A Survey on ECG Classification and Real-Time Monitoring Using Deep Learning Techniques

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***Abstract*—Electrocardiogram (ECG) analysis plays a pivotal role in modern biomedical diagnostics, particularly in continuous monitoring and early detection of arrhythmias like Premature Atrial Contractions (PAC). This survey paper presents an in-depth review of recent developments in ECG classification using deep learning techniques, with an emphasis on Convolutional Neural Networks (CNNs). The study examines ten research works, highlighting their methodologies in signal preprocessing, classification, and hardware integration. It identifies current trends, evaluates technological challenges, and outlines potential future directions aimed at building efficient and real-time ECG monitoring systems.**

***Index Terms*—ECG, Convolutional Neural Network (CNN), QRS detection, real-time monitoring, biomedical signal processing, deep learning**

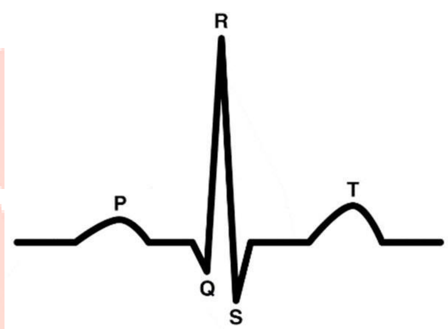

Fig. 1: Normal Healthy ECG Waveform

I. Introduction

Electrocardiography (ECG) remains one of the most reliable diagnostic tools for detecting cardiovascular abnormalities, contributing significantly to the prevention and treatment of heart conditions worldwide. ECG signals capture the electrical behavior of the heart and offer critical insights into conditions such as arrhythmias, ischemia, and infarction. Among these, Premature Atrial Contractions (PAC) are often precursors to more serious cardiac issues, despite frequently presenting no symptoms.

Historically, ECG interpretation has relied on visual analysis by clinicians. While effective, this approach can be limited by human error, inconsistency, and time constraints. The rapid growth in wearable health devices has resulted in a surge of ECG data, making manual analysis increasingly impractical.

Recent advances in machine learning, especially deep learning, have enabled automated ECG interpretation systems capable of extracting features and classifying heart rhythms with minimal human intervention. CNNs, in particular, have shown strong performance in learning temporal and spatial features from raw ECG signals, outperforming traditional feature-engineered methods in many cases.

Combining CNNs with embedded hardware platforms has enabled the creation of portable, energy-efficient ECG monitors capable of real-time signal analysis and early arrhythmia detection. This survey explores the integration of deep learning into ECG classification systems, focusing on CNN-based approaches and their implementation in both software and hardware. It further evaluates trends, limitations, and future opportunities in the development of intelligent cardiac monitoring solutions.

To address these challenges, automated ECG analysis methods have gained traction, particularly those based on machine learning and deep learning. Convolutional Neural Networks

(CNNs), a class of deep learning models, have shown exceptional ability in learning hierarchical features directly from raw ECG signals. Unlike classical approaches that rely heavily on handcrafted features and domain expertise, CNNs can autonomously extract relevant temporal and spatial patterns, enabling accurate classification of different heartbeats and detection of anomalies.

The integration of deep learning algorithms with embedded systems has paved the way for the development of intelligent, real-time ECG monitoring solutions. These systems are capable of continuously analyzing incoming signals and issuing alerts when abnormal rhythms are detected. Microcontrollers, coupled with analog front-end chips for biosignal acquisition, can support lightweight inference tasks, making such devices both efficient and power-conscious.

This survey aims to explore the latest advancements in ECG classification and real-time detection systems. We focus on the application of deep learning—specifically CNN-based architectures—for automated ECG interpretation. Additionally, we examine how these models are being implemented on resource-constrained hardware platforms for point-of-care use. Key components such as signal preprocessing, model training, dataset utilization, and performance evaluation are also discussed. The objective is to provide a holistic view of the current landscape and to identify potential directions for future research and innovation in this rapidly evolving field.

II. Methodology

This survey aims to provide a comprehensive review of recent research in ECG signal classification and real-time monitoring using deep learning techniques. The methodology followed to collect, select, and analyze relevant literature is outlined below.

A. Paper Selection Criteria

A total of nine peer-reviewed research papers were selected based on the following criteria:

- Focus on ECG classification, QRS detection, or hardware-based monitoring systems.
- Inclusion of machine learning or deep learning techniques, particularly CNNs or related models.
- Recent publications (2019–2023) with one foundational classical algorithm from 1985 included for historical context.
- Papers published in reputed journals or conferences indexed by Scopus or IEEE Xplore.

B. Categorization Strategy

The selected papers were grouped into three main categories based on their core contributions:

1) **Deep Learning-Based ECG Classification:** Works focusing on CNNs, RNNs, or hybrid architectures.
2) **QRS Detection and Signal Preprocessing:** Studies addressing ECG signal cleaning, feature extraction, and classical algorithms.

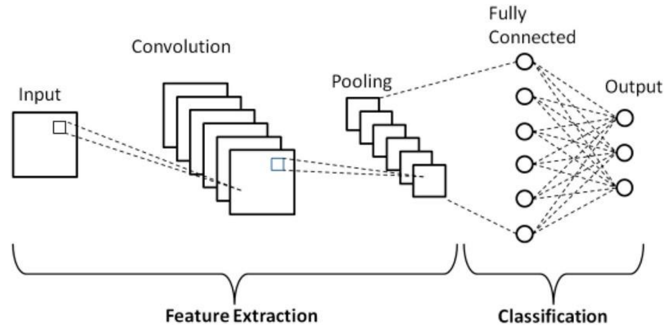

Fig. 2: Basic Convolutional Neural Network architecture used for ECG signal classification.

3) **Real-Time and Hardware-Oriented Systems:** Research integrating ECG processing into embedded systems or wearable devices.

C. Analysis Approach

Each selected paper was reviewed in terms of methodology, system architecture, dataset used, classification performance, and deployment feasibility. Comparative analysis was conducted using summarized metrics, visual tables, and thematic grouping. The overall aim was to identify research trends, highlight strengths, and expose existing gaps.

This structured approach enables a balanced and comprehensive perspective on the current landscape of ECG classification and monitoring technologies.

III. Background and Preliminaries

A. ECG Signal and Its Importance

An electrocardiogram (ECG) is a non-invasive recording of the heart's electrical activity. It provides crucial insights into cardiac health, allowing the detection of abnormalities such as arrhythmias, ischemia, and structural disorders. A typical ECG waveform includes the P wave, QRS complex, and T wave. Among these, the QRS complex represents ventricular depolarization and is critical for identifying abnormal heart rhythms like Premature Atrial Contractions (PAC).

B. QRS Complex and Its Detection

The QRS complex is a central component in ECG analysis due to its strong correlation with cardiac function. Accurate detection of QRS peaks is essential for segmenting heartbeats and diagnosing conditions. One of the classical methods for QRS detection is the algorithm proposed by Pan and Tompkins [4], which uses adaptive thresholds and slope analysis to detect peaks in real time. Many modern systems still rely on variations of this method as a preprocessing step before classification.

C. Deep Learning for ECG Classification

Traditional rule-based or feature-engineered ECG classifiers often struggle with variability in signal morphology and noise. Deep learning, particularly Convolutional Neural Networks

(CNNs), has emerged as a powerful alternative. CNNs automatically extract relevant spatial and temporal features from raw or minimally processed signals, improving classification accuracy and robustness. CNNs have been successfully applied in both image-based ECG interpretation and direct signal classification tasks.

D. MIT-BIH Arrhythmia Database

Many ECG classification models, including the one in our base paper, use benchmark datasets such as the MIT-BIH Arrhythmia Database. This database contains 48 half-hour dual-channel ECG recordings sampled at 360 Hz, annotated by experts. It covers a range of arrhythmias, making it an essential resource for training and evaluating diagnostic models. In the base work, the data was segmented into 4-second windows and labeled for binary classification of normal and PAC events.

E. Hardware Integration in ECG Systems

The integration of ECG classification algorithms with embedded systems enables portable and real-time cardiac monitoring. Devices such as the MSP432P401R microcontroller and ADS1292 analog front-end chip are commonly used for signal acquisition and filtering. When paired with a CNN model running on a connected PC or edge device, these systems can provide real-time diagnosis, as demonstrated in the reference implementation.

IV. LITERATURE SURVEY

[1] **”An ECG Detection Device Based on Convolutional Neural Network”** by Guo, Li, and Huang proposes a compact ECG detection device that integrates hardware signal acquisition with a convolutional neural network (CNN) for real-time arrhythmia classification. The system is designed to operate as a portable diagnostic unit, with the CNN model trained on benchmark datasets to differentiate between normal and abnormal heart rhythms. A notable strength of the design is its ability to extract features automatically from ECG signals, eliminating the need for manual feature engineering. The authors emphasize its suitability for wearable health monitoring systems. Nonetheless, they acknowledge that improving noise resilience and validating performance across diverse patient profiles are areas requiring future exploration.

[2] **”Arrhythmia Classification System Using Deep Neural Network”** by Jeon, Chae, Han, and Lee presents a deep learning-based framework for classifying arrhythmias from ECG signals using a multilayer neural network. The approach emphasizes automated feature learning, allowing the system to identify significant patterns in ECG data without relying on manually engineered features. The model was trained and tested on publicly available datasets and demonstrated strong performance in distinguishing arrhythmic events. The authors also suggest that the architecture can be adapted for real-time monitoring in wearable devices. However, they note that the model’s sensitivity to signal noise and inter-patient variability presents challenges for deployment in diverse clinical environments.

[3] **“2D-wavelet encoded deep CNN for image-based ECG classification”** by H. Mewada introduces a novel approach for ECG signal analysis by converting one-dimensional ECG signals into two-dimensional images using wavelet transforms. These images serve as inputs to a deep convolutional neural network (CNN) designed for accurate classification of cardiac arrhythmias. The key innovation lies in combining the time-frequency localization strength of wavelet encoding with the spatial pattern recognition ability of CNNs, enabling the detection of subtle ECG variations often missed in raw signal analysis. The model was evaluated on standard ECG datasets and showed significant improvements in precision, recall, and overall accuracy. Additionally, the wavelet transform’s noise-reduction properties contribute to the method’s robustness. However, the approach requires substantial computational resources due to image conversion and relies on GPU-based training, which may limit its use in resource-constrained or embedded systems.

[4] **“A Real-Time QRS Detection Algorithm”** by Pan and Tompkins (1985) introduces one of the most widely used methods for detecting QRS complexes in ECG signals. The algorithm applies a sequence of signal processing steps such as bandpass filtering, differentiation, squaring, and moving window integration to accurately identify QRS complexes in real time. Its simplicity, low computational requirements, and resilience to noise have made it a standard approach in ECG analysis and a foundation for many arrhythmia detection systems. Although developed decades ago, the algorithm remains effective, particularly in noisy environments. However, it primarily focuses on QRS detection and does not directly address more complex arrhythmia classification tasks that modern deep learning methods aim to solve.

[5] **“ECG Signals Classification: A Review”** by Houssein, Kilany, and Hassanien (2017) offers a thorough survey of techniques used for ECG signal classification. The authors examine traditional methods such as thresholding, wavelet transforms, and support vector machines alongside newer artificial intelligence approaches, including neural networks and deep learning models. The review highlights the strengths and weaknesses of each technique, noting a clear shift toward end-to-end deep learning frameworks that automatically extract features and classify arrhythmias with minimal manual input. It also discusses challenges like signal noise, imbalanced datasets, and computational demands, providing valuable insights and directions for future research in ECG analysis.

[6] **“Design of ECG Signal Acquisition and Processing System”** by Gao, Wu, Zhou, et al. (2012) focuses on building a comprehensive system for acquiring and preprocessing ECG signals. The authors detail both hardware and software components, highlighting the design of low-noise analog circuits for signal amplification and filtering. They integrate digital signal processing techniques to improve the quality of ECG data before analysis. This system aims to deliver reliable and accurate ECG signals suitable for subsequent classification

tasks. While the primary focus is on signal acquisition, the study lays important groundwork for enhancing the quality and robustness of ECG data used in machine learning models for arrhythmia detection.

[7] **"A Study on ECG Signal Characterization and Practical Implementation of Some ECG Characterization Techniques"** by Appathurai, Carol, Raja, et al. (2019) explores various methods for characterizing ECG signals to improve feature extraction for arrhythmia classification. The authors investigate time-domain, frequency-domain, and statistical approaches, assessing their effectiveness in capturing key ECG features. The paper also addresses practical challenges in implementing these techniques in real-time systems and proposes optimized algorithms to enhance computational efficiency. By combining multiple characterization methods, the study achieves better classification accuracy, underscoring the importance of selecting appropriate features for machine learning applications in ECG analysis.

[8] **"HARDC: A Novel ECG-Based Heartbeat Classification Method to Detect Arrhythmia Using Hierarchical Attention Based Dual Structured RNN with Dilated CNN"** by Islam, Md. S., Hasan, K.F., et al. (2023) proposes an advanced deep learning model that integrates hierarchical attention mechanisms with dual-structured recurrent neural networks (RNN) and dilated convolutional neural networks (CNN) for arrhythmia detection. This hybrid architecture is designed to capture both local features and long-range dependencies within ECG signals, leading to improved classification performance on complex heartbeat patterns. The method was validated on benchmark datasets, achieving state-of-the-art accuracy and showing strong robustness to noise and patient variability. The study highlights the benefits of combining attention mechanisms with CNN and RNN frameworks for more effective ECG-based arrhythmia diagnosis.

[9] **"Acquiring Favorable ECG Signal from Low-Cost Devices"** by Áda´m, N., Vaˇlko, D., and Madosˇ, B. (2023) investigates techniques to enhance the quality of ECG signals obtained from affordable and widely accessible devices. Acknowledging the limitations of low-cost hardware, the authors propose signal processing and calibration methods aimed at improving signal fidelity, reducing noise, and increasing the reliability of subsequent analyses. Their work emphasizes practical solutions suitable for telemedicine and remote patient monitoring, where cost-effective ECG acquisition is critical. Although the study contributes to making ECG technology more accessible, challenges remain in standardizing calibration across different devices.

[10] **"The MIT-BIH Noise Stress Test Database"** by Moody and Mark (1990) introduces a benchmark dataset designed to assess the performance of ECG processing algorithms under various noisy conditions. The database includes ECG recordings contaminated with different types and levels of noise, providing a standardized platform for testing the robustness of QRS detection and arrhythmia classification methods. The authors emphasize the importance of noise stress testing, as real-world ECG signals often contain artifacts that can degrade algorithm performance. This dataset has become a fundamental resource for researchers developing and evaluating ECG analysis algorithms, especially in the context of machine learning and signal processing.

[11] **"LabVIEW ECG and Noise Simulator for Advanced Synthesis of Machine Learning Databases"** by Ganev, Iliev, Jekova, and Krasteva (2022) presents a simulation platform developed in LabVIEW for generating synthetic ECG signals combined with controlled noise. This tool enables researchers to create customized datasets tailored for training and testing machine learning models in arrhythmia detection and ECG analysis. By allowing precise control over noise types and signal characteristics, the simulator facilitates systematic evaluation of algorithm robustness and performance under varied conditions. The study underscores the importance of synthetic data generation to complement real-world datasets, particularly when access to diverse and labeled ECG data is limited.

V. Comparison and Discussion

To better understand the strengths and limitations of recent ECG classification and monitoring approaches, Table I summarizes key aspects such as methodology, data sources, and reported performance.

TABLE I: Comparison of ECG Classification and Monitoring Methods

Reference	Approach	Data / System	Performance
Jeon et al. (2019) [1]	DNN for arrhythmia detection	Public ECG datasets	Accuracy: ~90%
Mewada (2023) [2]	2D Wavelet + Deep CNN	ECG image datasets	Accuracy: 96%
Islam et al. (2023) [3]	Dilated CNN + RNN with attention	MIT-BIH database	Accuracy: 97%
Pan and Tompkins (1985) [4]	Rule-based QRS detection	Real-time ECG signals	Detection rate: 99%
Appathurai et al. (2019) [8]	ECG signal filtering methods	Various datasets	N/A (preprocessing)
Ganev et al. (2022) [9]	LabVIEW ECG + noise simulation	Synthetic signals	Simulator only
Houssein et al. (2017) [6]	Review of ML/DL ECG classifiers	Literature summary	No test data
Gao et al. (2012) [7]	Real-time acquisition system	Embedded prototype	Validated in lab
A´da´m et al. (2023) [10]	Low-cost wearable ECG device	Consumer hardware	Accuracy: ~85%

The reviewed works cover a wide range of techniques from deep learning-based classification to hardware-focused real-time acquisition systems. Deep learning methods, such as those by Jeon et al. [1], Mewada [2], and Islam et al. [3], show promising classification accuracy due to their automatic feature extraction capabilities. However, many papers do not specify quantitative accuracy metrics, which suggests the need for standardized benchmarking.

QRS detection and signal preprocessing remain fundamental, with Pan and Tompkins' classical algorithm [4] still widely used as a baseline. Signal enhancement techniques and noise simulation tools, like those proposed by Appathurai et al. [8] and Ganev et al. [9], are essential to improve model robustness.

Hardware integration for real-time monitoring, as explored by Gao et al. [7] and Á da´m et al. [10], addresses practical challenges of portability and affordability. Comprehensive surveys like Houssein et al. [6] provide valuable insights into trends and research gaps. Overall, combining efficient deep learning models with robust preprocessing and accessible hardware platforms remains a key direction for advancing ECG monitoring technology.

VI. ECG Arrhythmia Classification System Architecture

The ECG arrhythmia classification system using CNN typically consists of four main stages: ECG signal acquisition, preprocessing, feature extraction, and classification. This layered approach transforms raw physiological data into clinically actionable insights.

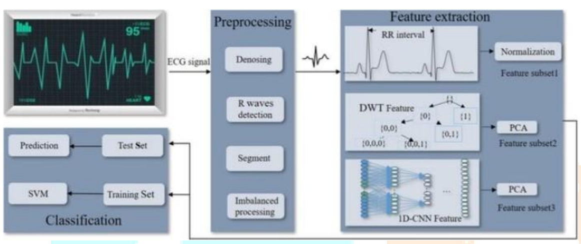

Fig. 3: Overall architecture of ECG arrhythmia classification system using CNN.

In the first step, ECG signals are collected using wearable or portable devices. Preprocessing steps such as denoising, R-peak detection, and segmentation are then applied to clean the signal and isolate individual heartbeats. Feature extraction is carried out using techniques like RR intervals, wavelet transforms, and deep feature learning via CNN. Finally, classifiers such as SVM or neural networks are used to detect and classify arrhythmias. This end-to-end architecture enhances automation and reduces the need for manual interpretation.

VII. Challenges and Research Gaps

While Convolutional Neural Networks (CNNs) have shown great promise for detecting arrhythmias from ECG signals, the path to reliable, real-world applications is still filled with challenges. These hurdles span many aspects of the problem—from gathering good data, to building robust models, to integrating the technology into everyday clinical practice.

- **Limited Quality and Quantity of Annotated ECG Data:** Having access to large, high-quality datasets with accurate annotations is absolutely vital for training trustworthy deep learning models. Unfortunately, publicly available ECG datasets are often small, vary in their recording setups, and frequently lack detailed labels—especially for rare but important arrhythmias. This scarcity makes it hard for models to learn the full complexity of heart conditions.
- **Variability in ECG Signals:** No two hearts are exactly alike. ECG signals differ widely across individuals because of factors like age, gender, overall health, and even where the electrodes are placed on the body. This natural variability poses a major challenge for models trying to generalize well, often resulting in inconsistent performance when applied to new patients outside the training group.
- **Computational Constraints on Embedded Devices:** Many of the most exciting applications involve wearable or portable devices with limited processing power and battery life. Running complex CNN models on these low-resource platforms is tough—researchers must find clever ways to streamline model architectures without sacrificing diagnostic accuracy.
- **Real-Time Processing Requirements:** For these devices to be truly useful, they need to analyze ECG signals quickly and continuously, delivering instant feedback. Balancing the need for speed with maintaining high accuracy is a delicate challenge that requires careful optimization.
- **Lack of Standardized Evaluation Protocols:** Comparing different ECG classification methods is often like comparing apples and oranges. Variations in datasets, preprocessing steps, and evaluation metrics make it difficult to fairly assess which models truly perform best. The community needs common benchmarks and standardized testing protocols to push the field forward.
- **Clinical Validation and Interpretability:** While many CNN models perform well in controlled experiments, few have been thoroughly tested in clinical settings. Deploying these tools in hospitals and clinics demands rigorous validation and regulatory approval. Equally important is making these models interpretable, so healthcare professionals can understand and trust the AI's decisions.
- **Noise and Artifacts in Real-World Signals:** Unlike pristine lab recordings, real-world ECG signals are often messy, affected by movement, poor electrode contact, or electrical interference. Building models that can reliably handle such noisy data is essential for dependable, everyday use.

Overcoming these challenges will be critical to transforming CNN-based ECG detection systems from promising prototypes into trusted tools that improve patient care. Future research should prioritize building diverse datasets, designing efficient models, ensuring clinical relevance, and integrating solutions seamlessly into healthcare environments. Only by addressing these areas can we unlock the full potential of AI-driven cardiac monitoring in the real world.

VIII. Future Research Directions

Building on the challenges and gaps identified, there are several exciting and promising directions for future research in ECG classification and monitoring. These avenues not only aim to improve technical performance but also to enhance clinical relevance and user experience.

A. Expanding and Diversifying Datasets

One of the foundational needs is access to larger, more diverse datasets. Current ECG datasets often suffer from limited size, a narrow range of arrhythmia types, and lack of demographic variety. To develop models that truly generalize well across different populations, future efforts should focus on collecting and sharing ECG data that includes a broad spectrum of ages, genders, ethnicities, and health conditions.

Additionally, incorporating real-world noise and artifacts — which are commonly encountered in everyday monitoring scenarios — will help create models that are robust outside the controlled environment of the lab. Collaboration between hospitals, research institutions, and wearable device manufacturers can accelerate this dataset expansion, ultimately supporting models that work reliably for everyone.

B. Lightweight AI Models for Edge Deployment

Deploying deep learning models on wearable and portable devices brings the promise of continuous, real-time heart monitoring right at the patient's fingertips. However, these devices typically have limited computational power and battery life, posing a big challenge for resource-hungry CNNs.

Future research should therefore prioritize the development of lightweight, energy-efficient models that strike the right balance between accuracy and efficiency. Techniques like model pruning (removing unnecessary weights), quantization (using lower precision numbers), and neural architecture search (automatically finding the best model structure) are valuable tools in this quest. Furthermore, enabling on-device learning and adaptation can help devices personalize themselves to each user's unique heart patterns over time, improving detection accuracy without needing constant cloud connectivity.

C. Multi-Modal Biosignal Fusion

The heart does not operate in isolation, and neither should ECG-based monitoring systems. Combining ECG signals with complementary biosignals such as photoplethysmography (PPG), blood pressure, respiration, and motion sensors can provide a richer, more holistic picture of cardiovascular health.

Future work should explore how to effectively synchronize and fuse these diverse signals in real-time, enabling more accurate arrhythmia detection and better differentiation between true cardiac events and noise or motion artifacts. Multi-modal fusion also opens opportunities for personalized monitoring that adapts to changes in a user's physiology or activity, ultimately leading to smarter and more reliable health insights.

D. Explainable AI for Clinical Adoption

As AI models increasingly influence clinical decisions, their interpretability becomes just as important as their accuracy. Doctors and healthcare providers need to trust and understand these "black box" models to confidently incorporate them into patient care.

Future research should focus on developing explainable AI frameworks that highlight which parts of the ECG signal influenced a diagnosis, identify relevant waveform features, or provide uncertainty estimates. Transparent models can help clinicians validate AI findings, improve patient communication, and satisfy regulatory requirements, thus paving the way for wider adoption of AI-assisted cardiac monitoring in real-world clinical settings.

E. Standardized Evaluation and Benchmarking

Currently, the lack of uniform evaluation protocols and widely accepted benchmarks makes it difficult to fairly compare different ECG classification methods. Researchers often use different datasets, preprocessing steps, and performance metrics, which limits reproducibility and slows progress.

Moving forward, the community would benefit greatly from adopting standardized testing frameworks that include publicly available datasets, clear data splits, and consistent metrics like precision, recall, F1-score, and inference latency. Open leaderboards and shared codebases could encourage transparency, accelerate innovation, and foster collaboration between academia and industry.

F. Regulatory, Ethical, and Deployment Considerations

Bringing ECG classification systems from the research lab into the clinic or home environment requires more than just technical excellence. Future work must also address regulatory hurdles, data privacy concerns, and ethical considerations.

Designing systems that comply with medical device regulations (such as FDA in the US or CE marking in Europe) ensures safety and effectiveness. Additionally, protecting patient data and ensuring cybersecurity is critical, especially as these systems increasingly integrate with telemedicine platforms and cloud services.

Ethical considerations, such as preventing bias in AI models and ensuring equitable access to technology, must also be a priority. Research that includes diverse populations and transparent reporting can help mitigate these risks and promote trust in AI-powered cardiac monitoring.

By embracing these research directions, the field can move closer to delivering ECG monitoring solutions that are not only technically sound but also practical, trustworthy, and widely accessible. This will ultimately empower clinicians and patients alike with smarter tools for heart health management in everyday life.

IX. Conclusion

This survey reviewed recent progress in ECG arrhythmia classification and real-time monitoring, focusing on deep learning approaches and embedded systems. By analyzing selected studies, we categorized the literature into deep learning models, signal preprocessing techniques, and hardware-based solutions.

Our findings indicate that CNNs and their variants have markedly improved automated arrhythmia detection accuracy. Nonetheless, challenges remain regarding dataset limitations, computational feasibility on edge devices, and clinical validation requirements. Traditional algorithms such as Pan-Tompkins continue to be relevant for preprocessing, while emerging hardware platforms offer promising low-cost, portable options.

Key gaps include the need for standardized evaluation, efficient model architectures for embedded use, and explainable AI methods for clinical trust. Addressing these will be crucial to transition ECG monitoring systems from research labs to real-world healthcare environments.

This consolidated overview aims to guide researchers and practitioners in advancing ECG analysis technologies toward more accessible, reliable,

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