ECG Arrhythmia Classification and Explainability using SVM and Random Forest

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Introduction

Electrocardiogram (ECG) analysis plays a crucial role in diagnosing cardiac arrhythmias. However, manual interpretation of ECG signals is both time-consuming and prone to human error. Machine learning models offer a promising alternative by automatically learning morphological patterns of ECG beats.

This case study focuses on the **MIT-BIH Arrhythmia Dataset**, containing ECG recordings from 47 patients across eight heartbeat classes.

Predictive Question

Can machine learning models accurately classify ECG heartbeats into different arrhythmia types, and what parts of the ECG signal do these models rely on?

We address this by:
1.Training Support Vector Machine (SVM) and Random Forest classifiers.
2.Evaluating two validation protocols: beat-holdout (random split) and patient-holdout (unseen patients).
3.Applying Permutation Feature Importance (PFI) to understand model decision-making.

Methods

Data Pre-processing

The following pipeline was applied to raw MIT-BIH ECG signals:

- R-peak detection using biosppy.
- Beat extraction: Each heartbeat was centred around the R-peak and fixed to 275 samples.
- Z-score normalization per beat.
- Label encoding of 8 arrhythmia classes (1 – 8).
- Appending patient ID for patient-level validation.
- Addressing imbalance through resampling (each class ≈ 800 samples).

Validation Protocols

Beat-holdout (75/25 split):
- Randomly splits beats across all patients → high accuracy but risk of data leakage.

Patient-holdout

- Testing on unseen patients: 104, 113, 119, 208, 210 → realistic generalization.

Models Used

1. Support Vector Machine (SVM, RBF kernel)

Tuned hyperparameters:

- **C = 5,**
- **gamma = "scale"**
- Chosen due to strong performance on high-dimensional time-series.

2. Random Forest

- 200 trees, unlimited depth
- Captures nonlinear interactions but less sensitive to subtle morphology than SVM.

Explainability Method

Permutation Feature Importance (PFI)

- ECG signal split into 5 temporal slices (~55 samples each).
- For each slice, values were randomly permuted.
- Performance drop (Δ accuracy) measures importance.
- 5-fold stratified cross-validation for robustness.

Results

1. Numerical Experiment Setup

Aspect	Choice
Training Data	Beat-holdout: 75% resampled beats (balanced)
Test Data	Remaining 25% (balanced)
Patient-holdout Test Set	Patients 104, 113, 119, 208, 210
Features	275-point ECG waveform
Labels	8 arrhythmia classes
Slices for PFI	5 slices × 55 points

2. Classification Performance

SVM (RBF) – Beat Holdout

Metric	Value
Accuracy	0.9574
Precision	0.9578
Recall	0.9574
F1-score	0.9574

SVM – Patient Holdout

Metric	Value
Accuracy	**0.9638**
Precision	0.9701
Recall	0.9638
F1-score	0.9667

Random Forest – Beat Holdout

Metric	Value
Accuracy	**0.9454**
Precision	0.9455
Recall	0.9454
F1-score	0.9453

3. Explainability – Permutation Feature Importance

PFI (5 slices):

Slice (temporal region)	Δ Accuracy Importance
Slice 1 (0 - 55)	0.0051
Slice 2 (55 - 110)	0.0036
Slice 3 (110 - 165)	**0.1701**
Slice 4 (165 - 220)	0.0213
Slice 5 (220 - 275)	0.0104

Interpretation

- Slice 3 shows dramatically higher importance for both SVM and Random Forest.
- These points correspond to the QRS complex, the most informative ECG region.
- Earlier/later slices (P-wave / T-wave) contribute far less.

Discussion

1. Model Performance Insights

- SVM outperformed Random Forest in beat-holdout classification.
- Patient-holdout SVM achieved excellent performance, suggesting strong generalization even for unseen patients.
- However, the absence of some classes in the patient-holdout test set artificially inflates certain metrics.

2. Beat-holdout vs. Patient-holdout

- Beat-holdout accuracy is high but may suffer from patient morphology leakage—beats from the same patient appear in both train and test.

- Patient-holdout is more realistic for clinical deployment.

3. Explainability Findings

- Both models rely heavily on QRS complex morphology, which is consistent with cardiology domain knowledge.
- SVM showed a sharper sensitivity peak (slice 3), indicating higher reliance on detailed morphology.
- Random Forest had smoother importance distribution—more robust but less precise.

4. Conclusions

- Machine learning models can effectively classify arrhythmia types from ECG beats.
- The QRS complex is the most informative signal segment for all classifiers.
- Explainability methods like PFI help verify alignment between ML decisions and clinical knowledge.
- Patient-holdout evaluation is crucial for trustworthy real-world performance.