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A Comprehensive Survey of Arrhythmia Classification Techniques

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Abstract

Arrhythmia classification is a critical area of research in cardiology, given the significant health risks associated with irregular heart rhythms. This research study presents a comprehensive survey of current methodologies employed for the detection and classification of arrhythmias from electrocardiogram (ECG) signals. The study examines a variety of methods, including sophisticated deep learning techniques like Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) in addition to more conventional machine learning algorithms like Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN). Additionally, the research study provides critical information that is relevant to medical diagnostics, such as the weak generalizability hampered by imbalanced datasets, whose management is well illustrated by the research study as a successful way to increase model performance.

Keywords: Arrhythmias, ECG Signals, Data Imbalance, Irregular Heart Rhythms, Classification Techniques.

1. Introduction

Cardiac arrhythmias are a very common problem with significant potential for the development of dangerous complications such as stroke, congestive heart failure, or sudden cardiac death if left undiagnosed and untreated. Electrocardiography is the most common method of diagnosing arrhythmia involving the tracing of electrical activity from the heart over time. However, manual analysis of ECG signals is labor-intensive, can be easily biased, and is simply not feasible in large-scale clinical practice where early diagnosis is critical for

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successful therapeutic intervention. The improvements and the development of novel efficient techniques in the field of machine learning along with deep learning have extended the probabilities of arrhythmia classification to improve more efficient rates of pre-identification of abnormal heart rhythm patterns. These technologies utilize sophisticated algorithms for sorting large data sets of ECGS thus identifying areas that are hard for the human eye to perceive. Nevertheless, there are still issues to address, for example, medical datasets are not balanced, arrhythmias' characteristics vary across patients, and training and deploying these models can be computationally expensive. This survey, however, plans to cover what is considered as the current state of figuring out the methodologies for the classification of arrhythmias, with particular attention to how various balancing techniques and algorithmizing procedures meet such challenges as the enhancement of classification accuracy and model generality, and the attainment of interpretability. The study explores several models ranging from the most basic machine learning method to more complex deep learning algorithms and analyze their efficiency on both unbalanced and balanced datasets. This analysis, seeks to highlight the strengths and limitations of existing methods while exploring potential avenues for future research.

2. Background on Arrhythmia and ECG Signals

2.1 Overview of Arrhythmias

Arrhythmias are classified into various types based on the part of the heart affected and the nature of the abnormal rhythm. The most common arrhythmias include: Normal beat (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unknown beat (Q), a fast but regular rhythm originating in the ventricles; and Ventricular Fibrillation (VF), a serious condition where the ventricles quiver instead of pumping blood effectively, often leading to cardiac arrest. Other notable arrhythmias include Bundle Branch Blocks (BBB) and Premature Ventricular Contractions (PVCs), which may not always be life-threatening but still require monitoring and management. Each of these arrhythmias presents distinct challenges for classification due to their varying morphological characteristics. For instance, S is marked by irregular, disorganized electrical signals that produce erratic ECG waveforms, while V and VF are rapid rhythms that may show large, broad QRS complexes. The complexity of these patterns underscores the need for advanced algorithms capable of distinguishing between these types with high precision.

2.2 Importance of ECG Signals

The electrical activity of the heart is represented as a time series by the ECG signal, which is usually recorded over a 10-second interval using a standard 12-lead setup. This configuration allows for a comprehensive assessment of the heart's electrical function by capturing the electrical impulses from multiple angles, offering vital information on the general health of the heart. The ECG waveform consists of several critical features that are vital for diagnosing arrhythmias: Atrial depolarization is represented by the P wave, ventricular depolarization by the QRS (Q wave, R wave, and S wave) complex, and ventricular repolarization by the T wave. These features reflect the sequence of electrical events that trigger heartbeats, and their precise morphology is essential for proper interpretation. While these features are easily recognizable in normal heart rhythms, they can become distorted or obscured in the presence of arrhythmias, making it difficult for even seasoned professionals to analyze data accurately.

3. Literature Survey

Table 1 summarizes the literature survey with the details of the algorithms used, the dataset used, its merits and demerits

Table 1. Literature Survey

Research Study	Algorithm Used	Dataset(s) Used	Merits	Demerits
[1]	CNN + PSO	MIT-BIH Arrhythmia Database	Automatic hyperparameter tuning, high accuracy in ECG classification due to optimized architecture	Computationally intensive due to PSO, imbalanced dataset affecting minority class representation
[2]	GSMD + SLT with deep learning (VGG19, ResNet-18, etc.)	Custom ECG dataset	High-resolution time-frequency representation, effective for nonstationary ECG data	Computational complexity, class imbalance leading to biased results on minority classes

[3]	HA-ResNet with SE Blocks and BConvLSTM	CUDB, AFDB, MITDB	Effective feature recalibration and temporal dependency modelling; interpretable with hidden attention	Limited generalization to diverse datasets, imbalance affects minority classes
[4]	Multimodal Neural Network (MM-NN) combining ECG with patient metadata	MIT-BIH with additional patient data	Improved accuracy with personalized data, effective preprocessing, and data balancing	Scalability across diverse patient populations needs further study
[5]	AutoEncoder with Human-in-the-Loop (HIL) for interpretability	MIT-BIH Arrhythmia Database	Enhanced model interpretability; maintains high classification performance	Complexity in integrating human knowledge into the model; HIL adjustments challenging to ensure accuracy
[6]	NEO-based thresholding + 1D CCNN	Wearable ECG device dataset	Suitable for low-power devices; optimized for embedded classification	Variability in performance due to ECG morphology differences; potential limitations in real-world applicability
[7]	Heartbeat Dynamics Feature with KNN, RF, SVM	MIT-BIH Arrhythmia Database	High interpretability and effective discrimination of heartbeats; promising for wearable devices	Needs further integration with other features for better generalization

[8]	Deep Multi-Scale Convolutional Neural Network Ensemble (DMSCE)	PTBXL-2020, CinC-training2017	High diagnostic accuracy: model interpretability focused on clinically relevant segments	Limited information on non-linear equation reduction for model simplification
[9]	Delta-Sigma Modulators (DSMs), Random Forest (RF)	CinC 2017 A-fib, QT Databases	Energy-efficient and resource-saving; robust to noise and missing values; suitable for wearable devices	Limited by the reduced sampling rate, which might miss finer ECG details.
[10]	DeepArrNet (CNN with depth-wise separable convolutions)	Benchmark ECG datasets	High accuracy, sensitivity, and specificity; effective noise reduction with wavelet denoising	May face challenges in handling real-time processing due to the complex architecture
[11]	ShuffleNet-based CNN	Benchmark ECG datasets	Lightweight and computationally efficient; suitable for resource-constrained devices	Reduced model complexity might limit accuracy for more complex arrhythmias
[12]	Group Sparse Mode Decomposition (GSMD), Superlet Transforms (SLT), Neural Networks	ECG dataset (unnamed)	Energy-efficient due to hierarchical classification; tailored to wearable devices	Dataset imbalance and hierarchical complexity can lead to system design challenges
[13]	Adaptive K-means Clustering (AKMC), Neural	ECG dataset (unnamed)	High classification accuracy with	Visual pattern features add complexity to training; RR intervals may not

	Networks (NN), SVM, KNN		enhanced feature discrimination	distinguish complex arrhythmias
[14]	Multi-label feature selection (MS-ECG), Multi-label classification (MC-ECG)	Long-term ECG dataset	Captures correlations across arrhythmias; reduces feature space while maintaining critical information	High computational demand; dataset-specific correlations may reduce the generalizability
[15]	2D-CNN	MIT-BIH Arrhythmia Database	Eliminates the need for manual feature extraction; superior performance to 1D-CNN for ECG spectrograms	Requires significant computational resources for transformation and model training
[16]	MLBF-Net (Multi-lead Branch Network)	12-lead ECG dataset	Effective integration of multi-lead information; high classification accuracy with a multi-loss approach	Complex architecture requires substantial computational resources, limiting real-world deployment potential
[17]	Deep Neural Networks (DNN)	Raw ECG data	End-to-end processing without handcrafted features; automatically learns informative features	Computationally intensive, making it less feasible for real-time or resource-constrained environments

3.1 Research Gaps and Objectives

In recent years, significant advancements have been made in the field of arrhythmia classification using deep learning and other machine learning approaches. While these methods have shown promise in improving diagnostic accuracy and efficiency, several challenges and limitations remain. Addressing these gaps is crucial for the development of more effective and practical solutions in real-world medical applications. In the following sections, the study will discuss some of the key research gaps that continue to hinder progress in this field and need further exploration.

A. Computational Intensity and Resource Constraints

The hybrid models and deep learning architectures used in arrhythmia classification, such as the [1] CNN-PSO approach or models like VGG19 and ResNet-18, demonstrate commendable improvements in accuracy and feature extraction. However, these approaches often suffer from high computational costs, particularly during training and real-time inference. Such computational intensity limits the scalability of these methods for low-resource environments like wearable devices or remote monitoring systems, where power consumption and memory usage are critical constraints. Moreover, while models such as [6] NEO-CCNN and [11] ShuffleNet aim to balance efficiency and accuracy, the challenge remains in creating an approach that does not sacrifice one for the other.

B. Interpretability

Deep learning models' black-box character continues to be a significant barrier to their use in medical diagnosis, where doctors need precise justifications for predictions. While in [5] mechanisms like attention layers or human-in-the-loop (HIL) interventions offer a degree of interpretability, these methods are still limited in providing comprehensive transparency that medical practitioners can confidently rely on. The creation of interpretable models that maintain the high accuracy of conventional deep learning architectures is lacking while providing clear, traceable decision pathways that can be reviewed and trusted by healthcare professionals.

C. Preprocessing and Feature Extraction

Complex preprocessing techniques such as wavelet-based denoising, [2] Superlet Transforms (SLT), or Group Sparse Mode Decomposition (GSMD), while improving signal quality and classification performance, add significant overhead in both computational and time resources. These techniques also require extensive manual intervention and careful parameter tuning, which is impractical in real-time monitoring scenarios or when processing large-scale ECG datasets. There is a gap in the exploration of more automated feature extraction methods, such as self-supervised learning, which can eliminate the need for manual feature engineering while learning robust features directly from raw ECG signals.

To such extent, it is appropriate to mention the following research objectives, which would be instrumental in overcoming the challenges and limitations of the current state of dealing with arrhythmia classification: The following sections of the research study, will define the major research aims that have to be achieved to close the gaps and enhance the efficiency of the developed arrhythmia classification systems.

D. Developing Efficient Models for Real-Time Applications

One of the primary research objectives is to design lightweight and efficient deep learning models capable of real-time arrhythmia detection. These models should be optimized for low-resource environments like wearable ECG devices, where computational power and memory are limited. Techniques such as quantization, pruning, and the development of compact neural networks like MobileNet or ShuffleNet can help achieve this balance.

E. Enhancing Data Balancing Techniques

A critical objective is to advance data balancing methodologies that can more effectively manage the severe class imbalances present in ECG datasets since many of existing implementations worked with imbalance issue present in datasets. Beyond traditional methods like SMOTE, the development of novel approaches such as generative models to synthesize new data points for underrepresented arrhythmia classes, or dynamic re-weighting during the training process, should be explored.

F. Improving Model Interpretability

Enhancing deep learning models' interpretability in a medical setting is the goal. This could involve integrating attention mechanisms, explainable AI frameworks, or visualization tools that highlight the specific ECG features driving the classification decisions. The goal is to allow medical professionals to validate and trust the predictions made by these models. Such interpretability should be clinically relevant, meaning that it helps clinicians understand why a specific diagnosis was made, ultimately contributing to the model's practical usability in healthcare settings.

To this end, the following research gaps and objectives must be addressed to enable the field of arrhythmia classification to move towards the improvement of more credible, productive, and feasible frameworks for the diagnosis of cardiac irregularities.

4. Datasets Used in Arrhythmia Classification

4.1 MIT-BIH Arrhythmia Dataset

One of the most popular datasets for training and assessing arrhythmia classification models is the MIT-BIH Arrhythmia Dataset [1]. It includes 48 half-hour recordings of ECG signals sampled at 360 Hz from 47 distinct people. The dataset [3-4] contains annotations for over 100,000 heartbeats, categorized into several arrhythmia types, including normal beats, ventricular ectopic beats, supraventricular ectopic beats, and others. Despite its popularity, the dataset is highly imbalanced, with normal beats comprising the majority of samples. The MIT-BIH dataset [7, 15] has been used for many arrhythmia classification studies, serving as a benchmark for evaluating new algorithms.

4.2 Other Datasets

In addition to MIT-BIH, several other datasets have been used to explore arrhythmia classification. The CUDB and AFDB datasets [3] focus on specific arrhythmias, such as Atrial Fibrillation, providing detailed recordings of irregular heart rhythms. The PTB-XL dataset [8] is another large-scale dataset that includes 12-lead ECG recordings of various cardiovascular conditions, offering a broader range of heart diseases for classification tasks. These datasets provide additional opportunities for model validation and benchmarking, but like MIT-BIH, they often suffer from class imbalance, requiring the use of specialized balancing techniques to ensure accurate classification across all arrhythmia types.

5. Preprocessing Techniques

Table 2 summarizes various preprocessing techniques applied to ECG signals, detailing their working mechanisms and the datasets for which they are suitable. These techniques play a crucial role in enhancing the quality of the data, thereby improving the performance of arrhythmia classification models.

Table 2. Preprocessing Techniques

Preprocessing Technique	**Working Mechanism**	**Suitable Dataset(s)**
Feature Extraction	Involves identifying key components of the ECG waveform, such as P-wave, QRS complex, and T-wave. These features provide critical information about the heart's electrical activity and are essential for traditional ML models like SVM and RF.	Traditional ECG datasets like MIT-BIH Arrhythmia Database
Deep Learning-Based Extraction	Convolutional Neural Networks (CNNs) analyse raw ECG data without requiring prior feature extraction. CNNs can perform pattern recognition and identify morphological transformations that characterize arrhythmias directly from the data.	Large datasets suitable for CNN training, e.g., PhysioNet datasets
Signal Denoising	Techniques like wavelet denoising preserve essential characteristics of the ECG signal while removing noise from sources such as muscle movement, electrode contact, and electrical interference.	Datasets with noise, e.g., MIT-BIH Arrhythmia Database, CUDB

Bandpass Filtering	Bandpass filters eliminate high-frequency noise and baseline wander, ensuring that only the relevant frequency components of the ECG signal are retained for analysis.	Datasets with baseline drift, e.g., Long-term ECG recordings
Normalization	Normalization ensures consistent amplitude and range across ECG signals, allowing models to focus on relative differences between beats rather than variations in signal intensity. This is critical when data is collected from diverse sources.	Multi-source datasets, e.g., CUDB, AFDB, and custom ECG datasets

6. Arrhythmia Classification Algorithms

Below are the most common machine learning and deep learning models in the classification of arrhythmia and an overview of their advantages, drawbacks, and approaches, commonly used in ECG signal analysis. The models include Conventional Models such as Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), and combinations of models, and non-conventional models such as Support Vector Machines (SVM), Random Forest (RF) and K-Nearest Neighbors (KNN).

6.1 Convolutional Neural Networks (CNN)

Indeed, Convolutional Neural Networks (CNNs) have emerged as one of the leading architectures for the arrhythmia classification owing to their virtue of learning spatiotemporal features from raw ECG signals. While traditional machine learning requires engineers to design the feature set that CNNs can learn from the raw ECG data. CNNs can spot the shape of P wave, QRS complex, and T wave [10, 11]. CNNs comprise several layers of convolutional filters that successively identify local patterns solely from the given ECG signal. There are pooling layers, which are used to make the data smaller and minimize the features offered to the model; enabling the model to be computationally efficient [1, 6,8,10, 11, 15].

6.2 Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory Networks (LSTMs) is a specific kind of RNN that is used with sequential data, and LSTMs are especially suited for time-series classification, such as arrhythmia detection. While CNNs seek for spatial patterns in the data, LSTMs are tuned to capture temporal patterns and thus can easily identify patterns over space within ECG signals such as heart rate variability and irregular intervals of the heart. LSTMs have memory cells to store the past information and were very useful in identifying an arrhythmia that doesn't show in a single beat but is separately noticeable in several consecutive beats [3].

6.3 Support Vector Machines (SVM)

Traditional Machine learning algorithm used for presenting arrhythmia data is Support Vector Machines (SVMs), are more commonly used in case of relatively low numbers of data samples. SVMs operated based on identifying the hyperplane that effectively classifies two or more types of data point such as normal and abnormal heartbeats based on the largest distance possible. SVMs are ideal for binary classification problems but are also extendable to k-class problems by strategies such as One-vs-One or One-vs-Rest. SVMs greatly depend on feature extraction; manually defined features may include the amplitude and duration of the ECG components, which include P wave, QRS complex, and T wave [7,13].

6.4 Random Forest (RF)

Random Forest (RF) is one of the classical machine learning algorithms used in arrhythmia classification settings. It does this during training by constructing many decision trees and returning the mode class (classification) or mean prediction (regression) of these trees. Of all the methods examined, RF is capable of dealing with missing data and of averting problems with overfitting since it builds several trees consecutively. RF is usually integrated with feature extraction where the best features to be used in classifying arrhythmia are determined [7,9].

6.5 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a simple, but efficient machine learning classifier for the classification of arrhythmia. This operation is done by associating to each data point the class that is most frequently found among its KNN in the feature space. Being a nonparametric method, KNN doesn't take into consideration the probability density function of the probability distribution of a feature set, which makes it flexible to apply in different fields. In relation to the classification of the arrhythmia, KNN may be applied to classify the beats in reference to its similarity to the one in the database or in the feature space been normal or arrhythmic beats [7,13].

7. Survey of Classification Models

7.1 Models on Unbalanced Datasets

This reviews the performance of trained models on unbalanced datasets, where the majority of samples represent normal heartbeats and only a small fraction represent arrhythmic beats. Despite achieving high overall accuracy, these models tend to perform poorly on minority classes due to the imbalance in the training data.

Table 3. Reported Accuracy of Models with Imbalanced Datasets

SI.no	Algorithm	Datasets used	Accuracy
1	CNN + PSO [1]	MIT-BIH Arrhythmia Database	97%
2	Random Forest [9]	CinC 2017 A-fib, QT Databases	95%
3	Neural Network [12]	ECG dataset (unnamed)	98.2%
4	KNN [13]	ECG dataset (unnamed)	97.70%
5	Multi Lead Branch Fusion Network [16]	12-lead ECG dataset	85%

Table 3 represents a compilation of many studies in the classification of arrhythmia shows high average accuracy of more than ninety percent achieved with traditional machine learning algorithms as well as Deep learning models. Nevertheless, it was common that these studies were based on unbalanced datasets and the number of samples in some of the arrhythmia classes especially in the minority ones was considerably lower than in the other. It is obvious that this imbalance is a major source of directionality in classification models; produces preferred predictions towards the dominant class. Therefore, it can be seen that although the percentage rates of accuracy determined not only solely reflect the percentage of major classification but reveal a fundamental weakness of the technique in its inability to define the pattern of occurrence of the minor yet clinically significant types of arrhythmias. Below with detailed explanations.

- **CNN + PSO:** Achieved an accuracy of 97% by optimizing the CNN architecture with Particle Swarm Optimization (PSO). However, the model struggled to classify rare arrhythmias accurately, as the majority class dominated the training process.
- **Neural Network (NN):** Achieved an accuracy of 98.2% on the MIT-BIH dataset, but similar to CNN + PSO, the model exhibited poor generalization to minority classes.
- **K-Nearest Neighbors (KNN):** Achieved an accuracy of 97.7%, but like other models, it struggled with the imbalanced nature of the dataset, leading to high accuracy for normal beats but poor detection rates for arrhythmias.

7.2 Models on Balanced Datasets

It has been demonstrated that balancing strategies like Random Over Sampling (ROS) greatly enhance the functionality of arrhythmia classification models. This reviews the results of models trained on balanced datasets.

- **LSTM with ROS:** Achieved an accuracy of 63%, demonstrating the importance of balancing techniques for improving the performance of temporal models like LSTM [4].
- **1D CNN with ROS:** Achieved an accuracy of 92.23%, a significant improvement over models trained on unbalanced data. The use of ROS helped ensure that the model received a more balanced representation of normal and arrhythmic beats, leading to better generalization across classes [11].

8. Advanced Techniques for Arrhythmia Detection

8.1 AutoEncoders with HIL Mechanism

A unique method for enhancing the precision and interpretability of arrhythmia classification models is provided by AutoEncoders in conjunction with Human-in-the-Loop (HIL) processes. Neural networks called auto encoders may learn to compress and reassemble input data, allowing them to capture the most relevant features of the ECG signal. When combined with HIL mechanisms, AutoEncoders allow human experts to refine the model's predictions, ensuring that critical features are not overlooked. In one study, an AutoEncoder with HIL achieved an accuracy of 96% on a balanced dataset of 2500 samples from PhysioNet [5].

8.2 MLBF-Net for 12-Lead ECG

MLBF-Net (Multi-Lead Branch Fusion Network) is a cutting-edge architecture designed to leverage the information from all 12 leads of an ECG recording. The model consists of lead-specific branches that learn features from individual leads, combined with a fusion module that integrates these features to give a thorough examination of the electrical activity of the heart. MLBF-Net has demonstrated significant improvements in arrhythmia classification, achieving an accuracy of 85% on benchmark datasets. However, the model's complexity and high computational requirements make it difficult to deploy in real-time applications, such as wearable ECG devices [16].

9. Conclusion

The field of arrhythmia categorization is a fast-developing issue, with continuous research aimed at enhancing machine learning models' interpretability and accuracy. Future work will likely explore hybrid architectures that combine multiple algorithms to utilize their individual strengths. Additionally, the development of more efficient balancing techniques will be critical for improving the classification of rare arrhythmias without introducing noise or artifacts into the dataset. Real-time arrhythmia detection using wearable devices is another promising area of research. As wearable technology becomes more prevalent, the need for lightweight, resource-efficient models will grow. One of the biggest challenges in the years to come will be creating models that can operate on low-power devices without compromising accuracy. Our analysis has shown that while unbalanced models can achieve high accuracy, they often fail to detect rare arrhythmias due to the dominance of normal beats in the training data. This problem is better addressed by balancing strategies like SMOTE, which increase the robustness and generalization of classification models.

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