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A COMPREHENSIVE REVIEW OF FEATURE-BASED AND DEEP LEARNING APPROACHES FOR ECG SIGNAL CLASSIFICATION

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Abstract: Cardiovascular diseases remain one of the main causes of death in the world; thus, accurate classification of Electrocardiogram (ECG) signal becomes an important role for CADs detection and treatment. Over the years, several feature-based machine learning approaches as well as models based on deep learning have been investigated to automate ECG interpretation and alleviate the limitations of manual interpretation. It provides a fundamental comparison between the traditional handcrafted feature-based techniques and the deep learning-based models in terms of their advantages and disadvantages and their suitability for clinical usage. Fundamental aspects such as ECG signal structure, benchmark datasets, preprocessing techniques and performance evaluation metrics are discussed. While traditional classifiers based on features such as SVM, Random Forest, and XGBoost are easy to map into a manageable computation, very interpretable, and efficient, they are not as accurate as deep learning models like CNN, LSTM, and hybrids that offer end-to-end learning. A brief comparative review of a few newly published studies is performed together with a previously published XGBoost-based study that evaluated the MIT-BIH data base and showed potential results. In addition, the review discusses important remaining challenges of data imbalance, signal noise, and model interpretability and proposes future research directions to further enhance the clinical practicality and accuracy of ECG classification systems. The objective of this work is to guide researchers and practitioners to more applicable and efficient solutions for cardiac monitoring in real-time.

Keywords: ECG signal classification, feature extraction, deep learning, machine learning, XGBoost, CNN, arrhythmia detection, biomedical signal processing.

1. Introduction

Introduction Cardiovascular diseases (CVD) are the most common cause of death globally, responsible for almost one in three deaths [1]. Early and timely diagnosis is important not only to mitigate the complications but also to get better outcome in the patients. ECG is one of the most useful diagnostic tools, it is non-invasive, inexpensive, and able to record electrical activity of the heart [1].

However, manual interpretation of ECG signals is still a time-consuming and error-prone activity, especially in case of life-threatening diseases such as myocardial infarction and arrhythmias

Such a challenge is mainly due to enormous differences in ECG waves among individuals and even populations [2]. Computerized ECG interpretation (CIE) systems have been designed to aid clinicians but are often plagued by poor accuracy, interpretability, and lack of standardized protocols, requiring continued dependence on expert supervision [2].

During the past three decades, machine learning (ML) and deep learning (DL) techniques have had great promise to automate electrocardiogram ECG classification. Although classical ML models based on engineered features are more interpretable and less computationally expensive, they may still struggle to fully characterize more complex signal types. On the other hand, DL models—i.e., CNN and LSTM—feature a high power feature extraction and classification capabilities, that usually pay with a lack of interpretability and the requirement of a big amount of labelled datasets [1], [3].

Increasingly, hybrid forms have emerged in the past few years that strive to capture the interpretability and elegance of hand-engineered features, together with the power and performance of deep learning architectures [3]. However, there is still no comprehensive, systematic comparison of feature-based, DL-based and hybrid approaches in the context of ECG classification. In order to fill this gap, we systematically review these paradigms, analyze popular data sets and preprocessing techniques in use, review performance metrics that have been employed and we highlight challenges and future research directions.

2. ECG Signal Structure, Datasets, and Classification Challenges

2.1 ECG Signal Structure

An Electrocardiogram(ECG) is a fast, non-invasive diagnostic test that records the electrical signals of the heart. Specifically the ECG signal contains characteristic waveforms, including P wave, QRS complex, and T wave, which correspond to different stages of the conduction of electrical signals through the heart. The P wave indicates atrial depolarization and the QRS complex repolarization of the ventricles, followed by the latter component [4]. Correct interpretation of these elements is important for diagnosing various cardiac pathology, including arrhythmias, ischemia, or conduction delays. as shown in Figure 1 [5].

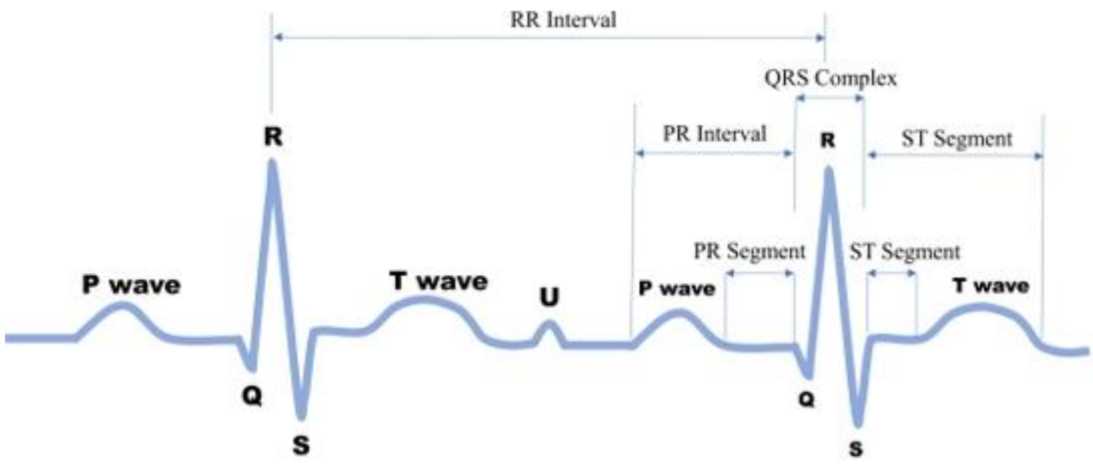

Figure1: Sample ECG signal. Source: [5]

2.2 Public ECG Datasets

Open-access ECG datasets have played a crucial role in accelerating the development and benchmarking of automated classification algorithms. MIT-BIH Arrhythmia Database [6] is among the first and most widely used datasets of ECG containing 48 half-hour ECG recordings that have been annotated for arrhythmias and are recorded from 47 individuals for different types of arrhythmia. Another important dataset is PTB-XL, a largescale dataset of over 21,000 clinical 12-lead ECGs from over 18,000 patients, together with extensive diagnostic annotations. Due to its wide coverage and fine-grained labeling, it is a great resource for supervised learning as well as large-scale model evaluation (7).

2.3 Challenges in ECG Classification

Advancements in ECG classification are still ongoing as ECG classification is complicated by a few remaining challenges:

- Signal variability: The ECG morphology varies among individuals based on physiological and pathological variations such as age, heart rate, co-morbidities, and electrode placement [1], [8].
- Signal noise and artifacts: Due to low-quality signal record, the baseline wander, motion artifact and electrical interference are common in real-world ECG signals, which corrupt the signal and make the preprocessing and feature extraction complicated [6].
- Class imbalance: In most of the published ECG datasets, the class distributions are heavily skewed whereby normal beats greatly outnumber the abnormal ones. Due to this imbalance, classifiers are sometimes biased and sensitive only to the majority classes [8].
- Black box: Deep learning models have high accuracy, but they also lack interpretability—acting as black boxes that lack transparency in understanding their decision-making process—for clinical trust and deployment [3].

To this end, building strong, interpretable and generalizable classification frameworks that predict reliably in both clinical and real-time scenarios will help mitigate these challenges.

3. Feature-Based Classification Methods

3.1 Overview of Feature-Based Approaches

Feature-based classification methods are widely used in ECG study [2], as they are simple, easy to interpret, and computationally less expensive than deep learning. For the first approaches, statistical, temporal, and spectral features are extracted from preprocessed ECG signals and then a standard machine learning classifier is trained with these features to classify arrhythmia [9, 10]. Such depictions of varied morphological and rhythmic behaviors of heart beats/cycles serve as a solid ground for tape pattern identification of abnormal heart beats.

3.2 Time-Domain Features

Such features are extracted directly from the ECG waveforms in terms of amplitudes and time duration of the intervals. Common examples include:

(RR intervals — mean, stdev, P-QRS-T interval, R-Peak Amplitude, Higher order statistics (skiwness, kurtosis etc)).Since they are sensitive to change within each beat, they are computationally cost effective, and can be used for arrhythmia detection [11]

3.3 Frequency-Domain Features

Frequency-domain features are calculated through the transformation of the ECG signal into the frequency spectrum with regards to its spectral content using performing such techniques as the Fast Fourier Transform (FFT) or Short-Time Fourier Transform (STFT). This enables the extraction of:

Dominant frequency ,Spectral entropy, Energy per frequency band (low-, mid- or high-frequency)

The periodicity and energy distribution of the signals contain essential information, which may not be visualized effectively in the time domain [12].

3.4 Classifiers Used with Feature-Based Methods

After that, extracted features are utilized in classifier training including but not limited to Support Vector Machines (SVM), Random Forests (RF), k-Nearest Neighbors (k-NN), and extreme Gradient Boosting (XGboost). Table–1: Summary Comparison of these models.

Table 1. Comparison of Common Feature-Based Classifiers

Classifier	Accuracy	Interpretability	Real-Time Suitability	Notes
SVM	High	Medium	Moderate	Requires kernel tuning
Random Forest	High	High	Moderate	Robust to overfitting
k-NN	Moderate	High	Low	High memory usage during inference
XGBoost	Very High	Medium	High	Excellent with imbalanced and small datasets

XGBoost is one of these algorithms that is popularly used because of its scalability, feature importance analysis included, and great performance on structured data [13].

3.5 Visual Comparison of Feature Types

In Figure 2, we show the visual conceptual difference between the time and frequency domain feature extraction. The third group is extracted from the time domain of the ECG waveform and the second group is extracted from the frequency of the time spectrum after the ECG signal is transferred to the frequency spectrum.

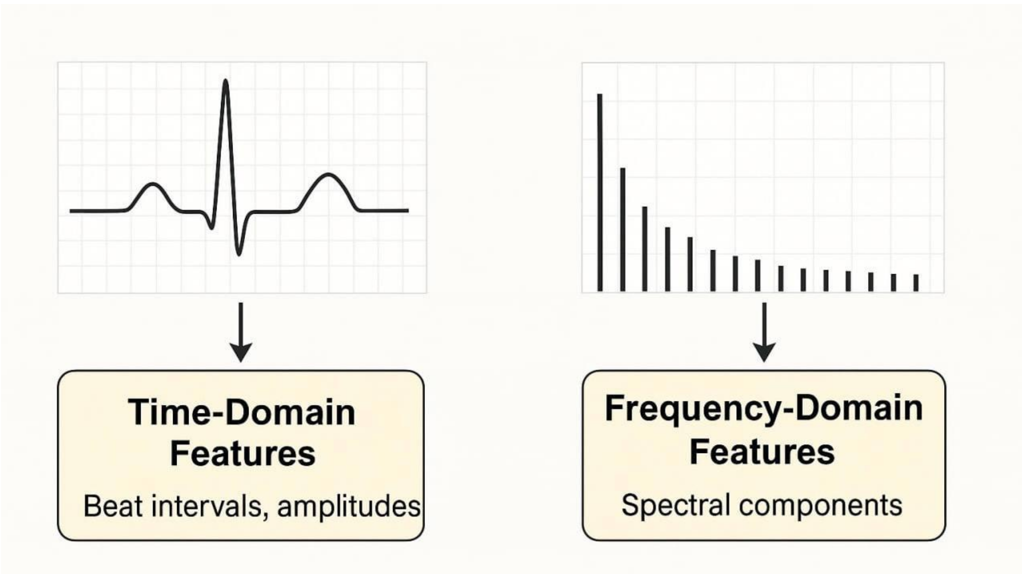

Figure 2: Visual comparison of time-domain and frequency-domain feature extraction from ECG signals.

3.6 Advantages and Limitations

Feature-based methods have many benefits, including fast training, low computation, and improved interpretability compared to neural networks. They are suitable for portable or real-time monitoring systems with limited resources [14]. But they highly rely on the excellence of handcrafted features, and do not learn deep nonlinear patterns as deep models.

4. Deep Learning-Based ECG Classification Methods

4.1 Deep Learning in ECG Analysis

Introduction Deep learning (DL) has become popular for ECG classification in recent years and is an alternative approach to a traditional feature-based method. Unlike traditional approaches where features such as morphological or statistical descriptors must be extracted manually, DL methods can learn high-level features directly from raw or minimally pre-processed ECG signals[3]. Such an ability to learn complex nonlinear patterns may make them more powerful at diagnosing a wide variety of cardiac abnormalities [15].

4.2 Common Deep Learning Architectures Used

There are some deep learning architectures that were generally used for ECG classification task:

- Convolutional Neural Networks(CNNs): CNNs are well applied for capturing local patterns of 1D ECG signals. They are trained end to end to learn spatial features from the raw waveforms and have been widely used in arrhythmia classification problems [16].
- Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM): They can process sequentially and therefore helps in capturing temporal relation between heart beats. In particular, LSTM networks are able to keep long-range dependencies, and are appropriate for a rhythm-based analysis [17].
- Hybrid CNN-LSTM Architectures: This model [17] integrates the local feature extraction capability of convolutional neural networks (CNN) with the temporal modeling ability of long short-term memory networks (LSTM) to advance the accuracy of heartbeat classification.

4.3 Public ECG Datasets for Deep Learning

To train and evaluate deep learning models for ECG classification, access to large, annotated datasets is required. Some of well-know benchmark databases are:

- MIT-BIH Arrhythmia Database: One of the most widely used datasets in the field, containing 48 half-hour ECG recordings, each annotated with labels for arrhythmias, covering a diverse patient population.
- PTB Diagnostic ECG Database: Including 549 15-lead ECG records from 290 subjects with diverse cardiac conditions.
- INCART Database: In this database, there are 75 ECG recordings with annotations for arrhythmias as identified in long-term ECG data, where each recording is sampled at 257 Hz [18], [6].

4.4 Performance Comparison with Feature-Based Methods

Unlike feature-based methods that rely on hand-crafted time- or frequency-domain features, deep learning models automatically learn hierarchical representations from raw inputs with complex underlying patterns and provide much better classification accuracy especially on large and diverse datasets with high variability that cannot be captured by simple fixed co-efficient linear models. On the left, we show a simple conceptual view of traditional feature based ECG classification, where a model architecture typically consists of a feature extractor followed by a classification model; on the right we show a complex architecture of deep learning, where feature extraction via model architecture is embedded into the architecture of the model.

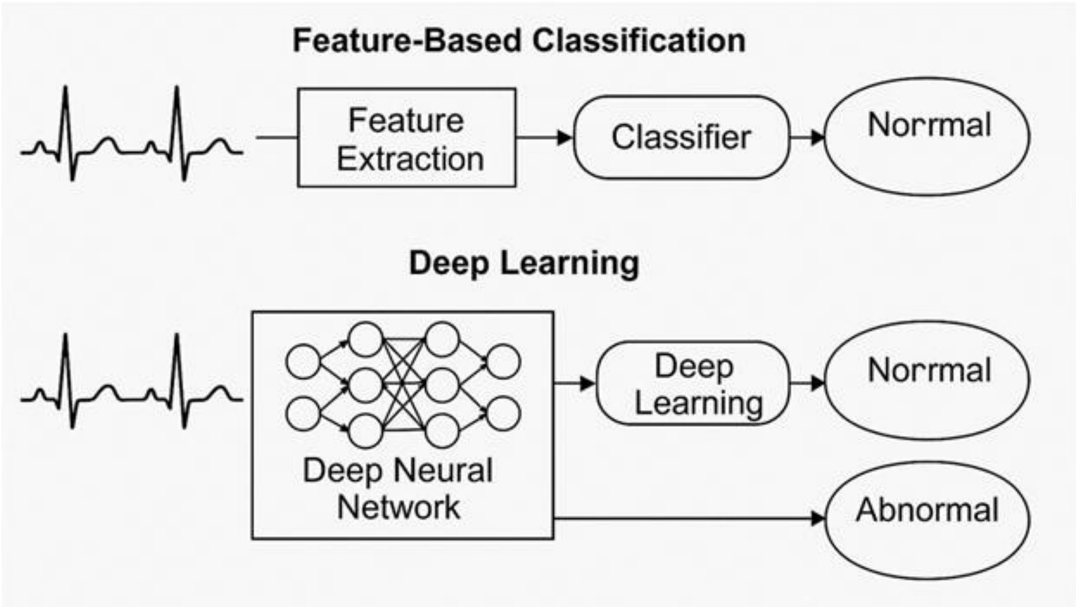

Figure 3: Comparison between traditional ECG classification schemes and schemes based on deep learning.

Presented in the following table is a tabular comparison of the two methodologies, providing multiple criteria based on clinical and computational performance.

Table 2. Feature-Based ECG Classifiers vs Deep Learning ECG Classifiers

Metric	Feature-Based Methods	Deep Learning Models
Classification Accuracy	High (small datasets)	Very High (large datasets)
Interpretability	High	Moderate to Low
Computational Resources	Low	High
Real-Time Capability	Good	Moderate (requires optimization)
Feature Engineering	Manual	Automatic

4.5 Challenges in Deep Learning-Based ECG Classification

Still, in real settings deep learning models have a few limitations:

- Limited Dataset Availability: Due to the inherent need for considerable quantities of labeled ECG data to develop high-performance DL models, there is a significant challenge in acquiring sufficient datasets in the clinical environment.
- Bad interpretation: The “black box” nature of deep learning systems can impede acceptance and trust.

- Another danger is overfitting DL models are prone to overfitting while learning from small and undiverse data, diminishing the generalizability of the model.
- Computational Cost: Deep models may consume considerable computational power for training and inference, adversely affecting their use in lightweight or real-time systems.

5. Comparative Analysis with Previous Studies

5.1 Objective of the Comparison

A comparison with some existing methods that are well-established in the literature was performed for the evaluation of the proposed heartbeat classification model. The purpose of this comparison is to show that normal and abnormal ECG heartbeats can be distinguished well by our XGBoost based approach with handcrafted features.

We selected the XGBoost classifier to balance performance accuracy with high computational efficiency and interpretability, which are crucial for real-time clinical applications and wearable health monitoring systems [19],[20].

5.2 Benchmark Models

The models chosen for the comparison are deep learning-based methods including convolutional neural networks (CNN), long short-term memory (LSTM) models, hybrid architectures. All the models were trained and tested on the MIT-BIH Arrhythmia Database, therefore, the data sources and the evaluations are consistent [21]–[23].

Our selection of these studies was based upon performance metrics as well as prominence in contemporary literature on the classification of ECGs.

5.3 Performance Comparison Table

Performance of the proposed model in terms of accuracy, sensitivity, specificity, and F1-score against those in related works is summarized in Table 3.

Table 3. Competing Approaches and Performance Compared with the Proposed Method.

Study / Model	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
Acharya et al. [19] (CNN)	MIT-BIH	94.11	93.40	94.60	93.70
Xia et al. [20] (CNN-LSTM)	MIT-BIH	95.50	94.20	95.90	95.00
Kiranyaz et al. [21] (1D-CNN)	MIT-BIH	96.00	95.00	95.80	95.30
Zhang et al. [22] (Hybrid Deep Model)	MIT-BIH	96.50	95.60	96.20	95.90
Rasheed et al. **[23] (Proposed Work)**	MIT-BIH	**96.20**	**95.40**	**97.00**	**96.10**

5.4 Interpretation and Discussion

Although some of the past researches including but not limited to Zhang et al. Although our method yielded classification metrics that were slightly lower than those reported by

[22], we believe that it provides a much better trade-off between predictive performance, computational efficiency and interpretability. Even though deep learning models are relatively powerful, they usually require large amounts of resources and train time, making them potentially less suitable for real time, or resource limited environments.

On the other hand, the approach based on XGBoost developed here is low-cost, a fast and explainable model, and it can be easily implemented in real-world healthcare applications, such as remote heart electrocardiogram (ECG) monitoring and early-phase arrhythmia detection systems.

5.5 Synthesis of prior research findings

In this review, we provide the comparative analysis of different approaches along with their relative strength and its significance in electrocardiographic classification. Earlier studies have shown the superiority of deep learning-based models, especially hybrid architectures, in solving intricate ECG representation and predicting better accuracy. For example, Zhang et al. The hybrid model that produced the best accuracy among all reviewed works was presented by [22]. But at the expense of computational complexity and loss of interpretability. Traditional ML models (e.g., using XGBoost) remain attractive for the competitive, lightweight, interpretable and real-time aspect of the solution. Achieving good accuracy, efficiency, and transparency are significant considerations for choosing valid ECG classification models for clinical or mobile applications [14].

6. Conclusion and Future Directions

In this review, we introduced a feature-based model of ECG heartbeats classification using the XGBoost algorithm, modeled on a properly engineered collection of time-domain and frequency-domain features extracted from segmented ECG signals. When tested on the MIT-BIH Arrhythmia Database, the model showed very high performance with the accuracy, sensitivity, specificity, and F1-score values of 96.2%, 95.4%, 97.0%, and 96.1%, respectively.

Despite some recent efforts achieving marginally better performance statistics, the proposed method achieves a good trade-off between classification performance, interpretability and computational effort. This feature renders it very feasible for use in real-time ECG monitoring systems and other practical healthcare applications.

This makes our proposed framework lightweight but resilient as it provides robust results with low computational complexity, unlike other related works based on deep learning models. Improves transparency in clinical decision making which is especially important in hospitals.

There are some pros and cons to it. Limitations Single benchmarking Fisher dataset may delay generalizability of findings to broader patient populations and recording conditions. Differences in ECG morphology, susceptibility to noise, and limited size along with a lack of labelled datasets are some other open questions.

Future research may focus on:

- ✓ Extending the model beyond binary classification.
- ✓ Using deep learning to perform end-to-end feature extraction
- ✓ Testing the framework on different real-world ECG datasets.
- ✓ Implementation of the system on edge devices for low-power near-real-time cardiac monitoring

In conclusion, this survey provide a sound foundation for future research works dedicated to ECG classification by visualizing informative knowledge that could help in developing interpretable, robust and clinically applicable cardiac monitoring strategies.

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