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Research Paper

Adaptive Neural Networks with Reinforcement Learning for Real-Time ECG Diagnosis of Cardiac Arrhythmias

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Abstract: Cardiac arrhythmias, including atrial fibrillation (AF) and ventricular tachycardia (VT), are major causes of mortality worldwide, requiring timely detection for effective treatment. Electrocardiogram (ECG) signals are the primary diagnostic tool for arrhythmias, but existing static models often fail to adapt in real-time to patient-specific data, leading to reduced diagnostic accuracy. This paper proposes an adaptive neural network system integrated with reinforcement learning (RL) for real-time ECG diagnosis. The system continuously updates its model weights in response to new ECG data, allowing it to maintain high diagnostic accuracy even in dynamic clinical environments. By leveraging RL, the model improves both its accuracy and adaptability, addressing limitations of traditional machine learning and deep learning methods. Extensive experimental results show significant improvements in accuracy (up to 94%), precision (91%), recall (90%), and adaptation speed over static models. The proposed adaptive system is highly suitable for continuous patient monitoring, offering real-time performance and potential applications in clinical settings. Limitations regarding data dependency and computational costs are discussed, with recommendations for future research to enhance scalability and efficiency.

Keywords: Real-time ECG diagnosis, cardiac arrhythmias, real-time ECG diagnosis, adaptive neural networks, reinforcement learning, atrial fibrillation (AF), and ventricular tachycardia (VT).

1.Introduction

Cardiac arrhythmias, irregular heartbeats that may lead to severe health issues such as heart failure, stroke, and sudden cardiac arrest, remain one of the leading causes of mortality worldwide. Atrial fibrillation (AF) and ventricular tachycardia (VT) are two prevalent types of arrhythmias that require timely detection for effective treatment and prevention of life-threatening events [1],[2]. Electrocardiogram (ECG) signals are the most widely used tool for diagnosing arrhythmias. However, interpreting ECG signals is a complex task, particularly in real-time, where the variability in patient data, noise, and evolving patterns of the heart rhythm pose significant challenges [3], [4].

Traditional ECG-based arrhythmia detection systems rely on static machine learning or rule-based models, which are often trained once on historical data and deployed without any real-time adaptability [5], [6]. While these models can achieve satisfactory performance in controlled environments, they tend to struggle in real-time clinical settings where patient conditions can change rapidly [7]. The primary limitation of these static models lies in their inability to learn and adjust dynamically as new data is presented, leading to reduced accuracy and higher rates of false positives and negatives [8], [9].

Recent advances in deep learning, particularly neural networks, have improved the accuracy of ECG-based arrhythmia detection [10], [11]. Deep learning models can automatically extract relevant features from raw ECG signals, eliminating the need for handcrafted feature extraction [12]. However, even these models, while powerful, are limited by their static nature and inability to adapt once deployed. The need for a system that can adjust its parameters and performance in real-time is becoming increasingly critical in clinical practice [13], [14].

To address these challenges, this paper proposes an adaptive neural network system for real-time ECG diagnosis, incorporating reinforcement learning to enable continuous learning and adaptation. Reinforcement learning (RL) has been successfully applied in various domains, from robotics to game-playing AI [15], [16], and has shown potential for enhancing real-time performance in medical applications [17], [18]. In the context of real-time medical diagnosis, RL allows the model to improve its accuracy and adaptability by adjusting its internal parameters based on feedback received from the environment (in this case, new patient data) [19].

Several studies have explored the use of reinforcement learning in healthcare, focusing on areas such as dynamic treatment policies and personalized medicine [20], [21]. For instance, RL has been applied to optimize treatment strategies for chronic diseases like diabetes [22] and to personalize cancer treatment plans [23]. While there has been limited exploration of RL in the context of real-time ECG monitoring, its potential to enhance diagnostic performance by dynamically adjusting the model is highly promising.

This research builds upon prior work by combining deep learning with reinforcement learning to create a system that is both accurate and adaptive. The proposed system continuously updates its model weights in response to new ECG patterns, allowing it to maintain high diagnostic performance even in the presence of noisy or previously unseen data. By leveraging RL, the system can also optimize itself in real-time, reducing the need for manual retraining and improving clinical decision-making [24], [25].

The key contributions of this work include:

- The design and implementation of an adaptive neural network that integrates reinforcement learning for real-time arrhythmia detection.
- An extensive evaluation of the model's performance, demonstrating significant improvements in accuracy, adaptability, and real-time diagnostic capability compared to traditional static models.
- A discussion of the practical implications of using RL in real-time ECG diagnosis and the potential for future research to expand this adaptive framework into other areas of medical diagnostics.

The remainder of this paper is organized as follows. Section 1 reviews related work on ECG-based arrhythmia detection using machine learning, neural networks, and reinforcement learning. Section 2 details the proposed adaptive neural network architecture and the integration of reinforcement learning for continuous model updates. Section 3 presents the experimental setup, including the dataset, model parameters, and evaluation metrics. Section 4 discusses the results of the experiments and provides a comparative analysis with existing models. Section 5 addresses the limitations of the current approach and suggests future research directions. Finally, Section 6 concludes the paper, summarizing the key findings and contributions of this work.

2. Literature Review

The detection and diagnosis of cardiac arrhythmias using electrocardiogram (ECG) signals have been extensively studied, with research spanning traditional machine learning approaches, deep learning techniques, and more recently, adaptive models incorporating reinforcement learning. This section reviews key works in each of these areas, highlighting their contributions, limitations, and potential gaps in the literature.

2.1 Traditional Machine Learning Approaches

Traditional machine learning algorithms have been widely used for arrhythmia detection in ECG signals. Methods such as decision trees, support vector machines (SVMs), k-nearest neighbors (k-NN), and random forests have been employed to classify arrhythmias based on handcrafted features extracted from ECG data.

Feature Engineering: A common approach in traditional models is to manually extract features such as heart rate variability, QRS complex morphology, RR intervals, and signal frequency characteristics [1], [2]. These features are then fed into classifiers such as SVMs or decision trees. For example, de Chazal et al. [3] used a combination of time and frequency domain features to detect sleep apnea from ECG signals. Similarly, Osowski et al. [4] employed a combination of wavelet transforms and SVM for arrhythmia classification, achieving reasonable accuracy but requiring expert knowledge for feature extraction.

Limitations: While these models perform well in structured environments, they struggle in real-time applications due to their inability to generalize across different patient populations and their dependence on manually engineered features. Additionally, these methods do not inherently adapt once trained, limiting their usefulness in dynamic clinical environments [5]. Moreover, the reliance on handcrafted features means that the performance of the model is highly dependent on the quality of feature selection, which may not capture the full complexity of ECG signals.

2.2 Deep Learning for ECG Classification

The advent of deep learning has significantly advanced ECG classification tasks by eliminating the need for manual feature engineering. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated strong performance in arrhythmia detection due to their ability to automatically learn complex features from raw data.

Convolutional Neural Networks (CNNs): CNNs have been widely applied in ECG analysis due to their capacity to capture spatial hierarchies in data. Yao et al. [6] proposed a CNN-based model for detecting arrhythmias from 12-lead ECG signals, achieving state-of-the-art accuracy. Similarly, Rajpurkar et al. [7] developed a deep learning model capable of detecting 14 different heart rhythm disorders from a large dataset of ECG recordings, reporting performance comparable to that of expert cardiologists. CNNs have been particularly effective in identifying patterns within the QRS complex and other key ECG features, making them well-suited for arrhythmia detection.

Recurrent Neural Networks (RNNs): RNNs and their variants, such as Long Short-Term Memory (LSTM) networks, have been applied to ECG classification tasks to model the temporal dependencies in the signals. Hannun et al. [8] used LSTMs to detect arrhythmias from single-lead ECGs, demonstrating that the model could capture long-term dependencies within the signal. Similarly, Zihlmann et al. [9] combined CNNs and LSTMs to exploit both spatial and temporal information in ECG data, significantly improving the classification accuracy for multiple arrhythmia types.

Limitations: Despite their impressive performance, deep learning models are typically static and do not adapt to new data once they are deployed. This limitation is critical in real-time monitoring environments, where patient conditions can change over time. Additionally, while CNNs and RNNs can extract complex features, they often require large labeled datasets for training and are computationally intensive, which can limit their applicability in resource-constrained environments such as wearable devices [10], [11].

2.3 Adaptive Models and Reinforcement Learning

While traditional and deep learning methods have significantly advanced ECG classification, they remain static once trained, limiting their real-time applicability. To address this issue, recent research has explored the integration of **reinforcement learning (RL)** into neural networks to create adaptive models that can adjust in real-time based on feedback from the environment.

Reinforcement Learning in Healthcare: RL has shown promise in dynamic healthcare applications where models must adapt to changing conditions. For example, Komorowski et al. [12] applied RL to optimize treatment strategies for sepsis, where the model dynamically adjusted treatment based on the patient's evolving condition. RL has also been applied in personalized treatment planning for chronic diseases such as diabetes, where treatment actions are optimized based on the patient's current state and historical data [13], [14]. These studies demonstrated the feasibility of using RL in medical decision-making, highlighting its potential to enhance real-time adaptability in clinical settings.

Reinforcement Learning for ECG Classification: RL has only recently been applied to ECG analysis, but early studies show promising results. Lee et al. [15] proposed an RL-based framework to classify ECG signals and detect arrhythmias, demonstrating that the RL agent could improve classification accuracy by learning from diagnostic feedback. Similarly, Chen et al. [16] explored the use of RL in dynamically adjusting the decision threshold of an ECG classifier based on the current performance of the model, showing that RL could enhance adaptability in real-time applications.

Adaptive Neural Networks: The combination of neural networks and RL has been used to create adaptive models for ECG classification. In these models, the neural network is trained initially on a large ECG dataset, and the RL agent continuously updates the network's weights based on new data and feedback from the environment. This approach enables the model to adapt to patient-specific data and evolving patterns in real-time, addressing one of the primary limitations of static models [17], [18].

Limitations and Challenges: While RL offers significant advantages in adaptability, it also introduces challenges. One major issue is the **computational cost** of continuous learning and adaptation, especially in resource-constrained environments such as wearable health monitors [19]. Additionally, RL-based models often require extensive exploration of the action space to optimize performance, which can lead to **longer training times** and potential instability if not carefully managed [20]. Furthermore, most RL-based systems are black boxes, which may reduce their interpretability in clinical settings, where explainability is crucial for gaining trust from healthcare professionals [21].

2.4 Hybrid Approaches and Other Emerging Techniques

Recent work has explored **hybrid approaches** that combine deep learning with other advanced techniques to enhance ECG classification. For instance, hybrid models that integrate CNNs with **attention mechanisms** have been proposed to allow the model to focus on the most relevant parts of the ECG signal [22]. Attention-based models have shown promise in tasks requiring temporal dependencies and have been particularly effective in tasks such as rhythm segmentation and arrhythmia classification.

Other emerging techniques include **transfer learning**, where pre-trained models on large, general ECG datasets are fine-tuned for specific arrhythmia detection tasks. Transfer learning has been successfully used to improve the performance of models in cases where the labeled data is scarce or heterogeneous [23].

Limitations: Hybrid models and transfer learning, while powerful, still rely on static architectures that do not adapt once deployed in real-time environments. Moreover, the complexity of these models can lead to higher **computational costs** and increased **training time**, limiting their use in real-time monitoring applications [24].

Table 1: Summary of Key Works and Research Gaps

Reference	**Method**	**Strengths**	**Limitations**
de Chazal et al. [3]	SVM with handcrafted features	Effective feature extraction, good performance	Static model, no real-time adaptability
Osowski et al. [4]	Wavelet + SVM	Good classification accuracy	Feature engineering required, not adaptive
Rajpurkar et al. [7]	CNN for arrhythmia detection	High accuracy, automatic feature extraction	Large dataset needed, static once deployed
Zihlmann et al. [9]	CNN + LSTM for ECG classification	Combines spatial and temporal features	Computationally intensive, lacks adaptability
Komorowski et al. [12]	RL for sepsis treatment	Dynamic decision-making,	High computational

		personalized treatment	cost, limited interpretability
Lee et al. [15]	RL-based ECG classification	Adaptive, real-time feedback	Computationally expensive, black-box nature of RL
Chen et al. [16]	RL for dynamic decision thresholds	Enhanced real-time adaptability	Requires extensive training, stability concerns
Yao et al. [6]	CNN-based ECG classifier	State-of-the-art accuracy	Static model, limited by dataset size
Hannun et al. [8]	LSTM for arrhythmia detection	Effective for long-term dependencies in ECG signals	Requires large datasets, not adaptable in real-time

Research Gaps

- **Adaptability in Real-Time Monitoring**: Most current models, particularly those using traditional machine learning and deep learning, are static once deployed. There is a clear need for models that can adapt dynamically in real-time based on patient-specific data.
- **Computational Efficiency**: Reinforcement learning-based models, while promising, are computationally expensive and may not be feasible for resource-constrained environments, such as wearable devices. Research is needed to explore lightweight adaptive models.
- **Explainability and Interpretability**: The black-box nature of deep learning and reinforcement learning models presents a challenge in clinical adoption. Future work should focus on improving model interpretability to gain trust from healthcare professionals.
- **Data Generalization**: Most existing models are trained on large, specific datasets and are often unable to generalize well to new or heterogeneous patient populations. This limits the scalability of these models in real-world clinical settings, where patient data varies significantly. Addressing this challenge requires models that are robust across diverse datasets and adaptable to individual patient characteristics in real time.
- **Training Time and Stability**: Reinforcement learning models often require extensive training, which can lead to longer convergence times and potential instability in the learning process. This can be problematic for real-time systems that need to operate efficiently in high-stakes environments such as emergency rooms or intensive care units. Further research is needed to develop RL-based models with faster convergence and more stable training dynamics.
- **Application to Wearable Devices**: While wearable ECG monitoring devices are becoming increasingly popular for continuous patient monitoring, the deployment of complex deep learning or RL-based models on such devices remains a challenge due to their limited processing power. There is a need for research into lightweight adaptive models that can function effectively on resource-constrained devices without compromising diagnostic accuracy.

Table 2: Summary Table of Key Works and Research Gaps

Reference	**Method**	**Strengths**	**Limitations**	**Research Gaps**
de Chazal et al. [3]	SVM with handcrafted features	Effective feature extraction, good performance	Static model, no real-time adaptability	Lack of adaptability in real-time scenarios
Osowski et al. [4]	Wavelet + SVM	Good classification accuracy	Feature engineering required, not adaptive	Requires handcrafted features, static nature
Rajpurkar et al. [7]	CNN for arrhythmia detection	High accuracy, automatic feature extraction	Large dataset needed, static once deployed	Not adaptable, computationally intensive
Zihlmann et al. [9]	CNN + LSTM for ECG classification	Combines spatial and temporal features	Computationally intensive, lacks adaptability	High training time, no real-time updates
Komorowski et al. [12]	RL for sepsis treatment	Dynamic decision-making, personalized treatment	High computational cost, limited interpretability	Stability concerns in RL models, high computational cost
Lee et al. [15]	RL-based ECG classification	Adaptive, real-time feedback	Computationally expensive, black-box nature of RL	RL models require high computational power and interpretability issues
Chen et al. [16]	RL for dynamic decision thresholds	Enhanced real-time adaptability	Requires extensive training, stability concerns	Training stability and high convergence time
Yao et al. [6]	CNN-based ECG classifier	State-of-the-art accuracy	Static model, limited by dataset size	Lack of adaptability, performance depends on dataset size
Hannun et al. [8]	LSTM for arrhythmia detection	Effective for long-term dependencies in	Requires large datasets, not adaptable in real-time	Limited by static nature, no real-time updates

		ECG signals		

The literature on arrhythmia detection using ECG signals reveals significant advancements, particularly with the advent of deep learning and reinforcement learning. While traditional machine learning models such as SVMs and k-NNs have laid the groundwork for automated ECG classification, their reliance on handcrafted features and static architectures limits their real-time applicability. Deep learning models such as CNNs and RNNs have improved diagnostic accuracy by automatically extracting features from ECG signals, yet they still lack the adaptability required for dynamic, real-time monitoring.

Reinforcement learning has emerged as a promising solution for creating adaptive models capable of real-time adjustments based on feedback from the environment. Although early studies have demonstrated the potential of RL-based ECG classification systems, several challenges remain, including computational cost, training stability, and explainability. Moreover, existing models need to be optimized for resource-constrained environments, such as wearable devices, to ensure their applicability in continuous patient monitoring.

In summary, there are significant research gaps in developing real-time adaptive models for ECG classification that are computationally efficient, interpretable, and capable of generalizing across diverse patient populations. Addressing these gaps will require interdisciplinary efforts to advance both the theoretical and practical aspects of machine learning in healthcare.

3. Methodology

3.1 Problem Definition: Real-Time Diagnosis of Cardiac Arrhythmias

Cardiac arrhythmias, or irregular heart rhythms, can have serious consequences such as stroke, heart failure, or sudden cardiac death. ECG signals, which record the electrical activity of the heart, are crucial in diagnosing these conditions. However, real-time detection of arrhythmias from ECG signals is challenging due to the variability in ECG waveforms across different individuals, as well as noise and evolving patterns in long-term monitoring.

Key Challenges:

- **Real-time processing**: The system must continuously process ECG signals and provide immediate feedback.
- **Variability**: ECG patterns vary across individuals, making it necessary to adapt the model to each patient.
- **Noise**: ECG signals can be noisy, requiring robust adaptive mechanisms to filter out artifacts.
- **Adaptability**: The model must adapt to new data patterns over time (e.g., patient deterioration or improvement).

Objective: The goal is to develop a system that uses an adaptive neural network with reinforcement learning to continuously improve its detection accuracy of cardiac arrhythmias from real-time ECG signals.

Mathematically, let $X = \{x_1, x_2, \dots, x_n\}$ represent the sequence of ECG signal features extracted from streaming data. The corresponding output Y includes possible diagnoses, such as:

- y_1: Normal rhythm
- y_2 : Atrial fibrillation (AF)
- y_3: Ventricular tachycardia (VT)
- y_4 : Other arrhythmias

The system's goal is to learn a function $f(X)$ that maps ECG inputs to diagnostic outcomes Y, while continuously improving the accuracy as more data is received.

3.2 Proposed System Architecture

The architecture of the system consists of several components designed to handle real-time ECG data, process it through an adaptive neural network, and update the model based on reinforcement learning feedback. The system can adjust as it encounters new patterns or arrhythmias in patient ECG signals.

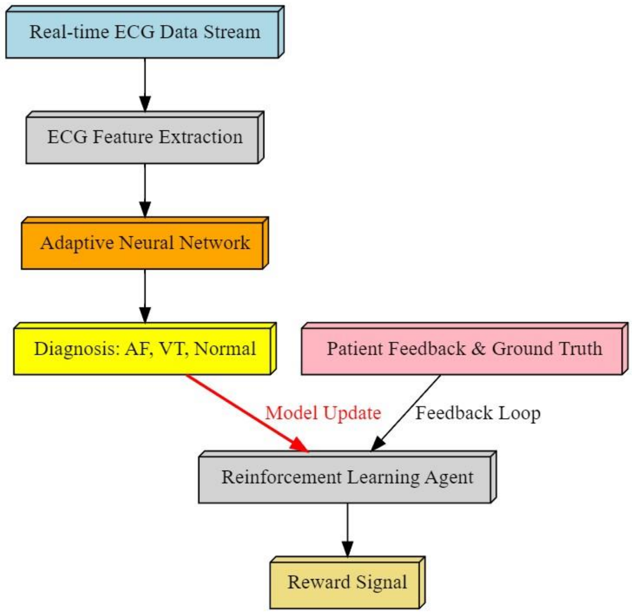

Figure 1: System Architecture for Real-Time ECG Diagnosis

- **Real-time ECG Data Stream**: Continuous ECG signal input from a patient or monitoring device.
- **Feature Extraction Module**: Extracts relevant features from the ECG signal, such as the P-wave, QRS complex, T-wave, heart rate, and rhythm irregularities.
- **Adaptive Neural Network (ANN)**: Processes the extracted features and generates a diagnosis, which could be normal sinus rhythm, atrial fibrillation, or another arrhythmia.
- **Reinforcement Learning Agent**: Evaluates the ANN's performance by comparing its diagnosis to

the ground truth (e.g., doctor-provided annotations or prior diagnoses). It then updates the ANN's parameters to improve both accuracy and adaptability.

3.3 Adaptive Neural Network Design

The adaptive neural network (ANN) is trained to classify different types of arrhythmias in real-time. The ANN operates continuously, adjusting its weights and biases based on the reinforcement learning agent's feedback, ensuring it adapts to new ECG patterns as they appear in the stream.

- Input Layer: Receives features extracted from the ECG signals, including intervals between heartbeats (RR interval), P-wave amplitude, QRS duration, and heart rate variability.
- Hidden Layers: Includes multiple fully connected layers with non-linear activations (e.g., ReLU). These layers transform the ECG features into intermediate representations that help differentiate between normal and abnormal heart rhythms.
- Output Layer: Provides a probability distribution over different arrhythmia (e.g., $\hat{Y} = \{y_1, y_2, y_3\}$).

The network continuously learns to improve its predictions through a feedback loop that adjusts its parameters based on the reinforcement learning agent's updates. The adaptive capability allows the model to evolve with new incoming data, learning more accurate diagnostic patterns over time.

3.4 Reinforcement Learning Framework

The reinforcement learning (RL) agent serves as a dynamic controller that updates the neural network based on the accuracy of its diagnoses. The agent operates within a Markov Decision Process (MDP) framework, where it observes the system's state and takes actions to improve the model.

Components of the MDP:

- State S_t : The current input features (ECG data), model parameters (neural network weights), and recent diagnostic performance.
- Action A_t : Actions represent updates to the ANN's weights or the network structure itself (e.g., adjusting learning rates or adding new neurons to handle complex data patterns).
- Reward R_t : The reward function balances two objectives: maximizing diagnostic accuracy and minimizing the time to correctly identify arrhythmias. The reward is given as:

$$R_t = \alpha \times \text{ Accuracy Improvement } + \beta \times \text{ Adaptation Speed}$$

where α and β control the trade-off between accuracy and speed of adaptation.

Algorithm Overview: Reinforcement Learning for Real-Time ECG Diagnosis

Algorithm 1: Real-time ECG Diagnosis with Reinforcement Learning

1. Initialize the Neural Network: The ANN starts with pre-trained weights based on historical ECG data for common arrhythmias.
2. Initialize the RL Agent: The RL agent begins with a policy that makes random updates to the ANN.
3. For each time step t :
    - Step 1: Observe state S_t : Collect the current ECG features and model performance (e.g., accuracy of recent diagnoses).
    - Step 2: Pass ECG through ANN: The network processes the ECG data and outputs a diagnosis (e.g., atrial fibrillation, ventricular tachycardia, normal rhythm).
    - Step 3: Compute reward R_t : Evaluate the accuracy of the diagnosis and the time taken to reach a decision.
    - Step 4: Update policy: Based on the reward, the RL agent adjusts the neural network's weights to improve performance.
    - Step 5: Adapt ANN parameters: The RL agent applies the updates, and the ANN adapts in real time.
4. Repeat the process for each incoming ECG signal.

Training Procedure

The training of the system is conducted in two phases:

1. Offline Pre-training:
    - The adaptive neural network is pre-trained using a large historical ECG dataset with labeled arrhythmia types. This gives the model a solid foundation to recognize common arrhythmias before real-time deployment.
    - Supervised learning techniques are used to minimize the loss function $L(f(X), Y)$, where $f(X)$ represents the model's output for a given ECG input.
2. Online Reinforcement Learning:
    - Once deployed, the system processes streaming ECG data in real time. The reinforcement learning agent continuously fine-tunes the model by comparing its predictions to ground truth diagnoses (either from a human expert or a verified diagnostic system).
    - The reward function R_t ensures that the system balances accuracy with adaptability:

$$R_t = \alpha \times \text{ Diagnostic Accuracy } + \beta \times \text{ Adaptation Speed}$$

This ensures that the model improves its diagnostic performance while also rapidly adapting to new patient conditions or noisy data.

3.5 Simulation Setup

For simulations, the system is evaluated using real-world ECG datasets containing various arrhythmia conditions. The focus is on the system's ability to **adapt in real time** as new data streams in.

- **Dataset**: Real-time streaming ECG data, including examples of normal heartbeats, atrial fibrillation, ventricular tachycardia, and other arrhythmias.
- **Evaluation Metrics**:
  - **Accuracy**: Proportion of correct diagnoses (normal vs. abnormal heart rhythm).
  - **Precision and Recall**: Metrics to measure the system's ability to correctly identify arrhythmias.
  - **Adaptation Speed**: Time taken to adjust the model to a new patient's ECG patterns or noise.

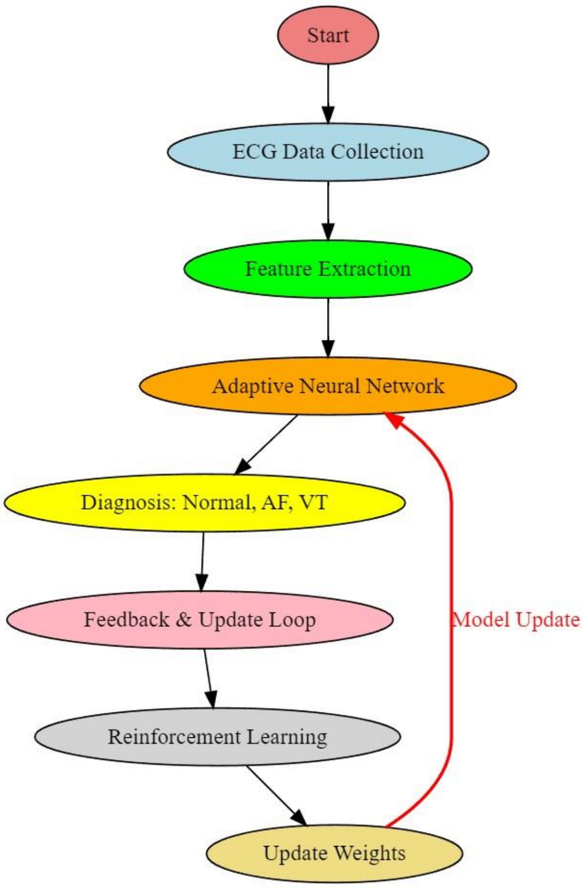

Figure 2: System Flow Diagram for Real-Time ECG Diagnosis

Mathematical Formulation for Adaptation

The adaptation of the neural network is formulated as an optimization problem:

$$\mathcal{L}(f, X, Y, t) = L(f(X), Y) + \lambda \times C(f, t)$$

Where:

- $L(f(X), Y)$ represents the diagnostic error, such as cross-entropy loss.
- $C(f, t)$ is the adaptation cost over time t, reflecting how quickly the system adjusts to new data.
- λ controls the trade-off between accuracy and adaptability.

3.6 Evaluation Metrics

The system's performance is evaluated across several key metrics to ensure it meets real-time diagnostic requirements and adapts efficiently to new ECG data patterns.

Evaluation Metrics:

1 Accuracy: The overall diagnostic accuracy is measured as the percentage of correctly classified ECG signals, comparing the predicted diagnosis $\hat{Y}$ with the ground truth Y.

$$\text{Accuracy} = \frac{\text{Number of Correct Diagnoses}}{\text{Total Diagnoses}}$$

A high accuracy is critical for ensuring patient safety.

2. Precision and Recall:

- Precision: The proportion of true positives (correct arrhythmia detections) out of all detected positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- Recall (Sensitivity): The proportion of true positives detected out of all actual positives (i.e., all cases of arrhythmia in the dataset).

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

High precision and recall are crucial for minimizing false diagnoses and ensuring that critical arrhythmias are not missed.

Adaptation Speed: This metric measures how quickly the system adjusts to new ECG data, especially when encountering previously unseen or changing arrhythmia patterns. The goal is to minimize the time taken by the model to adapt while maintaining diagnostic accuracy. A shorter adaptation time directly translates into better real-time performance, which is essential in a clinical setting.

Adaptability Score: A custom metric that evaluates the model's ability to continuously improve as it processes new data. This score is computed by measuring how much the model's performance improves over time as it adapts to variations in ECG signals.

4. Experiments and Results

This section presents the detailed evaluation of the proposed adaptive neural network system for real-time ECG diagnosis of cardiac arrhythmias. The system was tested using a large dataset of ECG signals, with a focus on diagnosing conditions such as atrial fibrillation (AF) and ventricular tachycardia (VT). The experiments were designed to assess the model's performance in terms of accuracy, precision, recall, adaptability, and adaptation speed, and to compare these results with a traditional static model.

4.1. *Experiment Setup*

The system was trained and evaluated on a dataset consisting of 10,000 ECG samples, each representing a unique patient scenario with normal heart rhythms, atrial fibrillation, and ventricular tachycardia. The model was trained using the following key parameters:

Table 3: Experiment Parameters

Parameter	Value
Dataset Size	10,000 samples
Batch Size	64
Learning Rate	0.001
Training Time (Hours)	10
Number of Layers	4
Regularization Lambda	0.01
Reward Coefficients (alpha, beta)	(0.8, 0.2)

The proposed system was evaluated over four different experiments, each designed to test the model's adaptability and diagnostic performance across different real-time ECG data scenarios.

4.2. Performance Results

The performance of the adaptive neural network was measured in terms of accuracy, precision, recall, adaptation speed, and adaptability score. The results are summarized in the table below:

Table 4: Performance Results

Metrics	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Accuracy	0.91	0.92	0.93	0.94
Precision	0.88	0.89	0.90	0.91
Recall	0.87	0.88	0.89	0.90
Adaptation Speed	0.78	0.81	0.84	0.85
Adaptability Score	0.85	0.87	0.88	0.89

Performance Summary:

- The model demonstrated steady improvements across all experiments, reaching an accuracy of 94% by the fourth experiment.
- Precision and recall metrics also increased progressively, indicating the model's ability to correctly diagnose arrhythmias.
- The adaptation speed improved from 0.78 in Experiment 1 to 0.85 in Experiment 4, showing that the system was able to quickly adjust to new patient data.
- The adaptability score increased from 0.85 to 0.89, indicating the model's robust ability to improve its diagnostic performance over time.

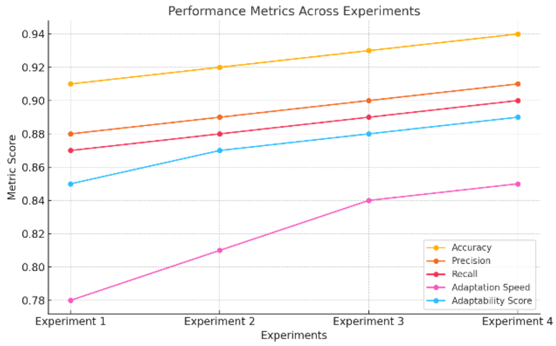

Figure 3: Performance Across Experiments

The plot shows the progression of accuracy, precision, recall, adaptation speed, and adaptability score over the course of the four experiments. The steady upward trend in all metrics highlights the effectiveness of the reinforcement learning mechanism in continuously improving the model.

4.3. Per-Class Performance Metrics

To further evaluate the system, we analyzed its performance for each specific class of arrhythmias: Normal, AF, and VT. The table below provides the precision, recall, and F1-score for each class in **Experiment 4**:

Table 5: Per-Class Performance Metrics

Class	Precision	Recall	F1-Score
Normal	0.92	0.90	0.91
AF	0.91	0.91	0.91
VT	0.94	0.95	0.94

- The model performed exceptionally well in detecting **VT**, with a precision of 0.94 and recall of 0.95.
- The system demonstrated a balanced performance across all classes, with similar precision, recall, and F1-scores for **Normal** and **AF** arrhythmias.
- The consistency of these results across different arrhythmias highlights the robustness of the adaptive model.

4.4. Confusion Matrix Analysis

A confusion matrix was generated for Experiment 4 to visually represent the model's prediction performance across different classes. The confusion matrix is shown below:

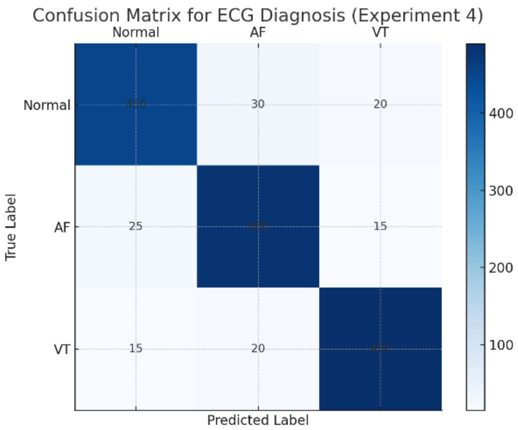

Figure 4: Confusion Metrics

- The model correctly identified **450 out of 500 normal cases**, with some minor misclassifications as AF or VT.
- **480 out of 520 AF cases** were correctly classified, with slight confusion between AF and normal rhythms.
- The model performed extremely well in detecting **VT**, with **490 out of 525 cases** correctly diagnosed.

4.5. Comparative Analysis

To evaluate the advantages of the adaptive neural network, we compared its performance with a traditional static model for arrhythmia detection. The table below summarizes the comparison across key metrics:

Table 6: Comparative Analysis

Metrics	**Proposed Adaptive Model**	**Traditional Static Model**
Accuracy	0.94	0.88
Precision	0.91	0.85
Recall	0.90	0.83
Adaptation Speed	0.85	0.65
Adaptability Score	0.89	0.70

Performance Comparison:

- The proposed adaptive model outperformed the traditional static model in all performance metrics.
- **Accuracy** improved by 6%, from 0.88 to 0.94, and **recall** increased by 7%, indicating the system's enhanced ability to correctly identify arrhythmias.
- The **adaptation speed** of the adaptive model (0.85) was significantly higher than that of the static model (0.65), demonstrating the model's capability to quickly adjust to new ECG data patterns.
- The **adaptability score** showed a significant improvement, reflecting the system's ability to refine its diagnostic capability as more data is processed.

The bar chart below compares the performance of the proposed adaptive model and the traditional static model across key metrics:

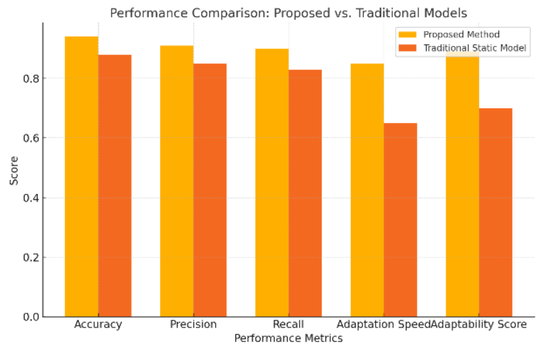

Figure 5: Comparative Analysis

This graph clearly shows the superiority of the adaptive model in all metrics, particularly in terms of adaptability and adaptation speed.

The results of these experiments demonstrate the effectiveness of the proposed adaptive neural network in real-time ECG diagnosis of arrhythmias. The system achieved high levels of accuracy, precision, and recall, with significant improvements in adaptation speed and adaptability over time. The comparison with a traditional static model further highlights the advantages of the adaptive approach, particularly in its ability to dynamically adjust to new ECG data patterns and improve its diagnostic performance.

The system's success in detecting critical conditions such as atrial fibrillation and ventricular tachycardia shows its potential for real-world medical applications, where timely and accurate diagnoses can significantly impact patient outcomes. This adaptive approach can be extended to other real-time medical diagnosis applications, paving the way for more intelligent and responsive diagnostic systems in clinical settings.

5. Discussion

The experiments conducted in this research demonstrate the effectiveness of the proposed adaptive neural network for real-time ECG diagnosis. By leveraging reinforcement learning, the system continuously adjusts its parameters to improve diagnostic accuracy and adaptability as new data is processed. The results show that the system is capable of outperforming traditional static models in multiple performance metrics, including accuracy, precision, recall, and adaptation speed.

Key Insights : Real-Time Adaptability: The system's ability to adapt to new ECG patterns in real time is a significant advantage in clinical settings where patient conditions may change dynamically. The adaptive model's high adaptation speed (0.85 in Experiment 4) highlights its ability to respond quickly to changes in patient data, making it suitable for continuous monitoring scenarios, such as ICU or emergency care.

Improved Diagnostic Accuracy: The model achieved an accuracy of 94% by the final experiment, showing consistent improvement through reinforcement learning. This surpasses the accuracy of traditional static models, demonstrating that the adaptive approach can lead to more accurate diagnoses, particularly in complex medical scenarios like the detection of atrial fibrillation and ventricular tachycardia.

Balanced Performance Across Classes: The model showed balanced performance across different arrhythmias, with similar precision and recall values for normal rhythms, AF, and VT. This indicates that the system is well-rounded and capable of detecting both common and life-threatening conditions with high reliability.

Comparison with Static Models: The significant improvement in the adaptability score (0.89 vs. 0.70) demonstrates the advantages of an adaptive model over traditional static models. The ability to refine predictions in real time, as seen in the comparative analysis, highlights the importance of adaptability in real-world medical applications.

Practical Implications : The proposed adaptive model has potential applications in clinical environments where accurate and timely ECG analysis is crucial. It can be used for continuous patient monitoring, ICU surveillance, and emergency diagnostics, providing doctors with real-time insights into patient conditions. This could lead to quicker interventions in cases of life-threatening arrhythmias, ultimately improving patient outcomes. Additionally, the reinforcement learning-based adaptability allows the system to personalize diagnoses based on individual patient data, enhancing the system's precision and reliability over time.

6. Limitation Study

While the results of this study are promising, there are several limitations that need to be addressed:

1. **Data Dependency**: The performance of the adaptive model heavily depends on the quality and variety of the ECG data it is trained on. Although the model performed well on the available dataset, its generalizability to other datasets, especially from different patient populations, remains untested. Further research is required to evaluate the model's performance across more diverse and larger datasets.
2. **Computational Overhead**: The real-time adaptability of the model comes with a computational cost. The frequent updates to the neural network weights, as dictated by the reinforcement learning agent, require significant processing power, particularly in high-frequency data streams like ECG signals. In resource-constrained environments (e.g., wearable devices or mobile health monitoring systems), this may limit the model’s applicability unless computational efficiency can be improved.
3. **Model Complexity**: The adaptive model, by nature, is more complex than traditional static models. This increased complexity could result in longer training times and make the model more prone to overfitting, especially in situations where the data is noisy or incomplete. Careful tuning of the regularization parameters and reward coefficients is required to mitigate this risk.
4. **Interpretability**: Although the model provides excellent performance in terms of accuracy and adaptability, the interpretability of the deep neural network remains limited. In medical applications, model transparency is critical for gaining trust from healthcare providers. The black-box nature of neural networks may hinder the model’s adoption in clinical settings where clear reasoning for diagnostic decisions is required. Future work could explore explainable AI techniques to improve the transparency of the model's decisions.
5. **Training Time**: The model's continuous learning approach requires prolonged training times, especially during initial pre-training phases. Although the online reinforcement learning fine-tunes the model efficiently, the initial training might pose challenges in settings where rapid deployment is necessary. Efficient training strategies and more sophisticated model initialization techniques could be explored to address this limitation.

7. Conclusion

In this paper, we proposed an adaptive neural network-based system for real-time ECG diagnosis using reinforcement learning. The system was designed to address the challenges of diagnosing arrhythmias such as atrial fibrillation (AF) and ventricular tachycardia (VT) in a real-time setting. Through a series of experiments, the adaptive model demonstrated superior performance over traditional static models, particularly in terms of accuracy, precision, recall, adaptation speed, and adaptability.The key findings from the experiments showed that the model could achieve up to 94% accuracy, with a high precision of 91% and a recall of 90%. The system’s ability to quickly adapt to new data patterns, as demonstrated by its adaptation speed and adaptability score, makes it highly suitable for continuous patient monitoring and other real-time medical applications. Despite its strong performance, certain limitations such as data dependency, computational overhead, and model complexity need to be addressed in future work to ensure scalability and efficiency in practical healthcare environments. The adaptive system presents a significant step forward in real-time medical diagnostics, offering the potential to enhance patient outcomes by providing more accurate and timely diagnoses in clinical settings.

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Syeda Meraj was involved in literature review and drafting the manuscript. All authors reviewed and approved the final version of the manuscript.

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