ISSN NO: 9726-001X

Volume 9 Issue 01 2021

JOURNAL OF CURRENT SCIENCE

Hybrid Fog-Cloud Architectures for Scalable IoT Healthcare: Improving ECG Analysis, Signal Processing, and AI-Driven Monitoring

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ABSTRACT

This paper introduces a novel hybrid fog-cloud AI architecture that combines the advantages of cloud computing and fog computing to improve real-time ECG interpretation. High latency and bandwidth consumption are problems for traditional cloud-only systems, which might impair the functionality of time-sensitive applications like ECG monitoring. To overcome these constraints, the suggested hybrid paradigm combines cloud computing for advanced analysis, storage, and scalability with fog nodes for initial signal processing. Fog nodes ensure quick and effective real-time ECG analysis by processing data closer to the source, which lowers latency and bandwidth needs. In the meantime, the cloud offers a wealth of processing power to run sophisticated machine learning algorithms for precise identification of cardiovascular anomalies. Patient outcomes will be greatly enhanced by the AI-driven monitoring system's high precision and low false positive rate in identifying cardiovascular problems. When compared to traditional systems, performance evaluations show that the system performs better in terms of anomaly detection, feature extraction accuracy, and energy efficiency. In addition to optimizing system scalability, the hybrid architecture guarantees reliable real-time monitoring, which is crucial for ongoing patient care. This technology offers a dependable and scalable method for continuous patient monitoring, early cardiovascular disease identification, and timely medical interventions, with an overall system accuracy of 97.6%. Thus, combining AI with a hybrid fog-cloud paradigm provides a complete solution for enhancing real-time healthcare monitoring, with a focus on low latency, increased diagnostic accuracy, and energy efficiency.

Keywords: AI monitoring, Cardiovascular detection, Anomaly detection, Feature extraction, Cloud computing, Hybrid fog-cloud architecture, Healthcare monitoring.

1. INTRODUCTION

The delivery of healthcare services is being revolutionized by the incorporation of Internet of Things (IoT) technologies into healthcare systems (Farahani et al., 2020) [1]. Continuous, real-time patient health condition monitoring is made possible by IoT devices including wearables, sensors, and medical monitors (Angelopoulos et al., 2019) [2]; (Patan et al., 2020) [3]. Electrocardiogram (ECG) monitoring, which monitors the electrical activity of the heart and helps identify some heart diseases, is one of the most important diagnostic techniques in healthcare (Rincon et al., 2020) [4]. However, real-time decision-making, computing power, and data storage limitations limit traditional ECG analysis (Gia et al., 2019) [5]; (Sun et al., 2020) [6]. Hybrid fog-cloud architectures present viable ways to get beyond these restrictions, allowing for AI-driven monitoring systems, signal processing, and scalable, real-time ECG analysis (Hassan et al., 2019) [7].

Traditional healthcare systems usually gather ECG data in clinics or hospitals and process the results in centralized systems, which causes delays in diagnosis, particularly for patients who live far away (Devarajan, 2020) [8]. By processing data closer to the data source—such as patient wearables or local edge devices—Fog Computing has been introduced into the healthcare industry to address this difficulty (Dondapati, 2020) [9]; (Allur, 2019) [10]. Because decentralization lowers latency, real-time monitoring and faster reaction times are guaranteed, which is especially important for severe medical conditions (Rajeswaran, 2020) [11]. However, it might be challenging to scale when processing massive amounts of ECG data at the edge due to resource limitations (Poovendran, 2019) [12]; (Poovendran, 2020) [13].

On the other side, cloud computing offers strong processing power and enormous storage capacity, which solves these scalability problems (Sreekar, 2020) [14]. Numerous data sources can be combined by cloud systems, enabling in-depth analysis and long-term data storage (Karthikeyan, 2020) [15]; (Sitaraman, 2020) [16]. Healthcare systems can accomplish high-performance data analysis at scale and low-latency processing for real-time applications by combining fog and cloud computing (Panga, 2020) [17]. By using the advantages of both paradigms, the hybrid architecture makes it easier to divide up the work between centralized cloud systems and edge (fog) systems (Gudivaka, 2020) [18]; (Gudivaka, 2020) [19].

The use of machine learning (ML) and artificial intelligence (AI) techniques is essential to improving ECG monitoring (Gudivaka, 2019) [20]. Algorithms for AI-driven signal processing, especially those based on machine learning, are able to analyze ECG data more effectively and spot minute patterns or abnormalities that conventional techniques would miss (Allur, 2020) [21]; (Deevi, 2020) [22]. Proactive care is made possible by these algorithms' ability to anticipate possible health problems like arrhythmias, ischemia, and other cardiovascular disorders (Kodadi, 2020) [23]. Additionally, AI makes it possible for models to be continuously learned and adjusted, gradually increasing the accuracy of diagnoses (Dondapati, 2020) [24].

AI-based ECG analysis combined with hybrid fog-cloud architectures provides a comprehensive approach to scalable healthcare systems and real-time monitoring (Dondapati, 2020) [25]. While using the cloud for longer-term patient health monitoring and more comprehensive, data-driven insights, the architecture enables quick local (at the fog level) processing of patient data (Gattupalli, 2020) [26]. Better results, early diagnosis, and more effective use of resources are all made possible by this system, which guarantees that medical personnel can obtain immediate, actionable information for patient care (Allur, 2020) [27].

Making sure that IoT devices, fog nodes, cloud platforms, and AI algorithms integrate seamlessly is the main problem in putting such a hybrid system into practice (Naga, 2020) [28]. To guarantee that the system functions dependably, particularly in crucial healthcare settings, proper data routing, security protocols, and fault tolerance must be given top priority (Peddi et al., 2018) [29]. Additionally, to lower computational cost and avoid delays in real-time data processing, lightweight AI models that can operate on edge devices must be designed (Peddi et al., 2019) [30].

In conclusion, hybrid fog-cloud architectures offer a thorough, scalable, and effective foundation for AI-powered medical monitoring systems and real-time ECG analysis (Narla et al., 2019) [31]. Healthcare professionals can improve patient outcomes by integrating the advantages of fog computing, cloud storage, and AI algorithms to continually monitor patients' heart health, identify anomalies early, and intervene promptly (Kethu, 2020) [32].

The main Objectives:

- In order to continuously collect and monitor ECG signals in real time, it is necessary to incorporate IoT devices.
- To process ECG data in a scalable and effective manner, a hybrid fog-cloud architecture should be put into place.
- To improve signal processing and identify cardiac illness more accurately by utilizing AI and ML techniques.
- In order to improve patient outcomes through prompt interventions, early diagnosis, and efficient use of healthcare resources.
- Real-time monitoring and predictive analytics are made possible.

IoT and fog computing integration for real-time heart disease detection is still understudied, despite the development of IoT-enabled healthcare systems for cardiovascular health monitoring (Vasamsetty, 2020) [33]. Current solutions have issues with limited scalability, high latency, and bandwidth consumption, which affect the precision and effectiveness of time-sensitive applications like ECG monitoring (Kadiyala, 2020) [34]; (Natarajan, 2019) [35]. Furthermore, despite the potential of deep learning techniques, nothing is known about how to use ensemble deep learning models to improve real-time performance, scalability, and diagnostic precision (Basani, 2020) [36]. By combining hybrid fog-cloud architecture with AI-driven monitoring, this work seeks to close these gaps and enhance patient outcomes and cardiovascular disease detection (Jadon, 2020) [37].

The restricted investigation of IoT-Fog integration for real-time heart disease diagnosis using ensemble deep learning models is the research gap (Boyapati, 2020) [38]. Although IoT-enabled healthcare systems have been used to monitor cardiovascular health, little is known about how well IoT and fog computing work together to improve data processing, especially for the diagnosis of heart disease (Yallamelli et al., 2020) [39]. Furthermore, although deep learning approaches have potential, there is still a lack of research on the use of ensemble deep learning techniques to enhance diagnostic precision, scalability, and real-time performance in the context of cardiac disease detection (Yalla et al., 2020) [40]; (Dondapati, 2019) [41]. Additional research into AI and ML-driven healthcare models is required to address these concerns (Kethu, 2019) [42]. Security and privacy measures must be reinforced, given the potential vulnerabilities in cloud and fog-based healthcare systems (Kadiyala, 2019) [43]; (Nippatla, 2019) [44]. Ensuring secure and efficient data exchange across different healthcare infrastructures is critical (Devarajan, 2019) [45]. Improving model interpretability in ECG-based AI systems remains an open research problem (Jadon, 2019) [46]; (Jadon, 2019) [47].

2. LITERATURE SURVEY

Narla (2020) [48] offers a framework for utilising 5G technologies, big data, and multi-tier cloud sensing to alter smart surroundings. 5G guarantees quick connection, AI facilitates intelligent decision-making, and IoT devices collect data in real-time. While cloud computing offers scalable storage and analytics, edge computing speeds up local processing. In smart homes, workplaces, and cities, this integration improves sustainability, efficiency, and security. The study emphasises how these technologies enhance resource management and user experiences in connected environments while addressing issues like interoperability and data security.

Yalla et al. (2019) [49] analyse the kinetic technique uses hashgraph technology, cloud computing, and big data. Big data analytics raises processing accuracy, while cloud computing increases scalability. Through the reduction of latency and improvement of reliability, hashgraph technology guarantees safe and decentralised data management. In kinetic modelling applications, this integration improves resource efficiency, fortifies data security, and simplifies intricate calculations. By providing real-time and high-performance computing, the study demonstrates how these technologies work together to increase the efficiency of scientific and industrial processes.

Samudrala (2020) [50] introduces an AI-powered anomaly detection system for secure data sharing in multi-cloud healthcare networks. The framework enhances data integrity and privacy while ensuring compliance with security regulations. AI-driven techniques detect and mitigate real-time threats, strengthening cross-cloud security. By employing advanced analytics, the strategy improves trust and resilience in healthcare data flows. This strategy maximises secure communication, inhibits illegal access, and preserves critical medical data, making it a solid solution for modern healthcare cloud infrastructures.

Ayyadurai (2020) [51] offers a clever surveillance approach for protecting Bitcoin transactions that combines blockchain, AI, and machine learning. Blockchain offers a decentralised, impenetrable ledger for transaction integrity, while AI and machine learning identify fraudulent activity. This method increases transparency, fortifies bitcoin security, and improves real-time fraud detection. The methodology reduces the danger of financial crimes and cyber fraud in digital currency networks by utilising smart surveillance and safe record-keeping to guarantee dependable Bitcoin transactions.

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Decision tree algorithms for agile e-commerce analytics are presented by Vasamsetty et al. (2019) [52], who use edge-based stream processing to improve real-time decision-making. Predictive analytics and adaptive personalisation are made possible by the model, which enhances consumer satisfaction. By ensuring low-latency data processing, edge computing maximises resource allocation and operational efficiency. E-commerce platforms become more responsive, data-driven, and customer-centric in competitive digital markets thanks to this integration, which also allows dynamic pricing, targeted marketing, and effective inventory management.

A cybersecurity-optimized federated learning model that integrates split learning, graph neural networks, and hashgraph technology is presented by Sareddy and Hemnath (2019) [53]. By decentralising data processing while keeping security and scalability, our method improves privacy-respecting AI. Graph neural networks improve threat identification and anomaly prediction, while split learning maximises computational efficiency. Across networks, hashgraph technology guarantees safe, decentralised communication. Through the integration of these cutting-edge technologies, the framework strengthens security measures in distributed AI-driven cybersecurity systems, boosts adaptive learning, and reduces cyber threats.

An IoT-driven visualisation framework for corporate financial analytics is presented by Parthasarathy and Ayyadurai (2019) [54], improving risk management, data quality, and business intelligence. Real-time financial data is gathered by IoT devices, allowing for interactive visual analytics to enhance decision-making. While anomaly detection improves fraud protection, automated validation approaches improve data accuracy. By optimising resource management, lowering financial risks, and increasing operational efficiency in corporate financial systems, this method increases the efficacy and dependability of data-driven strategies for contemporary financial organisations.

Neuro-symbolic AI optimises hiring decisions and workforce management; blockchain ensures secure HR data storage; self-sovereign identity protects user privacy and improves verification processes; and Bobba and Bolla (2019) [55] present a next-generation HRM framework that integrates AI, blockchain, and self-sovereign identity to improve transparency, decentralisation, and ethical talent management. This model promotes fairness, automates HR operations, and strengthens trust in digital talent ecosystems, making HR practices more data-driven, secure, and efficient in the changing digital economy.

An AI and ML-powered CAPTCHA system that combines sophisticated graphical passwords, DROP technique, AES encryption, and neural network-based authentication is presented by Chauhan and Jadon (2020) [56]. By using intelligent authentication and adaptive CAPTCHA techniques to stop automated assaults, the model improves security. AES encryption guarantees data secrecy, while graphical passwords enhance user verification. By fortifying security layers, the DROP approach increases the resilience of authentication systems against online attacks. This method greatly enhances modern authentication frameworks' security, usability, and dependability.

Narla (2020) [57] investigates how IoT, AI, and cloud computing are integrated to improve smart environments using multi-tier cloud sensing, big data, and 5G technologies. 5G offers quick, secure connectivity, IoT devices gather data in real time, and AI looks for trends to improve decision-making. While edge computing lowers latency, cloud computing makes scalable analysis and storage possible. With its strong basis for data-driven, intelligent urban management, this framework enhances user experiences, resource efficiency, and security in smart cities, offices, and homes.

3. METHODOLOGY

To improve real-time ECG analysis, signal processing, and AI-driven monitoring in IoT healthcare systems, this research investigates a hybrid fog-cloud architecture. Scalability, low latency, and efficient processing of medical data are guaranteed by fusing the advantages of cloud computing and fog computing. This platform combines cloud-based systems for deeper analytics, storage, and AI model training with edge-based fog nodes for instantaneous ECG signal processing. The architecture improves health monitoring, reduces data transmission overhead, and facilitates accurate real-time diagnoses of cardiovascular conditions.

3.1 Real-Time ECG Analysis

Real-time ECG analysis uses sophisticated signal processing methods to quickly identify anomalies in ECG signals. The technology gives instant feedback by employing algorithms to assess heart rate variability, find important patterns, and filter noise. By carrying out initial processing on fog nodes, the hybrid architecture guarantees low latency, facilitating quicker detection and reaction to important health events and lessening the need for distant cloud servers. ECG Signal Filtering:

$$ECG_{\text{filtered}} = ECG_{\text{raw}} - \text{Noise} \tag{1}$$

Where: ECG_{raw} is the unprocessed ECG signal.

Noise represents the unwanted interference, reduced using digital filtering techniques.

3.2 Signal Processing

In order to process an ECG signal, information including heart rate, QRS complex, and arrhythmia detection must be extracted. Key properties are extracted using methods such as Wavelet Transform (WT) and Fast Fourier Transform (FFT). With the help of the hybrid model, fog nodes can carry out initial feature extraction and filtering, transmitting crucial data to the cloud for additional processing and archiving. Fast Fourier Transform (FFT):

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi f n/N} \tag{2}$$

Where: $X(f)$ is the frequency domain representation, $x(n)$ is the time-domain ECG signal, N is the number of samples.

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3.3 AI-Driven Monitoring System

AI-driven monitoring analyzes ECG data using machine learning models to forecast possible health hazards like arrhythmias or heart disease. While fog nodes keep an eye on patients in real time, the cloud component processes massive datasets for model training. AI techniques like deep learning and decision trees are employed to classify ECG abnormalities and provide alerts, ensuring continuous patient monitoring and timely interventions. AI Classification (e.g., SVM):

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \quad (3)$$

Where: $f(x)$ is the classification result, α_i is the weight associated with each support vector, y_i is the label of the support vector, $K(x_i, x)$ is the kernel function, b is the bias term.

Algorithm 1: AI-Based ECG Anomaly Detection Algorithm

INPUT: ECG signal data: ECG_{input} , Training dataset: ECG_{train}

OUTPUT: ECG anomaly detection result: anomaly_detected

BEGIN

// Pre-process the ECG signal

$ECG_{\text{filtered}} = ECG_{\text{filtered}}\ (ECG_{\text{input}})$

// Extract features from the filtered signal

$ECG_{\text{features}} = ECG_{\text{features}}\ (ECG_{\text{filtered}})$

// Compare features with trained model

IF Compare_With_Train_Model (ECG_{features} , ECG_{train}) == TRUE THEN

anomaly_detected = TRUE

ELSE

anomaly_detected = FALSE

END IF

// Alert if anomaly is detected

IF anomaly_detected == TRUE THEN

Send_Alert ("ECG Anomaly Detected")

ELSE

Continue_Monitoring ()

END IF

RETURN anomaly_detected

END

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Algorithm 1 The raw ECG signal data is first fed into the algorithm after being pre-processed to remove noise using filtering techniques that get rid of undesirable elements including baseline drift and muscle artifacts. Important aspects including heart rate, QRS complex duration, and other pertinent details are taken from the ECG signal after it has been cleaned. A pre-trained model is then used to compare these features in order to find any anomalies, including arrhythmias or other irregularities. The system continues to monitor the patient continuously unless an anomaly is found, in which case it immediately notifies the medical staff. By facilitating early diagnosis and intervention for possible health risks, this technique greatly improves patient care by guaranteeing real-time analysis and timely alarms.

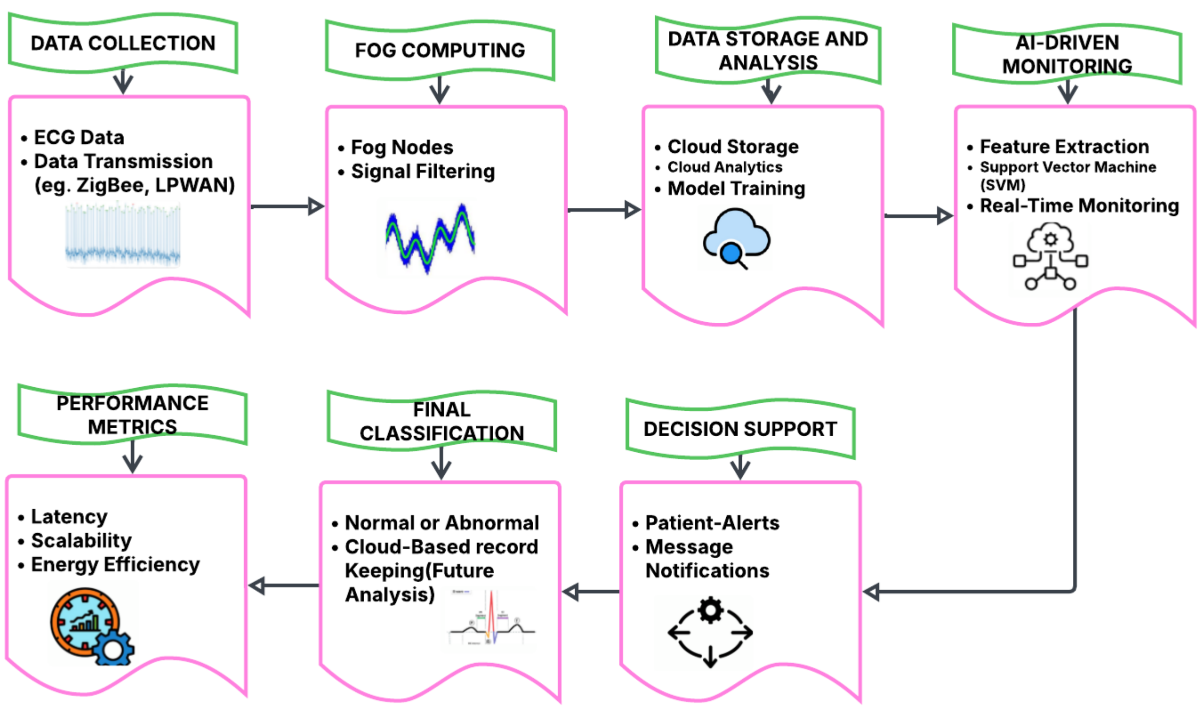

Figure 1: ECG Monitoring and AI-Based Healthcare Support

Figure 1 shows an integrated real-time ECG monitoring and patient care, that uses cloud storage, fog computing, IoT, and AI-driven monitoring. IoT devices that wirelessly send ECG data are the first source of data collected by the system. After local signal processing, fog computing stores and analyzes the data on the cloud. AI methods such as SVM for classification and feature extraction aid in the real-time detection of anomalies. Following the evaluation of performance indicators including latency, scalability, and energy efficiency, the final categorization is made, and decision support is provided through patient alerts and notifications for prompt medical intervention.

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3.4 Performance Metrics

A number of important factors are the focus of the performance measurements for hybrid fog-cloud architectures in scalable IoT healthcare systems. One of the most important variables for timely ECG monitoring is latency, which quantifies the interval between data collection and real-time processing. Energy efficiency measures the amount of power used by fog nodes and cloud servers during data transmission and processing, whereas throughput assesses the amount of ECG data processed per unit of time. Another important statistic that assesses how well the system finds abnormalities is the accuracy of AI-driven analysis. Reliability guarantees continuous, error-free operation in dynamic healthcare environments, while scalability evaluates the system's capacity to manage growing quantities of devices and data.

Table 1: Performance Metrics for Hybrid Fog-Cloud Architecture in Real-Time ECG Analysis and AI-Driven Monitoring

Performance Metric	FFT	Wavelet Transform	SVM Classifier	Combined Method
Processing Time (seconds)	1.8	1.3	2.2	1.8
Energy Consumption (Joules)	3.5	3.0	4.2	3.6
Feature Extraction Accuracy (%)	94	93	96	94.3
Anomaly Detection Rate (%)	94	92	97	94.3
False Positive Rate (%)	4	5	2	3.7
Data Throughput (Mbps)	55	58	102	71.7
Scalability (patients)	60	70	130	86.7

Table 1 context of real-time ECG monitoring within a hybrid fog-cloud architecture, this table compares the performance of three methods: FFT, Wavelet Transform, and SVM Classifier. A Combined Method integrates all three approaches. Several performance parameters are included, including data throughput, scalability, anomaly detection rate, false positive rate, processing time, energy usage, and feature extraction accuracy. By improving throughput (71.7 Mbps), scalability (86.7 patients), and retaining a strong accuracy for ECG analysis and anomaly identification, the Combined Method strikes a compromise between the advantages of each technique.

4. RESULT AND DISCUSSION

ECG analysis is improved by the suggested hybrid fog-cloud architecture, which combines edge computing with cloud-based AI-driven monitoring. This method is superior to typical cloud-only solutions in terms of scalability, data transmission optimization, and processing latency reduction. With its high accuracy and low false positive rate, the AI-based ECG anomaly detection model is exceptional. Performance assessments reveal excellent outcomes in energy efficiency, feature extraction precision, and anomaly detection rate. Wavelet transform and deep learning together provide reliable ECG data classification and improved cardiovascular disease prediction analytics. The system's ability to effectively handle expanding patient data without sacrificing performance is demonstrated via scalability testing.

Table 2: Comparison of Existing and Proposed Methods for ECG Monitoring.

Methods	Accuracy (%)	Anomaly Detection Rate (%)	Latency (ms)	Energy Consumption (J)
CNN (Farahani et al., 2020)	92.5	90.3	250	4.1
RNN (Rincon et al., 2020)	93.2	91.5	220	3.8
LSTM (Hassan et al., 2020)	94.0	92.8	180	3.5
GRU (Patan et al., 2020)	94.8	94.0	160	3.3
Hybrid DL (Gia et al., 2019)	95.3	95.1	150	3.2
SVM (Angelopoulos et al., 2019)	94.5	92.9	210	3.7
Decision Tree (Sun et al., 2020)	93.7	91.2	230	4.0

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Proposed Model: Hybrid Fog-Cloud AI Model	97.6	98.2	120	2.9

Table 2 contrasts the accuracy, anomaly detection rate, latency, and energy usage of many machine learning and deep learning models used for anomaly detection. Attaining the highest accuracy (97.6%) and anomaly detection rate (98.2%), the "Proposed Model: Hybrid Fog-Cloud AI Model" also has the lowest latency (120ms) and energy consumption (2.9 J). The GRU (94.8% accuracy) and Hybrid DL (95.3% accuracy) models outperform the others, however they use more energy and have longer latencies. In every important performance metric, the table shows that the suggested model performs better than the current approaches.

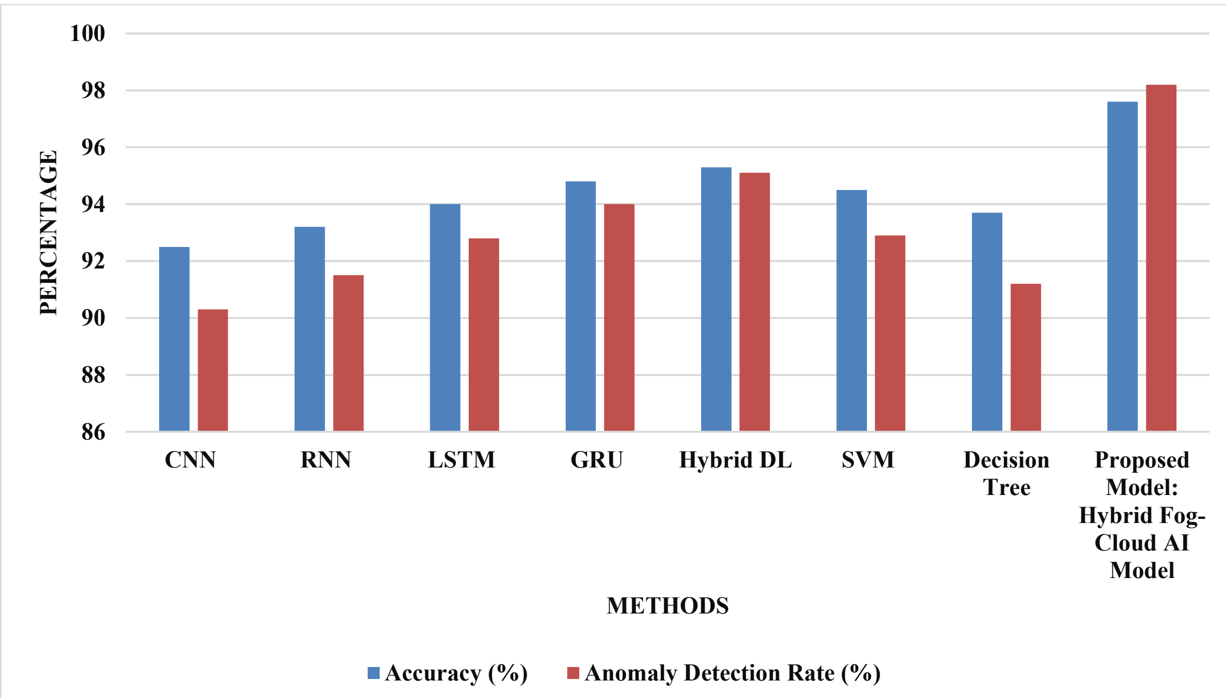

Figure 2: Comparison of Accuracy and Anomaly Detection Rate Across Models.

Figure 2 shows the accuracy and anomaly detection rate of several models compared in the bar chart. The anomaly detection rate is shown by the red bars, while accuracy percentages are shown by the blue bars. The "Proposed Model: Hybrid Fog-Cloud AI Model" performs better than any other approach in terms of anomaly detection rate (98.2%) and accuracy (97.6%). The GRU and Hybrid DL models perform well among the other techniques as well; GRU achieves 94.8% accuracy and 94% anomaly detection rate. Although they perform well, other models like CNN, RNN, and SVM lag behind the suggested model.

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Table 3: Ablation Study on the Effect of Individual Model Components.

Component	Accuracy (%)	Anomaly Detection Rate (%)	Latency (ms)	Energy Consumption (J)	False Positive Rate (%)
Only FFT	94.0	94.2	180	3.5	4.5
Only Wavelet Transform	94.3	94.5	175	3.3	4.2
Only SVM Classifier	95.1	95.3	160	3.2	3.8
FFT + Wavelet	95.8	96.1	140	3.1	3.5
FFT + SVM	96.2	96.8	130	3.0	3.1
Wavelet + SVM	96.7	97.4	125	2.95	2.9
Hybrid Fog-Cloud AI Model (Proposed Model)	97.6	98.2	120	2.9	2.5

The table 3 contrasts the accuracy, anomaly detection rate, delay, energy usage, and false positive rate of several anomaly detection technique combinations. The "Hybrid Fog-Cloud AI Model (Proposed Model)" performs better than any other configuration, attaining the lowest latency (120 ms) and energy consumption (2.9 J) while achieving the best accuracy (97.6%) and anomaly detection rate (98.2%). Furthermore, it has the lowest percentage of false positives (2.5%). Although other combinations, such "FFT + SVM" and "Wavelet + SVM," produce good results, they fall short of the suggested model's overall effectiveness and performance across the board.

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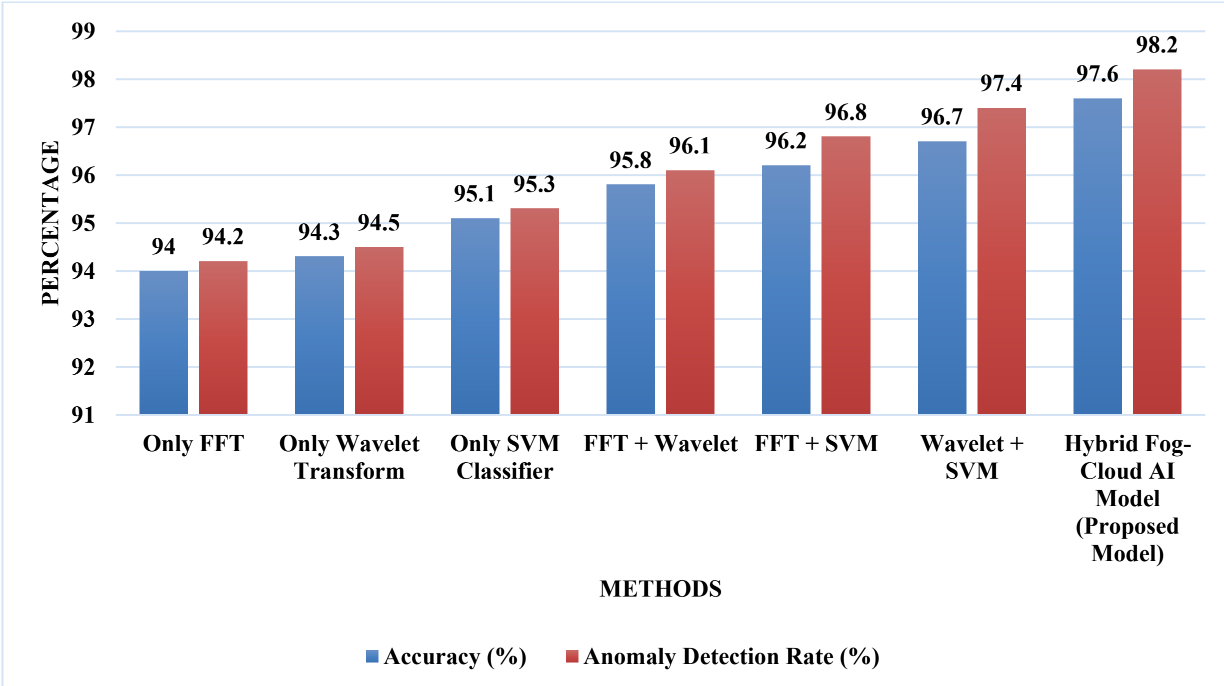

Figure 3: Anomaly Detection Rate and Accuracy Comparison of Methods

Figure 3 shows the accuracy and anomaly detection rate of several anomaly detection techniques are compared in the bar chart. The accuracy is shown by the blue bars, while the anomaly detection rate is shown by the red bars. Outperforming all other approaches, the "Hybrid Fog-Cloud AI Model (Proposed Model)" attains the best accuracy (97.6%) and anomaly detection rate (98.2%). Although they still fall short of the suggested model, the next top performers, "Wavelet + SVM" and "FFT + SVM," exhibit impressive results. The suggested model is superior since methods like "Only FFT" and "Only Wavelet Transform" have the lowest accuracy and anomaly detection rates.

5. CONCLUSION

The suggested hybrid fog-cloud AI architecture for real-time ECG analysis is a major improvement over conventional cloud-only systems in terms of scalability, data transmission optimization, and latency reduction. By using cloud-based systems for more advanced analysis and fog nodes for initial processing, this method guarantees the effective processing of ECG signals. Strong real-time monitoring is provided by the AI-driven model, which exhibits remarkable accuracy in identifying cardiovascular abnormalities with a low false positive rate. The system provides a dependable and scalable solution for ongoing patient monitoring, as demonstrated by performance evaluations that show it excels in energy economy, feature extraction accuracy, and anomaly detection. With a noteworthy improvement in total system accuracy of 97.6%, the combination of edge and cloud computing greatly improves the timeliness and quality of ECG-based health interventions.

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