Proceedings of the 4th International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/2026.34032

Enhancing Cardiovascular Diseases Prediction with a Novel QRS Relative Energy Ratio Feature

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Abstract. Automatic classification of electrocardiograms (ECG) is of great value for the auxiliary diagnosis of cardiovascular diseases. However, the existing methods still have significant deficiencies in terms of inconsistent feature selection and weak model interpretability. To address these issues, we constructed a feature set that consists of time-domain features and MFCC features, and designed a new feature, termed the relative energy ratio of QRS, to describe the energy distribution characteristics during the cardiac cycle. Based on this, six models, including SVM, KNN, random forest, XGBoost, LightGBM, and CatBoost, were used for classification. The model performance was evaluated through ten-fold cross-validation and an independent test set. The experimental results show that the ensemble learning model performs better overall. After introducing the new features proposed, the accuracy and F1-score of each model have increased. The feature importance analysis also further verified the effectiveness of this feature. In summary, the method presented in this paper not only improves the performance of ECG classification but also enhances the interpretability of the model, which has certain reference value for subsequent clinical applications.

Keywords: Electrocardiogram, Machine learning, QRS complex

1. Introduction

Cardiovascular diseases are the main cause of death nationwide, making early identification and diagnosis critical. Electrocardiogram (ECG) is a non-invasive and convenient technique that records the heart's electrical activity and is widely used in clinical practice. However, the traditional diagnosis relies on manual interpretation by clinicians, which is time-consuming and subject to individual experience, leading to variability in outcomes. This has motivated growing interest in using machine learning and deep learning for automatic ECG classification [1, 5].

In recent years, an increasing number of researches have explored data-driven approaches for ECG classification. Early methods typically extracted time-domain, frequency-domain and morphological features, and then applied classifiers such as support vector machine (SVM), K-nearest neighbor (KNN) or random forest to identify different types of cardiovascular diseases, and the results are quite satisfactory [6-13]. Afterwards, deep learning models, including convolutional neural networks (CNN) and recurrent neural networks (RNN), were introduced to automatically

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DOI: 10.54254/2755-2721/2026.34032

learn feature representations and further improve classification performance [14-16]. Meanwhile, model interpretability has become a concern, with methods like SHAP being used to analyze model decisions and enhance clinical credibility.

Despite this progress, several issues remain. Firstly, feature extraction and selection strategies vary widely across studies, lacking a unified standard and limiting model generalization. Secondly, deep learning models are often treated as black boxes, making clinical adoption difficult. Moreover, most existing features focus on statistical or spectral information, while the energy distribution of key structures in ECG (like the QRS complex) is insufficiently explored, even though such information is closely linked to cardiac abnormalities.

To address these issues, we focused on feature construction. A novel feature, the QRS relative energy ratio, was proposed, which quantifies the energy proportion of the QRS complex within a cardiac cycle, capturing the structural differences under different physiological conditions. Based on this, we constructed a set of ECG signal features and evaluated it with six machine learning models. Experimental results show that adding this feature consistently improves performance across multiple datasets.

Overall, this paper further explores the characteristics of ECG signals and, while maintaining the model's performance, enhances the interpretability of the features. This provides a feasible approach for ECG signals.

2. Introduction of data

In this study, there are three large public datasets being used, including PTB-XL [20-22], MIT-BIH Arrhythmia Database [22, 23] (MIT-BIH) and A large scale 12-lead electrocardiogram database for arrhythmia study [22, 24, 25] (CU-SPH-NFH). Firstly, the PTB-XL dataset comprises 21799 clinical 12-lead ECG records of 10 seconds length from 18869 patients, where 52% are male and 48% are female with ages covering the whole range from 0 to 95 years (median 62 and interquantile range of 22). Secondly, the MIT-BIH consists of 48 hours of two-channel dynamic electrocardiogram recordings, 23 of which are from a random sample (including 60% inpatients and 40% outpatients), and 25 include rare but clinically significant arrhythmias. Thirdly, the CU-SPH-NFH contains 12-lead ECGs of 45,152 patients with a 500 Hz sampling rate that features multiple common rhythms and additional cardiovascular conditions, which are all labeled by professional experts.

3. Methods

A flowchart of the entire experimental process is presented in the Figure 1.

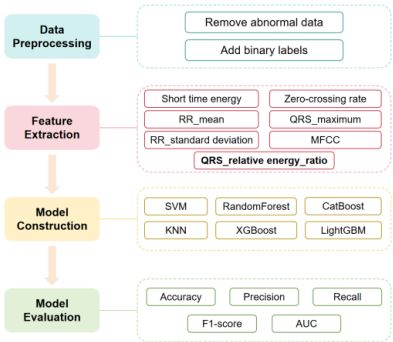

Figure 1. Flowchart of experiment process

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3.1. Data preprocessing

During ECG signal analysis, raw data often have abnormal records and inconsistent annotations, which can hurt model training and classification performance, so data preprocessing is necessary before feature extraction and model building. In this study, preprocessing includes two main steps: removing abnormal data and assigning binary labels.

Firstly, we read and checked the downloaded ECG datasets. Abnormal records, such as format errors or signals that don't look like normal ECG, are removed. which helps keep the data quality and consistency. Secondly, we created binary labels based on the original annotations. Samples with cardiovascular diseases are labeled as 1, while normal samples as 0. This gives us a unified format that works for the later machine learning tasks.

3.2. Feature extraction

Feature extraction is the key step in ECG signal classification, aiming to extract informative representations of cardiac electrical activity from the original signals. In this study, we extracted common features including short time energy, zero-crossing rate, RR interval means and standard deviation, QRS maximum amplitude and MFCC features. In the meantime, a novel feature, termed the QRS relative energy ratio, is proposed to describe the energy contribution of the QRS complex within the heart cycle. Let the ECG signal be $x(n)$, with a sampling length of N , and a sampling frequency of f_s .

3.2.1. Commonly used features

Short time energy can reflect the energy distribution of a signal over time and can be used to measure the signal strength. Signals with higher short time energy usually have more distinct characteristics in the ECG waveform. Zero-crossing rate reflects the frequency of changes in the signal waveform. It is defined as the number of times the signal's sign changes. RR interval mean reflects the average level of heart rate, and RR interval standard deviation reflects the heart rate variability. The QRS complex is the most prominent waveform in the ECG signal, and its maximum amplitude reflects the electrical signal intensity during the ventricular depolarization process. Mel Frequency Cepstral Coefficients, MFCC, is a widely used feature extraction method in speech signal processing. This method first performs short-time Fourier transform (STFT) on the signal to obtain spectral information. Then, it uses a Mel filter bank to perform nonlinear mapping on the frequencies, takes the logarithm of the filtered energy, and finally performs discrete cosine transform (DCT) to obtain MFCC features. In this study, we extracted 13-dimensional feature, and calculates their mean as the final feature.

3.2.2. Self-created feature: QRS relative energy ratio

In a normal ECG signal, QRS complex wave is usually the part with the highest concentration of energy, and it mainly reflects the ventricular depolarization process. When there are pathological changes in the heart, such as myocardial infarction and arrhythmia, the QRS waveform and its energy distribution often undergo alterations. Therefore, we proposed a new feature, QRS relative energy ratio, to describe the energy proportion of the QRS complex wave throughout the entire heart cycle.

Firstly, energy of a single heart cycle is defined as:

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$$E_{beat} = \sum_{n=r_i}^{r_{i+1}} x^2(n) \tag{1}$$

where r_i and $r_{i+1}$are the positions of two adjacent R peaks, respectively.

Then, a window is set near R peak with a width of $\pm w$(in this study $w = 0.05 f_s$), and the energy of QRS complex wave is

$$E_{QRS} = \sum_{n=r_i-w}^{r_i+w} x^2(n) \tag{2}$$

So the QRS relative energy ratio is defined as:

$$R_{QRS} = \frac{E_{QRS}}{E_{beat}+\varepsilon} \tag{3}$$

where $\varepsilon = 1 \times 10^{-8}$.

This feature can measure the energy contribution of QRS complex wave in a single heart cycle. For healthy individuals, the QRS waveform is usually sharp and energy-concentrated, so the ratio is usually high. However, in some cases of cardiovascular diseases, the QRS waveform may become wider or the energy distribution may change, resulting in significant change in the value of this feature. Therefore, this feature can effectively reflect the structural changes in the ECG signal and provide important information for the diagnosis of heart diseases.

3.2.3. Feature matrix construction

At last, we combined all seven features above to construct a complete feature matrix, which is used for the training and classification of subsequent machine learning training.

3.3. Model construction

After feature extraction, classification models are constructed to automatically identify the ECG signals. In this study, six representative machine learning algorithms are adopted, including SVM, KNN, random forest, XGBoost, LightGBM and CatBoost, which covered distance-based and ensemble learning methods.

For training stability, mean imputation and standardization like mean of 1 and unit variance are applied. The models are trained with commonly used settings. Specifically, SVM uses an RBF kernel, KNN uses k=5, random forest uses 100 decision trees, while XGBoost, LightGBM, and CatBoost are based on gradient boosting, which helps capture complex nonlinear relationships.

3.4. Model evaluation

To evaluate model performance objectively, we utilized 10-fold cross validation. The datasets were split into ten subsets randomly. In each round, nine subsets were used for training and the remaining one for validation. This process was repeated ten times, and the average of the results was taken, reducing bias caused by how the data is split and making the evaluation more reliable.

In terms of model performance evaluation, we selected evaluation indicators including accuracy, precision, recall and F1-score. Among them, accuracy shows the proportion of samples that the model classifies correctly, precision shows the reliability of positive class prediction, recall reflects the ability to identify all true positive cases, and F1-score is the harmonic mean of precision and recall.

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During the final model testing experiment, we split the datasets into 80% for training and 20% for testing. And we plotted confusion matrices and ROC curves, and calculated are under curve (AUC) as the main metric. We also conducted feature importance analysis for the tree-based models, enabling a comprehensive comparison in ECG signal classification.

4. Results

4.1. ROC curves

To comprehensively evaluate the distinguishing ability of each classification model in the binary classification task of ECG signal, we plotted the ROC curve of the six models, which are shown in Figure 2.

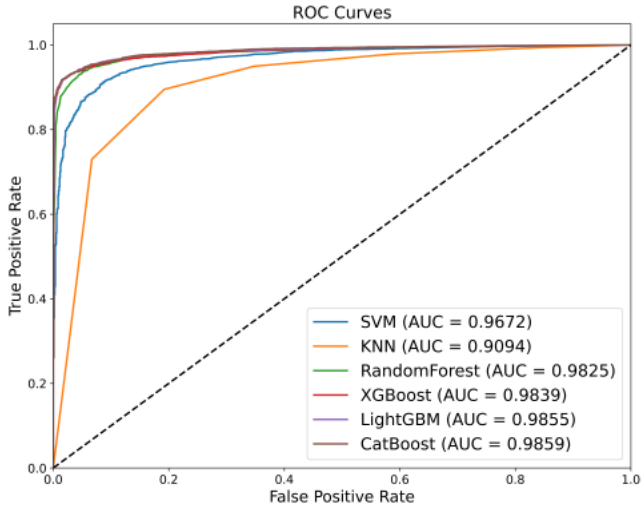

Figure 2. ROC curves. From left to right are PTB-XL, MIT-BIH and CU-SPH-NFH, respectively

The ROC curve plots the true positive rate against the false positive rate under varying thresholds. All models perform significantly above the random baseline, indicating good classification ability. Among them, ensemble learning models perform better than traditional methods do, with curves closer to the top-left corner. In terms of AUC, the gradient boosting models give values closer to 1, which indicates that their performance in identifying intricate feature combinations and capturing hidden disease patterns in ECG signals is stronger.

4.2. Model performance

The evaluation indicators of each model are listed in Table 1, Table 2 and Table 3. And the data will be rounded in four decimal places.

Table 1. Evaluation indicators on PTB-XL with QRS relative energy ratio

PTB-XL				
	Accuracy	Precision	Recall	F1-score
SVM	0.8200	0.8149	0.8167	0.8157
KNN	0.7146	0.7283	0.7307	0.7144
Random Forest	0.8073	0.8054	0.7958	0.7993

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Table 1. (continued)

XGBoost	0.8227	0.8180	0.8180	0.8180
LightGBM	0.8268	0.8223	0.8217	0.8220
CatBoost	0.8294	0.8247	0.8256	0.8251

Table 2. Evaluation indicators on MIT-BIH with QRS relative energy ratio

MIT-BIH				
	Accuracy	Precision	Recall	F1-score
SVM	0.9730	0.9754	0.9639	0.9693
KNN	0.9713	0.9734	0.9620	0.9674
Random Forest	0.9714	0.9728	0.9628	0.9676
XGBoost	0.9752	0.9756	0.9685	0.9719
LightGBM	0.9686	0.9694	0.9598	0.9644
CatBoost	0.9771	0.9779	0.9705	0.9740

Table 3. Evaluation indicators on CU-SPH-NFH with QRS relative energy ratio

CU-SPH-NFH				
	Accuracy	Precision	Recall	F1-score
SVM	0.9351	0.8632	0.8454	0.8539
KNN	0.9079	0.7995	0.7888	0.7940
Random Forest	0.9516	0.8934	0.8938	0.8936
XGBoost	0.9554	0.8994	0.9066	0.9029
LightGBM	0.9578	0.9042	0.9125	0.9083
CatBoost	0.9571	0.9024	0.9111	0.9067

From the data in the table, it can be seen that ensemble learning models outperform traditional models in overall performance. Across accuracy, precision, recall, and F1-score, the gradient boosting models consistently achieve the best or near-best results, especially on more complex datasets such as PTB-XL and CU-SPH-NFH. For example, CatBoost attains the highest F1-score (0.8251) on PTB-XL.

In contrast, KNN performs the worst, particularly on high-dimensional data (F1-score 0.7144 on PTB-XL). This suggests that KNN is sensitive to noise and data distribution. Random Forest shows stable but suboptimal performance. Besides, SVM performs better than KNN, but doesn't reach the level of the gradient boosting models.

By comparing and analyzing the experiment results of different databases, it can be found that as the complexity of the data increases, the performance gaps between models become more significant. This indicates that gradient boosting methods have an advantage in modeling complex nonlinear relationships. Overall, gradient boosting models show the best performance in ECG classification tasks.

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4.3. Effectiveness of self-created feature

To verify the effectiveness of the self-created feature in classification task, we conducted a ranking analysis based on the feature importance extracted from the tree models, and the feature importance ranking charts plotted are shown in Figure 3.

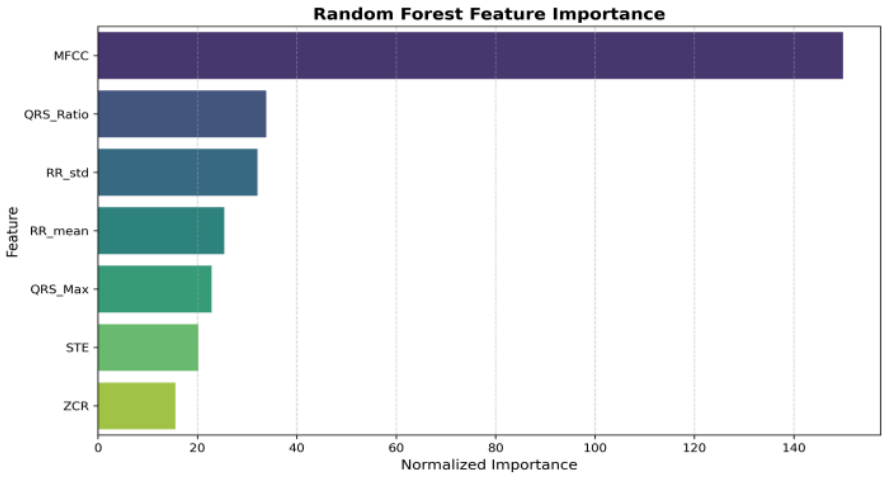

Figure 3. Feature importance ranking charts

The results of feature importance analysis show that different features contribute quite differently. Among them, the proposed QRS relative energy ranks the highest except MFCC features, indicating that it can effectively represent the critical pathological change information in the ECG signals: the QRS complex wave reflects the ventricular depolarization process, and the change of its energy ratio can, to some extent, distinguish normal from abnormal ECG signals. Therefore, this feature can strengthen the models' sensitivity to disease characteristics and improve the classification performance of the models.

4.4. Ablation study

4.4.1. ROC curves comparison

The ROC curves of ablation study as shown in Figure 4.

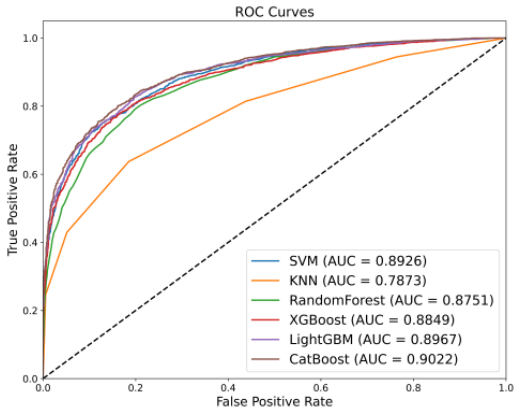

Figure 4. ROC curves without self-created feature. From left to right are PTB-XL, MIT-BIH and CU-SPH-NFH, respectively

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By observing the ROC curves with and without the self-created feature, it can be found that the ROC curve with the self-created feature shift to the left top corner, and AUC increases, which states that the distinguishing ability of all models has improved.

4.4.2. Model performance comparison

The evaluation indicators of each model in the ablation study are listed in Table 4, Table 5 and Table 6, and the data will be rounded in four decimal places.

Table 4. Evaluation indicators on PTB-XL without QRS relative energy ratio

PTB-XL				
	Accuracy	Precision	Recall	F1-score
SVM	0.8068	0.8014	0.8039	0.8025
KNN	0.7103	0.7223	0.7253	0.7101
Random Forest	0.7902	0.7864	0.7798	0.7823
XGBoost	0.8012	0.7958	0.7966	0.7961
LightGBM	0.8091	0.8041	0.8040	0.8039
CatBoost	0.8138	0.8087	0.8101	0.8093

Table 5. Evaluation indicators on MIT-BIH without QRS relative energy ratio

MIT-BIH				
	Accuracy	Precision	Recall	F1-score
SVM	0.9671	0.9704	0.9556	0.9625
KNN	0.9679	0.9699	0.9578	0.9635
Random Forest	0.9654	0.9680	0.9540	0.9605
XGBoost	0.9692	0.9697	0.9608	0.9650
LightGBM	0.9625	0.9636	0.9516	0.9572
CatBoost	0.9716	0.9729	0.9630	0.9677

Table 6. Evaluation indicators on CU-SPH-NFH without QRS relative energy ratio

CU-SPH-NFH				
	Accuracy	Precision	Recall	F1-score
SVM	0.9348	0.8627	0.8444	0.8531
KNN	0.9065	0.7972	0.7820	0.7892
Random Forest	0.9493	0.8865	0.8923	0.8893
XGBoost	0.9540	0.8956	0.9044	0.8999
LightGBM	0.9558	0.8983	0.9104	0.9043
CatBoost	0.9555	0.8980	0.9094	0.9036

As it can be seen form the above tables, after introducing the self-created features, all the evaluation indicators increase, indicating that the feature can effectively enhance the models' ability to identify abnormal ECG signals.

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4.4.3. Result analysis

The results of ablation study show that introducing the proposed feature improves performance on all datasets. The biggest enhancement appears on PTB-XL, where accuracy and F1-score increase by about 1.5%, which suggests the feature works well under complex and noisy conditions. On MIT-BIH, the baseline performance is already high, so the improvement is smaller, which is about 0.6%, but is still consistent. While on CU-SPH-NFH, the improvement is slight but stable.

Overall, the QRS relative energy ratio can consistently enhance model performance, whose effect is relatively most obvious on complicated datasets, which confirms that it helps extract discriminative ECG features.

5. Conclusion

This paper proposes an analysis method based on multi-feature fusion for the automatic classification of ECG signals. Existing studies have problems such as the lack of a unified feature system and poor model interpretability. To address these problems, we added a new feature, namely the QRS relative energy ratio, to describe the energy distribution of key wavebands during the cardiac cycle.

Experimental results show that different models can achieve good classification effects in this task. Among them, ensemble learning methods perform more stably. They can more effectively learn the complex patterns in ECG signals. We also conducted ablation studies, the results of which show that adding our new feature improves the accuracy and F1 score of each model. This means the feature helps to distinguish normal and abnormal ECG signals. Feature importance analysis also indicates that this feature contributes significantly to the decision-making process of the model.

Generally, our feature system not only improves the classification performance but also has certain interpretability. It provides a feasible idea for automatic ECG signal analysis. Future work can consider expanding the data sources, combining deep learning methods and multimodal information, and striving to improve the generalization ability and application value of the model in actual clinical scenarios.

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