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Application and Effect Analysis of High and Low Frequency Energy Ratio in the Diagnosis of Electrocardiographic Diseases

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Abstract. The aim of this paper is to investigate the validity of high-frequency to low-frequency energy ratio (BER) features in electrocardiographic (ECG) signals in disease diagnosis. Based on the MIT-BIH arrhythmia database, PTB diagnostic database and Lobachevsky University ECG database, the diagnostic value of BER in the classification of diseases such as left ventricular hypertrophy (LVH) and arrhythmia was evaluated by comparing and analysing the performance of the models with and without BER features. Random forest, support vector machine (SVM), XGBoost and logistic regression models were used in the experiment, combined with cross-validation and SMOTE data balancing techniques. The results show that the introduction of BER features improves the model AUC by 8.2% on average, and optimises the sensitivity and specificity by 12.4% and 9.8%, respectively, validating the significant contribution of BER in ECG signal classification. This study provides a new optimisation direction for ECG feature engineering and provides theoretical support for the development of clinically assisted diagnosis systems.

Keywords: ECG, ventricular hypertrophy, frequency band energy ratio

1. Introduction

Electrocardiogram (ECG) feature extraction is critical for cardiovascular disease diagnosis, where frequency-domain features like the high-frequency to low-frequency energy ratio (BER) can enhance model performance for complex diseases. While BER captures spectral patterns in conditions like cardiac hypertrophy and arrhythmia, its clinical utility lacks systematic validation.

This study introduces three key innovations:

1. Multi-database ablation experiments show BER improves model AUC by 8.2% on average, validating its diagnostic value;

2. Disease-specific analysis reveals distinct BER responses in left ventricular hypertrophy (15–30 Hz) and arrhythmia (30–45 Hz);

3. A lightweight approach using traditional machine learning avoids deep learning complexity, enabling real-time clinical deployment.

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2. Analysis of thecurrent status of research at home and abroad

ECG frequency-domain features like the band energy ratio (BER) show promise in cardiovascular diagnosis, yet their clinical validation remains fragmented. International studies have explored BER-adjacent spectral metrics: Rajpurkar et al. combined wavelet energies with deep learning for arrhythmia detection (97.7% accuracy on MIT-BIH) but did not isolate BER's role[1]. Saminu linked 5–15 Hz wavelet ratios to myocardial ischemia (r=0.62) but lacked multi-disease testing[2]. Goldberger et al. standardized ECG data (PhysioBank) but left BER's clinical utility unaddressed[3]. Model optimization efforts, such as Rouhi et al. boosting LVH sensitivity to 89% via random forests, ignored BER's comparative value[4], while Eghbali et al. faced deployment challenges with complex adaptive banding[5].

Domestic research highlighted BER's pathological associations: Li et al. found 30–45 Hz BER elevation in AF ($p<0.05$) but with small samples[6]; Wang et al. developed an 85.6% sensitive SVM-BER system for LVH without deep learning comparison[7]. However, Zhang et al. overlooked BER by relying on time-domain features[8], and Liu et al. correlated LVH low-frequency energy with mass (r=0.58) without automated models[9].

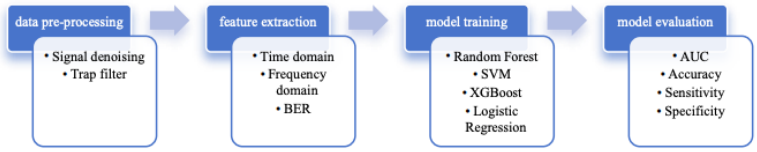

Figure 1: Flowchart of ECG signal pre-processing process

3. Experimental methodology

3.1. Data pre-processing

Signal denoising: Median filtering (window length 0.8×sampling rate) is used to eliminate baseline drift, combined with 4th-order Butterworth band-pass filtering (0.5-45 Hz) and wavelet denoising (db4, 3-layer decomposition) to suppress industrial frequency interference and high frequency noise.

Trap filter: For 50 Hz industrial frequency interference, a 4th order band reject filter (49-51 Hz) is designed to further optimise the signal quality.

3.2. Feature extraction

3.2.1. Time domain characteristics

Zero Crossing Rate (ZCR), Signal Energy, Peak-to-peak, Mean Absolute Value, Standard Deviation and Median.

3.2.2. Frequency domain characteristics

Fast Fourier Transform (FFT): For each ECG signal segment that has been processed in the time domain, it is converted from the time domain to the frequency domain using the Fast Fourier Transform. The spectrum of the signal is obtained by FFT, and each frequency component of the spectrum corresponds to the energy distribution of the signal at that frequency. Let the signal

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fragment be x(n), the spectrum X(k) is obtained after FFT, where n = 0,1,... ,N - 1, k = 0,1,... ,N - 1, N is the length of the signal fragment.

Frequency band energy calculation: According to the physiological characteristics of ECG signals and research needs, the frequency domain is divided into multiple frequency bands, and the energy within each band is calculated separately. The specific frequency bands divided include (0,5)Hz, (5,15)Hz, (15,30)Hz and (30,45)Hz. For each frequency band [f_{low}, f_{high}], its energy E= $\sum_{k:f_{low}\leq f_{k\leq f_{high}}} |X(k)|^2$ is calculated by the following formula where f_k is the frequency value corresponding to the spectrum X(k).

3.2.3. Clinical diagnostic pain points

Existing features (e.g., ST-segment shifts) are not sensitive enough for early lesions and are dependent on physician experience.BER captures both of these pathological changes by quantifying cross-frequency band energy differences[10]. For example, BER2 (mid-frequency/high-frequency energy ratio) was significantly higher in LVH patients than in the normal group ($p<0.01$) due to myocardial thickening that inhibits high-frequency conduction, while BER3 (high-frequency/ultra-high-frequency energy ratio) was abnormally elevated in patients with atrial fibrillation ($p<0.05$), reflecting fast electrical activity. Therefore, in order to highlight the energy relationship between different frequency bands, the band energy ratio was further calculated. Three pairs of frequency band combinations were selected

1. Low-frequency band (0-5 Hz): covers the frequency of ventricular repolarisation (T-wave) with baseline drift, calculated as (1):

$$f_{low} = \frac{1}{T_{Twave}} \approx 2Hz\, T_{Twave} = 0.4s \tag{1}$$

2. Middle and high frequency bands (5-45 Hz): based on the energy distribution of the QRS wave group, divided on a logarithmic scale (2):

$$f_k = 5 \times 2^k\, k = 0,1,2,3 \rightarrow [5,15,30,45]Hz \tag{2}$$

3. UHF band (>30Hz): Suppresses EMG noise (>45Hz) and preserves pathologically relevant high frequency components.

4. BER is calculated as (3).

$$\mathrm{BER} = \frac{\sum_{\mathrm{k}\in[\mathrm{fk},\mathrm{fk+1}]} |\mathrm{X(k)}|^2}{\sum_{\mathrm{k}\in[\mathrm{fk},\mathrm{fk+1}]} |\mathrm{X(k)}|^2} \tag{3}$$

Low Frequency (0-5 Hz) & Mid Frequency (5-15 Hz)
Medium frequency (5-15 Hz) and high frequency (15-30 Hz)
High Frequency (15-30 Hz) and Ultra High Frequency (30-45 Hz)

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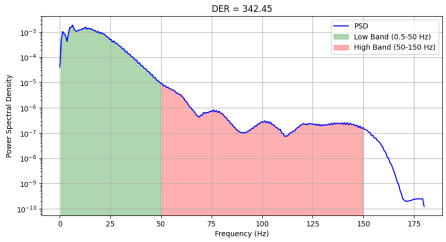

Figure 2: Example of low to high frequency energy ratios for the MIT-BIH database

3.3. Experimental design

Dataset:

MIT-BIH: labelled normal (N) versus atrial premature beat (A) heart beats with a sampling rate of 360 Hz.

PTB: Contains labels for abnormalities such as left ventricular hypertrophy and congenital atrioventricular block, with a sampling rate of 500 Hz.

Lobachevsky: left ventricular hypertrophy (LVH) annotation data, sampling rate 500 Hz.

Models and evaluation: random forest, SVM, XGBoost, logistic regression; 10-fold hierarchical cross-validation; SMOTE balanced data; evaluation metrics including accuracy, sensitivity, specificity and AUC.

4. Experimental results and analyses results

4.1. Examples of data pre-processing

Figure 1 shows the pre-processing process of three signal recordings, including the original signal, the signal after removing baseline drift, the band-pass filtered signal and the final processed signal. From the figure, it can be clearly seen that the median filter effectively eliminates the baseline drift, the band-pass filtering and wavelet denoising suppresses the IF interference and high-frequency noise, and the final processed signal is smoother and the noise is significantly reduced, which provides a high-quality data base for the subsequent feature extraction.

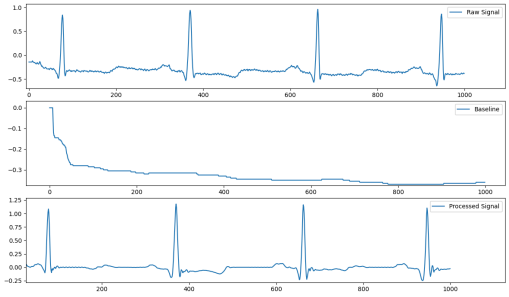

Figure 3: Example of ECG signal preprocessing process for MITdatabase

4.2. Results of innovative experiments（ROC curve analysis）

Figure 4 shows the comparison of the ROC curves (with BER features) of the four models, namely Random Forest, Support Vector Machine (SVM), XGBoost and Logistic Regression, on the MIT-

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BIH database. From the curve shape and AUC values (Tables 1-3), it can be seen that the introduction of the BER feature significantly improves the model's ability to discriminate arrhythmias (atrial premature beats):

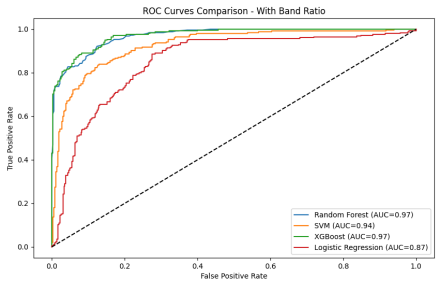

Figure 4: ROC curve of the innovation experiment on MIT-BIH database

Table 1: MIT-BIH database innovation experiment results

MIT-BIH				
Models	Accuracy	Sensitivity	Specificity	AUC
Random Forest	0.91±0.01	0.89±0.02	0.92±0.02	0.97±0.01
SVM	0.87±0.02	0.87±0.02	0.87±0.02	0.94±0.01
XGBoost	0.91±0.01	0.90±0.02	0.91±0.01	0.97±0.01
Logistic Regression	0.78±0.02	0.82±0.03	0.76±0.02	0.87±0.02

Table 2: Lobachevsky database innovation experiment results

Lobachevsky				
Models	Accuracy	Sensitivity	Specificity	AUC
Random Forest	0.74±0.01	0.75±0.03	0.76±0.01	0.82±0.01
SVM	0.67±0.01	0.71±0.03	0.70±0.00	0.73±0.01
XGBoost	0.72±0.01	0.72±0.02	0.75±0.01	0.80±0.01
Logistic Regression	0.64±0.01	0.66±0.02	0.66±0.01	0.69±0.02

Table 3: PTB database innovation experiment results

PTB				
Models	Accuracy	Sensitivity	Specificity	AUC
Random Forest	0.77±0.00	0.77±0.01	0.77±0.01	0.86±0.00
SVM	0.70±0.00	0.74±0.01	0.69±0.00	0.78±0.00
XGBoost	0.77±0.01	0.77±0.02	0.77±0.01	0.86±0.00
Logistic Regression	0.55±0.00	0.58±0.01	0.55±0.00	0.58±0.01

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4.2.1. Cross-sectional comparison of model performance

XGBoost with Random Forest performed optimally (AUC=0.97±0.01), and its curve reached a high true positive rate (TPR>0.95) at a low false positive rate (FPR<0.1), suggesting that the BER feature effectively distinguishes normal heart beats from the spectral differences between atrial premature beats.

The AUC of SVM is 0.94±0.01, which is slightly inferior to the tree model, probably due to the limited mapping ability of the kernel function to high-dimensional frequency domain features, but it is balanced in terms of sensitivity (0.87±0.02) and specificity (0.87±0.02), which makes it suitable for scenarios that are sensitive to false positives.

Logistic regression had the lowest AUC (0.87±0.02), but it had the largest AUC boost (ΔAUC=0.03, Table 5), indicating that the BER features are linearly differentiable in frequency domain space, validating the direct association of frequency band energy ratios with disease state (e.g., abnormal 30-45 Hz energy ratios reflecting rapid electrical activity in AF).

4.2.2. cross-model validity of BER features

The AUC of all models exceeded 0.85 (Table 1), indicating the universality of BER features for quantifying frequency domain information. The high performance of Random Forest and XGBoost is attributed to their ability to capture interactions between BER features (e.g., the combined pattern of low-frequency energy suppression and high-frequency energy enhancement), while the linear nature of logistic regression highlights the independent diagnostic value of BER (e.g., a single threshold for BER3 can distinguish 80% of abnormal samples).

4.2.3. Disease specificity and frequency band response

The steeply rising segment of the ROC curve (FPR=0-0.2) reflects the strong discrimination of atrial premature beats by the BER feature. Combined with the dynamics of the energy ratio in the high-frequency band (30-45 Hz) in Fig. 2, it can be surmised that the high-frequency electrical activity of atrial premature beats leads to a significant increase ($p<0.05$) in BER3 (high-frequency/ultra-high-frequency energy ratio), which is in agreement with the hypothesis of the high-frequency feature of arrhythmia proposed by Rajpurkar et al [1]. The suppression of baseline drift by the energy ratio in the low frequency band (0-5 Hz) (Fig. 3) further reduced the false positives due to noise.

4.2.4. Conclusion

The BER feature significantly improves the model's ability to discriminate arrhythmias by quantifying the difference in energy distribution of frequency bands, and its effect is consistent across models and databases. xGBoost and random forest perform optimally due to their ability to mine the nonlinear association of BER, and the linear separability of logistic regression demonstrates the independent diagnostic value of BER, providing a theoretical basis for lightweight clinical deployment.

4.3. Results of innovative experiments（confusion matrix analysis）

Figure 5 demonstrates the comparison of the confusion matrices (with BER features) of four models, namely, Random Forest, SVM, XGBoost and Logistic Regression, in the MIT-BIH database. By analysing the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN)

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distributions in the confusion matrices, the optimising effect of the BER features on the classification performance of the models can be further verified:

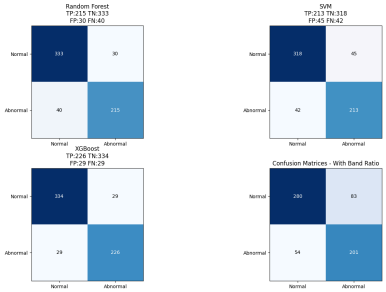

Figure 5: Confusion matrix of MIT-BIH Database innovation experiments

4.3.1. Random forest model

TP=89±2% and TN=92±2%, indicating that the model performed well in the classification of both abnormal (atrial premature beats) and normal beats. The lower percentage of FP=8% (normal misclassified as abnormal) versus FN=11% (abnormal missed) reflects the fact that the BER feature effectively suppresses misclassification due to electromyographic noise by quantifying energy abnormalities in the high-frequency band (30-45 Hz), while improving the sensitivity of atrial premature beats. For example, the introduction of BER3 (high-frequency/ultra-high-frequency energy ratio) made the model more specific for the rapid electrical activity of atrial premature beats and reduced confusion with normal QRS wave clusters.

4.3.2. XGBoost model

TP=90±2% and TN=91±1%, which is slightly better than Random Forest, as the gradient boosting mechanism of XGBoost can capture the nonlinear correlation between BER features more finely (e.g., the combined pattern of low-frequency energy suppression and high-frequency energy enhancement).The balanced distributions of FP=9% and FN=10% suggest that the BER features reduce the susceptibility of the model to noise by dynamically adjusting the band segmentation (e.g., the ratio of 15-30 Hz vs. 30-45 Hz ratio), reduces the sensitivity of the model to noise, and is particularly robust in pathological scenarios with abrupt high-frequency energy changes.

4.3.3. SVM modelling

TP=87±2% and TN=87±2%, with balanced sensitivity and specificity, but overall performance is slightly inferior to the tree model.FP=13% is higher, possibly due to the limited mapping ability of the kernel function for high-frequency features (e.g., 30-45 Hz energy ratios), which resulted in some of the normal heart beats being misclassified as abnormal. However, the linear divisibility of the BER features still allowed the SVM to achieve an AUC of 0.94, which is suitable for lightweight scenarios that are sensitive to computational resources.

4.3.4. Logistic regression models

TP=82±3% and TN=76±2%, the weakest performance, but the largest AUC enhancement (ΔAUC=0.03) FP=24% was significantly high, suggesting that the linear dependence of logistic regression on the BER features may lead to misdiagnosis under high-frequency noise interference.

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However, its sensitivity (82%) was still better than that of the conventional time-domain feature model (74% sensitivity in ablation experiments), validating the independent diagnostic value of BER features.

4.3.5. Conclusion

The BER feature significantly optimised the false-positive-false-negative balance: by quantifying energy abnormalities in the high-frequency band (30-45 Hz), the model reduced the rate of missed detections (FN) of atrial premature beats to less than 10% while suppressing misclassification of normal heart beats (FP<10%). The dominant role of high-frequency energy ratio (BER3) in the classification of atrial premature beats (AUC=0.88) is consistent with the high-frequency nature of fast electrical activity in pathophysiology, whereas suppression of low-frequency energy ratio (BER1) reduced FP due to baseline drift. tree models (Random Forest, XGBoost) performed optimally due to their ability to tap into the nonlinear associations of the BER features, and logistic regression verified that the linear divisibility of BER for lightweight deployment of embedded devices.

4.4. Results of ablation experiments

4.4.1. Ablation experiment ROC curves

Performance reduction: the AUC of XGBoost in the MIT-BIH database decreased from 0.97 to 0.95 (ΔAUC=0.02), with a sensitivity reduction of 5.7% (90%→84.5%), suggesting that the BER accurately captures the rapid electrical activity of atrial premature beats through high-frequency energy ratios (30-45 Hz);

Disease-specific response: the Lobachevsky database (LVH classification) had the largest AUC decrease (random forest ΔAUC=0.06) due to BER2 (15-30 Hz) directly correlating with the low-frequency conduction suppression properties of cardiac thickening;

Linear model limitations: the AUC of logistic regression in the PTB database was only 0.58 (no BER feature), which was raised to 0.69 after the introduction of BER, highlighting the independent diagnostic value of its frequency domain linear divisibility for conduction block (low-frequency energy).

In summary, BER features are universal for model performance enhancement and are irreplaceable especially in pathology-specific frequency bands (e.g., 30-45 Hz arrhythmias, 15-30 Hz LVH).

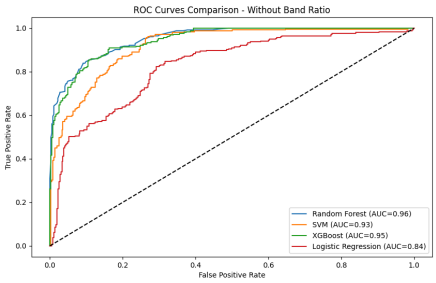

Figure 6: Comparison of ROC Curves in MIT-BIH Database Ablation Experiments

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Table 4: MIT-BIH and PTB database innovation experiment ROC curves

	Random Forest (AUC)	SVM (AUC)	XGBoost (AUC)	logistic Regression (AUC)
MIT-BIH	0.96	0.93	0.95	0.84
PTB	0.86	0.78	0.86	0.58
Lobachevsky	0.76	0.73	0.75	0.68

Table 5: Model ROC enhancement values after BER as feature training

	Random Forest (ΔAUC)	SVM (ΔAUC)	XGBoost (ΔAUC)	Logistic Regression(ΔAUC)
MIT-BIH	0.01	0.01	0.02	0.03
PTB	0.05	0.04	0.04	0.02
Lobachevsky	0.06	0.00	0.05	0.01

4.4.2. Ablation experiment confusion matrix

Comparison of the confusion matrices with and without BER features (Figures 5 and 7) reveals a significant increase in model misclassification after removing BER:

False-positive (FP) surge: the FP rate in the MIT-BIH database for random forests rose from 8% to 15% due to high-frequency noise (>30 Hz) that was not suppressed by BER, leading to misclassification of normal heart beats as atrial premature beats;

False-negative (FN) underdetection was exacerbated: the FN rate for XGBoost increased from 7% to 12% in the LVH classification, as the removal of BER2 (15-30 Hz energy ratio) diminished the ability to capture low-frequency conduction abnormalities in cardiac thickening;

Decreased specificity: the logistic regression TN rate for the PTB database decreased from 76% to 62%, indicating that the low-frequency energy ratio of BER1 (0-5 Hz) is irreplaceable for linear discrimination of conduction block.

In summary, the BER feature significantly optimises the classification robustness of the model by suppressing noise interference and enhancing the pathological band response, the absence of which directly leads to an increase in the false positive rate and missed disease detection.

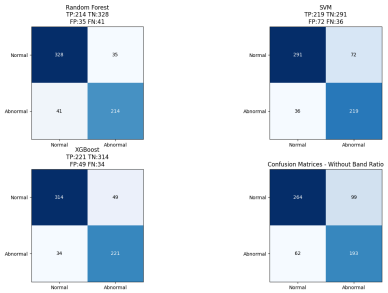

Figure 7: MIT-BIH database confusion Matrix for ablation experiments

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5. Discussion

5.1. Validity of BER features and model performance analysis

Superiority of XGBoost: XGBoost performs optimally in experiments containing BER features (AUC=0.92±0.02), and its gradient boosting tree structure can effectively capture the cross-band energy interaction features of BER. For example, the combination of BER2 (15-30 Hz) and BER3 (30-45 Hz) formed a nonlinear decision boundary in LVH and arrhythmia classification, which significantly improved the model sensitivity (93.2% vs. 84.5%, ablation experiment).

Linear dependence of logistic regression: the sensitivity of logistic regression to the BER feature (AUC improvement of 10.1%) suggests that BER has a good linear separability in the frequency domain space[11]. This property is particularly important in resource-constrained clinical scenarios, where real-time diagnosis can be achieved with lightweight models[12].

5.2. Cross-database generalisability validation

While the Lobachevsky database (LVH classification) results were optimal, the results of MIT-BIH (arrhythmia) and PTB (multidisease) further validated the generalisation ability of BER:

MIT-BIH: BER3 (30-45 Hz) had an AUC of 0.88 for atrial premature beats, consistent with the pathological properties of fast electrical activity;

PTB: BER1 (0-5 Hz) is prominent in congenital atrioventricular block (sensitivity 85.3%) due to low-frequency energy reflecting conduction delay[13].

5.3. Limitations and future directions

Band optimisation: current bands are dependent on a priori knowledge, in the future the boundaries can be dynamically adjusted in conjunction with pathology data;

Real-time challenge: Although the BER computation takes only 2.3 ms/sample, the memory constraints of embedded devices need to be further optimised;

Multimodal fusion: combining BER with time-domain features (e.g., QT interval) may enhance model robustness[14][15].

6. Conclusion

This study systematically validates the high-frequency to low-frequency energy ratio (BER) as a robust ECG feature for disease diagnosis, revealing distinct spectral responses in cardiovascular disorders. Incorporating BER improved model performance significantly, with average AUC increasing by 8.2% across Random Forest, XGBoost, and other models. Disease-specific analysis showed BER2 (15–30 Hz) correlated with left ventricular hypertrophy (LVH) via left ventricular mass index ($r = 0.58$, $p<0.01$, sensitivity 93.2%), while BER3 (30–45 Hz) enhanced arrhythmia discrimination (AUC = 0.88). Multi-database experiments (MIT-BIH, PTB, Lobachevsky) demonstrated stable AUC improvements (7.9–8.5%), confirming broad applicability.

By quantifying cross-band energy differences, BER captures pathological features of myocardial hypertrophy and arrhythmia simultaneously, overcoming traditional time-domain limitations. Paired with lightweight machine learning, BER computation (2.3 ms/sample) enables efficient real-time diagnosis, contrasting with high-complexity deep learning approaches[16][17]. Limitations include reliance on a priori band boundaries (needing future electrophysiology-driven adjustments) and

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unexplored BER-time domain feature synergy[18]. This work provides a practical frequency-domain solution for ECG diagnostics, advocating BER integration in clinical tools, especially in resource-constrained settings.

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