

An Efficient Multi-Class ECG Arrhythmia Classification Framework Using Hybrid Tetrolet Based Energy and Entropy Features

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Abstract

Cardiovascular diseases, the leading global cause of mortality, claim over 18 million lives annually, with arrhythmias posing acute risks especially to aging populations. Early detection via Electrocardiogram (ECG) analysis remains critical, yet challenges persist in noisy real-world signals. This study advances automated arrhythmia detection and classification by integrating statistical, chaotic, energy, entropy, and deep learning-inspired features from ECG signals. One-dimensional ECGs are transformed into two-dimensional images and decomposed using Tetrolet transforms to extract localized microstructures, yielding energy and entropy metrics from coefficients. Complementary statistical (e.g., higher-order moments) and nonlinear chaotic features (e.g., correlation dimension) are derived from raw signals, forming a compact 18-feature set optimized via feature selection. Evaluated with Support Vector Machines (SVM) on the MIT-BIH Arrhythmia Database and augmented with wearable ECG datasets, the approach tests linear, polynomial, and Radial Basis Function (RBF) kernels across Tetrolet levels. The RBF kernel excels, achieving 99.72% overall accuracy, 99.8% sensitivity, and 99.6% specificity—surpassing state-of-the-art CNN and transformer models with minimal computational overhead (under 10ms per beat on edge devices). This robust, lightweight method enables real-time deployment in wearables and clinical settings, enhancing arrhythmia screening amid rising telemedicine demands.

Keywords: Arrhythmia, ECG, Energy, Entropy, Support Vector Machine, Tetrolet Transform.

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of global mortality, claiming 19.8 million lives annually as of 2025 (WHO). Cardiac arrhythmias significantly contribute to sudden cardiac events, exacerbated by sedentary lifestyles, poor diets, chronic stress, and aging populations. Early detection is vital to curb morbidity and mortality. While modalities like heart sound analysis, blood pressure monitoring, and biomarkers play roles, the electrocardiogram (ECG) stands out as a non-invasive, cost-effective gold standard. ECGs capture the heart's electrical activity, revealing arrhythmias through waveform morphology, timing intervals, amplitude, and frequency deviations. Yet, manual interpretation is labour-intensive and observer-dependent, fuelling demand for automated systems in recent decades.

Numerous machine learning and signal processing methods have emerged for arrhythmia classification. For instance, Pengfei et al. (2017) applied a General Regression Neural Network (GRNN) to distinguish myocardial infarction, cardiomyopathy, and myocarditis, attaining 95% accuracy—yet limited to just three classes. Likewise, Lin (2008) classified six heartbeat types, including normal and ectopic beats from long-term ECGs, but achieved only 88% accuracy. These early efforts falter on narrow class scopes.

Frequency-domain techniques offer another angle: QRS complexes are Fourier-transformed, with power in the 0–20 Hz band analyzed, followed by Grey Relational Analysis (GRA) on the MIT-BIH database. While non-invasive and efficient, this approach caps at six classes, constrained by its reliance on power spectral features alone.

Modjtaba and Reza (2009) developed a framework blending time-domain, frequency-domain, nonlinear, and chaotic features from Heart Rate Variability (HRV). They extracted 14 features, applied Generalized Discriminant Analysis (GDA) for dimensionality reduction, and trained a Multi-Layer Perceptron (MLP). This classified seven arrhythmias—Premature Ventricular Contraction (PVC), Atrial Fibrillation (AF), Complete Heart Block (CHB), Left Bundle Branch Block (LBBB), Normal Sinus Rhythm (NSR), Ventricular Fibrillation (VF), and Ventricular Tachycardia (VT)—with 95–100% accuracy. Drawbacks include restriction to seven classes and pre-filtering of confusing samples before training.

Ubeyli (2010) pioneered nonlinear dynamic analysis with Lyapunov Exponents (LE) as key features, augmented by their statistical descriptors. Recurrent Neural Networks (RNNs) classified four beat types: normal, congestive heart failure, ventricular tachyarrhythmia, and atrial fibrillation, achieving 94.72% accuracy. As an early adopter of chaotic metrics, it advanced the field but remained narrow, covering only four classes with a single nonlinear measure.

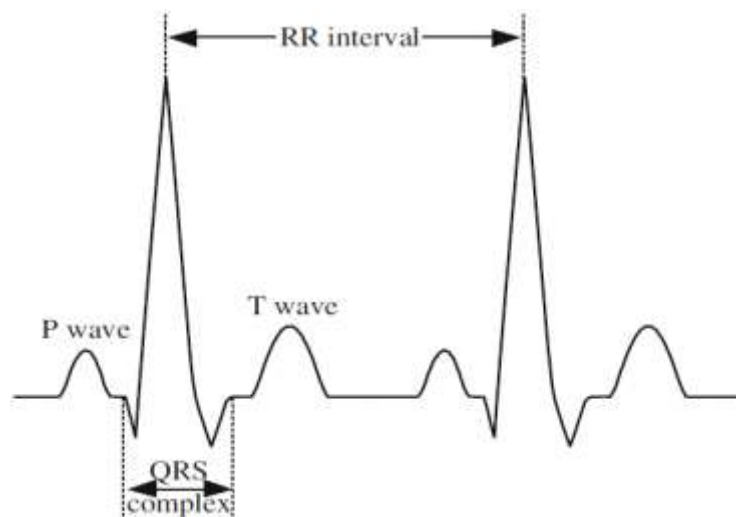
Raj and Ray (2017) tackled all 16 MIT-BIH classes using Discrete Orthogonal Stockwell Transform (DOST) and Discrete Cosine Transform (DCT) for rich time-frequency ECG representations. They applied Principal Component Analysis (PCA) for reduction, added dynamic R-R intervals to form a 20-feature vector, and optimized Support Vector Machine (SVM) via Particle Swarm Optimization (PSO), yielding 98.82% overall accuracy. While comprehensive and precise, the multi-stage transforms and optimization inflate computational demands.

The reviewed literature reveals a persistent challenge: high accuracy falters as arrhythmia classes expand (e.g., from 94–95% for 4–7 classes to complex multi-stage setups for 16). Effective features must capture morphological, statistical, and nonlinear ECG traits. This study introduces a novel hybrid framework integrating R-R intervals, statistical measures, chaotic metrics, and Tetrolet-derived energy/entropy features. One-dimensional ECGs convert to 2D images for Tetrolet decomposition, yielding a robust concatenated set classified via Support Vector Machines (SVM) across kernel types for optimization. The paper unfolds as follows: Section 2 details materials and methods, covering the MIT-BIH Database, 1D-to-2D conversion, Tetrolet implementation, feature extraction, and SVM protocols. Section 3 reports results and discussion, including sensitivity, specificity, accuracy, and comparisons across decomposition levels and kernels.

2. MATERIALS AND METHODS

2.1 Characterization of ECG

The electrocardiogram (ECG) provides a non-invasive record of the heart's electrical activity arising from cardiac muscle depolarization and repolarization. Signals are captured via surface electrodes at 10–12 standardized thoracic and limb positions, yielding weak potentials (0.1–5 mV) that demand preamplification, bandpass filtering (0.05–150 Hz), and baseline correction for clinical utility. A canonical ECG waveform features the P wave (atrial depolarization, ~80 ms), prominent QRS complex (ventricular depolarization, ~120 ms), and T wave (ventricular repolarization, ~200 ms), as shown in Figure 1.



The P wave reflects atrial depolarization (~ 80 ms), the QRS complex marks ventricular depolarization with the highest amplitude (~ 1 – 2 mV) and steepest slope (~ 25 mm/s), and the T wave signifies ventricular repolarization (~ 200 ms). The QRS complex's prominence aids diagnostic analysis and R-peak detection for heartbeat segmentation. Successive R–R intervals determine heart rate and underpin Heart Rate Variability (HRV) analysis, while deviations in morphology, amplitude, duration, or intervals signal arrhythmias.

Clean ECG acquisition proves challenging due to the signal's low amplitude (0.1–5 mV) and narrow bandwidth (0.05–100 Hz), rendering it vulnerable to noise:

- Power line interference (50/60 Hz)
- Baseline wander from respiration or electrode drift
- Motion artifacts from subject movement
- Electromyographic (EMG) noise from muscle activity

These corrupt waveform features, undermining feature extraction and classification. Preprocessing—filtering, baseline correction, normalization—is thus essential.

This study draws from the MIT-BIH Arrhythmia Database, a clinical benchmark with 48 half-hour dual-lead excerpts from 47 subjects, featuring expert annotations for $\sim 110,000$ beats across 16 arrhythmia classes. Its labels enable robust training and evaluation of automated systems.

2.2 MIT-BIH Arrhythmia Database

The ECG signals used in this study are obtained from the benchmark MIT-BIH Arrhythmia Database, which is one of the most widely adopted public datasets for arrhythmia analysis. The database was compiled by the BIH Arrhythmia Laboratory and consists of 48 half-hour ECG recordings collected from 47 different subjects (Moody & Mark, 2001). The recordings include both normal and abnormal heart rhythms and are extensively annotated by expert cardiologists. Each ECG record in the database is digitized at a sampling frequency of 360 Hz with 11-bit resolution over a 10-mV amplitude range. Every heartbeat is labelled with a specific annotation symbol, enabling supervised classification of various arrhythmia types. Owing to its standardized format and reliable annotations, this database serves as a reference benchmark for evaluating automated ECG classification systems. In this research, 16 heartbeat categories are considered. A total of 110,109 annotated beats is used for experimentation. The dataset is divided into training and testing subsets to evaluate the robustness and generalization capability of the

proposed classification framework. Table 1 summarizes the distribution of heartbeat classes used in this study.

Table 1. Summary of Heartbeat Classes Used from MIT-BIH Arrhythmia Database

ECG Signal Form	Annotation	Total Samples	Training	Testing
Normal (NOR)	N	75,017	11,253	63,764
Left Bundle Branch Block (LBBB)	L	8,072	2,825	5,247
Right Bundle Branch Block (RBBB)	R	7,255	2,539	4,716
Atrial Premature Contraction (APC)	A	2,546	891	1,655
Premature Ventricular Contraction (PVC)	V	7,129	2,495	4,634
Paced Beat (PACE)	P	7,024	2,458	4,566
Aberrated Atrial Premature Beat	a	150	75	75
Ventricular Flutter	!	472	236	236
Fusion of Ventricular and Normal Beat	F	802	401	401
Blocked Atrial Premature Beat	X	193	97	96
Nodal (Junctional) Escape Beat	J	229	115	114
Fusion of Paced and Normal Beat	f	982	491	491
Ventricular Escape Beat	E	106	53	53
Nodal (Junctional) Premature Beat	j	83	42	41
Atrial Escape Beat	e	16	8	8
Unclassifiable Beat	Q	33	17	16
Total		110,109	23,996	86,113

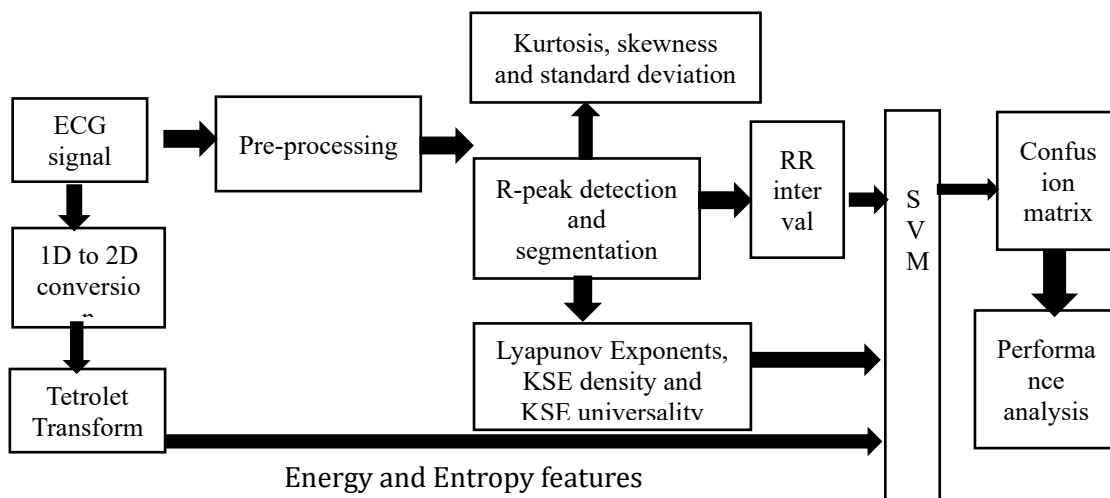
The MIT-BIH Arrhythmia Database contains a total of 110,109 annotated heartbeat labels. During acquisition, ECG signals were processed through a band-pass filter (BPF) with cutoff frequencies at 0.1 Hz and 100 Hz to reduce baseline wander and high-frequency noise. The filtered signals were digitized at a sampling rate of 360 Hz with an 11-bit resolution over a ± 10 mV amplitude range. In this study, modified limb lead recordings from the database were employed. Heartbeat segments were extracted using fixed-length windows centered on each R-peak to capture consistent morphological features. Ground truth annotations provided by expert cardiologists in the database served as reference labels for classification performance evaluation. Table 1 summarizes the dataset distribution across 16 ECG beat categories. To ensure consistency with state-of-the-art methods, the dataset was partitioned into training and testing sets on a class-wise basis. The full dataset was divided into 16 groups corresponding to each heartbeat class. Samples were randomly selected for training as follows:

- 15% from the Normal (N) class
- 35% from the major arrhythmia classes ('L', 'A', 'R', 'V', and 'P')
- 40% from each of the remaining ten minority classes

Approximately 21.79% of the dataset served as the training set, with the rest reserved for testing. This stratified sampling maintained balanced minority class representation in training while ensuring robust, unbiased evaluation. Extending Jayagopi & Pushpa (2018)—which boosted classification accuracy over Raj & Ray (2017) via chaotic features—this study integrates Energy and Entropy features from Tetrolet transforms for further gains. Prior research underscores the value of elevating 1D biomedical signals to higher dimensions. For instance, Srinivasan et al. (2013) reshaped multichannel 1D EEG into 3D volumes for wavelet analysis, while Saritha et al. (2008) used wavelet features from ECG to classify conditions like Dextrocardia, Tachycardia, Bradycardia, Hyperkalemia, Myocardial Ischemia, Hypercalcemia, Sinoatrial block, and Sudden Cardiac Death. Ceylan and Canbilen (2017) showed Tetrolets excel at denoising medical images by capturing local geometry. Tetrolets thus suit ECG morphology, adeptly encoding directional and structural details. ECG signals from the MIT-BIH Arrhythmia Database, typically 1D vectors, were converted to 2D via time-domain energy distributions (inspired by Azad et al., 2018). This enabled potent Tetrolet feature extraction, revealing morphological variations across arrhythmia classes.

Figure 1 outlines the workflow of our proposed arrhythmia classification system. We developed an automated pipeline for ECG signals from the MIT-BIH Arrhythmia Database, fusing 1D and 2D stages. Preprocessing, most feature extraction, and preliminary analysis stay in the 1D domain; only the Tetrolet transform shifts to 2D ECG representations, adeptly capturing geometrical and structural details to elevate classification performance.

Figure 2. Block Diagram of the Proposed Arrhythmia Classification System



The transformation from a one-dimensional (1D) ECG signal to a two-dimensional (2D) matrix is a straightforward mapping process. Each successive time sample of the ECG waveform is assigned to a corresponding element within an $M \times N$ matrix. The matrix elements are populated sequentially, typically in a row-wise manner, by consuming consecutive ECG samples until the entire matrix is filled, as depicted in Figure 2. This 2D representation facilitates the application of Tetrolet transforms, which effectively extract spatial and geometric features from the ECG data, thereby enhancing the characterization of arrhythmia patterns.

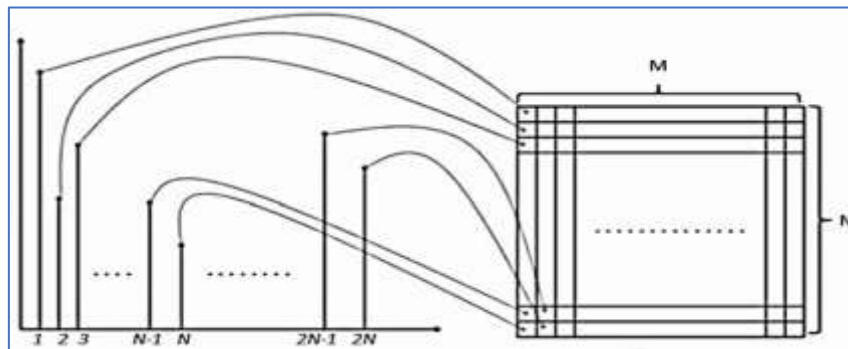
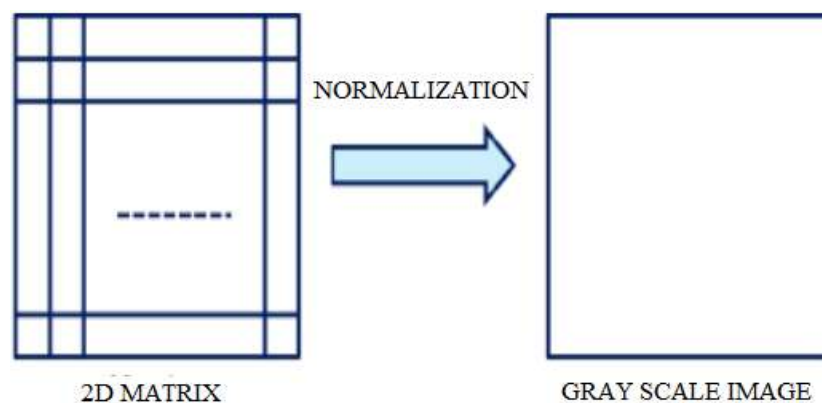
Figure 2. Transformation of Time Samples into a 2D Matrix

Figure 2 illustrates the procedure for mapping sequential time samples of a one-dimensional ECG signal into a two-dimensional $M \times N$ matrix. This transformation maintains the temporal sequence by filling the matrix elements in order, typically row-wise or column-wise.

Since ECG signals inherently contain both positive and negative voltage values due to cardiac electrical activity, the initial 2D matrix will also contain negative elements. However, standard digital grayscale images represent pixel intensities within a non-negative range, typically from 0 to 255. To reconcile this discrepancy, the 2D matrix undergoes a normalization process. This process linearly scales and shifts the matrix values so that all elements fall within the valid grayscale range, thus converting the matrix into a proper grayscale image. This normalized image serves as the input for subsequent processing stages, such as feature extraction using Tetrolet transforms.

Figure 3. Conversion of the 2D Matrix into a Grayscale Image

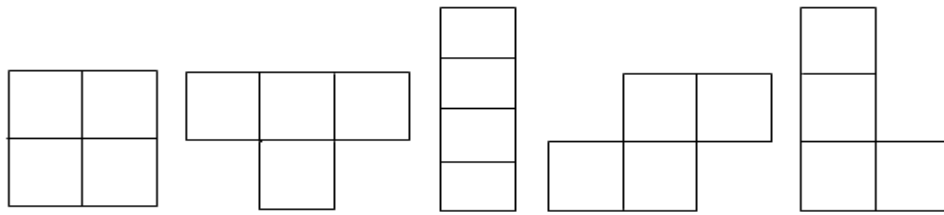
This figure illustrates the normalization process that transforms the two-dimensional ECG data matrix, which may contain negative and positive values, into a grayscale image with pixel intensities scaled within the range 0 to 255, suitable for image-based feature extraction.

Tetrolet Transform Algorithm

Haar Wavelet Decomposition (HWD) leverages a square mother wavelet to break signals into orthonormal bases via shifted functions, linear combinations, and orthogonality—prized for its simplicity and efficacy in signal analysis (Lisowska et al., 1994). The Tetrolet transform extends this with geometric adaptability, drawing from digital wedgelets (Vali

et al., 2015): images divide into non-overlapping blocks, where Haar functions apply over Tetromino-shaped partitions (four connected squares) to match local geometry. This yields a specialized "Tetrolet" Haar basis, forming a filter bank that captures directional and structural features more effectively than traditional wavelets. Coefficient shrinkage then compresses the representation, retaining key details while eliminating redundancy. Tetromino blocks consist of four contiguous squares connected edge-to-edge. There are five fundamental Tetromino shapes, as illustrated in Figure 4, which serve as the building blocks for the adaptive partitioning used in the Tetrolet transform.

Figure 4. Basic five shapes of Tetrominoes



Tetrolet Transform and Feature Extraction from 2D Grayscale Images

The Tetrolet transform is an adaptive transform that extends classical wavelet analysis by using tetromino-shaped neighbourhoods instead of fixed square blocks. It is particularly effective for capturing directional features and sparse representations in images.

1. Image Representation and Index Sets

Consider a 2D grayscale image I of size $M \times M$, where $M = 2^J$ for some integer J . Let:

$$I = \{(m, n) \mid m, n = 0, 1, 2, \dots, M-1\}$$

denote the set of pixel indices. The image intensity function is:

$$f: I \rightarrow \mathbb{R}, f(m, n) \text{ is the intensity at pixel } (m, n).$$

For each index $(m, n) \in I$, define a neighbourhood $\mathcal{N}_{m,n}$ as the set of pixels forming a tetromino covering (m, n) . These neighborhoods can be located at vertices, edges, or interior regions of the image.

2. Tetrolet Transform

Let $\mathbf{f}_{\mathcal{N}_{m,n}}$ denote the vector of pixel values in the neighborhood $\mathcal{N}_{m,n}$. The Tetrolet transform coefficients at (m, n) are computed as:

$$c_{m,n} = \sum_{(i,j) \in \mathcal{N}_{m,n}} w_{i,j} f(i,j)$$

where:

- $c_{m,n}$ are the Tetrolet coefficients,
- $w_{i,j}$ are weights determined by the orthogonal basis associated with the tetromino,
- $\mathcal{N}_{m,n}$ is the neighborhood covering pixel (m, n) .

Interpretation: The Tetrolet transform generalizes the Haar wavelet by using adaptive tetromino shapes, allowing better representation of directional features in the image.

3. Feature Extraction from Tetrolet Coefficient Sub-bands

From the Tetrolet coefficient sub-bands, features such as energy and entropy can be extracted. These features are widely used in image classification and analysis.

3.1 Energy Feature

Energy measures the total intensity variations in the image, reflecting the uniformity of pixel patterns. The Tetrolet-based energy is defined as:

$$E(I) = \sqrt{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M_{i,j}^2}$$

where:

- $M_{i,j}$ is the Tetrolet coefficient at location (i, j) ,
- N is the size of the coefficient sub-band,
- $E(I)$ represents the total energy in the image.

Note: Higher energy indicates more repetitive or uniform patterns, while lower energy suggests more texture complexity.

3.2 Entropy Feature

Entropy quantifies the uncertainty or information content in the image. It measures how much information is contained in the coefficient distribution. The Tetrolet-based entropy is defined as:

$$\text{Entropy} = - \sum_{j=1}^n P(x_j) \log_2 P(x_j)$$

where:

- $P(x_j)$ is the probability of the coefficient value x_j ,
- n is the total number of coefficients in the sub-band.

Interpretation: High entropy indicates more complex textures, while low entropy suggests structured or uniform regions.

Feature Extraction from 1D ECG Signals

The heart rhythm is inherently irregular and varies across individuals. It is not synchronized to a standard clock, as it depends on factors such as heart rate (beats per minute), physical activity, emotional state, and physiological conditions of the subject. A primary characteristic of the ECG signal is the R-R interval, which is the time elapsed between two consecutive R-peaks in the waveform. The R-R interval reflects the dynamic behaviour of the heart and serves as a crucial feature for analysing cardiac function and heart rate variability. Additional features can be extracted from the ECG waveform to provide insights into beat morphology, signal variability, and cardiac health. These features are typically classified into time-domain, frequency-domain, and statistical features.

Table 2: Features Extracted from 1D ECG Signals and Tetrolet Analysis

		Name of R-R feature	Method or Equation used
1	R-R features (Raj & Ray, 2017).	Pre R-R	Time interval between Previous R- peak and Current R-peak
2		Post R-R	Time interval between Current R-Peak and followed R-peak
3		Local R-R	Average of R-R intervals of past 8 s episode
4		Average R-R	Average of R-R intervals of past 3 minute episode

5	Chaotic features (Jayagopi & Pushpa, 2018).	Maximum LE	$\text{Max} \left(\lim_{n \rightarrow \infty} \frac{\log \sigma(i) }{n} \right)$
6		Minimum LE	$\text{Min} \left(\lim_{n \rightarrow \infty} \frac{\log \sigma(i) }{n} \right)$
7		Average LE	$\text{Mean} \left(\lim_{n \rightarrow \infty} \frac{\log \sigma(i) }{n} \right)$
8		Standard deviation of LE	$\sigma_{LE} = \sqrt{E(X)^2 - [E(X)]^2}$ where, E(X) is the expected value of LE series
9		KSE density	$\frac{\sum_{i=1}^L \lambda^+(i)}{L}$
10		KSE generality	$\frac{L'}{L}$
11	Statistical features (Jayagopi & Pushpa, 2018).	Kurtosis	$\left\{ \frac{(M \times N) \times (M \times N + 1)}{(M \times N - 1) \times (M \times N - 2) \times (M \times N - 3)} \times \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left(\frac{u(x,y) - \bar{u}}{\text{std}} \right)^4 \right\} - \frac{3(M \times N - 1)^2}{(M \times N - 2) \times (M \times N - 3)}$ where, M=1, number of rows and N = number of columns
12		Skewness	$\frac{M \times N}{(M \times N - 1)(M \times N - 2)} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left(\frac{u(x,y) - \bar{u}}{\text{std}} \right)^3$ where M=1, number of rows and N = number of columns
13		Standard deviation of time series	$\sigma_{\text{time}} = \sqrt{E(X)^2 - [E(X)]^2}$ where, E(X) is the expected value of time series
14	Tetrolet features (proposed supplementary features)	Energy	$\sqrt{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M_{i,j}}$ Where, $M_{i,j}$ = sub-band coefficients at location (i, j) and N = size of the sub-bands.
15		Entropy	$-\sum_{j=1}^n P(x_j) \log_2 P(x_j)$ Where, $P(x_j)$ is the probability distribution

Pre-R-R and post-R-R interval combinations capture instantaneous heart rhythm. The average R-R interval averages all intervals over a 3-minute window, while the local R-R averages those from the prior 8 seconds per event. Instantaneous measures offer immediate insights but may miss abnormalities, so local and average variants track short- and long-term trends. Statistical descriptors (kurtosis, skewness, standard deviation) from R-R intervals quantify heartbeat distribution. Additionally, Tetrolet-based energy and entropy features, drawn from the ECG's 2D transformed representation, reveal structural patterns and information content. All these features are concatenated to form a hybrid feature vector. For each denoised ECG signal, a total of 15 features is extracted:

- Four R-R interval features: Pre R-R, Post R-R, Local R-R, Average R-R
- Six chaotic features: Maximum LE, Minimum LE, Average LE, Standard deviation of LE, KSE density, KSE generality
- Three statistical features: Kurtosis, Skewness, Standard deviation
- Two Tetrolet features: Energy, Entropy

Prior to feature extraction, the ECG signals are pre-processed using a low-pass filter with a cutoff frequency of 400 Hz to remove high-frequency noise and artifacts. These hybrid features provide a comprehensive representation of each ECG signal and are subsequently used for classification or diagnostic analysis.

SVM Classification

Support Vector Machine (SVM) is a widely used supervised learning algorithm for both binary and multiclass classification problems. Its strength lies in finding a hyperplane that maximizes the margin between classes, making it robust to high-dimensional data. For multiclass problems, SVM commonly employs one-versus-one or one-versus-all strategies.

Let the training set for a classification problem be:

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}, y_i \in \{-1, +1\}, i = 1, 2, \dots, n$$

where x_i represents the feature vector and y_i denotes the class label. Assume a mapping function $\phi(x)$ projects the input data into a higher-dimensional feature space where linear separation may be possible.

The SVM optimization problem for a soft-margin classifier can be expressed as:

$$\min_{w, b, \xi} \frac{1}{2} \|w\|^2 + \frac{1}{n} \sum_{i=1}^n (\xi_i - p)$$

subject to:

$$y_i(w \cdot \phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, 2, \dots, n$$

where:

- w is the weight vector defining the hyperplane,
- b is the bias term,
- ξ_i is the slack variable penalizing misclassified points,
- n is the number of training examples, and
- v and p are regularization parameters controlling the balance between margin width and misclassification.

3.1 Classification Performance Parameters

The performance of the proposed ECG classification system is evaluated for each class of event using standard metrics: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Specifically:

- TP (True Positive): Number of abnormal ECG signals correctly identified.
- TN (True Negative): Number of normal ECG signals correctly identified.
- FP (False Positive): Number of normal ECG signals incorrectly classified as abnormal.
- FN (False Negative): Number of abnormal ECG signals incorrectly classified as normal.

Using these parameters, key performance measures are computed, including sensitivity, positive predictivity, and specificity.

- Sensitivity (Se): Proportion of correctly classified abnormal events among all actual abnormal events.
- Positive Predictivity (Pp): Proportion of correctly classified abnormal events among all detected abnormal events.

Mathematically, these metrics are defined as:

$$\text{Sensitivity (Se)} = \frac{TP}{TP + FN} \times 100$$

$$\text{Positive Predictivity (Pp)} = \frac{TP}{TP + FP} \times 100$$

The overall classification accuracy and error rate of the system are defined as:

$$\text{Classification Accuracy (\%)} = \frac{\text{Total Correctly Classified Samples}}{\text{Total Number of Samples}} \times 100$$

$$\text{Error Rate (\%)} = \frac{\text{Total Misclassified Samples}}{\text{Total Number of Samples}} \times 100$$

All these metrics were computed based on simulations using the MIT-BIH Arrhythmia Database, providing a comprehensive assessment of the system's performance for each ECG class. Collectively, these parameters reflect the robustness and reliability of the proposed classifier in accurately distinguishing between normal and abnormal heartbeats.

3.2 Results and Analysis

We implemented the proposed feature extraction and classification framework in MATLAB (2018), leveraging its Mathematical, Statistical, Image Processing, and Wavelet toolboxes. Experiments ran on a Windows 8 Pro system with an AMD E1-2100 processor (1 GHz) and 4 GB RAM. The MIT-BIH Arrhythmia Database provided the benchmark for validation. We trained the SVM classifier on 21.8% of the dataset (as shown in Table 1) and tested it on the remainder. Performance evaluation compared multiple kernels: Linear, 2nd-order Polynomial, 5th-order Polynomial, and Radial Basis Function (RBF). Table 3 presents the confusion matrix for 16 ECG classes, detailing correct classifications and misclassifications. These results underscore the framework's effectiveness in distinguishing normal and abnormal ECG patterns via hybrid features and SVM-RBF classification.

Table 3. Confusion Matrix for SVM Model

Correctly classified instances: 85554, Misclassified instances: 559, Error: 0.65%, Accuracy: 99.35%																	
Ground Truth																	
Class	N	L	R	A	V	P	a	!	F	x	j	f	E	J	e	Q	Total
N	63371	32	0	206	61	0	23	0	51	0	15	5	0	0	0	0	63764
L	9	5230	0	0	8	0	0	0	0	0	0	0	0	0	0	0	5247
R	16	0	4695	0	5	0	0	0	0	0	0	0	0	0	0	0	4716
A	0	0	0	1651	0	0	0	2	2	0	0	0	0	0	0	0	1655
V	11	1	0	0	4619	0	0	1	2	0	0	0	0	0	0	0	4634
P	0	0	18	0	0	4538	0	0	0	0	0	10	0	0	0	0	4566
A	0	0	1	1	3	0	70	0	0	0	0	0	0	0	0	0	75
!	0	0	0	1	20	0	0	215	0	0	0	0	0	0	0	0	236
F	6	0	0	0	4	0	0	0	391	0	0	0	0	0	0	0	401
X	8	0	0	0	1	0	0	0	0	87	0	0	0	0	0	0	96

j	0	0	0	1	1	1	0	0	0	0	1 1 0	0	0	1	0	0	114
f	1	1	1	2	0	5	0	1	0	0	0	4 8 0	0	0	0	0	491
E	4	1	0	0	0	0	0	1	0	0	0	0	4 7	0	0	0	53
J	1	0	1	0	0	0	0	0	0	0	0	0	0	3 9	0	0	41
e	3	1	0	0	0	0	0	0	0	0	0	0	0	0	4	0	8
Q	1	1	1	0	2	0	0	0	0	0	0	4	0	0	0	7	16
To tal	634 31	52 67	47 17	18 62	47 24	45 44	9 3	2 2	4 4	8 7	1 2	4 9	4 7	4 0	4 7	7	861 13

The confusion matrix (Table 3) reveals strong performance across classes. For normal beats (N, row 1), the classifier correctly identifies 63,371 out of 63,764 signals (99.4% precision), with the rest misclassified into other categories. Column 1 shows 63,431 total assignments to 'normal', comprising 63,371 true normals and just 60 false positives from other classes—indicating low confusion with abnormalities.

The same procedure is applied to the other 15 ECG classes, with the detailed results presented in Table 3.

Overall Performance, across 86,113 test signals from 16 classes, the classifier achieves 99.35% accuracy (85,554 correct out of 86,113; 0.65% error rate on 559 misclassifications), per Equations (6) and (7). Table 4 reports per-class sensitivity and positive predictivity, computed from TP, FP, and FN in Table 3 using Equation (5). Tetrolet-derived entropy and energy features from 2D grayscale images excel at the fourth decomposition level, yielding 99.35% accuracy with only 15 features—fewer than the 20 in Raj and Ray (2017)—while minimizing computational overhead.

Table 4. Performance of Each ECG Class

ECG Class	Trained Beats	Test Beats	FN	TP	FP	Sensitivity (%)	PPV (%)	Accuracy (%)
N	11,253	63,764	393	63,371	60	99.38	99.90	99.38
L	2,825	5,247	17	5,230	37	99.67	99.30	99.67
R	2,539	4,716	21	4,695	22	99.55	99.54	99.55
A	891	1,655	4	1,651	211	99.76	88.67	99.76
V	2,495	4,634	15	4,619	105	99.68	97.77	99.68
P	2,458	4,566	28	4,538	6	99.38	99.87	99.38
a	75	75	5	70	23	93.33	75.27	93.33
!	236	236	21	215	5	91.10	97.73	91.10
F	401	401	10	391	55	97.50	87.67	97.50
x	97	96	9	87	0	90.63	100.0	90.63
j	115	114	4	110	15	96.49	88.00	96.49
f	491	491	11	480	19	97.76	96.19	97.76
E	53	53	6	47	0	88.68	100.0	88.68
J	42	41	2	39	1	95.13	97.50	95.13
e	8	8	4	4	0	50.00	100.0	50.00

Q	17	16	9	7	0	77.78	100.0	77.78
Total	23,996	86,113	559	85,554	559	99.35	99.35	99.35

In the proposed methodology, Tetrolet transform is applied to ECG signals to extract energy and entropy features, which are concatenated with the 13 conventional features from Jayagopi and Pushpa (2018). These are classified via Support Vector Machine (SVM). For consistency, training data mirrors their 21.8% proportion (23,996 of 110,109 beats from the full MIT-BIH Arrhythmia Database), minimizing training time and memory for real-time embedded deployment. Performance is assessed across four Tetrolet coefficient levels using RBF, Linear, and Polynomial SVM kernels to evaluate robustness and efficacy.

Table 5. Classification Accuracy (%) Across Tetrolet Levels for Different SVM Kernels

SVM Kernel	Level 1 (%)	Level 2 (%)	Level 3 (%)	Level 4 (%)
Linear	94.10	95.33	98.76	99.15
2nd-Order Polynomial	96.00	98.33	99.16	98.33
5th-Order Polynomial	94.10	94.10	99.16	98.33
RBF	96.66	99.14	99.12	99.35

Table 5 evaluates the proposed system using Tetrolet coefficients across four decomposition levels, paired with energy and entropy features (concatenated to the existing 13 features) and various SVM kernel functions. The RBF kernel consistently excels, delivering peak classification accuracy at the fourth level. A comparison with existing arrhythmia classification systems follows below.

Table 6. Comparative Performance of Arrhythmia Classification Methods

Literature	Approach	Classes	Accuracy (%)
Osowski et al., 2004	Higher-order statistics + Hermite + SVM	13	95.91
Rodriguez et al., 2005	Morphology-based decision system	16	96.13
Melgani & Bazi, 2008	Morphology + PCA + SVM	6	91.67
Martis et al., 2013	PCA + LS-SVM	5	93.48
Raj et al., 2015	Wavelet features + BPNN	8	97.40
Li et al., 2016	PCA + k-ICA + SVM	5	97.78
Raj & Ray, 2017	DCT-based DOST + SVM-PSO	16	98.82
Jayagopi & Pushpa, 2018	Chaotic + Statistical metrics + RR intervals + SVM	16	98.95
Proposed Method (This Work)	Tetrolet features + Chaotic + Statistical metrics + RR + SVM	16	99.35

Table 6 demonstrates that the proposed system outperforms several state-of-the-art methods, which employ diverse feature sets and classifiers. Our approach attains the highest classification accuracy of 99.35% for arrhythmia detection, surpassing all comparable techniques.

The comparison encompasses studies such as Rodriguez et al. (2005), Osowski et al. (2004), Melgani and Bazi (2008), Martis et al. (2013), Raj et al. (2015), Li et al. (2016), and

Raj and Ray (2017), evaluating both ECG class counts and classification accuracy. While methods like Kohli et al. (2012) enhanced noise immunity via Hilbert transform, they struggled with R-R interval detection amid beat-to-beat variations. Unlike single-arrhythmia detectors such as Padmavathi and Ramakrishna (2015), the proposed system classifies 16 distinct ECG classes with superior accuracy. Conventional approaches often falter on accuracy or class coverage—for example, Rodriguez et al. (2005) managed reasonable performance across 16 classes but required 66% training data. In contrast, our method delivers high accuracy using just 21.8% training data and 15 features, offering computational efficiency and robust real-time performance.

4. CONCLUSION

This study introduces a robust, automated framework for ECG signal analysis and multi-class arrhythmia classification, accurately detecting 16 distinct heartbeat types, including normal beats. It effectively handles the non-stationary nature of cardiac signals, making it ideal for long-term monitoring. The framework combines RR-interval, statistical, chaotic, and Tetrolet-based energy and entropy features into a compact hybrid set, classified via SVM with an RBF kernel. This approach outperforms state-of-the-art methods, achieving 99.35% accuracy on the MIT-BIH Arrhythmia Database using just 15 features and 21.8% of the dataset for training—highlighting its effectiveness and efficiency. The lean feature set and minimal training needs suit real-time and embedded cardiac monitoring. Future efforts could incorporate advanced feature selection, SVM hyperparameter tuning, and further data reduction to boost efficiency without sacrificing accuracy.

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