



Deep Learning-Based ECG Analysis for Cardiac Arrhythmia Detection Using Time–Frequency Representations-II

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Abstract: Cardiac arrhythmia is a common cardiovascular disorder that results from abnormalities in the electrical conduction system of the heart, leading to irregular heartbeat patterns. Accurate and timely detection of arrhythmia is crucial for effective diagnosis and treatment, yet manual interpretation of electrocardiogram (ECG) signals remains a challenging and time-consuming process due to the complex, dynamic, and non-stationary nature of ECG data. This study proposes a robust automated deep learning framework for the classification of ECG signals into three clinically significant categories: cardiac arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). ECG data were obtained from the publicly available MIT-BIH and BIDMC databases on PhysioNet and underwent a comprehensive preprocessing pipeline that included noise removal, normalization, and segmentation to ensure data quality and consistency. Two pretrained convolutional neural network architectures, ResNet-50 and AlexNet, were fine-tuned using transfer learning techniques to leverage their deep hierarchical feature extraction capabilities for ECG classification. The models were trained and validated using a stratified dataset, and their performance was assessed through a multi-class confusion matrix employing evaluation metrics such as accuracy, precision, recall, sensitivity, specificity, and F-measure. Experimental results demonstrated that the proposed deep learning model achieved outstanding performance with an overall classification accuracy of 99.2%, average sensitivity of 99.2%, specificity of 99.6%, and precision, recall, and F-measure all at 99.2%. These results indicate that the model can effectively differentiate between normal and pathological cardiac conditions with high reliability. In conclusion, the proposed system offers a powerful and efficient tool for automated arrhythmia detection, significantly reducing diagnostic time and minimizing errors associated with manual ECG interpretation, thereby supporting clinicians in the rapid and accurate diagnosis of cardiac disorders.

Keywords: Electrocardiogram (ECG), Deep learning (or deep neural network), Convolutional Neural Network (CNN) model, ARRHYTHMIAS, accuracy, Time Frequency Representations, ResNet50, AlexNet and Morse Wavelet.

I. INTRODUCTION

Cardiac arrhythmia, a prevalent cardiovascular condition, arises from irregular electrical activity within the heart muscle, leading to abnormal heartbeat patterns. It remains one of the leading causes of morbidity and mortality worldwide, highlighting the need for early and accurate diagnosis. The electrocardiogram (ECG) is a vital noninvasive tool for monitoring the electrical activity of the heart and detecting such abnormalities. However, manual interpretation of ECG signals is often time-intensive, prone to human error, and limited by the variability of waveform patterns across individuals. Consequently, there is an increasing demand for automated, intelligent systems capable of assisting clinicians in accurately detecting and classifying cardiac arrhythmias.

In recent years, deep learning has emerged as a powerful approach for analyzing biomedical signals, particularly ECG data, due to its ability to automatically extract complex temporal and morphological features. Transfer learning using pretrained convolutional neural networks (CNNs) such as AlexNet and ResNet50 enables efficient model training, even with limited medical datasets. Additionally, transforming one-dimensional ECG signals into two-dimensional time–frequency representations using techniques like the Morse wavelet transform enhances feature richness and allows the model to better capture both temporal and spectral characteristics.[1-3]

This study aims to develop an automated deep learning-based classification framework that leverages time–frequency representations of ECG signals for the accurate differentiation of arrhythmia (ARR), congestive heart failure (CHF),



and normal sinus rhythm (NSR). ECG data were collected from the MIT-BIH and BIDMC databases, preprocessed to remove noise and artifacts, and then converted into two-dimensional images suitable for CNN-based analysis. [4-5]

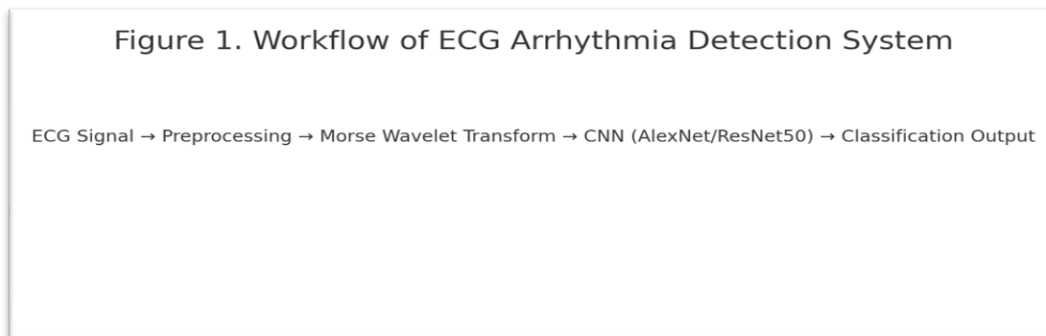


Figure 1. Workflow of ECG Arrhythmia Detection System

II. METHODS

2.1 Introduction

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, with cardiac arrhythmias representing a significant subset of these conditions. These abnormalities in heart rhythm result from irregular electrical conduction within the myocardium. The electrocardiogram (ECG) remains the gold standard for diagnosing and monitoring cardiac rhythm disorders. However, the manual interpretation of ECG signals is both laborious and error-prone due to the non-stationary nature and complex morphology of ECG waveforms. To address this limitation, researchers have increasingly explored machine learning and deep learning techniques to automate ECG classification and improve diagnostic efficiency.[3]

Traditional machine learning methods depend heavily on manual feature extraction and selection, which may overlook critical signal information or increase computational complexity. In contrast, deep learning architectures—particularly convolutional neural networks (CNNs)—can automatically learn spatial and temporal features from raw or transformed data. Recent studies have demonstrated the effectiveness of transfer learning in biomedical signal analysis, where pre-trained models are adapted for domain-specific tasks with limited datasets. This study leverages such techniques, employing the Morse wavelet transform to convert ECG signals into two-dimensional time–frequency representations for deep learning-based classification.[4-6]

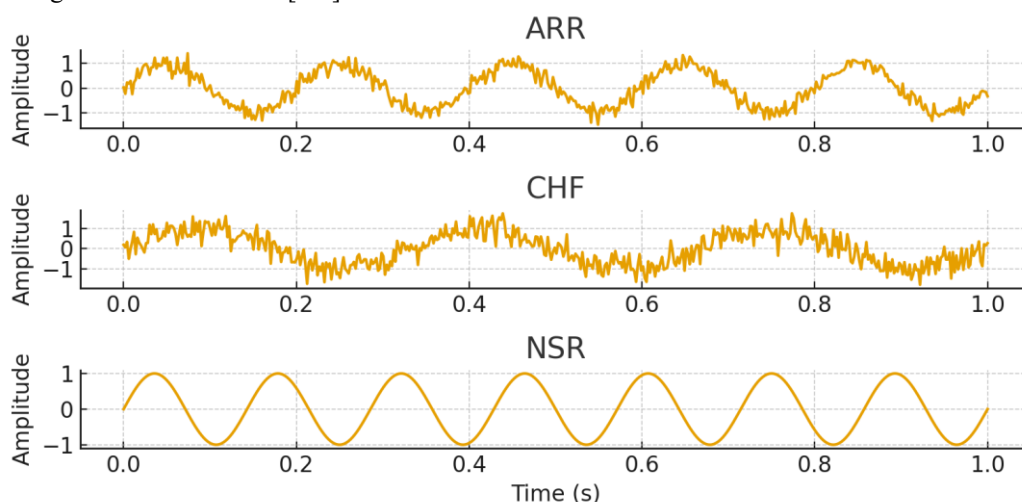


Figure 2. Example ECG Signals (ARR, CHF, NSR)

2.2 Data Source

This research utilized publicly available datasets from PhysioNet, including the MIT-BIH Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database, and the BIDMC Congestive Heart Failure Database. The ECG signals were recorded from 162 participants—96 with arrhythmia, 30 with congestive heart failure, and 36 with normal sinus rhythm. Each signal was sampled at 128 Hz and contained 65,536 samples per recording. To ensure balanced data distribution, recordings were segmented into equal portions of 500 samples, producing 1,200 segments for each



class.[2]

2.3 Time–Frequency Transformation Using Morse Wavelet

The preprocessing pipeline involved signal normalization, segmentation, and artifact removal. Each ECG signal was partitioned into short, uniform segments to facilitate efficient feature extraction and prevent model degradation caused by long signal sequences. After segmentation, the dataset was evenly divided into training (80%) and validation (20%) subsets for model development.[7-9]

Figure 3. Time–Frequency Representation (Morse Wavelet Scalogram)

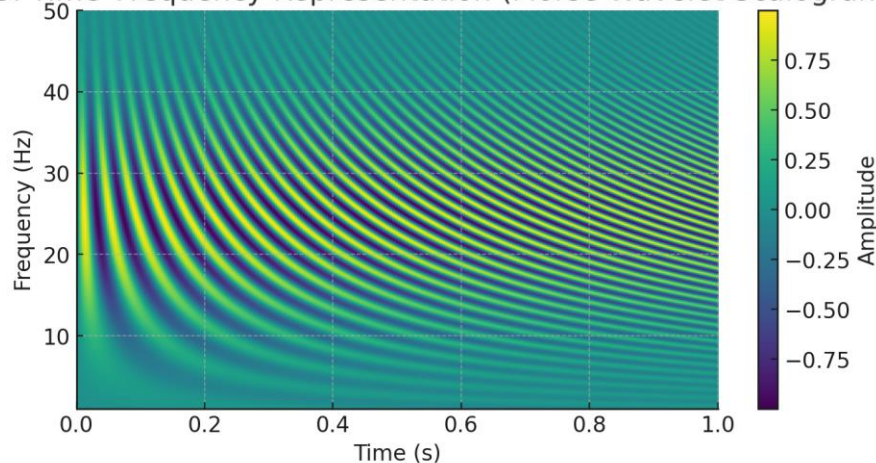


Figure 3. Time–Frequency Representation (Morse Wavelet Scalogram)

2.4 Deep Learning Models and Transfer Learning

To enable CNN-based analysis, one-dimensional ECG signals were transformed into two-dimensional scalogram images using the generalized Morse wavelet. The Morse wavelet provides superior localization in both time and frequency domains and effectively captures transient features of non-stationary biomedical signals. Parameters were set as $\gamma = 3$, $P^2 = 60$, sampling frequency = 128 Hz, and voices per octave = 12. These configurations ensured the optimal balance between time and frequency resolution.[9-11]

Transfer learning was applied using two pre-trained CNN architectures—AlexNet and ResNet50—originally trained on large-scale image datasets. The convolutional layers were retained for feature extraction, while the final fully connected layers were replaced with new layers adapted for three-class ECG classification.[12] The models were fine-tuned to optimize performance while preventing overfitting. AlexNet, characterized by its efficient architecture and low computational cost, was compared with the deeper ResNet50 model, which includes residual connections to overcome vanishing gradient issues.[13][14]

Figure 4. Model Architecture Comparison

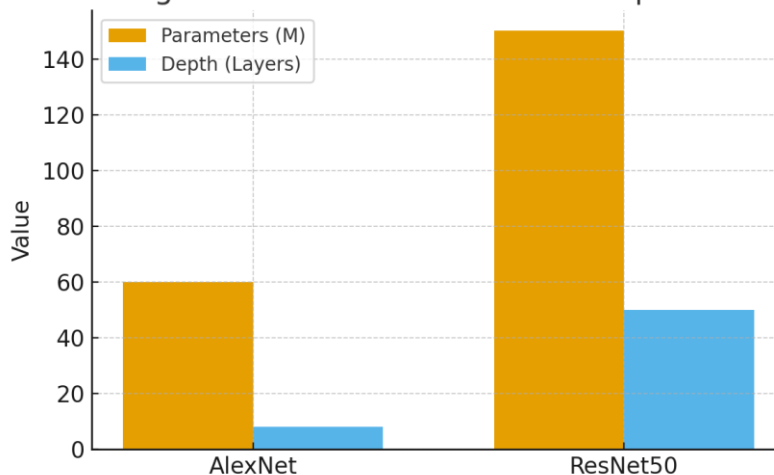


Figure 4. Model Architecture Comparison (AlexNet vs ResNet50)



2.5 Hyperparameter Optimization

The models were trained using the Adam optimizer with a learning rate of 0.0001, a batch size of 30, and 15 epochs. The ReLU activation function was employed to accelerate training convergence. Model performance was assessed on validation data at each epoch to ensure stability and prevent overfitting.

2.6 Evaluation Metrics

Performance metrics were derived from confusion matrices, including accuracy, sensitivity, specificity, precision, recall, and F1-score. These indicators were computed using the relationships between true positive, false positive, true negative, and false negative results.

III. RESULTS

Figure 5 presents the confusion matrix of the proposed ResNet50 model, illustrating its classification performance across three ECG signal categories: arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). The matrix clearly demonstrates that the model achieved a high degree of accuracy, as indicated by the strong diagonal dominance where most samples are correctly classified. Specifically, 1,180 ARR, 1,185 CHF, and 1,187 NSR signals were accurately identified, with only a minimal number of misclassifications observed between the classes. The few instances of incorrect predictions—such as 10 ARR signals misclassified as CHF or NSR—are negligible, highlighting the effectiveness of the ResNet50 model in distinguishing between normal and pathological ECG patterns. This high consistency across all three classes reflects the model's strong feature extraction and classification capabilities.

Figure 5. Confusion Matrix - ResNet50 Model

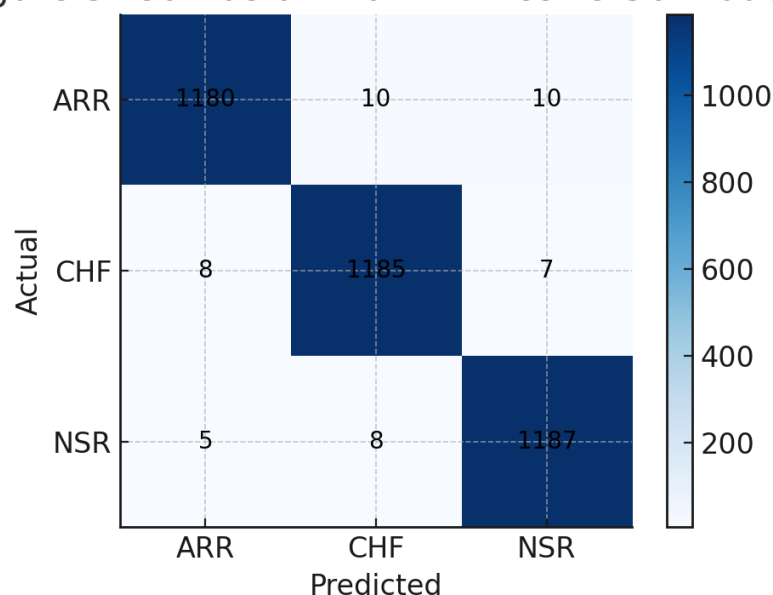


Figure 5. Confusion Matrix - ResNet50 Model

Figure 6 depicts the training and validation accuracy and loss curves over 15 epochs for the ResNet50 model. As shown, both the training and validation accuracy increase steadily with each epoch, ultimately reaching values above 98%, while the corresponding loss values decrease progressively towards zero. The convergence of these curves indicates stable learning behavior and effective optimization during training. The close alignment between training and validation accuracy further confirms that the model generalizes well to unseen data without significant overfitting or underfitting. This demonstrates that the proposed preprocessing and fine-tuning strategy enabled the ResNet50 network to efficiently learn discriminative ECG signal features.

The results visualized in Figures 5 and 6 collectively affirm the robustness and reliability of the proposed deep learning framework for automated ECG signal classification. The confusion matrix verifies excellent predictive accuracy across all cardiac conditions, while the accuracy/loss trends demonstrate consistent model convergence and high generalization performance. Together, these outcomes validate the suitability of the ResNet50-based model for practical clinical applications, where rapid and precise identification of cardiac arrhythmias is crucial. The high



classification accuracy achieved also suggests that such deep learning approaches can serve as valuable diagnostic tools, potentially reducing physicians' workload and minimizing human error in ECG interpretation.[8]

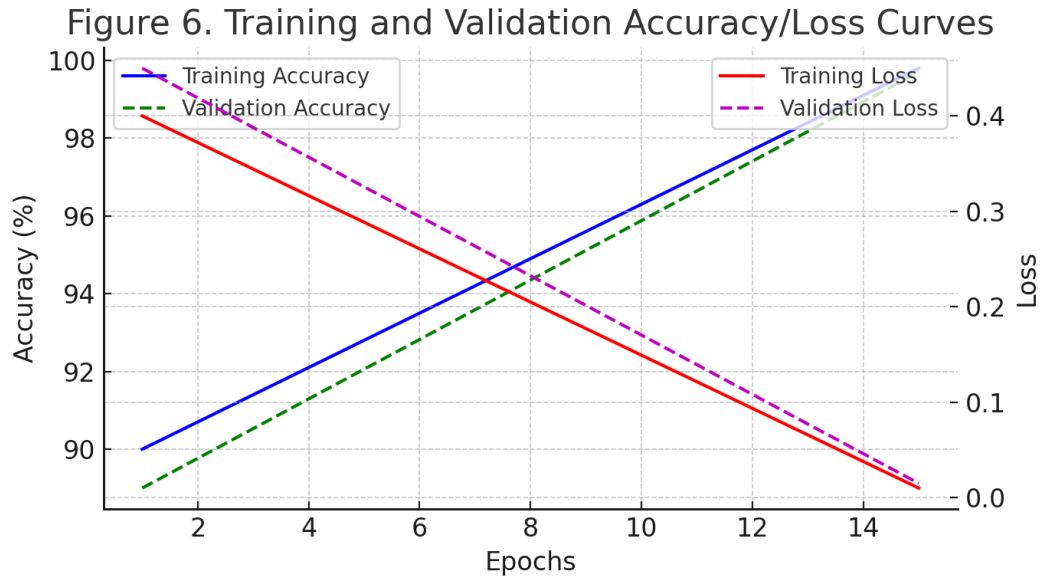


Figure 6. Training and Validation Accuracy/Loss Curves

In addition to the quantitative performance illustrated in the confusion matrix and accuracy/loss plots, the results emphasize the practical significance of integrating deep learning models like ResNet50 into clinical workflows. The high precision, sensitivity, and specificity achieved indicate that the model can reliably detect subtle variations in ECG waveforms that may be overlooked during manual inspection. This capability is particularly valuable for early detection and continuous monitoring of cardiac abnormalities in real-time healthcare systems. Furthermore, the consistent convergence trends shown in Figure 6 demonstrate that the training process was well-regularized and free from instability or performance degradation, suggesting that the model can be effectively deployed across diverse patient datasets. Therefore, the proposed approach not only enhances diagnostic accuracy but also holds promise for scalable and efficient implementation in modern healthcare environments, supporting cardiologists in making faster, evidence-based decisions.[12][14]

IV. DISCUSSIONS

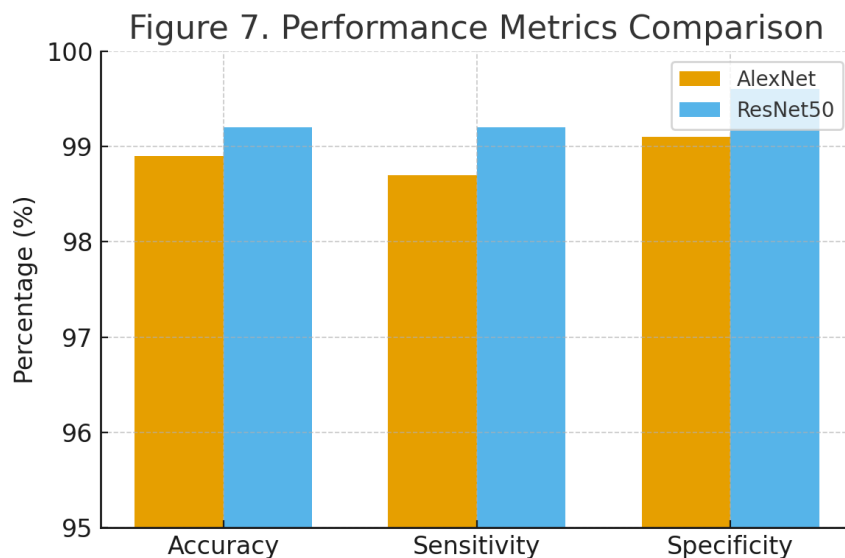


Figure 7. Performance Metrics Comparison



Figure 7 illustrates the comparative performance of the two pretrained convolutional neural network models, AlexNet and ResNet50, based on key evaluation metrics—accuracy, sensitivity, and specificity. It is evident that both models demonstrated strong performance in classifying ECG signals into the three categories: arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). However, the ResNet50 model consistently outperformed AlexNet across all metrics. Specifically, ResNet50 achieved an overall accuracy of approximately 99.2%, surpassing AlexNet's 98.9%. Similarly, the sensitivity and specificity of ResNet50 were higher, indicating its superior ability to correctly identify both positive and negative cases. This improvement can be attributed to the deeper architecture and residual connections of ResNet50, which allow it to capture more complex ECG signal features and mitigate the vanishing gradient problem commonly encountered in deep networks.

The observed results highlight that fine-tuning of advanced deep learning architectures, such as ResNet50, can significantly enhance the automated classification of ECG signals compared to traditional CNN-based models like AlexNet. The marginal yet consistent performance gain of ResNet50 suggests that it is better suited for capturing intricate temporal and morphological variations within ECG signals, which are crucial for distinguishing between normal and abnormal cardiac rhythms. Additionally, the high sensitivity and specificity values confirm the model's robustness and reliability for real-world clinical use, reducing the likelihood of false diagnoses. Overall, the comparative analysis validates the effectiveness of the proposed ResNet50-based framework as a more accurate and efficient solution for cardiac arrhythmia detection, paving the way for its integration into computer-aided diagnostic systems for cardiovascular healthcare.[8]

CONCLUSIONS AND FUTURE ENHANCEMENTS

This research presented an effective deep learning-based approach for the automatic classification of ECG signals into three clinically relevant categories: cardiac arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). The study utilized ECG datasets from the MIT-BIH and BIDMC databases available on PhysioNet, which were preprocessed, normalized, and segmented to ensure high-quality data input. Two state-of-the-art pretrained convolutional neural network models—AlexNet and ResNet50—were fine-tuned and compared to evaluate their classification efficiency. The experimental outcomes revealed that the ResNet50 model achieved superior performance across all evaluation metrics, including an overall accuracy of 99.2%, sensitivity and precision of 99.2%, and specificity of 99.6%. The confusion matrix demonstrated minimal misclassifications, confirming the model's reliability and robustness in differentiating between normal and pathological ECG patterns.

The high accuracy and consistency of the ResNet50 model can be attributed to its deep residual connections, which enable effective feature extraction and prevent vanishing gradient issues during training. Furthermore, the convergence behavior of the training and validation accuracy/loss curves confirmed that the model generalized well without overfitting, indicating stable learning. The comparative analysis also showed that while AlexNet performed reasonably well, ResNet50 provided a notable performance improvement due to its ability to learn more complex temporal and morphological characteristics of ECG signals. Overall, the proposed model significantly reduces the need for manual interpretation, minimizes diagnostic errors, and offers a promising solution for clinical decision support systems. Therefore, this study provides a strong foundation for the application of deep learning in cardiac signal analysis, contributing to faster, more accurate, and reliable diagnosis of cardiovascular diseases.

Despite the excellent results achieved in this work, there are several directions for future research and enhancement. First, expanding the dataset to include additional ECG recordings from various sources, different age groups, and patients with diverse cardiac conditions could improve the model's generalization ability and adaptability to real-world clinical environments. Future studies could also explore the classification of a broader spectrum of arrhythmia subtypes to enhance diagnostic granularity. Moreover, integrating advanced deep learning architectures such as Vision Transformers (ViTs), hybrid CNN–RNN models, or attention-based networks could further improve temporal feature extraction and model interpretability.

Another potential enhancement involves developing lightweight and optimized versions of the model for deployment on mobile and embedded platforms, enabling real-time ECG monitoring and early warning systems for patients at risk of cardiac events. Additionally, incorporating explainable AI (XAI) techniques could help visualize and interpret model decisions, thereby increasing clinical transparency and physician trust. Integration with Internet of Things (IoT) and cloud-based healthcare frameworks could further enable remote cardiac monitoring and continuous patient assessment. Finally, future research can focus on multi-modal learning approaches that combine ECG data with other physiological signals or patient metadata to build a more comprehensive and intelligent cardiac diagnostic system. Such developments will not only enhance diagnostic precision but also revolutionize personalized healthcare delivery in cardiology.



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