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International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

A Comparative Study of Time-Domain, Wavelet, And Morphological Features for ECG Beat Classification Using Random Forest

Priyanka Jha [1], Neelu [2], Neha Choudhary [3], Prerna[4], Shruti Verma[5], Akriti [6]

[1]Assistant Professor, Department of Electronics and Communication Engineering, Government Engineering College Vaishali, 844115, Bihar, India, Email: priyanka.gecv@gmail.com
[2]Assistant Professor, Department of Electronics and Communication Engineering, Government Engineering College Buxar, 802103, Bihar, India, Email:neelukri1119@gmail.com
[3]Assistant Professor, Department of Electronics and Communication Engineering, Government Engineering College Vaishali, 844115, Bihar, India, Email:nehachoudharygecv@gmail.com
[4]Assistant Professor, Department of Electronics and Communication Engineering, Government Engineering College Vaishali, 844115, Bihar, India, Email: prerna.gecv@gmail.com
[5]Assistant Professor, Department of Electronics and Communication Engineering, Government Engineering College Buxar, 802103, Bihar, India, Email:shruti_1921ee21@iitp.ac.in
[6]Assistant Professor, Department of Electrical Engineering, Government Engineering College Buxar, 802103, Bihar, India, Email:sharma.akriti5@gmail.com

Abstract

Automated classification of electrocardiogram (ECG) beats can facilitate analysis of long-term cardiac recordings. This study performs a controlled comparison of statistical time-domain, discrete wavelet transform (DWT), and morphological features for three-class ECG beat classification. The MIT-BIH Arrhythmia Database was processed using a record-level training/testing protocol. Forty-eight records were considered, with 37 records assigned to training and 11 reserved for independent testing. A maximum of 2,000 beats per class was selected from the training records, resulting in 5,999 training beats from normal (N), supraventricular (S), and ventricular (V) classes. The independent test set retained its original distribution and contained 19,207 beats. Ten statistical time-domain features, 24 DWT features, and eight morphological descriptors were extracted from 270-sample ECG beat segments. Random Forest, support vector machine (SVM), and XG Boost classifiers were evaluated. Five-fold grouped cross-validation was performed using record identity as the grouping variable.

The wavelet-morphology representation with Random Forest achieved 83.84% accuracy, 69.02% balanced accuracy, and 58.61% macro F1-score on the held-out test set. The class-wise F1-scores for N, S, and V were 90.48%, 10.66%, and 74.69%, respectively. Grouped cross-validation yielded 61.03 ± 5.34% balanced accuracy and 57.57 ± 7.42% macro F1-score. The results indicate that wavelet features provide useful multiscale information beyond the evaluated statistical time-domain descriptors, while simple morphological descriptors provide a modest additional improvement. Supraventricular beat recognition remains a significant limitation.

Index Terms—ECG beat classification, discrete wavelet transform, morphological features, Random Forest, machine learning, MIT-BIH Arrhythmia Database.

I. Introduction

The electrocardiogram (ECG) is one of the most widely used non-invasive tools for evaluating cardiac electrical activity. Long-term ECG recordings contain large numbers of cardiac beats, making automated heartbeat classification useful for reducing the burden associated with manual analysis. The MIT-BIH Arrhythmia Database is a widely used benchmark for automated arrhythmia analysis; it contains 48 half-hour, two-channel ambulatory ECG recordings from 47 subjects, sampled at 360 samples/s, with expert beat annotations [1], [2].

Automated ECG beat classification commonly involves signal preprocessing, beat segmentation, feature extraction, and classification. Wavelet-based approaches are attractive because ECG signals are non-stationary and contain information distributed across multiple temporal and frequency scales.

Morphological information provides complementary descriptions of amplitude, waveform width, slopes, and local shape.

Previous work has combined normalized RR-interval information with wavelet- and linear-prediction-based morphological features for N/S/V classification on MIT-BIH [3]. Wavelet-packet entropy with Random Forest has also been investigated under an inter-patient evaluation scheme [4]. Earlier work by de Chazal et al. used ECG morphology and heartbeat interval features for five AAMI-recommended heartbeat classes [5]. These studies demonstrate that both feature representation and evaluation protocol can substantially affect reported performance.

In this study, we perform a controlled comparison of statistical time-domain, DWT, and morphological ECG features for three-class beat classification. The experiments use record-level separation of training and testing data, with Random Forest as the primary classifier. Additional SVM and XGBoost experiments are included for comparison. The objective is to determine whether wavelet and morphological descriptors improve performance over conventional statistical time-domain features, with emphasis on balanced accuracy and macro F1-score because of the imbalanced independent test distribution.

II. Materials And Methods

A. Dataset

The MIT-BIH Arrhythmia Database was used as the ECG source. The database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings from 47 subjects, digitized at 360 samples/s per channel [1]. Three beat classes were considered: normal (N), supraventricular ectopic (S), and ventricular ectopic (V). Fusion (F) and other/unknown (Q) categories were excluded from the final classification task.

B. Record-Level Partition and Class Selection

Records were divided at the record level rather than by randomly splitting individual beats. The final partition contained 37 training records and 11 independent test records, with no record appearing in both sets. To reduce class imbalance during model training, a maximum of 2,000 beats per class was randomly selected from the training annotations using a fixed random seed of 42. This produced 5,999 training beats: 2,000 N, 2,000 S, and 1,999 V. The independent test set was not resampled and retained its original distribution: 17,415 N, 435 S, and 1,357 V beats.

C. ECG Beat Extraction

Each annotated beat was represented by a 270-sample ECG segment, corresponding to approximately 0.75 s at 360 Hz. The resulting training and test waveform matrices contained 5,999 × 270 and 19,207 × 270 samples, respectively.

D. Time-Domain Features

Ten statistical descriptors were extracted from each beat: mean, standard deviation, variance, root mean square, minimum, maximum, median, range, skewness, and kurtosis.

E. Discrete Wavelet Features

A five-level discrete wavelet transform was applied using the Daubechies-4 (db4) wavelet. Mean, standard deviation, energy, and entropy were calculated for six coefficient groups, producing 24 wavelet features per beat. The resulting representation was evaluated independently and also combined with morphological descriptors.

F. Morphological Features

Eight waveform-shape descriptors were extracted: peak amplitude, peak position, peak-to-peak amplitude, absolute signal area, maximum slope, minimum slope, number of detected peaks, and approximate waveform width around the dominant peak. These descriptors were treated as signal-shape measures rather than clinically validated ECG intervals.

G. Machine-Learning Models

Random Forest was used as the primary classifier with 300 trees, balanced class weighting, and random seed 42. SVM was evaluated using the time-domain representation. XGBoost was evaluated using the wavelet representation with 300 estimators, maximum tree depth of 5, learning rate of 0.05, subsampling of 0.8, column subsampling of 0.8, and random seed 42.

H. Evaluation Metrics

Accuracy, balanced accuracy, precision, recall, F1-score, and macro F1-score were calculated. Balanced accuracy was defined as the arithmetic mean of recall across the three classes. Macro F1 was calculated as the unweighted mean of the class-wise F1-scores. Because the independent test set was substantially imbalanced, balanced accuracy and macro F1 were emphasized. Confusion matrices were also examined.

I. Grouped Cross-Validation

Five-fold stratified grouped cross-validation was performed using record identity as the grouping variable. Thus, beats from the same ECG record were not distributed between the training and validation portions of a fold. The wavelet Random Forest representation was compared with the wavelet-morphology Random Forest representation, and results were summarized as mean ± standard deviation across folds.

III. Results

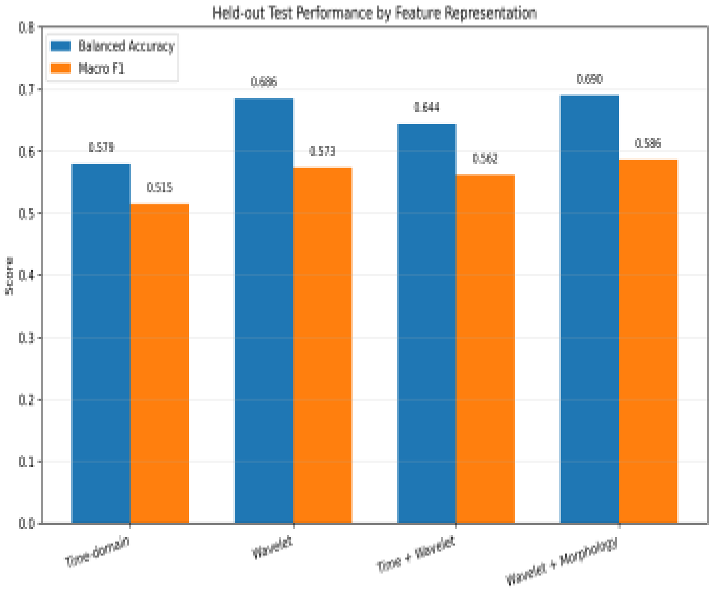
A. Classification Performance

The time-domain Random Forest achieved 70.21% accuracy, 57.94% balanced accuracy, and 51.52% macro F1-score. SVM using the same representation achieved 67.77%, 57.72%, and 49.95%, respectively. Wavelet Random Forest achieved 83.74% accuracy, 68.57% balanced accuracy, and 57.33% macro F1-score. XGBoost achieved slightly higher accuracy at 84.46%, but lower balanced accuracy (64.73%) and macro F1-score (57.19%). Combining time-domain and wavelet features yielded 82.07% accuracy, 64.44% balanced accuracy, and 56.21% macro F1-score. The wavelet-morphology Random Forest achieved the best balanced accuracy and macro F1-score: 83.84%, 69.02%, and 58.61%, respectively.

TABLE I PERFORMANCE COMPARISON OF EVALUATED APPROACHES

Feature representation	Classifier	Accuracy (%)	Balanced accuracy (%)	Macro F1 (%)
Time-domain	Random Forest	70.21	57.94	51.52
Time-domain	SVM	67.77	57.72	49.95
Wavelet	Random Forest	83.74	68.57	57.33
Wavelet	XGBoost	84.46	64.73	57.19
Time + Wavelet	Random Forest	82.07	64.44	56.21
Wavelet + Morphology	Random Forest	83.84	69.02	58.61

Fig. 1. Held-out test performance by feature representation.



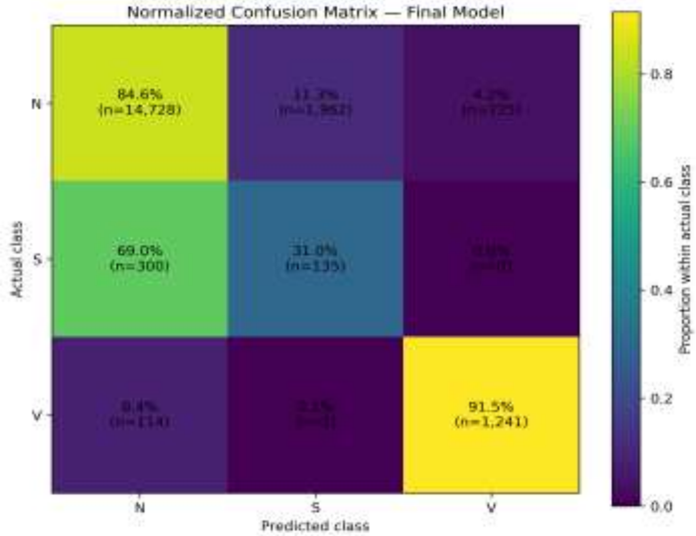
B. Class-Wise Performance

The final model achieved F1-scores of 90.48%, 10.66%, and 74.69% for N, S, and V, respectively. N recall was 84.57% and V recall was 91.45%, whereas S recall was 31.03%. Of 17,415 N beats, 14,728 were correctly classified. Of 435 S beats, 135 were correctly classified and 300 were classified as N. Of 1,357 V beats, 1,241 were correctly classified.

TABLE 2. CLASS-WISE PERFORMANCE OF THE FINAL MODEL

Class	Precision (%)	Recall (%)	F1-score (%)	Support
N	97.27	84.57	90.48	17,415
S	6.43	31.03	10.66	435
V	63.12	91.45	74.69	1,357
Macro average	55.61	69.02	58.61	19,207

Fig. 2. Row-normalized confusion matrix of the final model; percentages are normalized within each actual class and raw counts are shown in parentheses.



C. Grouped Cross-Validation

Wavelet Random Forest achieved 59.67 ± 4.16% balanced accuracy and 56.16 ± 5.89% macro F1-score. Adding morphology increased these values to 61.03 ± 5.34% and 57.57 ± 7.42%, respectively.

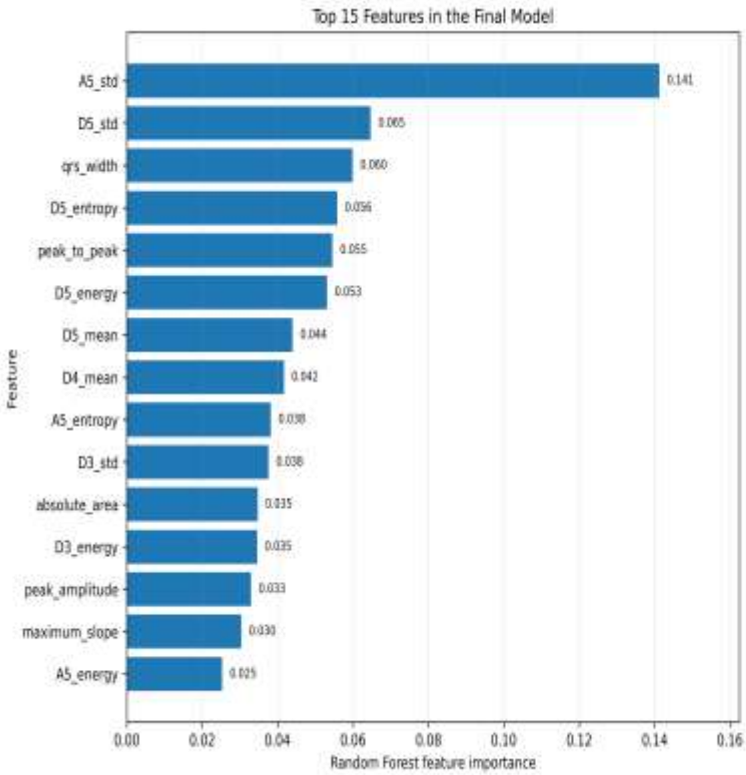
TABLE .3FIVE-FOLD GROUPED CROSS-VALIDATION RESULTS

Representation	Balanced accuracy (%)	Macro F1 (%)
Wavelet + Random Forest	59.67 ± 4.16	56.16 ± 5.89
Wavelet + Morphology + Random Forest	61.03 ± 5.34	57.57 ± 7.42

D. Feature Importance

The most influential features in the final Random Forest included wavelet coefficient statistics and morphology descriptors. The highest-ranked feature was c0_std, followed by c1_std, approximate waveform width, c1_entropy, and peak-to-peak amplitude. Thus, both multiscale and waveform-shape descriptors contributed to the final model. Feature importance is interpreted as a model-specific measure of predictive contribution rather than clinical significance.

Fig. 3. Top 15 Random Forest feature-importance values for the final wavelet-morphology representation.



IV. Discussion

The results demonstrate that feature representation substantially influenced ECG beat classification performance. Wavelet features produced considerably higher balanced accuracy than the evaluated statistical time-domain representation, indicating that multiscale information was useful for distinguishing the selected beat classes.

Adding morphological descriptors produced a modest improvement: balanced accuracy increased from 68.57% to 69.02% and macro F1 from 57.33% to 58.61% on the held-out test set. Grouped cross-validation showed the same direction of improvement, although the fold-to-fold variability indicates that the gain is not uniform across records.

XGBoost achieved the highest raw accuracy (84.46%), but Random Forest achieved higher balanced accuracy and marginally higher macro F1 for the wavelet representation. This illustrates the importance of class-balanced metrics for an imbalanced test set.

The principal limitation was the S class. Most incorrectly classified S beats were assigned to N, indicating difficulty separating supraventricular and normal beats with the selected compact features. This finding is consistent with the broader challenge of distinguishing supraventricular ectopic beats when their morphology resembles normal beats and rhythm context is important [3].

The record-level split and grouped cross-validation reduce the risk of overly optimistic estimates caused by distributing beats from the same record across training and testing. Nevertheless, the study uses a single database and should not be interpreted as demonstrating clinical deployment performance.

V. Limitations

- Only N, S, and V classes were considered.
- The training set was limited to approximately 2,000 beats per class, so not all available training beats were used.
- The independent test set retained a highly imbalanced distribution.
- Only the MIT-BIH Arrhythmia Database was evaluated, limiting assessment of generalizability to other populations and acquisition systems.
- The morphological descriptors were simple waveform-shape measures rather than clinically validated ECG intervals.
- Deep-learning and more advanced representation-learning methods were not evaluated.

VI. Conclusion

This study evaluated statistical time-domain, wavelet, and morphological feature representations for three-class ECG beat classification using machine learning. Wavelet features substantially outperformed the evaluated time-domain representation, while simple morphological descriptors produced a modest further improvement. The final wavelet-morphology Random Forest achieved 83.84% accuracy, 69.02% balanced accuracy, and 58.61% macro F1-score on the independent record-level test set. However, the low S-class F1-score indicates that supraventricular beat recognition remains challenging. The findings support compact multiscale and waveform-shape descriptors as an interpretable feature-engineering approach, while further validation on additional ECG datasets is required.

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