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From ECG Signals to Intelligent Diagnosis: A Survey on Deep Learning-Based Arrhythmia Classification and Deployment

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Abstract: *Electrocardiogram (ECG) analysis is a fundamental tool for diagnosing cardiac arrhythmias and enabling continuous heart monitoring. Recent advancements in machine learning, particularly deep learning, have significantly improved the accuracy and automation of ECG-based arrhythmia classification. This survey presents a comprehensive review of recent research focusing on ECG signal preprocessing, deep learning architectures, hybrid and ensemble models, data imbalance mitigation techniquesand deployment-oriented solutions for wearable and edge devices. Emphasis is placed on comparing convolutional neural networks (CNNs), recurrent neural networks (RNNs), CNN–LSTM hybrids, generative data augmentation strategies and lightweight models suitable for real-time applications. A detailed comparative analysis of representative studies highlights current trends, performance metrics and deployment feasibility. The survey also identifies challenges and future research directions for robust and clinically reliable ECG arrhythmia detection systems*

Keywords*:* ECG signal processing, Arrhythmia classification, Deep learning, CNN-LSTM, Data imbalance, Wearable healthcare

I. INTRODUCTION

Cardiovascular diseases are among the leading causes of mortality worldwide, with cardiac arrhythmias contributing significantly to sudden cardiac deaths. Electrocardiography (ECG) is a widely used, non-invasive diagnostic technique that records the electrical activity of the heart and provides critical information for arrhythmia detection. However, manual ECG interpretation by clinicians is time-consuming and susceptible to subjective variations, particularly in long-term monitoring scenarios.

To address these challenges, automated ECG analysis systems have been extensively studied. Early approaches relied on handcrafted feature extraction combined with traditional classifiers such as support vector machines and decision trees [18]. While these methods achieved moderate success, their performance was limited by dependence on domain expertise and sensitivity to noise and inter-patient variability [1].

Fig. 1 illustrates a typical electrocardiogram (ECG) waveform highlighting the P wave, QRS complex and T wave, which correspond to atrial depolarization, ventricular depolarization and ventricular repolarization, respectively. The x-axis represents time in milliseconds, while the y-axis denotes signal amplitude in millivolts.

Recent years have witnessed a paradigm shift toward deep learning-based methods, which learn discriminative representations directly from raw or minimally processed ECG signals. Convolutional neural networks (CNNs) have demonstrated strong capability in capturing morphological features, while recurrent neural networks (RNNs), including long short-term memory (LSTM) and bidirectional LSTM (BiLSTM), effectively model temporal dependencies in ECG signals [2], [3]. Hybrid architectures combining CNN and LSTM layers have further improved classification accuracy by integrating spatial and temporal information [4].

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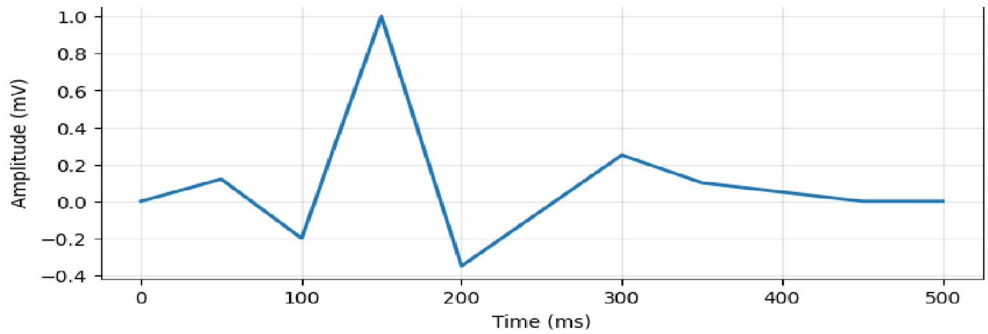

Fig. 1. Typical electrocardiogram (ECG) waveform illustrating the P wave, QRS complex and T wave, representing atrial depolarization, ventricular depolarization and ventricular repolarization, respectively.

In addition to model accuracy, contemporary research increasingly focuses on addressing practical challenges such as class imbalance in ECG datasets, real-time inference requirements and deployment on resource-constrained wearable or edge devices [5]. Ultra-lightweight and hardware-aware models have emerged to enable continuous monitoring with low power consumption [6].

This survey systematically reviews recent ECG arrhythmia classification methods, emphasizing signal preprocessing, deep learning architectures, data augmentation strategies and deployment-oriented designs. The primary contributions of this survey are:

- A structured taxonomy of modern ECG arrhythmia classification approaches.
- A comparative analysis of deep learning models and data imbalance handling techniques.
- A discussion on edge, wearable and cloud-assisted deployment frameworks.
- Identification of open research challenges and future directions.

Fig. 2 presents a comprehensive taxonomy of ECG arrhythmia classification approaches discussed in this survey. The workflow begins with ECG signal acquisition, followed by preprocessing operations such as filtering, denoising and normalization. Subsequent stages include data representation, deep learning-based classification and deployment on cloud, edge or wearable platforms.

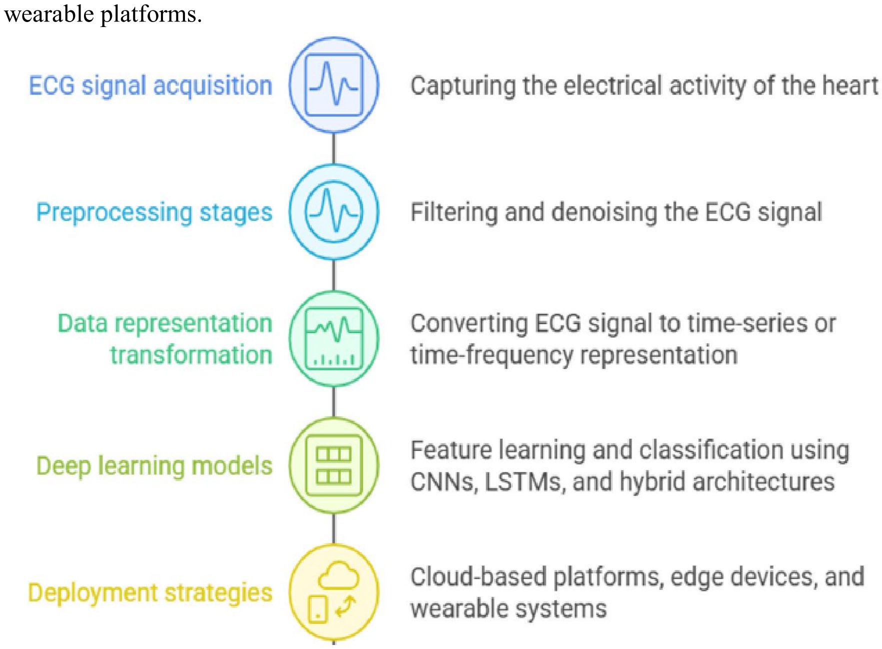

Fig. 2.Taxonomy of ECG arrhythmia classification approaches illustrating the stages from signal acquisition and preprocessing to deep learning-based classification and deployment.

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II. ECG SIGNAL PROCESSING AND DATA REPRESENTATION

ECG signal preprocessing is a critical stage in automated arrhythmia classification systems, as raw ECG recordings are often corrupted by various types of noise such as baseline wander, power-line interference, motion artifactsand electromyographic noise. Effective preprocessing improves signal quality and enhances the reliability of subsequent classification stages.

A. ECG Signal Preprocessing

Most studies employ band-pass filtering to suppress low-frequency baseline drift and high-frequency noise. Typical cutoff frequencies range from 0.5 Hz to 40 Hz, preserving clinically relevant ECG components while reducing artifacts [1]. Wavelet-based denoising methods are also widely adopted due to their ability to localize noise in both time and frequency domains [8].

R-peak detection and beat segmentation form the foundation for heartbeat-level analysis. Accurate localization of the QRS complex enables extraction of meaningful cardiac cycles and temporal features such as RR intervals, which are essential for arrhythmia discrimination [9]. Some recent approaches avoid explicit segmentation by feeding fixed-length ECG windows directly into deep learning models, reducing preprocessing complexity [10],[12].

B. ECG Data Representation

Two dominant ECG data representations are observed in recent literature:

1) One-Dimensional Time-Domain Representation

In this approach, raw or filtered ECG signals are directly used as one-dimensional sequences. CNN-based models exploit local convolutional filters to learn morphological patterns such as QRS shape variations, while LSTM and BiLSTM layers capture long-term temporal dependencies between heartbeats [2], [15]. This representation preserves the original signal characteristics and is computationally efficient, making it suitable for real-time and embedded implementations [6].

2) Time–Frequency Representation

To capture both temporal and spectral characteristics of ECG signals, several studies convert ECG data into two-dimensional representations using short-time Fourier transform (STFT), continuous wavelet transform (CWT), or scalogram images. These representations are particularly effective when combined with CNN architectures, as they allow the network to learn discriminative frequency-domain features associated with different arrhythmias [13],[14].

Stacked time–frequency scalogram images generated from multi-lead ECG signals further enhance spatial feature learning by integrating information across multiple leads. Such approaches have demonstrated improved robustness and classification performance, especially for complex arrhythmia classes [14].

C. Multi-Lead and Data Standardization Considerations

While single-lead ECG is commonly used in wearable devices, multi-lead ECG recordings provide richer spatial information and improve diagnostic accuracy. Twelve-lead ECG configurations are frequently employed in clinical datasets and research benchmarks, although they impose higher computational and storage requirements [15].

Standardization of ECG signal length, sampling frequency and normalization techniques remains a challenge across studies. Differences in preprocessing pipelines and labelling strategies often hinder direct comparison between methods, highlighting the need for unified benchmarking protocols [16].

III. DEEP LEARNING ARCHITECTURES FOR ECG ARRHYTHMIA CLASSIFICATION

Deep learning has emerged as the dominant paradigm for ECG-based arrhythmia classification due to its ability to automatically learn discriminative features from raw or minimally processed signals. Unlike traditional machine learning approaches that rely on handcrafted features, deep learning models jointly optimize feature extraction and classification in an end-to-end manner, resulting in improved robustness and scalability [2], [3].

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A. Convolutional Neural Networks (CNNs)

CNNs are widely used for ECG classification because of their effectiveness in capturing local morphological patterns such as QRS complex shape, ST-segment variations and waveform distortions. One-dimensional CNNs apply convolutional filters directly to ECG time-series data, enabling efficient learning of spatially localized features [8].

Recent studies demonstrate that deep CNN architectures can achieve high classification accuracy when trained on large ECG datasets. Lightweight CNN models have also been proposed to reduce computational complexity, making them suitable for deployment on resource-constrained platforms [6], [12]. However, CNN-only architectures may struggle to capture long-term temporal dependencies inherent in ECG signals.

B. Recurrent Neural Networks (LSTM and BiLSTM)

Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, are designed to model sequential data and temporal dependencies. LSTM-based ECG classifiers effectively capture inter-beat relationships and temporal variations across cardiac cycles [10].

Bidirectional LSTM (BiLSTM) networks further enhance temporal modelling by processing ECG sequences in both forward and backward directions. This allows the model to utilize past and future contextual information, leading to improved classification performance, especially for complex arrhythmia patterns [11]. Despite their advantages, pure RNN-based models typically exhibit higher computational cost compared to CNNs.

C. Hybrid CNN–LSTM Architectures

To leverage the strengths of both CNNs and LSTMs, hybrid CNN–LSTM architectures have become increasingly popular. In these models, CNN layers first extract local morphological features from ECG signals, which are then fed into LSTM or BiLSTM layers to learn temporal dependencies [12].

Hybrid models consistently outperform standalone CNN or LSTM architectures across multiple datasets, achieving higher accuracy and better generalization [13]. Variants such as CNN–BiLSTM and CNN–GRU architectures have also been explored to further improve efficiency and classification performance [14].

Fig. 3 depicts a generic CNN–LSTM hybrid architecture commonly employed for ECG arrhythmia classification. Convolutional layers are used for automatic feature extraction from raw ECG signals, while LSTM or BiLSTM layers capture temporal dependencies across heartbeats. The extracted features are finally classified using fully connected layers and a softmax output.

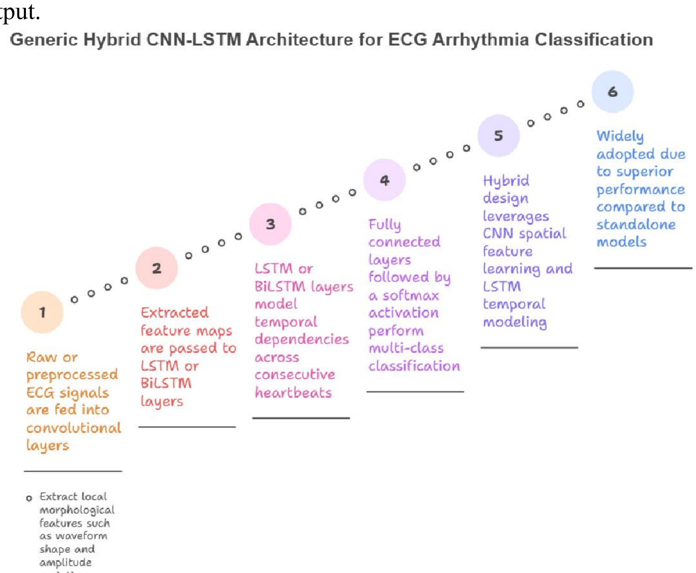

Fig. 3. Generic CNN–LSTM hybrid architecture for ECG arrhythmia classification, combining convolutional feature extraction with temporal sequence modelling.

D. Attention Mechanisms and Ensemble Models

Attention mechanisms enable models to focus on the most informative segments of ECG signals, improving interpretability and classification accuracy. Attention-based hybrid models have demonstrated superior performance by dynamically weighting relevant temporal features during inference [15].

Ensemble learning strategies combine predictions from multiple deep learning models to enhance robustness and reduce variance. Multi-model ensembles integrating CNNs, LSTMs and classical features have shown improved sensitivity to minority arrhythmia classes, particularly in imbalanced datasets [5], [16].

IV. DATA IMBALANCE AND AUGMENTATION TECHNIQUES

One of the major challenges in ECG arrhythmia classification is the severe class imbalance present in most publicly available datasets. Normal heartbeats significantly outnumber abnormal and rare arrhythmia classes, leading to biased classifiers that favour majority classes. Addressing this imbalance is essential for achieving reliable clinical performance, particularly for detecting life-threatening arrhythmias.

A. Conventional Oversampling and Reweighting Methods

Traditional techniques such as random oversampling and class-weighted loss functions have been widely used to mitigate data imbalance in ECG datasets [11]. Cost-sensitive learning approaches modify the loss function by assigning higher penalties to misclassification of minority classes. Several deep learning-based ECG classifiers incorporate weighted cross-entropy or focal loss to improve minority class recognition without altering the data distribution [16].

B. Generative Adversarial Network (GAN)-Based Augmentation

Recent research increasingly adopts generative adversarial networks (GANs) to address ECG data imbalance. GANs consist of a generator that synthesizes realistic ECG signals and a discriminator that distinguishes between real and generated samples. By training these networks, GANs can produce high-quality synthetic ECG signals that closely resemble real data [7].

GAN-based ECG synthesis has been shown to significantly improve arrhythmia classification performance, particularly for underrepresented classes. Studies demonstrate that classifiers trained with GAN-augmented datasets achieve higher sensitivity and F1-scores compared to traditional oversampling techniques [6], [11]. Conditional GAN variants further enable class-specific ECG generation, enhancing control over synthesized data quality.

C. Impact of Augmentation on Model Generalization

While data augmentation improves performance on imbalanced datasets, excessive or poorly controlled augmentation may lead to overfitting or reduced generalization. Some studies emphasize the importance of combining GAN-generated data with real samples in controlled proportions to maintain physiological plausibility [18].

Moreover, evaluation across multiple datasets remains limited and most studies report results on a single benchmark dataset. This highlights the need for standardized evaluation protocols to assess the true generalization capability of augmentation-based approaches[16], [19].

Fig. 4 illustrates a GAN-based ECG data augmentation framework used to address class imbalance in arrhythmia datasets. The generator synthesizes realistic ECG samples from random noise and class labels, while the discriminator distinguishes between real and synthetic signals. The generated ECG samples are subsequently used to enhance classification model performance.

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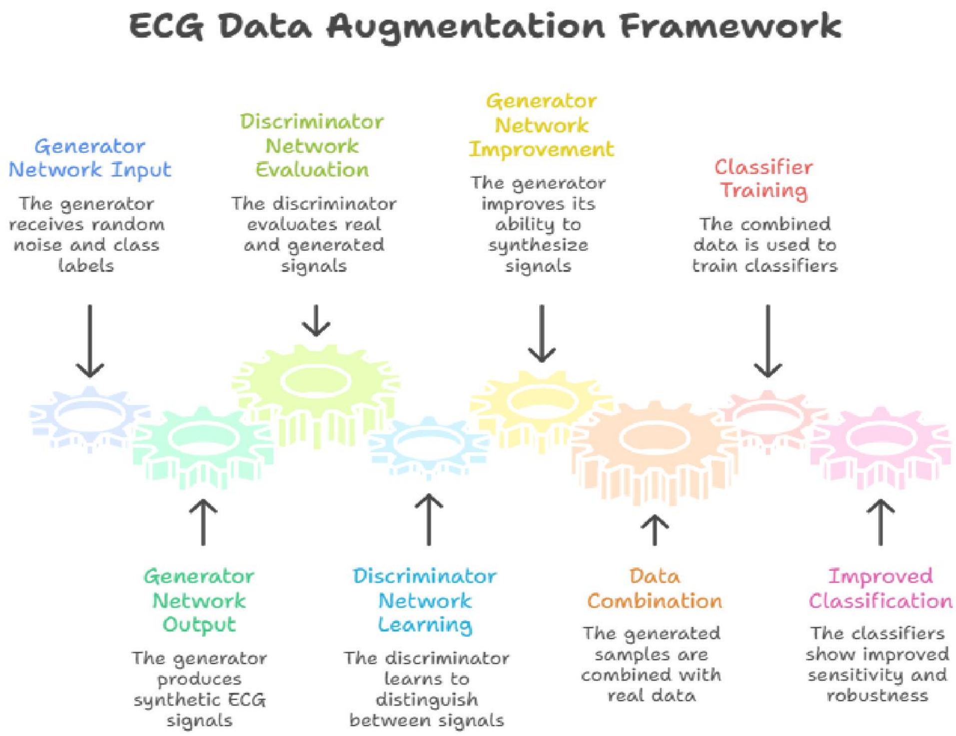

Fig. 4. GAN-based ECG data augmentation framework showing the generation of synthetic ECG samples and their evaluation using a discriminator alongside real ECG signals.

V. ENSEMBLE MODELS , DECISION SUPPORT AND CLOUD BASED SYSTEMS

As ECG arrhythmia classification systems move closer to real-world clinical adoption, recent research has expanded beyond standalone classifiers toward ensemble learning frameworks and integrated decision support systems. These approaches aim to improve diagnostic reliability, interpretability and scalability in clinical environments.

A. Ensemble Learning for ECG Arrhythmia Classification

Ensemble learning combines predictions from multiple models to enhance classification robustness and reduce variance. In ECG analysis, ensembles typically integrate CNN, LSTM and hybrid CNN–LSTM models, leveraging complementary strengths of different architectures .

Bagging and stacking-based ensembles have demonstrated improved sensitivity for minority arrhythmia classes compared to single-model systems. By aggregating outputs from diverse learners, ensemble methods mitigate overfitting and improve generalization, particularly in imbalanced datasets [16], [20]. However, ensemble models generally incur higher computational cost, which may limit their suitability for resource-constrained environments.

B. Intelligent Decision Support Systems (IDSS)

Intelligent Decision Support Systems integrate ECG classification algorithms with clinical workflows to assist physicians in diagnosis and treatment planning. Such systems typically include modules for signal preprocessing, automated classification, risk assessmentand result visualization [15], [18].

Recent IDSS frameworks employ deep learning models to analyse ECG data in real time and provide actionable insights such as arrhythmia type, severity level and suggested clinical interventions. These systems aim to reduce clinician workload while improving diagnostic consistency and response time [18].

C. Cloud-Based ECG Analysis Platforms

Cloud-based ECG analysis platforms enable scalable storage, processing and analysis of large volumes of ECG data. In these systems, ECG signals collected from wearable or bedside devices are transmitted to cloud servers, where deep learning models perform classification and analytics [15].

Cloud integration facilitates continuous model updates, centralized data management and remote access to diagnostic results. Hybrid architectures combining local inference with cloud-based analytics have also been proposed to balance latency, privacyand computational load [17]. However, concerns related to data security, patient privacy and network reliability remain critical challenges.

Fig. 5 illustrates a cloud-assisted ECG decision support system integrating deep learning-based analysis with clinical visualization.

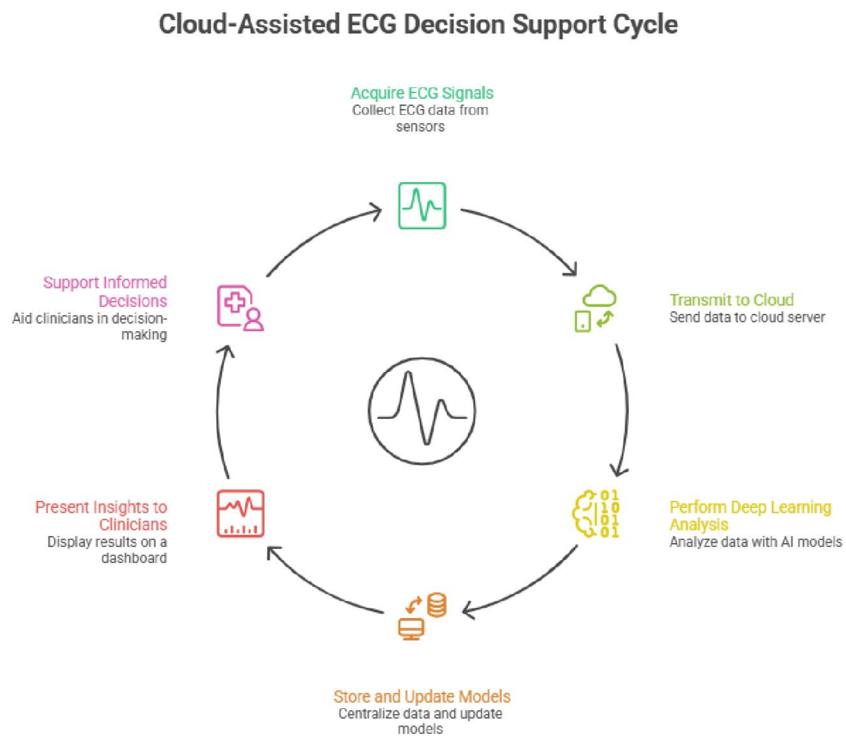

Fig. 5. Cloud-assisted ECG decision support system demonstrating ECG data acquisition, cloud-based deep learning analysis and clinical visualization.

VI. EDGE, WEARABLE AND LIGHTWEIGHT DEPLOYMENT STRATEGIES

For continuous cardiac monitoring and early arrhythmia detection, ECG classification systems must operate under strict constraints on power consumption, latencyand hardware resources. As a result, recent research emphasizes deployment-oriented designs targeting edge devices such as wearable sensors, microcontrollers and field-programmable gate arrays (FPGAs).

A. FPGA-Based ECG Processing Systems

FPGAs offer a balance between computational performance and energy efficiency, making them suitable for real-time ECG signal processing. FPGA-based implementations exploit parallelism to accelerate preprocessing, feature extractionand classification tasks [13]. Studies demonstrate that FPGA implementations can achieve low latency and reduced power consumption compared to general-purpose CPUs and GPUs.

Several works implement arrhythmia detection pipelines entirely on FPGA, integrating signal conditioning, feature extraction and classification into a single hardware architecture. These systems are particularly well suited for wearable

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healthcare devices requiring continuous real-time monitoring [13]. However, FPGA-based solutions may involve higher development complexity and limited flexibility when updating models.

B. Microcontroller and Ultra-Lightweight Neural Networks

Microcontroller-based implementations have gained significant attention due to their low cost, low power consumptionand programmability. Ultra-lightweight neural networks are specifically designed to minimize parameter count and arithmetic operations, enabling real-time inference on low-power microcontrollers [6].

Recent research demonstrates that carefully optimized end-to-end ECG classifiers can achieve competitive accuracy while operating within the memory and energy constraints of microcontroller units (MCUs). Such approaches eliminate the need for external accelerators and are well suited for long-term wearable ECG monitoring [6], [8].

An edge-based ECG arrhythmia classification system designed for real-time wearable monitoring is shown in Fig. 6.

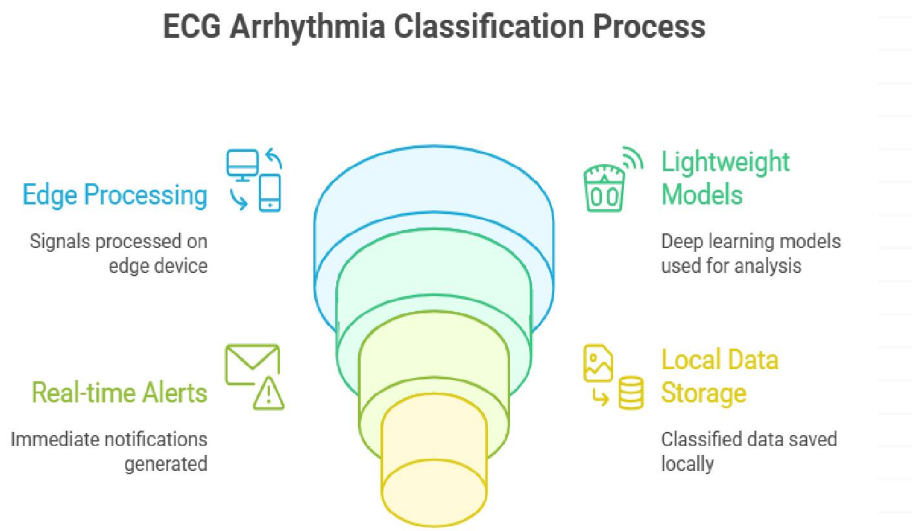

Fig. 6. Edge-based ECG arrhythmia classification system highlighting on-device inference using lightweight deep learning models for real-time monitoring.

C. Algorithm–Hardware Co-Design Considerations

Effective deployment of ECG classifiers requires close coordination between algorithm design and hardware architecture. Techniques such as model quantization, parameter pruningand fixed-point arithmetic are commonly employed to reduce memory footprint and computational load [13].

Algorithm–hardware co-design ensures that deep learning models maintain acceptable accuracy while meeting real-time and power constraints. Trade-offs between flexibility and efficiency remain a key consideration, particularly when comparing FPGA, MCU and application-specific integrated circuit (ASIC) solutions [18], [19].

VII. COMPARATIVE ANALYSIS

This section presents a comparative analysis of recent ECG arrhythmia classification studies reviewed in this survey. The comparison focuses on model architecture, data representation, dataset usage, data imbalance handling, performance metrics and deployment feasibility. The objective is to highlight trends, strengths and limitations across different methodological choices.

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[1] A. Comparison of Learning Architectures

Table I summarizes the deep learning architectures adopted in recent studies. It can be observed that hybrid CNN–LSTM architectures dominate recent literature due to their ability to jointly model morphological and temporal ECG features.

TABLE I: Summary of Representative ECG Arrhythmia Classification Methods

Authors / Paper Title	Model / Technique	Dataset	Key Contribution
Pan & Tompkins, A real-time QRS detection algorithm[1]	Rule-based signal processing	MIT-BIH	Foundational real-time QRS detection algorithm
Acharya et al., A deep convolutional neural network model to classify heartbeats[2]	1D CNN	MIT-BIH	Automatic feature extraction from ECG signals
Rajpurkar et al., Cardiologist-level arrhythmia detection with CNNs[3]	Deep CNN	Large-scale ECG dataset	Achieved cardiologist-level classification accuracy
Kiranyaz et al., Patient-specific ECG classification using CNNs[4]	1D CNN	MIT-BIH	Real-time patient-specific learning
Essa & Xie, Multi-model deep learning ensemble[5]	Ensemble CNN models	MIT-BIH	Improved robustness using ensemble learning
Zhang et al., Hybrid CNN–BiLSTM model[15]	CNN–BiLSTM	MIT-BIH	Captures spatial and temporal ECG features
Reddy et al., Multi-scale CNN–LSTM–Dense network[19]	Multi-scale CNN–LSTM	MIT-BIH	Improved performance via multi-scale feature learning

[2] B. Data Imbalance Handling Comparison

Handling data imbalance is essential for clinically reliable arrhythmia detection. Table II compares imbalance mitigation strategies adopted in recent works.

TABLE II: Comparison of Data Imbalance Handling Techniques in ECG Classification

Authors / Paper Title	Technique Used	Purpose	Outcome
Shaker et al., CNN generalization using GANs[6]	GAN-based augmentation	Handle class imbalance	Improved generalization of CNN models
Wulan et al., Generating ECG signals by deep learning[8]	Deep generative model	ECG signal synthesis	Enhanced dataset diversity
Sarkar & Etemad, CardioGAN[9]	Conditional GAN	ECG synthesis from PPG	Improved arrhythmia detection
Janbhasha et al., GAN-based data imbalance techniques[11]	GAN-based oversampling	Minority class enhancement	Improved classification accuracy
Arjovsky et al., Wasserstein GAN[10]	WGAN	Stable GAN training	Reduced mode collapse

[3] C. Performance and Deployment Comparison

Beyond accuracy, deployment feasibility is a critical factor for real-world adoption. Table III compares performance and deployment targets.

TABLE III: Performance and Deployment-Oriented Comparison of ECG Arrhythmia Classification Systems

Authors / Paper Title	Deployment Platform	Model Type	Key Feature
Xiao et al., ULECGNet[12]	Edge / Wearable	Lightweight CNN	Ultra-low latency ECG inference
Mandal et al., Low-power VLSI	FPGA / ASIC	Hardware-optimized	Energy-efficient ECG

architectures[13]		models	processing
Li et al., Edge-AI based ECG monitoring[14]	Edge devices	CNN-based	Real-time wearable monitoring
Zhang et al., Hybrid CNN–BiLSTM[15]	Cloud-based	CNN–BiLSTM	High-accuracy centralized analysis
Bouaziz & Boutana, MLP with PSO[17]	Cloud-based	Optimized MLP	Improved heartbeat classification

TABLE IV: Summary of ECG Arrhythmia Classification Trends

Aspect	Observed Trend
Model design	Shift from CNN-only to CNN–LSTM hybrids
Data imbalance	Growing use of GAN-based augmentation
Deployment	Increased focus on MCU and FPGA
Clinical focus	Integration with cloud and IDSS
Key limitation	Lack of cross-dataset validation

VIII. DISCUSSION

The comparative analysis reveals several key trends:

1. Architectural convergence: CNN–LSTM and CNN–BiLSTM hybrids have become the dominant design choice due to their balanced performance.
2. Shift toward deployment-aware design: Recent studies increasingly consider power, memory and latency constraints.
3. Growing importance of data augmentation: GAN-based approaches are emerging as effective solutions for data imbalance.
4. Limited cross-dataset validation: Most studies evaluate performance on a single dataset, limiting generalization claims.

IX. CHALLENGES AND FUTURE DIRECTION

Despite significant progress in ECG-based arrhythmia classification, several challenges remain that must be addressed before these systems can be reliably deployed in large-scale clinical and wearable applications.

A. Generalization Across Datasets and Populations

Most reviewed studies evaluate performance on a single benchmark dataset, commonly the MIT-BIH Arrhythmia Database [8], [12]. While high accuracy is often reported, models trained on one dataset may not generalize well to data collected from different populations, devices or clinical settings. Variations in sampling frequency, lead configuration, noise characteristics and annotation standards pose significant challenges to model robustness [16], [19].

Future research should prioritize cross-dataset evaluation and domain adaptation techniques to improve generalization. Federated learning and transfer learning approaches may offer promising solutions by enabling collaborative model training across distributed datasets while preserving data privacy.

B. Explainability and Clinical Interpretability

Deep learning models are often criticized for their black-box nature, which limits trust and adoption in clinical practice. Although attention mechanisms and visualization techniques have been introduced to highlight important ECG segments, interpretability remains limited in most current systems [15], [18].

Future work should focus on integrating explainable artificial intelligence (XAI) methods that provide clinically meaningful explanations, such as highlighting waveform segments associated with specific arrhythmias. Improved interpretability can enhance clinician confidence and support regulatory approval processes.

C. Standardization of Evaluation Protocols

Lack of standardized evaluation protocols makes it difficult to compare results across studies. Differences in class definitions, train -test splits and performance metrics lead to inconsistent reporting [11], [17].

Establishing standardized benchmarking frameworks, including unified datasets, class taxonomies and evaluation metrics, would significantly improve reproducibility and comparability in ECG arrhythmia research.

D. Deployment and Energy Efficiency

Although lightweight and edge-oriented models have demonstrated promising results, further optimization is required to support long-term continuous monitoring. Balancing classification accuracy with energy efficiency, memory usage and latency remains a critical challenge, particularly for battery-powered wearable devices [6], [14].

Future research should explore adaptive models that dynamically adjust complexity based on signal quality and clinical relevance, as well as co-design methodologies that jointly optimize algorithms and hardware architectures.

X. CONCLUSION

This survey presented a comprehensive review of recent advancements in ECG-based arrhythmia classification, focusing on signal preprocessing, deep learning architectures, data imbalance handling, ensemble strategies and deployment-oriented designs. The evolution from handcrafted feature-based methods to hybrid and end-to-end deep learning models has significantly improved classification accuracy and automation.

Comparative analysis of twenty recent studies highlights the effectiveness of CNN–LSTM hybrid architectures, GAN-based data augmentation techniques and lightweight models designed for edge and wearable platforms. While cloud-based decision support systems offer scalability and integration with clinical workflows, edge-based solutions provide low-latency and privacy-preserving alternatives for continuous monitoring.

Despite these advances, challenges related to generalization, interpretability, standardization and energy efficiency remain. Addressing these issues will be essential for translating research prototypes into reliable clinical and consumer healthcare solutions. Continued interdisciplinary efforts combining signal processing, machine learning and hardware design are expected to drive the next generation of intelligent ECG monitoring systems.

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