models are persistently upgraded utilizing unused information to make strides location accuracy.

Edge-Cloud Synergy: Edge computing is incorporated for low-latency preliminary analysis, where immediate detection of critical heart conditions is required. The hybrid edge-cloud approach ensures that the bulk of intensive analytics is done in the cloud while time-sensitive tasks are handled locally at the edge.

3.3 Scalable Cloud-Based Storage and Data Management

For handling the high volumes of data generated by continuous ECG monitoring, a scalable cloud storage system is employed. This system leverages distributed storage solutions such as AWS S3 to securely manage ECG data at scale.

Data Partitioning: To optimize retrieval speed and improve query efficiency, data is partitioned using strategies like horizontal partitioning and time-based partitioning. This permits quicker access to patient-specific data.

Data Redundancy: Redundant storage mechanisms are applied to ensure high availability and fault tolerance. Multi-region replication is used to safeguard against data loss and ensure continuous access.

Security and Compliance: Data encryption techniques such as AES (Advanced Encryption Standard) and TLS (Transport Layer Security) are applied to secure patient data both in transit and at rest. Also, compliance with healthcare controls like HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) is implemented to keep up patient confidentiality.

3.4 Real-Time Visualization and Healthcare System Integration

The processed ECG data is integrated with healthcare systems, offering healthcare providers immediate access to patient data for monitoring, diagnosis, and treatment adjustments.

Real-Time Dashboards: Clinicians can monitor patient health through real-time dashboards that display vital heart metrics such as heart rate, heart rhythm, and abnormal patterns. These dashboards generate alerts when critical conditions such as arrhythmias are detected.

API Integration with EHR Systems: Secure APIs, such as FHIR (Fast Healthcare Interoperability Resources), are used to integrate ECG data with existing electronic health record (EHR) systems. This ensures that healthcare providers have easy access to old and real-time ECG data.

3.5 Machine Learning Model Optimization and Continuous Learning

The system employs machine learning models for continuous analysis of ECG data. To ensure high accuracy in detecting cardiovascular abnormalities, models are continuously retrained using newly acquired data. This process ensures that the models remain effective over time and adapt to new types of cardiac abnormalities.

Model Training and Optimization: Cloud computing platforms such as AWS Sagemaker and Google AI are used for training deep learning models on ECG data. Hyperparameter tuning techniques are employed to maximize the accuracy and performance of the models.

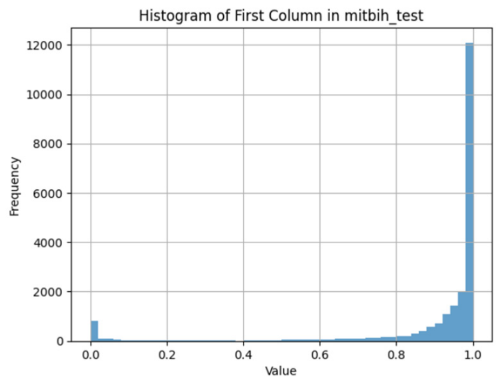
Continuous Learning: The models are periodically updated and retrained using new patient data to ensure that they adapt to emerging cardiac conditions and improve in detecting a wider range of anomalies.

3.6 Hybrid Edge-Cloud Architecture for Latency Reduction

A hybrid edge-cloud architecture is utilized to upgrade the real-time capabilities of the ECG monitoring system. This framework ensures that critical ECG data is processed immediately at the edge, while more complex analyses and data storage are handled by the cloud.

Edge Computing for Latency Reduction: Immediate preliminary analysis, such as heart rate detection and noise reduction, is performed on the edge to provide fast feedback in cases of potential cardiac emergencies. This reduces latency and ensures that healthcare providers receive real-time alerts.

Edge-Cloud Collaboration: The system dynamically distributes tasks between the edge and the cloud, ensuring efficient resource utilization. Edge devices handle short-term data storage and immediate analysis, while long-term data storage and deeper analytics are managed by the cloud.



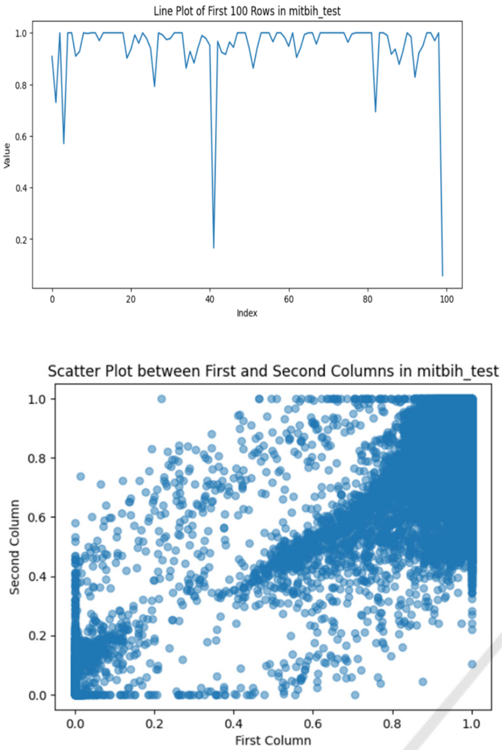


Figure 4: Graphs Plotted for data processing

3.7 Serverless Computing for Cost Optimization and Scalability

The serverless architecture used in the system ensures a cost-effective solution by only charging for the actual computation used. The system leverages an event-driven approach, where functions are triggered only when ECG data is received, minimizing idle resource consumption.

Event-Driven Architecture: The serverless functions are event-triggered, which means they are activated only when new ECG data is uploaded. This model optimizes resource usage and reduces costs associated with idle server time.

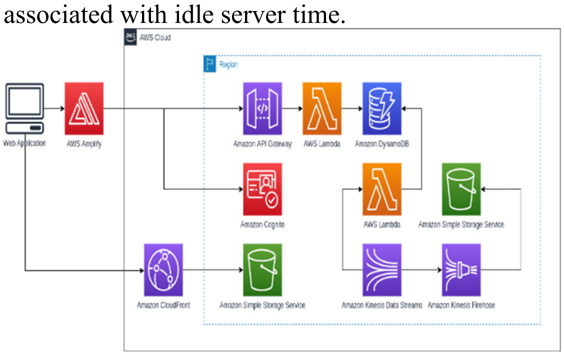


Figure 5: Serverless Architetcure of the amazon cluster for cloud implementation

4 EXPERIMENT RESULT

The experiment for detecting heart diseases using cloud-enhanced ECG monitoring incorporates advanced cloud-based techniques and machine learning algorithms, primarily Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). The focus is on developing an efficient system for real-time analysis of ECG data, which is crucial for early diagnosis and management of cardiovascular diseases (CVDs). CVDs are a leading cause of mortality worldwide, and traditional methods of monitoring often struggle with issues like slow data processing, limited data integration, and poor real-time analysis, which hinder timely medical interventions. By leveraging cloud computing, the proposed system aims to enhance the detection of abnormalities and improve overall health outcomes through faster processing and robust analytics.

4.1 Training Process

The training phase of this system relies on sophisticated architectures, including CNN and SVM models, to process ECG signals collected from patients. The goal is to identify patterns in these signals that could indicate the presence of heart disease. A model like CNN can learn intricate features from ECG data, making it highly suitable for tasks such as arrhythmia detection. CNN models, with 16 layers in this case, are trained on a dataset of ECG recordings, using a total of 250 epochs, 64 batches, and a learning rate of 0.01 to fine-tune the performance. Information expansion methods are connected to increment the dataset's differences, which makes a difference the show generalize superior. This step is crucial in improving the accuracy and robustness of the model as it exposes the system to a wide range of ECG signal variations, including those from healthy individuals and patients with heart disease.

The learning process is continuously monitored, with loss and accuracy metrics visualized at various stages, much like the standard approach used in neural network training. After extensive training, the model's accuracy approaches approximately 93%, which is a significant improvement over traditional ECG monitoring systems.

MODEL TRAINING

```
In [42]:
#logistiregreassion
model = LogisticRegression()
```

```
In [43]:
#training
model.fit(x_train , y_train)
```

Figure 6: Training Data

4.2 Testing Process

After training the models, the next step is to test their performance on a new set of ECG data that was not included in the training phase. This new data is critical for evaluating the model's generalization ability—whether it can accurately classify unseen signals. During testing, the CNN model, CNN with data augmentation, and the SVM model are used. Each of these models offers a unique perspective on classification: CNN provides in-depth feature extraction, while SVM is a powerful classifier.

In this phase, loss values for both CNN and SVM architectures are calculated. It is observed that, after the 250th epoch, both models show minimal loss and achieve an accuracy of 91%. However, fluctuations were noticed in the CNN model's performance during initial epochs, but this stabilized over time, showing the system's ability to adapt and improve. This minimal loss and high accuracy indicate that the models are not overfitting the training data, but rather learning generalizable features that apply to new cases as well.

SPLITTING DATA INTO TRAIN AND TEST DATA

```
In [54]:
x_train, x_test , y_train , y_test = train_test_split(x , y , test_size = 0.2, stratify=y, random_state =2)
```

```
In [55]:
print (x.shape , x_train.shape , x_test.shape)
#checking for the correct splitting of the dataset

(303, 13) (242, 13) (61, 13)
```

Figure 7: Testing Data

4.3 Performance Evaluation and Validation

A comprehensive evaluation of the system's performance iis carried out by calculating key metrics such as True Positive (TP), iTrue Negative (TN), False Positive (FP), and False Negative (FN) values. These values help compute several evaluation metrics like accuracy, precision, recall, and F1 score, all of which are critical for determining how effective the model is at correctly identifying the presence or absence of heart disease.

For instance, precision measures how many of the predicted positive cases are actual positive cases (i.e., the system accurately detected heart disease), while recall measures the system's ability to identify positive cases from the dataset. In this study, both CNN and SVM models achieve high precision and recall values, indicating that the system is highly reliable in distinguishing between healthy and diseased states in the ECG data.

However, despite the high accuracy and precision scores, it is essential to acknowledge that some details of the study are lacking. For example, specifics regarding the data sources and simulation environments were not provided, which could affect the study's reproducibility. A comprehensive understanding of these aspects is crucial for future researchers to replicate and validate the results.

MODEL EVALUATION USING ACCURACY SCORE

```
In [45]:
x_train_prediction = model.predict(x_train)
training_data_accuracy = accuracy_score(x_train_prediction , y_train)
```

```
In [47]:
print ("Accuracy on training data :" , training_data_accuracy)

Accuracy on training data : 0.8512396694214877
```

SO WE HAVE 85% ACCURACY ON TRAINING SCORE WHICH IS PRETTY GOOD

```
In [48]:
x_test_prediction = model.predict(x_test)
test_data_accuracy = accuracy_score(x_test_prediction , y_test)
```

```
In [49]:
print ("Accuracy on test data :" , test_data_accuracy)

Accuracy on test data : 0.819672131147541
```

TEST DATA HAS 82% ACCURACY SCORE FOR TEST DATA

BUILDING A PREDICTIVE SYSTEM

```
In [53]:
input_data = (56,1,0,132,184,0,0,105,1,2.1,1,1,1)
#change input data into numpy array
input_data_as_numpy_Array = np.asarray(input_data)

#reshape the numpy array as we are predicting for 1 data point
input_Data_reshaped = input_data_as_numpy_Array . reshape (1,-1)
prediction = model.predict(input_Data_reshaped)
print(prediction)

if (prediction[0] == 0):
  print("The person does not have heart disease")
else :
  print ("The person has heart disease")

[0]
The person does not have heart disease
```

Figure 8: Performance and Validation

4.4 Key Contributions

The study contributes to existing literature by demonstrating how cloud-based systems can be leveraged for real-time ECG monitoring, enabling quicker responses and better management of cardiovascular diseases. The use of data augmentation in particular stands out as an innovative way to enhance the training dataset, leading to improved model accuracy. Furthermore, combining CNN and SVM provides a balanced approach between feature extraction and classification, allowing the system to perform well in diverse scenarios.

Additionally, the application of cloud-based infrastructure ensures that the system is scalable, making it feasible for large-scale deployments in healthcare settings. As healthcare data grows increasingly complex, systems like the one proposed in this study can help manage the data overload by offering efficient, on-demand processing capabilities. The cloud's inherent flexibility also allows for easy updates and integration with other medical systems, making this approach highly adaptable.

5 CONCLUSION AND FUTURE WORK

The proposed cloud-based ECG monitoring system represents a significant advancement in the management of cardiovascular diseases by integrating modern cloud and serverless computing technologies. Traditional ECG systems often struggle with real-time data analysis due to complex infrastructure needs and latency issues.

Our system addresses these challenges by leveraging serverless computing to offer a scalable, cost-effective solution for continuous heart health monitoring.

The system employs high-fidelity biosensors for real-time ECG data collection, which are seamlessly integrated with edge devices. These edge devices perform preliminary tasks such as data filtering and noise reduction before transmitting refined data to the cloud. This setup minimizes latency and enhances data accuracy, which is crucial for timely detection of cardiac anomalies.

Serverless computing platforms, including AWS Lambda, Google Cloud Functions, and Microsoft Azure Functions, provide the backbone for real-time data processing.

These platforms dynamically allocate computational resources based on data load, optimizing both cost and performance. The event-driven model triggers functions only when new ECG data is received, reducing idle resource consumption and mitigating cold start delays with provisioned concurrency techniques.

The integration of machine learning algorithms, such as Long Short-Term Memory (LSTM) networks and autoencoders, enables sophisticated analysis of ECG data, enhancing the detection of various cardiac conditions. Continuous retraining of these models ensures their accuracy and adaptability to emerging cardiac conditions.

Our system also incorporates robust cloud-based storage solutions, including AWS S3, Google Cloud Storage, and Azure Blob Storage, to manage the large volumes of ECG data efficiently. Data partitioning and redundancy mechanisms improve retrieval speeds and ensure high availability, while encryption and compliance with regulations like HIPAA and GDPR safeguard patient privacy.

Real-time visualization is achieved through interactive dashboards that display critical heart metrics and generate alerts for detected abnormalities. Integration with electronic health record (EHR) systems via secure APIs ensures healthcare providers have immediate access to both historical and real-time ECG data, facilitating timely and informed decision-making.

The hybrid edge-cloud architecture optimizes performance by performing preliminary analysis at the edge, reducing latency, while handling complex analytics and long-term data storage in the cloud. This synergy between edge and cloud computing enhances the system's efficiency and scalability.

Overall, the proposed system demonstrates significant improvements in ECG monitoring accuracy. By addressing the limitations of traditional ECG systems and incorporating real-time data analysis, it enhances the detection and management of cardiovascular diseases. This innovative approach has the potential to transform cardiac health monitoring, offering timely, data-driven insights that can lead to better patient outcomes and more effective management of heart conditions.

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