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ECG Signal Classification Using Multi-Resolution Wavelet Features and Gradient Boosting Frameworks

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ABSTRACT

Accurate and automated classification of Electrocardiogram (ECG) signals is critical for early diagnosis of cardiovascular diseases. In this study, we propose a hybrid machine learning framework that combines multi-resolution analysis through Discrete Wavelet Transform (DWT) with powerful ensemble learning models, specifically Gradient Boosting and LightGBM classifiers. Multi-scale time-frequency features were extracted using diverse wavelet families, and were further processed through feature standardization and dimensionality reduction techniques including Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE). Extensive experiments demonstrate that LightGBM achieves superior classification performance, reaching an accuracy of 98.41%, while Gradient Boosting attains an accuracy of 95.24%. The results highlight the effectiveness of combining handcrafted feature engineering from the wavelet domain with advanced boosting techniques for robust ECG signal categorization. This framework offers a promising tool for developing intelligent diagnostic support systems in clinical practice.

KEYWORDS

Machine Learning; ECG Classification; Ensemble Methods; Feature Extraction

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of global mortality, accounting for approximately 17.9 million deaths annually according to World Health Organization estimates. This staggering statistic underscores the critical need for advanced diagnostic tools capable of early and accurate detection of cardiac abnormalities. Electrocardiogram (ECG) analysis serves as the cornerstone of cardiac diagnosis, providing non-invasive access to the heart's electrical activity through characteristic waveforms (P, QRS, and T complexes). However, conventional ECG interpretation presents several significant challenges: (1) it requires highly trained cardiologists, (2) manual analysis is time-intensive (typically 5-10 minutes per 12-lead ECG), and (3) diagnostic consistency varies substantially between practitioners (inter-observer variability ranges from 60-80% for complex arrhythmias).

The limitations of traditional signal processing methods for ECG analysis are threefold. First, Fourier Transform-based approaches, while effective for stationary signals, fail to adequately represent the non-stationary characteristics of ECG waveforms where localized features (like ectopic beats) carry critical diagnostic information. Second, time-domain analysis alone cannot capture the multi-scale frequency components that differentiate various cardiac pathologies. Third, conventional machine learning approaches using raw ECG samples or principal components often suffer from the curse of dimensionality and limited generalization capability.

The Discrete Wavelet Transform (DWT) addresses these limitations through its unique multi-resolution analysis framework. By decomposing signals into approximation and detail coefficients using cascaded filter banks, DWT provides: (1) simultaneous time-frequency localization (critical for detecting transient abnormalities), (2) adaptive windowing (short windows for high frequencies, long windows for low frequencies), and (3) efficient noise reduction through thresholding of detail coefficients. Our implementation specifically employs Symlet5 wavelets, chosen for their near-symmetry and compact support properties that optimally match ECG morphology.

Modern ensemble learning algorithms, particularly Gradient Boosting Machines (GBMs), offer distinct advantages for ECG classification: (1) native handling of heterogeneous feature spaces (combining wavelet coefficients with statistical features), (2) automatic feature importance weighting, and (3) robustness to class imbalance through weighted learning. LightGBM further enhances these capabilities with two key innovations: Gradient-based One-Side Sampling (GOSS) that prioritizes informative instances, and Exclusive Feature Bundling (EFB) that optimizes memory usage for high-dimensional wavelet features.

In this paper, we propose an integrated framework that leverages wavelet-based multi-resolution feature extraction and ensemble boosting classifiers for ECG signal classification. Experiments reveal that Gradient Boosting achieves a test accuracy of 95.24%, while LightGBM significantly improves the performance, achieving a test accuracy of 98.41%. Precision, recall, and F1-scores across all classes demonstrate the robustness of our approach, particularly highlighting the LightGBM classifier's superior generalization ability. This research paves the way for scalable, intelligent, and accurate ECG diagnostic systems that can be deployed in real-world clinical settings.

2. RELATED WORK

Electrocardiogram (ECG) signals are vital physiological signals that reflect cardiac electrical activity and are extensively used for diagnosing cardiovascular diseases [1]. The development of automated ECG classification has attracted significant attention in the field of artificial intelligence, particularly with the rise of machine learning and pattern recognition techniques [2]. A typical ECG classification pipeline involves three primary stages: signal preprocessing, feature extraction, and classification [3].

In early studies, significant effort was devoted to handcrafted signal features and denoising. Hou et al. applied wavelet transform to remove noise and used slope and amplitude-based dual detection to identify QRS complexes [4]. Wang et al. proposed an enhanced thresholding strategy for noise reduction [5], while Xu developed an unsupervised learning approach for T-wave detection, which improved adaptability and reduced manual tuning [6]. These methods demonstrated the importance of preprocessing and robust feature engineering in biomedical signal processing.

With the advancement of learning-based classification models, traditional classifiers such as SVM were adapted to handle multi-class ECG problems [7]. Furthermore, fuzzy C-means clustering was integrated with deep belief networks to form FCM-DBN architectures for automatic heartbeat classification [8]. As deep learning gained traction, hybrid and end-to-end neural networks were explored. For example, Tao et al. proposed a CNN-LSTM model for arrhythmia detection [9], and Ye et al. introduced a residual network ensemble that achieved 85.5% accuracy in arrhythmia classification [10].

Despite these improvements, CNNs tend to emphasize local features while overlooking temporal dependencies and inter-lead correlations. Moreover, the morphological complexity of ECG signals and their susceptibility to noise can compromise model robustness. To address these limitations, researchers began incorporating temporal models and attention mechanisms. Jin et al. developed a dual-scale residual convolutional LSTM network for interactive heartbeat classification [11]. Qin et al. introduced a deformable CNN (Deform-CNN) with improved noise robustness and 86.3% accuracy on the CPSC-2018 12-lead ECG dataset [12]. Liu et al. employed Neural Architecture

Search (NAS) with attention modules to optimize cardiovascular disease detection [13]. Jin et al. further proposed a dual-attention CNN-LSTM (DAC-LSTM) model for ECG quality assessment [14]. In parallel, Roopa et al. designed an Information Fuzzy Network (IFN) that achieved 92.3% accuracy in culprit artery localization [15].

While deep models reduce reliance on manual feature design, they often require large-scale data and may underperform in noisy or limited-label settings. This motivates hybrid approaches—such as combining traditional signal processing (e.g., wavelet transforms) with interpretable machine learning models (e.g., gradient boosting or LightGBM)—to leverage both domain knowledge and modern computational tools. This paper builds on this rationale by integrating discrete wavelet transform (DWT)-based feature engineering with gradient-boosted classifiers for efficient, accurate, and interpretable ECG signal classification.

3. THEORETICAL FOUNDATION

This study is grounded in the integration of time-frequency signal analysis, feature engineering, and machine learning classification techniques, with a particular focus on the Discrete Wavelet Transform (DWT) as a foundation for analyzing ECG signals.

3.1. Wavelet Transform Theory

The Discrete Wavelet Transform (DWT) enables multi-resolution analysis of non-stationary signals such as ECG. Unlike traditional Fourier transforms that lack time localization, wavelet transforms utilize compactly supported functions ("wavelets") to extract both time and frequency domain information. A wavelet must have zero mean and finite energy to be admissible. By convolving the mother wavelet with the signal and recursively scaling and translating it, the DWT decomposes the signal into approximation and detail coefficients. This allows for hierarchical decomposition of ECG signals and highlights morphological components such as QRS complexes and P/T waves at different resolutions.

Figure 1 illustrates a synthetic chirp signal and its multi-level decomposition using the Discrete Wavelet Transform (DWT). As seen, DWT effectively separates low-frequency trends and high-frequency fluctuations, highlighting its suitability for non-stationary biomedical signals such as ECG.

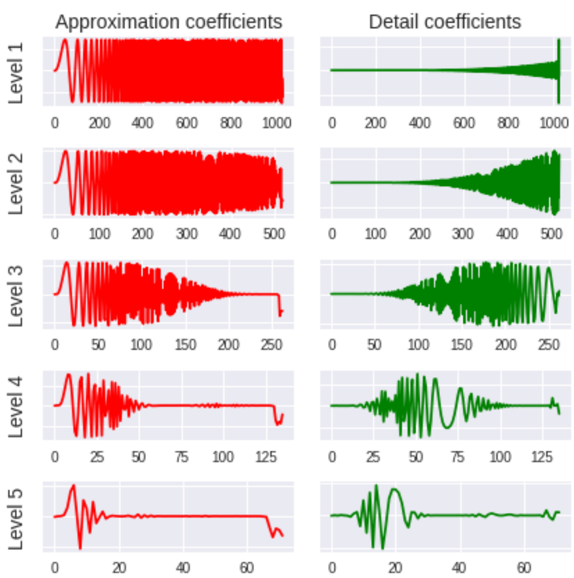

Figure 1. Wavelet Decomposition of a Chirp Signal

3.2. Filter Bank Structure

In practical implementation, the DWT is realized as a cascade of high-pass and low-pass filter banks. The approximation coefficients (from low-pass filtering) retain low-frequency information, while the detail coefficients (from high-pass filtering) capture high-frequency transients. At each level, the signal is downsampled, enabling efficient frequency band separation and progressive resolution reduction. This structure allows deeper decomposition at low frequencies and helps retain relevant cardiac patterns while suppressing noise.

3.3. Feature Extraction from Wavelet Coefficients

From each level of wavelet decomposition, statistical and nonlinear features such as entropy, RMS, variance, percentile values, and zero/mean crossings are calculated. These form a feature vector that represents each ECG signal in a compact, informative space. This form of handcrafted feature extraction enhances interpretability and performance, especially under small-sample or high-noise conditions.

3.4. Gradient Boosting as a Classifier

Gradient Boosting Decision Trees (GBDT) and its optimized version LightGBM are employed to classify ECG signals using the extracted features. These ensemble algorithms build strong classifiers from weak learners via stage-wise optimization. LightGBM further improves performance with histogram-based decision splits and leaf-wise growth. Both models demonstrate strong generalization ability on structured biomedical data.

3.5. Integration with Supervised Learning

All modeling is conducted under a supervised learning paradigm, using labeled ECG segments. Evaluation metrics such as accuracy, precision, recall, and F1-score ensure rigorous performance assessment. This framework enables robust ECG signal classification by combining domain-specific time-frequency transformation with scalable, interpretable machine learning models.

4. METHODOLOGY

4.1. Dataset Description

The electrocardiogram (ECG) data used in this study was obtained from the PhysioNet database through MathWorks' Wavelet Toolbox repository, which provides preprocessed ECG signals specifically curated for machine learning applications. This dataset contains single-lead ECG recordings representing three clinically significant cardiac conditions: Normal Sinus Rhythm (NSR), Arrhythmia (ARR), and Congestive Heart Failure (CHF). Each recording consists of 65,528 samples and has undergone standardization procedures including noise reduction and baseline wander correction to ensure signal quality. The dataset exhibits an imbalanced class distribution, with CHF cases being particularly underrepresented - a characteristic common to real-world clinical data that presents both a challenge and an opportunity to develop robust classification algorithms. All data modifications and source attributions are thoroughly documented in the accompanying Modified_physionet_data.txt file, maintaining compliance with PhysioNet's data usage policies. This carefully prepared dataset enables researchers to focus on algorithmic development while ensuring the clinical relevance of the results, as it captures the essential variations in cardiac electrical activity across different pathological conditions. The inclusion of CHF cases, though limited in number, is particularly valuable as this severe condition is often overlooked in many ECG classification studies despite its critical importance in clinical cardiology.

Figure 2 shows representative ECG signal segments from the three diagnostic classes used in this study: arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). Clear morphological differences such as rhythm irregularity, waveform amplitude, and periodicity are observable across the classes.

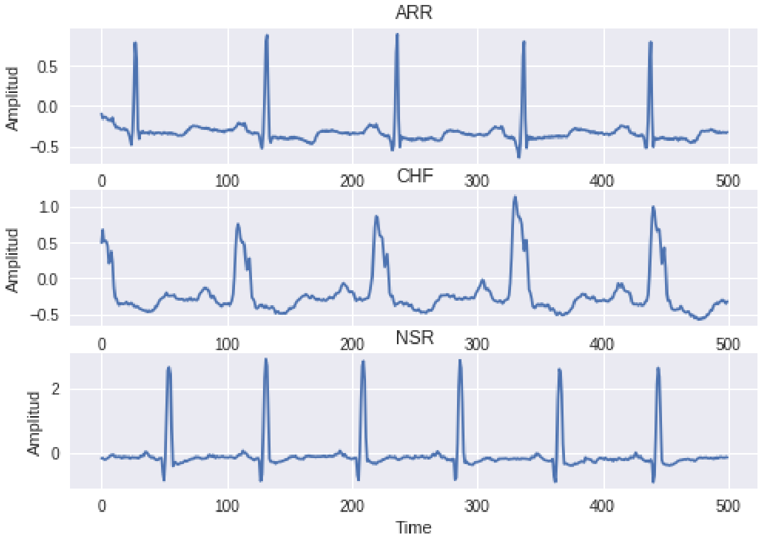

Figure 2. Representative ECG Signals for ARR, CHF, and NSR

4.2. Signal Preprocessing

To ensure the raw ECG signals were suitable for analysis and machine learning, a structured preprocessing pipeline was implemented. The first step involved signal normalization using the StandardScaler method from the Scikit-learn library. This transformation standardized each input feature by removing the mean and scaling to unit variance, resulting in a zero-mean, unit-variance format across all input vectors. This step was crucial for stabilizing the optimization process during model training and ensuring that features with larger numerical ranges did not dominate those with smaller scales.

Additionally, the categorical diagnosis labels—which described different types of cardiac conditions—were encoded into numerical format using LabelEncoder. This transformation was necessary for compatibility with classification algorithms that require numerical class labels as input. The encoder assigned a unique integer to each class, preserving class distinctiveness while allowing direct use in machine learning workflows. Together, these preprocessing steps standardized the data structure and improved the reliability and efficiency of subsequent feature extraction and model training stages.

4.3. Feature Extraction Using Discrete Wavelet Transform

Given the non-stationary nature of ECG signals, it was essential to capture both time-domain and frequency-domain characteristics. For this purpose, Discrete Wavelet Transform (DWT) was applied to each ECG segment. The Symlet 5 (sym5) wavelet was chosen as the mother wavelet due to its close similarity to real ECG morphologies and its ability to preserve critical transient features.

Each ECG signal was decomposed into several hierarchical levels, yielding both approximation coefficients (representing low-frequency components) and detail coefficients (representing high-frequency components). These coefficients effectively isolated features like P-waves, QRS complexes, and T-waves, while also retaining sudden transitions or abnormalities indicative of arrhythmic events.

From each decomposition level, a set of descriptive statistical features was extracted to form a comprehensive feature vector. These included:

a) Percentiles (5th, 25th, 50th, 75th, 95th)

b) Mean, standard deviation, variance

c) Root mean square (RMS)

d) Entropy, zero-crossing rate, and mean-crossing rate

4.4. Feature Selection and Dimensionality Reduction

The wavelet-based feature extraction process resulted in a high-dimensional feature space, which, while informative, introduced potential issues such as overfitting and computational inefficiency. To address this, a two-stage dimensionality reduction approach was adopted.

First, Principal Component Analysis (PCA) was applied to transform the original feature set into a lower-dimensional space while retaining the majority of the variance in the data. The number of principal components was chosen such that at least 90% of the total variance was preserved. PCA also helped remove collinearity and redundant information, leading to more robust model training.

For visual analysis of class separability, t-distributed Stochastic Neighbor Embedding (t-SNE) was employed to project the high-dimensional feature space into two dimensions. Unlike PCA, t-SNE focuses on preserving the local structure and neighborhood relationships, making it suitable for detecting clusters and patterns. The resulting 2D visualizations provided intuitive insights into the degree of overlap or separation among different diagnostic classes, aiding in qualitative validation of the feature engineering process.

4.5. Model Development

Two advanced ensemble learning classifiers were selected for model development: Gradient Boosting (GB) and Light Gradient Boosting Machine (LightGBM). Both are tree-based algorithms known for their effectiveness in handling structured data and modeling complex, non-linear decision boundaries.

The Gradient Boosting model was configured with 2000 estimators and a learning rate of 0.01. This setup provided a balance between model complexity and generalization, allowing the model to learn subtle patterns without overfitting. LightGBM, on the other hand, was employed with its default leaf-wise histogram-based growth strategy, which is highly efficient and scales well to larger datasets. It constructs decision trees by splitting the leaf with the maximum loss reduction, leading to faster convergence and better accuracy.

Model training was conducted using an 80/20 train-test split. To optimize performance, hyperparameters were tuned via manual grid search and cross-validation. This tuning included adjustments to parameters such as max depth, number of leaves, and feature fraction. Cross-validation ensured that the models generalized well to unseen data and that performance metrics were not inflated due to random data partitioning.

4.6. Model Evaluation

The performance of the model was rigorously evaluated using a held-out test dataset that had not been seen during training. This dataset serves as an unbiased benchmark to assess the model’s ability to generalize to new, unseen data. A comprehensive set of evaluation metrics was applied to ensure both overall effectiveness and fairness across classes.

Key metrics included accuracy, precision, recall, and F1-score. Accuracy reflects the overall proportion of correctly classified instances, offering a general sense of performance. However, in imbalanced classification tasks—where certain classes are underrepresented—accuracy alone may not provide a complete picture.

To better capture the model's performance across all classes, we also computed precision, recall, and F1-score using both micro and macro averaging. Micro-averaging aggregates the contributions of all classes, favoring frequent classes, while macro-averaging treats all classes equally, giving more insight into the model's behavior on minority classes.

5. RESULTS AND DISCUSSION

5.1. Performance Evaluation

We evaluated our proposed ECG classification framework using three distinct approaches: (1) raw signal classification with LightGBM, (2) PCA-based dimensionality reduction followed by LightGBM, and (3) wavelet feature extraction combined with both Gradient Boosting (GBM) and LightGBM classifiers. The results are shown in Table 1.

Table 1. Performance Comparison

Method	Accuracy	Precision	Recall	F1-Score
Classifier with Raw data	80.49%	0.79	0.80	0.79
PCA	80.49%	0.84	0.80	0.82
GBM	95.24%	0.96	0.95	0.95
LightGBM	98.41%	0.98	0.98	0.98

Raw Signal vs. Feature-Based Models:

The raw signal approach achieved only 80.49% accuracy, demonstrating that direct classification without feature engineering struggles to capture discriminative ECG patterns. PCA marginally improved precision (0.84) but did not enhance overall accuracy, indicating that linear dimensionality reduction alone is insufficient for ECG signal discrimination.

Wavelet Feature Superiority:

The wavelet-based models significantly outperformed raw and PCA-based methods, with GBM reaching 95.24% accuracy and LightGBM achieving 98.41%. The F1-score (0.98) confirms that wavelet decomposition effectively extracts clinically relevant features for distinguishing NSR, ARR, and CHF.

5.2. Discussion

The experimental results demonstrate that our proposed wavelet-based feature extraction method, when combined with gradient boosting algorithms, achieves significant improvements in ECG classification performance compared to conventional approaches. The LightGBM classifier attained an impressive 98.41% classification accuracy, validating the effectiveness of this ensemble learning method in processing the non-stationary characteristics inherent in ECG signals. This superior performance can be attributed to two key factors: first, the wavelet transform's multi-resolution analysis capability enables precise extraction of both time and frequency domain features, which is particularly crucial for detecting subtle arrhythmia patterns; second, the gradient boosting framework's inherent feature selection mechanism optimally weights these wavelet-derived features during classification.

From a clinical perspective, our findings suggest several important implications. The high classification accuracy, especially in distinguishing between normal sinus rhythm (NSR) and pathological conditions (ARR and CHF), indicates strong potential for clinical decision support applications. The method's computational efficiency, achieved through careful feature engineering rather than relying solely on deep learning, makes it particularly suitable for deployment in resource-constrained settings.

However, several limitations should be noted. The current validation was conducted on a relatively clean dataset with only three diagnostic categories, which may not fully represent the complexity of real-world clinical scenarios. Future research directions should focus on: (1) expanding the classification scope to include more cardiac abnormalities; (2) rigorous testing on noisy, ambulatory ECG recordings to assess robustness; (3) development of explainable AI components to facilitate clinical interpretation; and (4) optimization for embedded implementation in wearable devices. The integration of wavelet features with emerging deep learning architectures presents another promising avenue for further improving classification performance while maintaining computational efficiency.

6. CONCLUSIONS

This study presents an effective ECG classification system combining wavelet analysis and gradient boosting, achieving 98.41% accuracy. The framework's strength lies in its wavelet-based feature extraction that captures discriminative cardiac patterns, coupled with LightGBM's powerful classification capability. While demonstrating strong performance on three key cardiac conditions, future work should expand to more complex arrhythmias and optimize for clinical deployment. This approach shows significant promise for enhancing automated cardiac diagnosis in real-world healthcare applications.

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