

Numerical Methods and Computational Algorithms for ECG Signal Processing and Cardiac Abnormality Detection: A Review

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INFORMATION

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Numerical Methods and Computational Algorithms for ECG Signal Processing and Cardiac Abnormality Detection: A Review

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ABSTRACT

Electrocardiogram (ECG) signal processing plays a critical role in the early detection and diagnosis of cardiovascular diseases; however, reliable automated interpretation remains challenging due to noise contamination, inter-patient variability, and nonstationary signal characteristics. This review provides a critical and structured analysis of numerical methods and computational algorithms used in ECG signal processing and cardiac abnormality detection. Unlike conventional descriptive surveys, this work emphasizes the comparative evaluation of preprocessing techniques, feature extraction strategies, and machine learning and deep learning models under varying conditions such as noise intensity, dataset size, and real-time deployment constraints. The review systematically examines baseline correction, filtering, wavelet and decomposition-based denoising, fiducial point detection, and feature representation methods, highlighting their computational trade-offs, robustness, and clinical applicability. Furthermore, it critically contrasts classical machine learning approaches with modern deep learning and transformer-based models, identifying scenarios in which each paradigm is most effective. Key limitations of widely used datasets, particularly the MIT-BIH Arrhythmia Database, are analyzed in terms of generalization and evaluation bias. Emerging challenges, including domain shift, annotation inconsistency, interpretability, and deployment in wearable systems, are discussed with concrete research directions such as hybrid modeling, explainable AI, and federated learning. The review concludes that high-performance ECG analysis systems require an integrated pipeline combining numerically stable preprocessing with adaptive and interpretable learning frameworks, rather than reliance on standalone classification models.

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1 Introduction

Cardiovascular disease (CVD) has been a major cause of death among all people globally, with its representation of a large percentage of yearly deaths worldwide [1,2]. Cardiac abnormalities are also extremely important and should be diagnosed and treated in an effective manner through early detection and proper monitoring [1]. The electrocardiogram (ECG) has been one of the most common, inexpensive and noninvasive diagnostic tools for handling cardiac-related diagnosis [3]. The ECG

is used to capture the electrical activity of the heart and that very activity offers critical data on cardiac activity, the conduction routes, and the health status of the heart muscle [4,5]. In clinical diagnosis, ECG examination is regularly employed to identify an array of diseases such as cardiac arrhythmias, conduction delay, ischemic alterations, chamber enlargement, repolarization anomalies and Eco-systematically induced electrophysiological reactions [6,7]. Although ECG signals automated interpretation is an old practice that has been in use by numerous clinics, it still is a difficult issue [8,9]. ECG signals are not stationary, i.e., their statistical characteristics vary with time [10,11]. Also, ECG records have been found to be highly inter-patient (variability over a population of individuals) and intra-patient (variability within the same individual over time) about their values [12,13]. Noise and artifacts, including baseline wander, interference by muscle activity, power-line noise, and movement artifacts of electrodes, also make automated analysis even more difficult [14,15]. Such difficulties render the creation of effective computational algorithms for ECG interpretation an active and significant field of study. The last improvements in artificial intelligence (AI), machine learning (ML), and deep learning (DL) seriously impacted the electrocardiography field [16,17]. Numerous recent works emphasize the shift to the data-based diagnostic platform, wearable fitness bracelets, and real-time ECG analysis systems [18,19]. ECGs are being deployed now as smart systems that connect with Internet of Medical Things (IoMT) platforms, providing the ability to do continuous monitoring and remote health care applications [20,21]. Nevertheless, although the popularity of deep learning models has increased, recent literature unanimously highlights that sound preprocessing and physiologically relevant signal modeling still should be considered an important part of reliable ECG analysis [22,23].

The Fig. 1 shows the general procedure of acquiring and analyzing electrocardiogram (ECG) signals. The electrodes are attached to the surface of the body to detect electroactivity that is produced by the human heart. Such electrodes record the minute bioelectrical responses during the depolarization and repolarization of the heart. The signals are then sent to an ECG acquisition device, where the signals are amplified, digitized and presented as an ECG waveform. The signal that is recorded is subjected to signal preprocessing to be stripped of noise and artifacts. Relevant features of the ECG waveform are extracted after the preprocessing stage and processed by signal processing methods or machine learning methods. Lastly, the processed information helps practitioners in identifying cardiac anomalies and aids in clinical diagnosis.

Traditionally, ECG signal processing pipelines were overtaken by classical deterministic signal-processing. These methods usually involve band-pass noise filtering, derivative-based QRS complex enhancements, adaptive threshold QRS-peak detection, beat segmentation and derivation of hand-engineered time-domain or frequency-domain features [5]. The classical techniques are popular due to their interpretability, computational efficiency and ease of implementation, which are applicable in embedded systems and portable medical devices [24]. Nevertheless, purely determined methods can be ineffective in situations that affect ECG signals in severe base drift, non-normal morphologies of waveforms, motion artifact, or inter-dataset domain shifts [25]. To address these drawbacks, recent machine learning and deep learning systems have been suggested to learn and represent complex signals directly out of the data. Deep neural networks and convolutional neural networks (CNNs), and recursive structures like LSTMs have a high level of classification accuracy when applied within a large dataset. However, these methods can be costly in terms of computational costs, size and annotated data, as well as need caution with regards to interpretability, strength and broad generalization [26].

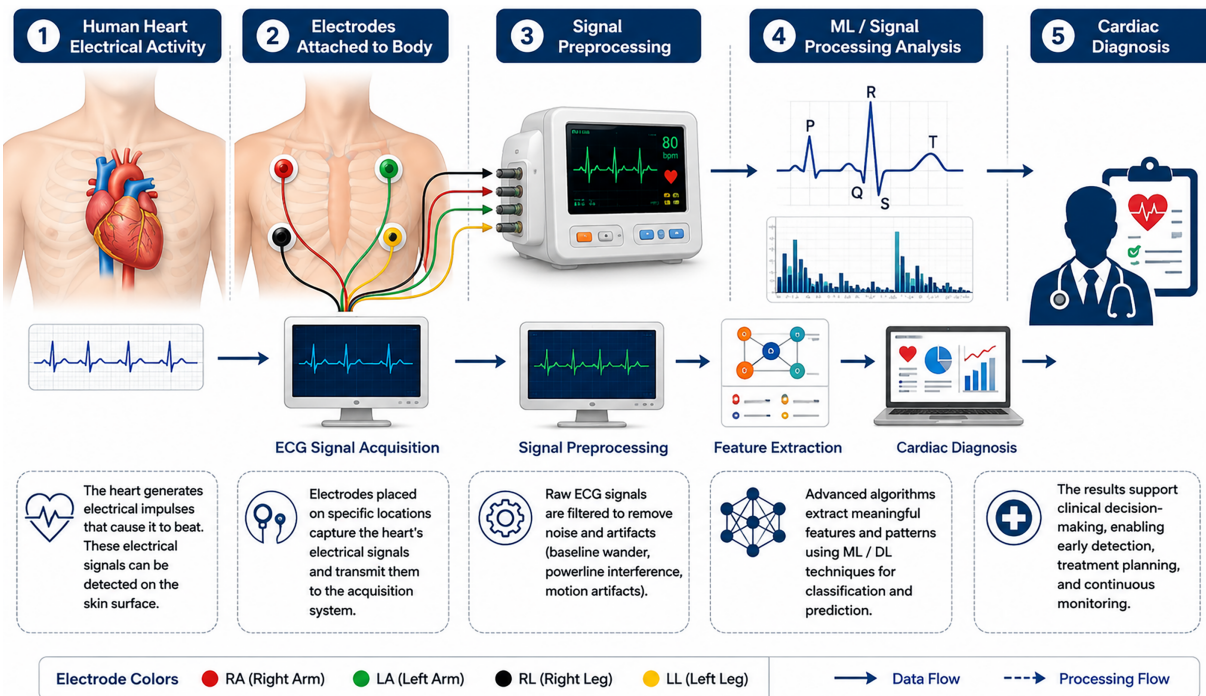


Figure 1: ECG signal acquisition and analysis process from the human body

This makes the adoption of hybrid ECG analysis models, which combine traditional numerical processing methods with contemporary artificial intelligence models, important, as indicated in recent studies [27]. In these systems, physiological interpretability and numerical preprocessing and feature extraction are enhanced to improve the quality of signals, and machine learning models are used to achieve high-quality classification. Such a combination view enables the benefits of the two paradigms to be combined into a single analysis pipeline of ECG data.

In this respect, the current review is restricted to the numerical techniques and computation algorithms of ECG signal processing and cardiac abnormality detection. The main thesis of this paper is that the effectiveness of high-performing ECG analysis systems is not completely determined by their classifier but is also defined by the quality of numerical/mathematical operations performed beforehand to preprocess and denoise the ECG signal, as well as to segment and represent it. Thus, the review investigates the whole computational history, such as signal modeling, noise removal, waveform delineation, feature extraction, machine learning-based classification, performance measurement, and new research directions. Through a well-organized evaluation of these elements, the article will equip researchers and practitioners with a clear scope of demand on computational principles underlying the intelligent ECG analysis system, and the prospects of AI-aided cardiac diagnosis appear [6].

The common workflow of automated systems of ECG analysis is conducted in Fig. 2. The outcome of this process starts with the acquisition of ECG signals by sensors or monitoring devices. Then the recorded signal is preprocessed and denoised to eliminate artifacts, including baseline wander and power-line interference. At the stage of composite ECG, main waveform constituents such as P wave, QRS complex, and other waveforms are identified. This is followed by the extraction of important features in the signal at time or frequency. The machine learning or deep learning model is

used to analyze these features to classify cardiac abnormalities. Lastly, it utilizes the results in clinical decision support, which aids in the identification of the disease and the monitoring of a patient [7].

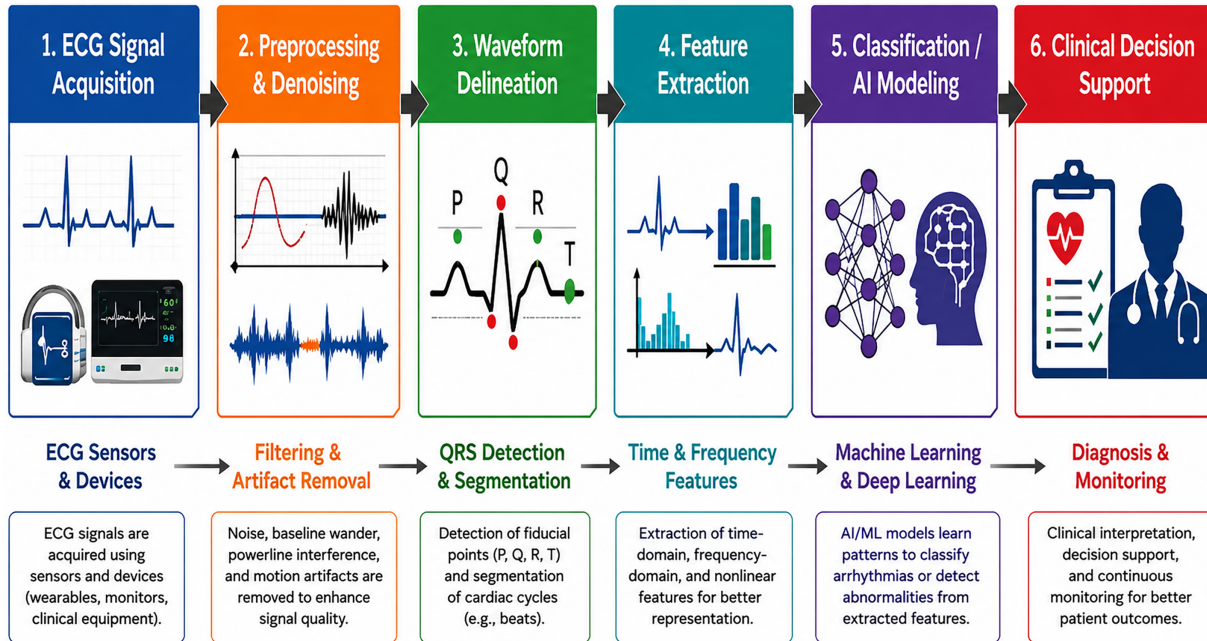


Figure 2: General computational pipeline for automated ECG analysis

Typical ECG analysis systems follow a structured workflow:

- (a) **ECG Signal Acquisition**
Signals are collected from ECG sensors, wearable devices, or clinical monitoring systems.
- (b) **Preprocessing and Noise Removal**
Numerical filtering techniques remove artifacts such as baseline wander, power-line interference, and muscle noise.
- (c) **Waveform Delineation**
Algorithms detect fiducial points such as P wave, QRS complex, and T wave.
- (d) **Feature Extraction**
Time-domain, frequency-domain, or time–frequency features are computed.
- (e) **Classification/AI Modeling**
Machine learning or deep learning models classify cardiac abnormalities.
- (f) **Clinical Decision Support**
Results assist clinicians in diagnosis and monitoring.

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide [28], necessitating accurate, timely, and scalable diagnostic tools. The electrocardiogram (ECG) is a widely used non-invasive modality that provides valuable insights into cardiac electrophysiological activity [7]. It is routinely employed to detect a variety of conditions, including arrhythmia, ischemic abnormalities, conduction disorders, atrial fibrillation, and repolarization irregularities [29,30].

Despite its clinical importance, automated ECG interpretation remains a challenging problem due to several factors. First, ECG signals are inherently nonstationary [11] and exhibit significant inter-patient and intra-patient variability [31]. Second, recordings are often corrupted by multiple noise sources such as baseline wander, power-line interference, electromyographic noise, and motion artifacts, particularly in wearable and ambulatory monitoring systems [32]. Third, different clinical tasks impose distinct requirements on signal quality, feature representation, and algorithm design.

To address these challenges, ECG analysis must be understood as a set of task-specific computational problems, rather than a single classification task. These include:

- QRS detection and fiducial point delineation
- Beat-level arrhythmia classification
- Rhythm-level analysis (e.g., atrial fibrillation detection)
- ST-segment and ischemia assessment
- Long-term monitoring in wearable systems

Each task differs in terms of signal resolution, noise tolerance, evaluation metrics, and model requirements. For example, QRS detection demands high temporal precision, while arrhythmia classification requires robust feature representation across patients. Similarly, wearable ECG systems impose strict constraints on computational complexity and energy consumption.

Recent advances in artificial intelligence, particularly deep learning and transformer-based architecture, have significantly improved classification performance [33]. However, growing evidence suggests that model accuracy alone does not guarantee reliability in real-world clinical settings [34]. Instead, the effectiveness of ECG analysis systems depends on the entire computational pipeline, including preprocessing, delineation, feature extraction, and evaluation methodology [35].

This review, therefore, adopts a pipeline-oriented and critically analytical perspective, emphasizing that ECG abnormality detection is fundamentally a numerically sensitive, multi-stage problem. It aims to bridge classical numerical signal processing methods with modern machine learning approaches, while systematically analyzing their trade-offs, limitations, and suitability across different clinical and deployment scenarios (Table 1).

Table 1: Different preprocessing methods are suitable under different signal conditions. No single approach is universally optimal [36–72]

Method	Best use case	Strength	Limitation
Polynomial detrending	Low-noise ECG	Simple for low orders	Overfitting risk [36–40]
Spline interpolation	Smooth drift	Preserves morphology	Can be computationally intensive for large datasets [41–45]
Notch filtering	Power-line noise	Effective, simple	Narrowband only [46–53]
Wavelet denoising	Nonstationary signals	Multi-resolution	Parameter tuning needed [53–60]
Adaptive filtering	Wearable ECG	Handles dynamic noise	Requires reference signal [61–65]
Decomposition methods	Multi-noise scenarios	Effective for denoising	Computationally expensive [66–72]

2 Scope and Review Methodology

This article is written in a narrative technical review, instead of a systematic review done in PRISMA style. Instead, we intend to present a systematic and critical literature review of the existing literature along the entire line of ECG signal-processing. The main rationale behind the choice of a narrative review format is the fact that the topic of ECG processing research has intensively been affected by a variety of related fields such as numerical analysis, biomedical signal processing, machine learning, deep learning, hardware-related implementation, and clinical interpretation, yet it is highly likely that these very fields are actively researched independently but in reality depend on each other greatly. A staged technical audit is then more appropriate to clarify the impact of preprocessing quality, delineation, feature extraction, as well as representation quality on the cardiac abnormal detection performance.

The areas of this review are the major algorithmic layers of the modern ECG analysis systems. These are characteristics of ECG signals and mathematical models, taxonomy of noise types and artifact types, removal of baseline wander, power-line interference, wavelet-based, decomposition-based and adaptive denoising, identification of QRS and fiducial points, identification of markers of clinical interest, time-frequency feature extraction, machine-learning based traditional models, deep-learning models, and transformer-based models, public ECG benchmark datasets, performance metrics, and remaining challenging aspects of clinical translation. In that regard, the review is sufficiently broad to encapsulate the general signal-processing theory into more recent AI-based ECG interpretation, but at the same time, it has a particular theme: how numerical and computational algorithms are used to detect cardiac abnormalities. Specific focus is given to those methods that can be mathematically explained, are computationally significant, and have a common occurrence in the recent ECG literature. This spans both traditional methods (including but not limited to: polynomial detrending, cubic-spline interpolation, notch filtering, numerical differentiation, and moving-window integration) and recent methods (including but not limited to: wavelet shrinkage, empirical and variational decomposition methods, convolutional and recurrent neural networks, attention mechanisms, transformer-based classifiers, explainable AI frameworks and low-resource/wearable-oriented ECG analytics). The review is thus intended to fill two common perspectives on ECG analysis commonly considered separately in literature: the classical perspective of ECG analysis as a cascade of numerically stable signal-processing processes, and the modern one of ECG analysis as a representation-learning and classification problem [8–10].

The pieces of literature taken into consideration in this review article will be picked regarding the recent publishing dates of peer-reviewed Journal articles and benchmark-oriented technical publications, but will mostly be focused on the timeframe of 2022–2025, as it reflects the dynamics of the ongoing active transformations in explainable AI, transformers-based ECG modeling, and denoising wearables and deployable cardiac monitoring. Newer reviews also state that recent ECG studies are more interested not in accuracy but in transparency and generalization as well as real time monitoring [73,74].

When choosing material, four categories of sources were selected. To determine general trends in the methodology and common issues, firstly, recent review papers were given priority. Second, the studies that are based on benchmark-oriented arrhythmia were selected due to disclosing the combination of preprocessing, feature extraction, and classification in reproducible ECG pipelines. Third, explainable AI and attention-based research were deemed to be relevant since interpretability has become a central concern in ECG analysis, which is clinically of interest. Fourth, studies that were wearable, real time and federated ECG were (particularly due to the growing recurrence of

smartwatches, ambulatory monitors and distributed health systems) included since current ECG analytics is shifting to smart watches, ambulatory monitors and distributed health system analysis instead of relying solely on offline clinical analysis. The choice strategy was adapted to strike a balance between a deep methodological approach and practical relevance. Public benchmark reports in the PhysioNet were also included since it was still central in the reproducible development of the ECG algorithms. Specifically, the MIT-BIH Arrhythmia Database remains one of the most frequent reference collections of ECG studies. PhysioNet refers to it as having 48 half-hour samples of ambulatory ECG of two channels data taken on 47 patients and associated PhysioNet repositories also give specialized data sets of long-term atrial fibrillation, ST-segment data, and other clinically significant rhythm disorders. The importance of these resources lies particularly in the fact that they aid in coherent benchmarking, comparison of algorithms and reproducibility across studies. Organizationally this review is organized based on the processing stage, and not only of the algorithm family. This choice is deliberate. Even a review solely of models, such as that broken down into SVMs, CNNs, LSTMs, and transformers, would hide the fact that ECG abnormality detection requires a full computational chain where one stage conditions the next. As a matter of fact, QRS localization depends on baseline correction, beat segmentation depends on QRS localization, time-domain and time-frequency representations depend on beat segmentation, and classifier performance is directly related to the quality of these representations [75]. The article eventually enables classical numerical tools, handcrafted-feature methods, and end-to-end deep models to be presented as one unified entity by structuring the review as a pipeline—starting with signal characteristics and preprocessing, delineation, feature extraction, classification, datasets, and future directions.

The second aspect that leads to this choice of structure is that it is more consistent with real world biomedical engineering designs of the ECG system. In the deep-learning workflows of today, preprocessing is difficult to be considered irrelevant. Under these situations, e.g., noisy records, particularly recorded with ambulatory or wearable equipment, numerically robust denoising and delineation can significantly enhance the reliability of downstream models [76]. Similarly, there remains a significant number of so-called end-to-end learning systems that still have a hidden assumption of either filtering, segmentation, windowing, normalization, or transform-domain representation [77]. A review that is carried out step by step would be more realistic and technically useful to describe the field than a summary by pure taxonomy [14].

Another point to observe is that, since this is a narrative technical review, the article does not purport to have comprehensive coverage of all articles on ECG published during the review period. Rather, it focuses on the representative, influential, and methodologically relevant studies that contribute to an explanation of the field developing. They are aimed at achieving conceptual clarity, technical continuity and critical comparison as opposed to an exhaustive bibliometric catalogue. Such a strategy is particularly suitable in the context of ECG studies, where the initial successes in the field are not determined by a single type of algorithm, but rather the joint development of the denoising, delineation, representation learning, interpretability, and deployment [78]. Comprehensively, the review methodology would be aimed at supporting three results. To begin with, it gives a single technical flow diagram of the ECG processing pipeline. Second, it points out the fact that numerical stability and design of the computer calculations take center stage even in the age of deep learning [79]. Third, it determines the direction the literature is taking today, namely, explainable models, wearable monitoring, benchmark-aware evaluation and similar deployable intelligent ECG systems [14]. In that regard, the review is aimed at not only the summary of the existing work, but also elucidation of such methodological connections that will define an upcoming generation of ECG-based abnormality detection research on cardiac issues.

The Fig. 3 shows the overall process of ECG signal processing and cardiac abnormality detection as discussed in this review. It starts with surface electrode recording of ECGs of the human body. The digitized samples are then preprocessed and denoised using various methods to eliminate artifacts like baseline wander, muscle noise and power-line interference. Following the noise removal, the ECG signal is estimated based on the important components and is used to retrieve the valuable time-domain, frequency-domain, or time-frequency features. Such features are then analyzed based on numerical, signal processing or machine learning algorithms to determine and detect cardiac anomalies. Lastly, the results derived are useful in cardiovascular healthcare systems, clinical diagnosis, monitoring, and decision support.

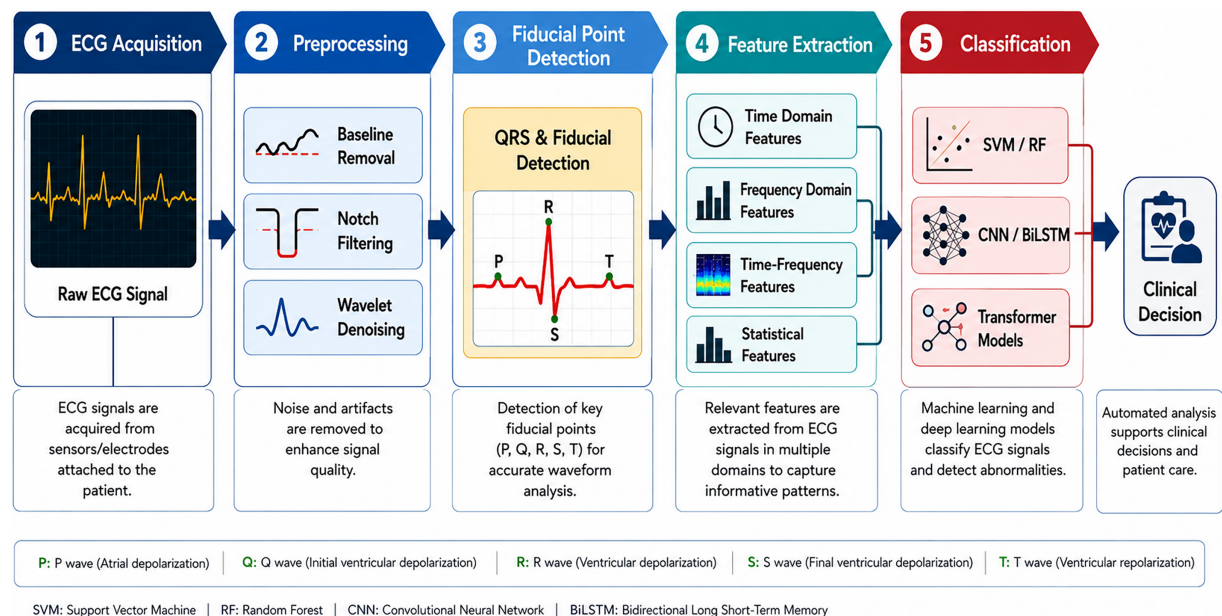


Figure 3: Overall framework of ECG signal processing and cardiac abnormality detection reviewed in this article

This review adopts a structured narrative approach to provide a comprehensive and critical analysis of numerical methods and computational algorithms used in ECG signal processing and cardiac abnormality detection. Although the study is not conducted as a fully systematic review, several PRISMA-inspired methodological principles were incorporated to improve transparency, consistency, reproducibility, and literature selection quality.

2.1 Literature Search Strategy

Relevant studies were collected from major scientific databases, including IEEE Xplore, PubMed, Scopus, and ScienceDirect. The literature search employed combinations of keywords related to ECG signal analysis and intelligent cardiac diagnosis, including:

- ECG signal processing
- QRS detection
- arrhythmia classification
- ECG deep learning

- wavelet ECG denoising
- transformer-based ECG analysis
- wearable ECG systems

The review primarily focuses on publications from 2022 to 2025 to capture recent developments in deep learning, explainable artificial intelligence, wearable healthcare technologies, and transformer-based ECG analysis systems.

2.2 *PRISMA-Based Study Selection Framework*

To improve methodological transparency, a PRISMA-inspired study selection framework was adopted. The study selection process was conducted in multiple stages, including identification, screening, eligibility assessment, and final inclusion of relevant studies.

Initially, articles were identified through database searches and duplicate records were removed. Subsequently, titles and abstracts were screened to eliminate unrelated studies. Full-text evaluation was then performed to identify representative and methodologically significant studies covering different stages of the ECG processing pipeline.

Special emphasis was placed on:

- Benchmark-oriented ECG studies,
- Explainable and attention-based artificial intelligence methods,
- Wearable and real-time ECG monitoring systems, and
- Hybrid approaches combining numerical signal processing with machine learning or deep learning techniques.

The PRISMA-based workflow adopted in this review is illustrated in the corresponding study in [Fig. 4](#).

2.3 *Research Gap*

Despite significant advancements in ECG signal processing and intelligent cardiac abnormality detection, several important research gaps remain in the current literature.

First, many existing studies focus primarily on classification accuracy while providing limited attention to preprocessing robustness, signal quality preservation, and numerical stability. However, inaccurate preprocessing and fiducial point detection can significantly degrade downstream classification performance [80].

Second, numerous deep learning-based studies rely heavily on benchmark datasets such as the MIT-BIH Arrhythmia Database, resulting in limited generalization across different patient populations, devices, and clinical environments. Domain shift, inter-patient variability, and wearable sensor noise continue to affect model reliability in real-world deployment scenarios [80].

Third, comparative evaluation practices remain inconsistent. Several studies use different preprocessing pipelines, class grouping strategies, and patient-splitting methods, making fair comparison difficult. Beat-level random splitting often leads to overly optimistic performance estimates due to data leakage [80,81].

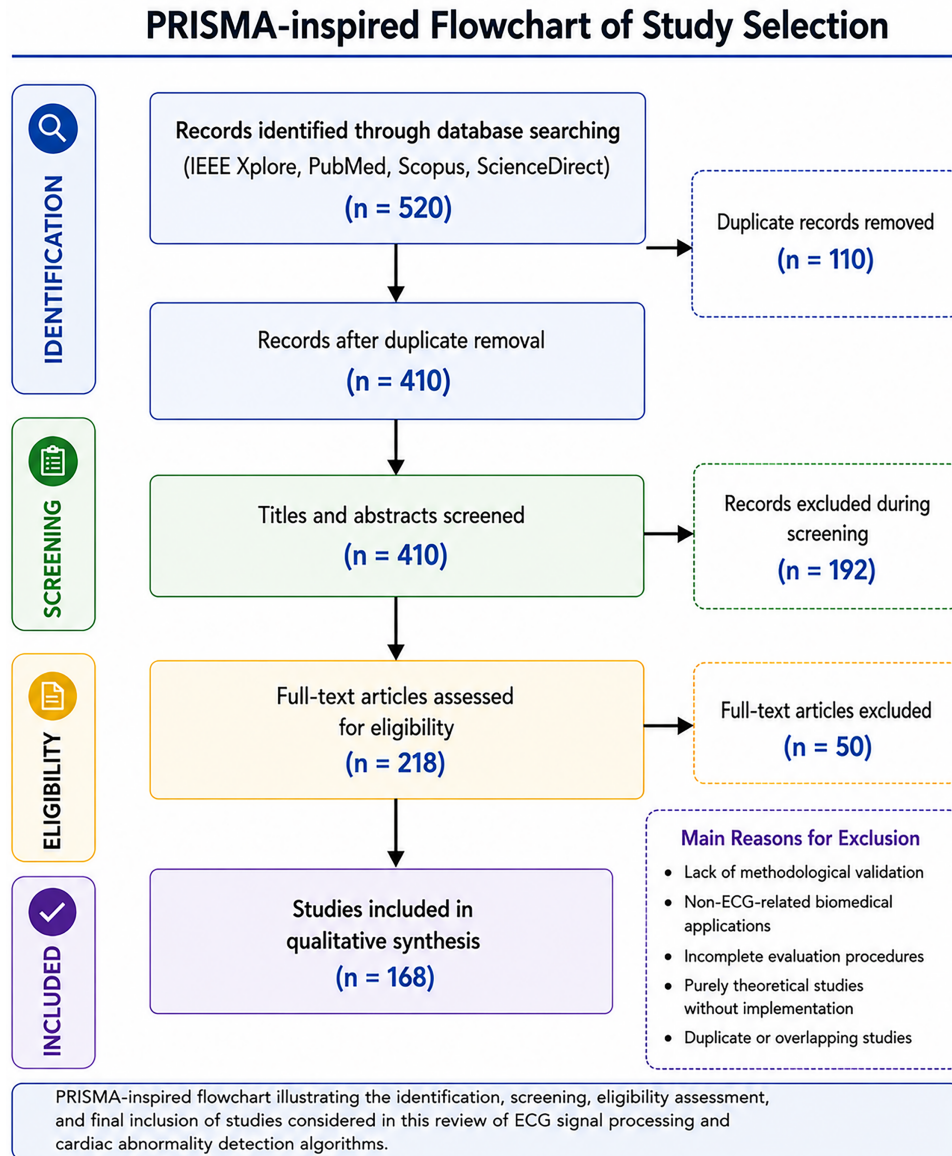


Figure 4: PRISMA-inspired flowchart illustrating the identification, screening, eligibility assessment, and final inclusion of studies considered in this review of ECG signal processing and cardiac abnormality detection algorithms

Fourth, although transformer-based and explainable AI approaches have recently gained attention, limited research has systematically integrated numerical signal processing principles with interpretable deep learning frameworks. Most existing reviews discuss classical signal processing and artificial intelligence models separately rather than analyzing their combined computational pipeline.

Fifth, wearable and real-time ECG monitoring systems introduce additional constraints related to computational complexity, latency, memory usage, and energy efficiency [82,83]. Many high-performing deep learning models remain unsuitable for low-power edge deployment [83].

Therefore, this review aims to bridge these gaps by providing:

- A pipeline-oriented analysis of ECG processing,
- Critical comparison of numerical and AI-based approaches,
- Discussion of evaluation and benchmarking challenges,
- Analysis of deployment-related constraints, and
- Identification of future research directions involving hybrid, explainable, and wearable-oriented ECG analysis systems.

3 ECG Signal Characteristics and Noise Modeling

A comprehensive understanding of ECG signal characteristics is essential before discussing pre-processing and computational algorithms for cardiac abnormality detection. The electrocardiogram represents the electrical activity of the heart as recorded from the body surface, and its morphology reflects coordinated depolarization and repolarization processes of atrial and ventricular myocardium [15]. Although conceptually simple, the ECG signal is mathematically complex due to its nonlinear, nonstationary, and morphology-dependent nature [84,85].

3.1 Physiological Structure of the ECG Signal

The standard ECG waveform consists primarily of:

- **P wave**—atrial depolarization
- **QRS complex**—ventricular depolarization
- **T wave**—ventricular repolarization

Additionally, clinically important intervals and segments include:

- PR interval
- QT interval
- ST segment
- RR interval

From a modeling perspective, the clean ECG signal can be represented as:

$$s(t) = p(t) + qrs(t) + t(t),$$

where $p(t)$, $qrs(t)$, and $t(t)$ correspond to atrial depolarization, ventricular depolarization, and ventricular repolarization components, respectively.

Unlike stationary signals whose statistical properties remain constant over time, ECG signals are inherently nonstationary, meaning that their amplitude, frequency content, and morphological features change across cardiac cycles. For example:

- Heart rate variability alters RR interval spacing [86].
- Ischemic conditions modify ST segment elevation [87].
- Atrial fibrillation suppresses consistent P-wave morphology [88].
- Premature ventricular contractions alter QRS width and amplitude [16].

This variability complicates modeling because assumptions of constant spectral characteristics or fixed waveform templates are often invalid.

Recent literature on intelligent ECG systems consistently emphasizes that inter-patient morphological variability is one of the most significant challenges in automated ECG interpretation, especially when models trained on benchmark datasets are applied to new populations [89,90].

3.2 Mathematical Representation of Observed ECG Signals

In practical settings, the observed ECG signal is contaminated by multiple noise sources. It can be expressed as:

$$x(t) = s(t) + n(t),$$

where $s(t)$ is the underlying clean cardiac signal and $n(t)$ represents the aggregate noise.

A more detailed decomposition is:

$$x(t) = s(t) + n_{bw}(t) + n_{pl}(t) + n_{emg}(t) + n_{ma}(t),$$

where:

- $n_{bw}(t)$: baseline wander
- $n_{pl}(t)$: power-line interference
- $n_{emg}(t)$: electromyographic noise
- $n_{ma}(t)$: motion artifact

After digital sampling with period T_s , the discrete-time representation becomes:

$$x[n] = s[n] + \sum_{i=1}^K n_i[n].$$

This additive model is widely used because it supports independent design of filters targeting specific frequency bands or statistical properties. However, in real wearable scenarios, the assumption of independent additive noise may not always hold strictly, particularly when motion artifacts distort waveform morphology rather than simply adding noise.

3.3 Classification of ECG Noise Sources

Noise in ECG recordings is typically categorized into four major types:

3.3.1 Baseline Wander

Baseline wander is a low-frequency artifact (typically <0.5 Hz) caused by respiration, electrode impedance variation, and body movement. It appears as a slow drift of the ECG baseline and primarily affects ST-segment and P-wave interpretation [91,92].

Mathematically, baseline wander can be modeled as a slowly varying function:

$$n_{bw}(t) = A(t) \sin(2\pi f_r t),$$

where f_r corresponds to respiratory frequency.

Baseline drift is particularly problematic in long-term ambulatory recordings and wearable ECG devices [93,94].

3.3.2 Power-Line Interference

Power-line interference is a narrowband sinusoidal disturbance centered around 50 or 60 Hz: [95,96]

$$n_{pl}(t) = B \sin(2\pi f_0 t + \phi).$$

It arises from electromagnetic coupling between ECG leads and the surrounding electrical environment. Although often small in amplitude, it can distort QRS detection if not properly filtered [20].

3.3.3 Electromyographic (EMG) Noise

EMG noise originates from skeletal muscle activity and typically occupies a broad frequency band (20–200 Hz). Unlike baseline wander and power-line interference, EMG noise overlaps significantly with ECG frequency content, making separation more difficult [21].

EMG contamination is especially prominent in stress testing and wearable devices [97].

3.3.4 Motion Artifacts

Motion artifacts arise from electrode displacement, cable movement, and skin-electrode impedance fluctuations [98]. Unlike additive sinusoidal noise, motion artifacts can distort waveform morphology in complex ways [99]. They are particularly severe in smartwatches and chest-strap ECG monitors [100].

Recent wearable ECG reviews highlight motion artifact as one of the most challenging problems for real-world deployment [101].

3.4 Frequency Characteristics of ECG Components

Understanding the spectral distribution of ECG is essential for designing filters and time–frequency representations.

Typical frequency ranges:

Component	Approximate Frequency Range
P wave [102]	0.5–10 Hz
QRS complex [103]	5–25 Hz
T wave [102]	0.5–7 Hz
Baseline wander [92]	<0.5 Hz
Power-line noise [104]	50/60 Hz
EMG noise [105]	20–200 Hz

The QRS complex contains the highest energy and most rapid transitions, which is why derivative-based detection methods are effective [106]. However, lower-amplitude P waves and ST segments occupy similar low-frequency ranges as baseline drift, making denoising challenging [107].

This overlap in frequency bands explains why overly aggressive high-pass filtering may distort diagnostically important components [108].

3.5 *Nonstationary and Time–Frequency Considerations*

Because ECG signals change dynamically over time, classical stationary spectral analysis (e.g., global Fourier transform) may fail to capture transient morphological changes [109].

For example:

- Atrial fibrillation introduces irregular RR intervals [110].
- Ventricular ectopic beats produce abrupt morphological deviations [111].
- ST elevation evolves gradually during ischemia [112].

These characteristics justify the use of time–frequency methods such as STFT and wavelet transforms. Recent transformer-based ECG models also leverage time–frequency representations to improve classification of arrhythmias [113].

3.6 *Inter-Patient and Intra-Patient Variability*

One of the most critical modeling challenges is variability:

- Amplitude scaling differs by body mass and electrode placement [114].
- Morphology varies across age groups and pathologies [115].
- Heart rate variability changes across physical and emotional states [116].

Recent personalized ECG diagnostic reviews identify cross-patient variability as a major limitation of models trained solely on benchmark datasets [117].

This variability motivates:

- Adaptive preprocessing methods
- Patient-specific modeling
- Transfer learning
- Federated ECG analysis

3.7 *Implications for Numerical and Computational Design*

The signal characteristics discussed above have several implications:

1. Preprocessing must preserve morphology while suppressing noise.
2. QRS detection must be robust to amplitude and morphology variation.
3. Feature extraction must account for nonstationary.
4. Classification models must generalize across patients and devices.
5. Real-time wearable applications require computational efficiency.

In summary, ECG signal modeling reveals that cardiac abnormality detection is not purely a classification problem. It is fundamentally a numerically sensitive inverse problem in which the quality of signal conditioning strongly influences downstream computational inference.

4 Numerical Methods for ECG Preprocessing

Preprocessing remains one of the most important stages of ECG analysis because errors introduced here propagate downstream into fiducial detection, feature extraction, and classification. Recent reviews specifically dedicated to ECG and magneto cardiogram denoising categorized methods by

artifact type and noted that no single denoiser is universally optimal across baseline wander, power-line interference, EMG noise, and motion artifact.

4.1 Baseline Wander Removal

Baseline wander is a low-frequency drift caused primarily by respiration, posture change, electrode impedance variation, or slow movement. It can distort the isoelectric line and compromise the interpretation of P waves and ST segments.

A common numerical approach is polynomial determination, in which the baseline is approximated as

$$\hat{b}[n] = \sum_{k=0}^m a_k n^k,$$

and the corrected ECG is obtained from $x_d[n] = x[n] - \hat{b}[n]$. This method is computationally inexpensive and straightforward, but its performance depends on polynomial order. Overly high orders may introduce ill-conditioning or overfit the waveform itself [31–33].

A more flexible alternative is cubic spline interpolation, where slowly varying baseline points are connected using piecewise cubic polynomials:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3.$$

Spline-based correction can model nonlinear drift more naturally than a single global polynomial and is widely used when morphology preservation is critical.

4.2 Power-Line Interference Suppression

Power-line contamination typically appears at 50 or 60 Hz and can be attenuated using a digital notch filter,

$$H(z) = \frac{1 - 2\cos(\omega_0)z^{-1} + z^{-2}}{1 - 2r\cos(\omega_0)z^{-1} + r^2z^{-2}},$$

where $\omega_0 = 2\pi f_0/f_s$. The parameter r controls notch sharpness. While notch filters remain standard, adaptive filtering can be preferable when line noise is unstable or when neighboring spectral content must be preserved more carefully [34–36].

4.3 Wavelet-Based Denoising

Wavelet denoising remains one of the most widely adopted preprocessing tools because ECG is transient-rich and nonstationary [57]. Using a discrete wavelet transform,

$$x[n] = \sum_{j=1}^J d_j[n] + a_J[n],$$

noise can be suppressed by thresholding detail coefficients:

$$\hat{d}_{j,k} = \text{sign}(d_{j,k}) \max(|d_{j,k}| - \lambda, 0).$$

Wavelet shrinkage supports multiresolution analysis and often preserves QRS morphology better than aggressive linear smoothing [118,119]. Recent studies also combine wavelets with optimization or swarm-based tuning to improve denoising quality [37–39].

4.4 Adaptive, Decomposition-Based, and Hybrid Methods

Beyond classical filtering, recent ECG denoising research increasingly uses empirical mode decomposition, variational mode decomposition, empirical wavelet transforms, independent component analysis, trend filtering, and diffusion-inspired or pruning-assisted restoration methods [120]. These methods are especially useful when several artifact types coexist or when morphology preservation is prioritized. Wearable ECG studies also report ICA-style and redundant denoising methods for motion-contaminated signals.

Overall, the literature suggests that preprocessing performance should be judged not only by noise reduction but by its effect on downstream tasks such as R-peak localization and arrhythmia classification [40,41].

5 Fiducial Point Detection and Delineation

QRS detection remains the backbone of ECG analytics [121]. Once R peaks are known, one can estimate heart rate, beat timing, RR variability, and search windows for P waves and T waves [122,123]. Classic QRS detection still relies heavily on slope enhancement, nonlinear energy transformation, and adaptive thresholding [124,125].

A representative derivative-based operator is

$$y[n] = \frac{1}{8T} (2x[n] + x[n-1] - x[n-3] - 2x[n-4]),$$

followed by a squaring stage,

$$z[n] = (y[n])^2,$$

and moving-window integration,

$$w[n] = \frac{1}{N} \sum_{k=0}^{N-1} z[n-k].$$

A dynamic threshold is then applied to identify candidate R peaks [124,126]. These steps remain popular because they are fast, interpretable, and effective on many rhythm patterns [103,127].

The panel in Fig. 5 shows a flowchart representation of the general process of the numerical approach to QRS complex detection in ECG signals. It starts with the acquisition of the raw ECG signal which is then preprocessed and filtered to eliminate noise sources including power-line perturbations and baseline wandering. The filtered signal is then analyzed by signal enhancement techniques, i.e., differentiation, squaring or moving-window integration, to bring out the characteristics of the QRS complex. Once improved, thresholding or decision rules are used to detect the position of QRS complexes. Lastly, the identified R-peaks and QRS are further analyzed through heart rate computation, beat fragmentation, as well as cardiac anomaly spotting. Nonetheless, fiducial delineation is further than the R-peak detection. Onset/offset of P-waves, QRS onset/offset and T-wave boundaries are still more problematic since they are less pronounced and respond more to residual noise. Recent research has thus addressed trend-filtering schemes, wavelet-based delineating, beat-wise QRS-centered detection strategies, and localization assisted by deep-learning. Benefits Trend filtering has been presented as a rapid two-pass ECG delineation technique, and beat-based QRS-centered techniques have been reported to be used with atrial fibrillation. Practically, preprocessing is of critical importance in delineation quality. Suboptimal correction of the baseline can blur P waves and ST segments and imprecise timing of the QRS can influence the segmentation of beats and matching

features. This dependency motivates the fact that even fully-fledged deep models show the advantage of numerically stabilized preprocessing in lieu of pure raw input learning.

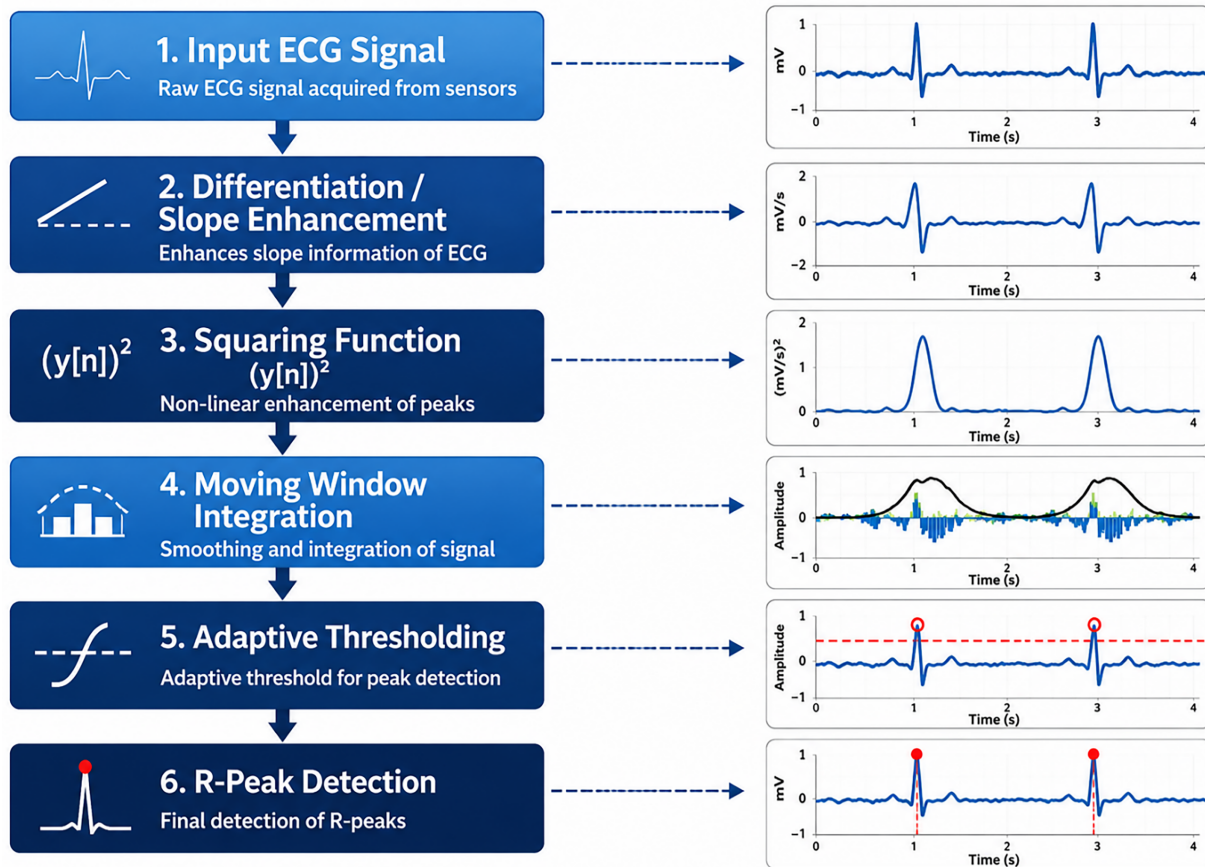


Figure 5: Generalized flowchart of numerical QRS detection methods

6 Feature Extraction Techniques

Feature extraction maps the ECG waveform into a representation that supports discrimination of normal and abnormal cardiac patterns. The literature can be grouped into time-domain, frequency-domain, time–frequency, statistical, and learned latent features.

6.1 Time-Domain Features

Time-domain features include RR interval, PR interval, QRS duration, QT interval, R-peak amplitude, wave areas, and beat-to-beat variability measures. These descriptors are attractive because they are clinically interpretable and computationally lightweight. Classical machine learning models frequently rely on such features [40].

6.2 Frequency-Domain Features

Using the discrete Fourier transform,

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N},$$

one can derive spectral power, dominant frequency, entropy, and band-specific energy measures. While ECG is nonstationary, frequency-domain features can still capture rhythm irregularity and repetitive structure, especially in rhythm classification tasks [128,129].

6.3 Time-Frequency Features

Because ECG morphology evolves over time, time-frequency analysis has become increasingly important [35,130]. The short-time Fourier transform is

$$X(t, f) = \int x(\tau) w(\tau - t) e^{-j2\pi f\tau} d\tau,$$

and the continuous wavelet transform is

$$W(a, b) = \frac{1}{\sqrt{a}} \int x(t) \psi^* \left(\frac{t - b}{a} \right) dt.$$

Wavelet scalograms and related time-frequency maps are now widely used as CNN or transformer inputs [131,132]. A recent Heliyon study combined continuous wavelet transform with a multi-branch transformer and reported strong ECG classification results, reflecting a broader trend toward transform-assisted deep learning [133].

6.4 Statistical and Complexity Characteristics

More advanced statistics are also now in use (skewness, kurtosis, entropy, Hjorth parameters, nonlinear complexity measures, etc.) particularly with irregular tread patterns and noisy ambulatory recordings [134,135].

6.5 Learned Features

Deep learning continues to minimize the need for explicit feature design by directly learning latent representations based on 1D waveforms or 2D time-frequency images [136,137]. Despite this, explicit feature extraction can still be useful in cases that are low on data, interpretability is important or even in cases where low-computation deployment is necessitated [138,139].

7 Deep Learning and Machine Learning in Cardiac Abnormalities-Detection

7.1 Classical Machine Learning

SVM, random forests, k-nearest neighbor, and decision-tree ensembles are also significant as a baseline, and viable alternatives, particularly in cases where strong handcrafted features exist [140,141]. Their key strengths include moderate training price, interpretability and fairly good performance on structured sets of features [8,142].

7.2 Recurrent and Convolutional Deep Learning

Convolutional neural networks are useful to acquire the local structure of waveforms like the QRS form, ST form, and beat-specific texture [143]. LSTM and BiLSTMs recurrent models can be

used to detect sequential beat dependencies and are effective in rhythm analysis in longer windows [144]. Hybrid CNNBiLSTM models are hence still popular as they fuse locus shape learning and time context modeling [38,39].

7.3 Attention and Transformer-Based Models

One of the most prominent current trends is the use of transformer architectures for ECG analysis [145]. They consist of component-aware transformers, masked transformers, multi-branch transformers, and Swin-transformer-like models, which learn long-range correlations and interactions between tokens [146]. Analyzing ECG with deep learning and personalized diagnostics. Reviews of deep learning ECG analysis and personalized diagnostics indicate transformer-based approaches as a significant direction of today, particularly where multibeam context and scalability are essential [41].

7.4 Explainable and Directed Models

The issue of interpretability has been of significant concern since the clinicians need an assurance of model decision being related to any clinically relevant region of waveforms. Elicitable deep-learning structures and guided attention processes have thus come into the limelight. A 2024 study in Computer Methods and Programs in Biomedicine was able to find that requirements guided by domain knowledge led to better classification and explainability as opposed to just using a standard guided attention. In a 2025 systematic review in Computers in Biology and Medicine, explainable deep learning was important to ECG-based heart disease classification [42–45].

7.5 Federated, Personalized and Wearable ECG Learning

Another way is cross-institutional and privacy-conscious learning. A 2024 article on federated transfer learning on ECG classification had a focus on heterogeneous dimensions of the input and distributed training among institutions. Simultaneous development of patient-specific ECG diagnostics shows inter-Patient variance and patient-specific modeling.

The Fig. 6 illustrates the conceptual architecture commonly used in modern ECG abnormal detection systems. The process begins with ECG signal acquisition, where electrical signals generated by the heart are recorded using sensors or wearable devices. The raw signals are then passed through a preprocessing stage, where filtering and denoising techniques are applied to remove artifacts and improve signal quality. After preprocessing, relevant features are extracted from the ECG waveform using time-domain, frequency-domain, or time–frequency analysis methods. These features are subsequently processed by machine learning or deep learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to classify and detect cardiac abnormalities. The final stage involves decision making and clinical interpretation, where the system outputs assist healthcare professionals in diagnosing cardiovascular conditions and monitoring patient health [43–45].

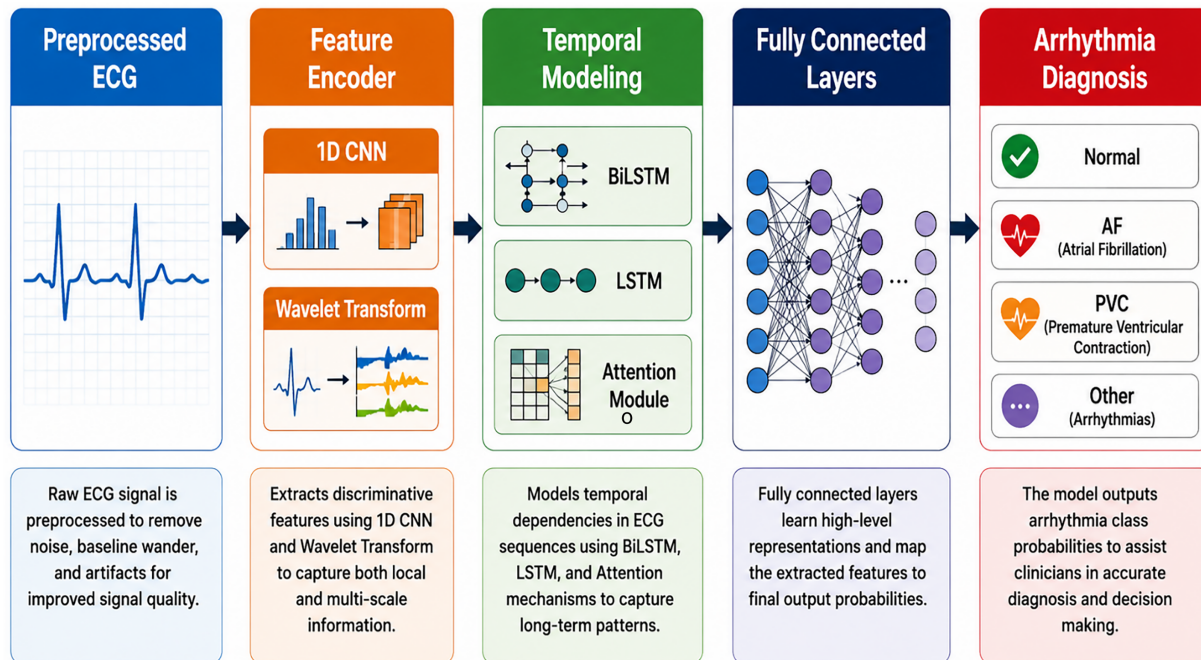


Figure 6: Conceptual architecture of modern ECG abnormality detection algorithms

8 Datasets, Metrics, and Comparative Analysis

Publicly available datasets play a foundational role in ECG research because they enable reproducibility, cross-study comparison, and benchmarking of numerical and computational algorithms. Over the past three decades, PhysioNet has emerged as the primary repository for ECG databases used in algorithm development, validation, and comparative evaluation.

8.1 Public ECG Databases

The MIT-BIH Arrhythmia Database remains one of the most widely used ECG benchmark datasets in the literature. It consists of 48 half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects, sampled at 360 Hz and manually annotated beat by beat. The database contains both normal and abnormal rhythms, including premature ventricular contractions, atrial premature beats, bundle branch blocks, and paced beats. Its detailed annotation makes it particularly suitable for QRS detection, heartbeat classification, and arrhythmia evaluation.

In addition to MIT-BIH Arrhythmia, PhysioNet distributes several specialized ECG repositories, including:

- **MIT-BIH Atrial Fibrillation Database (AFDB):** 25 long-term ECG recordings, primarily focused on atrial fibrillation episodes.
- **MIT-BIH Supraventricular Arrhythmia Database (SVDB):** 78 half-hour recordings enriched with supraventricular arrhythmia examples.
- **Long-Term ST Database:** Designed for ST-segment analysis and ischemia research.
- **Normal Sinus Rhythm Database:** Long-term recordings of subjects without significant arrhythmia.

These databases differ in sampling rate, annotation granularity, recording duration, and patient diversity. Consequently, performance comparisons across studies must account for dataset characteristics, class distribution, and annotation protocols.

More recent research has also incorporated wearable ECG datasets, multi-lead hospital-grade datasets, and 12-lead ECG repositories. However, MIT-BIH remains dominant due to its long-standing use and standardized annotation scheme [147].

8.2 Dataset Challenges

Despite their importance, public ECG datasets present several limitations:

1. **Limited patient diversity** relative to large clinical populations.
2. **Class imbalance**, particularly in arrhythmia datasets.
3. **Device homogeneity**, since many benchmark datasets were recorded under controlled conditions.
4. **Lead configuration constraints**, often limited to 1 or 2 leads.

These limitations affect model generalization. Several recent reviews emphasize that models trained exclusively on MIT-BIH often show reduced performance when applied to real-world wearable ECG recordings or multi-center clinical data [148].

8.3 Evaluation Metrics

Evaluation of ECG processing algorithms depends on the specific task (e.g., QRS detection vs. arrhythmia classification), but several core metrics are consistently reported.

For classification tasks, the most common metrics include:

$$\text{Sensitivity (Recall)} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{F1 - score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

For multi-class arrhythmia classification, macro-averaged and weighted F1-scores are often more informative than accuracy alone, particularly under class imbalance [149].

For QRS detection tasks, additional metrics include:

- Positive Predictive Value (PPV) [150]
- Detection Error Rate (DER) [150]
- Mean detection delay [151]
- Timing jitter [151]

Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) are commonly used to summarize discriminative ability across decision thresholds.

8.4 Computational and Deployment Metrics

With the growth of wearable ECG systems and real-time cardiac monitoring, algorithm evaluation now extends beyond classification accuracy.

Important deployment-related metrics include:

- Inference latency (ms per segment or beat) [151]
- Model memory footprint (MB) [152]
- Computational complexity
- Energy consumption for embedded systems [110]
- Robustness under synthetic noise injection [152]

Reviews of consumer and wearable ECG systems emphasize that deployment constraints—such as battery life, embedded processor limits, and memory capacity—are increasingly critical considerations [152,153]. Therefore, computational efficiency is no longer secondary to diagnostic performance [152].

8.5 Comparative Reporting Issues

A persistent issue in ECG research is inconsistency in experimental design and reporting practices. Studies often differ in:

- Patient-level vs. beat-level splitting
- Intra-patient vs. inter-patient evaluation
- Data augmentation strategies
- Class grouping schemes (e.g., AAMI standard vs. custom labels)
- Preprocessing assumptions
- Noise handling procedures

For example, a beat-wise random split can artificially inflate performance by allowing beats from the same patient to appear in both training and testing sets [154]. In contrast, inter-patient splits are more realistic but typically yield lower reported accuracy [81].

Similarly, different class aggregation schemes can significantly affect F1-score and sensitivity values.

Recent literature on personalized diagnostics and ECG beat classification stresses the need for standardized benchmarks, transparent preprocessing documentation, and explicit reporting of data splits.

8.6 Comparative Tables

Table 2 provides a summary of the most common sources of noise in ECG recordings and their common causes and common preprocessing methods which are applied to remove noise. The artifacts expected to contaminate ECG signals are related to respiration or electrode movement (baseline wander), electrical environments (power-line interference), muscle contractions (EMG noise), and body movement (motion artifact). The table identifies popular signal processing methods, such as, high-pass filtering, notch filtering, wavelet denoising, adaptive filtering, and decomposition-based methods, which are usually useful to enhance the quality of the ECG signal before the subsequent analysis.

Table 2: Common ECG noise sources and representative preprocessing methods

Noise source	Typical cause	Representative methods
Baseline wander	Respiration, posture, electrode drift	Polynomial detrending, spline interpolation, high-pass filtering
Power-line interference	Electrical environment	Notch filtering, adaptive filtering
EMG noise	Muscle activity	Wavelet denoising, adaptive filtering
Motion artifact	Electrode displacement, wearables	ICA, decomposition-based denoising, hybrid methods

Table 3 provides the key feature domains applied in the ECG signal analysis and examples thereof, as well as the essence of their strengths. ECG features may be obtained from several domains, most commonly time-domain features, such as RR intervals and waveform amplitudes, frequency-domain qualities like spectral power and entropy statistics, and time-frequency analysis features, including short-time Fourier transform (STFT) or continuous wavelet transform (CWT) [155,156]. Other learned latent features are also offered by deep learning architectures like convolutional neural networks and transformer architectures for ECG analysis [157]. All domains have their own advantages, starting with interpretability and computational efficiency up to better representation of complex and nonstationary ECG signals [156,158].

Table 3: Common feature domains in ECG analysis

Feature domain	Examples	Main benefit
Time domain	RR, PR, QRS, QT, amplitudes	Interpretable, computationally lightweight
Frequency domain	Band power, dominant frequency, entropy	Rhythm characterization
Time–frequency domain	STFT maps, CWT scalograms	Suitable for nonstationary ECG
Learned latent features	CNN embeddings, transformer tokens	High nonlinear representational power

A comparison of key classifier categories mostly applied to detect ECG abnormalities is offered in **Table 4**. The table highlights classical machine learning methods that include support vector machine,

random forests and k-nearest neighbors, and deep learning models that comprise convolutional neural network and recurrent neural network. It also puts into the limelight transformer-based models, which embrace long-range influences in ECG signals, and hybrid designs, which integrate various learning mechanisms. Each category is summarized in the table that reflects the key advantages and drawbacks, contributing to the representation of the trade-offs between interpretability, computational needs and the classification results in the current ECG analysis frameworks.

Table 4: Representative classifier categories in ECG abnormality detection

Classifier type	Examples	Strength	Limitation
Classical ML	SVM, RF, kNN	Interpretable, moderate compute	Depends on feature engineering
Deep learning	CNN, LSTM, BiLSTM	Automatic feature learning	Data- and compute-intensive
Transformer-based	Multi-branch transformer, masked transformer, Swin transformer	Captures long-range context	Higher computational cost
Hybrid models	CNN-BiLSTM, CNN-Transformer	Combines local and temporal learning	Increased architectural complexity

9 Challenges, Limitations, and Future Directions

However, even with the remarkable advances in the processing of ECG signals, as well as the detection of cardiac abnormalities, there are still several challenges inhibiting the implementation of effective clinical systems.

9.1 Generalization and Domain Shift

Most ECG models are effective in benchmark data sets like MIT-BIH but not in datasets outside their benchmark, like other hospitals, devices, lead configurations, or patient populations [159,160]. This is because of domain shift and inter-patient variation. Additional research must be done on cross-dataset testing, transfer learning, domain adaptation, data enhancement, and federated research to enhance model robustness in the future.

9.2 Clinical Trust and Interpretability

Deep learning models are commonly black box systems, thus changing clinicians with the understanding of how predictions are generated [161]. Models to achieve clinical adoption need to have explanations associated with physiological ECG characteristics of P wave, QRS complex and T wave [142]. Explainable AI (XAI) is also potentially useful to enhance transparency and clinical trust [162].

9.3 Real-Time and Low-Power Deployment

ECG monitoring systems implemented with wearables and IoT demand efficient algorithms in terms of the low complexity of computations, memory consumption, and energy consumption [163].

Lightweight models, hybrid systems that combine numerical processing with deep learning, model compression, pruning, and quantization, are of value to edge deployment in real-time [164].

9.4 Consistency and Reproducibility in Evaluations

The existing ECG research typically employs varied data-cutting approaches, data-preprocessing pipelines, and assessment metrics, therefore, complicating comparisons [165]. Such studies in the future ought to be guided by standardized benchmarking [166], precise publication of the preprocessing methodology, and release of datasets or code to enhance reproducibility [167, 168].

9.5 Future Research Emerging

The future of ECG analytics is taking a few promising directions, encompassing the application of self-supervised learning to large unlabeled ECG experiments, multimodal fusion with other physiological signals (e.g., PPG and blood pressure) [145], privacy-preserving federated learning, patient-specific modeling, wearable device-contextualized denoising, and explainable transformer-based architectures [117]. Altogether, solving these difficulties will allow creating more stable, interpretable, and operational ECG analysis systems to be deployed in the context of real-life healthcare.

10 Conclusion and Future Research Directions

This review has presented a critical analysis of numerical methods and computational algorithms for ECG signal processing and cardiac abnormality detection. Unlike conventional surveys that focus primarily on classification models, this work emphasizes the importance of the entire computational pipeline, including preprocessing, delineation, feature extraction, and evaluation.

The analysis demonstrates that high-performing ECG systems cannot be achieved through isolated optimization of individual components. Instead, reliable cardiac abnormality detection requires a tightly integrated pipeline in which numerically stable preprocessing, robust feature representation, and adaptive learning models operate cohesively.

A key insight emerging from this review is that the effectiveness of modern deep learning models is strongly influenced by upstream signal conditioning and dataset characteristics. While deep and transformer-based models have significantly advanced classification performance, they remain sensitive to noise, domain shift, and annotation inconsistencies. In contrast, classical numerical methods continue to play a critical role in ensuring signal quality, interpretability, and computational efficiency, particularly in resource-constrained environments.

10.1 Future Research Directions

Several research challenges and opportunities remain:

- (a) **Domain Generalization and Cross-Dataset Robustness**
Future models must address performance degradation across different datasets, devices, and patient populations. Domain adaptation, transfer learning, and federated learning offer promising solutions.
- (b) **Explainable and Clinically Interpretable Models**
Enhancing model transparency is essential for clinical adoption. Future work should focus on physiologically informed explainable AI frameworks that align predictions with ECG morphology.
- (c) **Lightweight and Energy-Efficient Architectures**

With the rise of wearable ECG systems, there is a growing need for models that balance accuracy with computational efficiency, memory usage, and energy consumption.

(d) Improved Annotation and Benchmarking Standards

Standardized evaluation protocols, high-quality annotations, and multi-center datasets are required to ensure reproducibility and fair comparison across studies.

(e) Hybrid Modeling Approaches

Combining numerical signal processing with deep learning remains a highly promising direction. Such hybrid systems can leverage the strengths of both paradigms to achieve robustness, interpretability, and scalability.

(f) Multimodal and Personalized Healthcare Systems

Future ECG analysis systems should integrate multiple physiological signals and incorporate patient-specific adaptation to improve diagnostic accuracy.

In conclusion, the future of ECG-based cardiac abnormality detection lies in the development of integrated, interpretable, and deployable intelligent systems that bridge numerical rigor with data-driven learning. Advancing along these directions will enable more reliable, scalable, and clinically meaningful cardiac monitoring solutions.

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