Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 2s (2024)

Integrating Morphological Characteristics with Empirical Mode Decomposition for Robust ECG Signal Classification

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Article History:

Received: *27-03-2024*

Revised: *12-05-2024*

Accepted: *24-05-2024*

Abstract:

Hyperkalemia, a critical concern, is the primary cause of sudden cardiac deaths in patients with chronic kidney disease (CKD). Traditionally, blood tests serve as the gold standard for hyperkalemia detection. Electrocardiogram (ECG) signals offer a non-invasive means to assess cardiac activity and identify hyperkalemia in CKD patients. Hyperkalemia often presents ECG changes such as elevated T-waves, changes in P-wave morphology, prolonged PR intervals, widened QRS complexes, and, in severe instances, the onset of ventricular arrhythmias and sinusoidal waves. This study proposes a method for the classification of ECG signals for hyperkalaemia using a feature set extracted from electrocardiogram (ECG) signals. Our approach integrates morphological attributes, including P-wave amplitude, T-wave amplitude, QRS interval, PR interval, and ST depression, with spectral attributes such as total power, spectral entropy, variance, skewness, and singular values extracted from Intrinsic Mode Functions obtained through empirical mode decomposition., aiming to capture both structural and frequency domain information inherent in ECG signals. Morphological features provide insights into cardiac abnormalities associated with hyperkalemia and spectral features extracted from IMF, offer valuable information regarding the frequency distribution and complexity of ECG signals. The performance of three classifiers—Kernel Naïve Bayes (KNB), AdaBoost Ensemble Classifier, and Artificial Neural Networks (ANN) is assessed using the extracted features. Among these classifiers, AdaBoost Ensemble Classifier demonstrated the most favorable classification results with sensitivity of 97.7, specificity of 98.84 and accuracy of 98.3%. These findings align with existing state-of-the-art approaches for hyperkalemia classification.

Keywords: Potassium imbalance, hyperkalemia, machine learning, chronic kidney disease, ECG.

1. INTRODUCTION

Chronic kidney disease (CKD) is a pervasive health issue with far-reaching implications, often compounded by complications such as hyperkalemia. Hyperkalemia, characterized by elevated levels of potassium in the bloodstream, poses a significant threat to patients with CKD, as it is a leading cause of sudden cardiac deaths within this population. Timely detection and monitoring of hyperkalemia are critical for patient care, necessitating a reliable diagnostic approach. Currently, the gold standard for hyperkalemia detection involves blood tests, yet the quest for non-invasive, efficient, and accurate methodologies remains ongoing.

Electrocardiography (ECG) has long been a primary tool for the diagnosis of heart disorders due to its non-invasive nature, affordability, and widespread availability. The ECG signal provides a graphical representation of the heart's electrical activity, offering insights into various pathological conditions. By scrutinizing ECG patterns, healthcare providers can gain insights into cardiac health, recognizing signs that may have life-saving implications. Hyperkalaemia, characterized by elevated potassium levels (>5.3mEq/L) in the blood, is one such condition that leaves a distinct footprint on the ECG waveform. High levels of potassium can lead to sudden cardiac deaths in patients suffering from Chronic Kidney Disease [1]. Early detection of hyperkalaemia-induced ECG changes can aid in rapid clinical intervention, preventing potential life-threatening complications.

Recent studies have utilized deep learning models [2] [3] [4] [5] to classify between normal and hyperkalaemia classes. Deep learning models require vast amounts of data to train effectively without over-fitting. Model explainability also poses a significant concern in the context of deep learning models [3]. Given the limited size of our dataset, we opted for machine learning approach over deep learning techniques.

Feature extraction plays a very important role in Machine Learning. Many feature extraction techniques have been adopted in literature for ECG Signal Classification. Morphological features [6], derived from the intricate shapes and patterns within the ECG waveform, can be highly indicative of various cardiac anomalies. In another study a single lead ECG connected to smart phone was employed to estimate blood potassium in patients undergoing haemodialysis with an error of 9% [7]. Although this study focussed on T wave, T wave amplitude, T wave duration as the extracted features the specific methodology for feature extraction remains undisclosed. A computational model based on quadratic estimator was developed to quantify potassium levels from ECG based on digital analysis of Twave [8]. Furthermore, an investigation involving 12 features derived from the slope, amplitude, and area of T, R, and S waves from leads V2-V5 was used to predict hyperkalemia with the assistance of machine learning models [9].The accurate extraction of these morphological features is dependent upon the quality and consistency of the ECG recordings and the algorithms being used to extract it. Any slight distortion, noise, or variability in the waveform can lead to inaccuracies in feature extraction, which can subsequently mislead and negatively influence the performance of the classifier.

Decomposition based Feature Extraction have been gaining importance in recent years. Empirical Mode Decomposition (EMD) has emerged as a powerful signal processing technique for the analysis and classification of biomedical signals, including Electroencephalogram (EEG) and Electrocardiogram (ECG) signals. EMD offers a data-driven approach to decompose non-stationary and nonlinear signals into a set of oscillatory components called Intrinsic Mode Functions (IMFs), which capture the underlying dynamics of the signal. This decomposition allows for the extraction of relevant features that can be used for classification purposes. In the field of EEG signal processing, EMD has been widely utilized for various applications, including seizure detection [9] [10], sleep stage classification, and emotion recognition [11]. Similarly, EMD has shown promise in the classification of ECG signals for diagnosing various cardiac abnormalities. In [12] the authors investigated the use of EMD for feature extraction from ECG signals and its application in arrhythmia detection. They demonstrated that features extracted from IMF components using EMD could effectively discriminate between different arrhythmia types. Furthermore, in [13] the authors proposed a method for ECG-

based heartbeat classification using EMD and deep learning techniques, achieving high accuracy in distinguishing between normal and abnormal heartbeats.

This study proposes a feature set combining five morphological features which are indicators of hyperkalemia along with eight features extracted from IMF obtained from EMD. Table 1 presents the morphological features extracted based on the hyperkalemia changes in ECG. Our ultimate goal is to use a combination of these features to enhance the detection of hyperkalemia.

TABLE I: Hyperkalemia and its effect on ECG

Hyperkalemia range	***Effect on ECG***	***Features Extracted***
Mild Hyperkalemia(5.5-6.5 mEq/L)	Thin, tall, narrow based and peaked T waves	T- wave amplitude, P-wave Amplitude, PR Interval, QRS Interval, ST Depression
Moderate Hyperkalemia(6.5-7.5 mEq/L)	P wave flattening, P-R interval prolongation, Widening of QRS complex	
Severe Hyperkalemia(>7.5 mEq/L)	ST depression, P wave disappears and the PQRST is replaced by a smooth diphasic sine wave	

The remainder of this paper is as follows: In Section 2, we introduce the detail the methodology, encompassing data preparation, pre-processing, feature extraction and classification. Section 3 presents the implementation details and results. Section 4 presents the discussion. Finally, Section 5 offers our conclusions, summarizing key insights and implications drawn from the study.

2. METHODS

This section describes the overall methods used for the classification task. Figure 1 presents the block diagram of the methodology used in this paper.

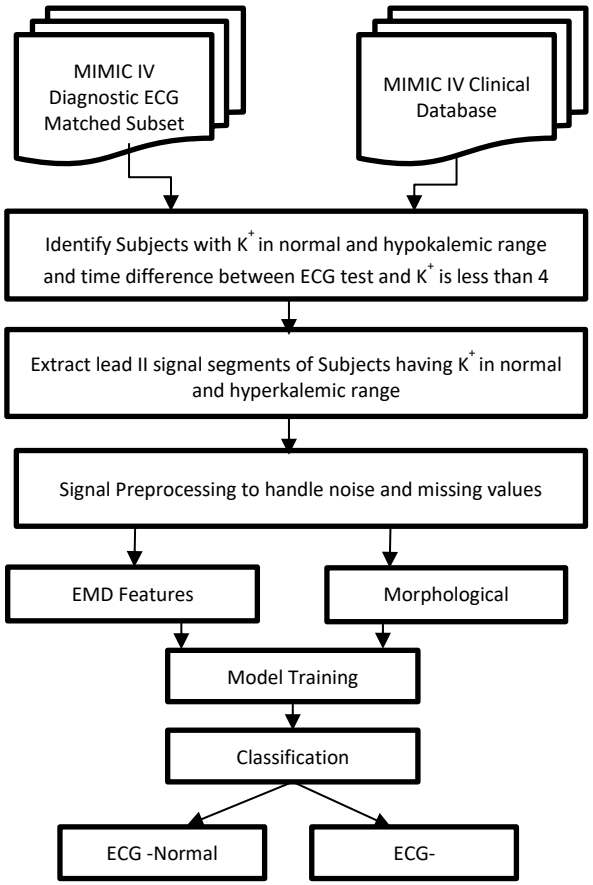

Figure 1. Methodology

2.1 Dataset

The "Medical Information Mart for Intensive Care" or MIMIC is a large single-center database that contains data on patients admitted to critical care units at large tertiary care hospitals. The dataset used in this work is extracted from MIMICS IV ECG: Diagnostic Electrocardiogram Matched Subset [13] [14]. The MIMIC-IV-ECG module encompasses around 800,000 diagnostic electrocardiograms from close to 160,000 distinct patients. These diagnostic ECG recordings, comprising 12 leads each and lasting 10 seconds, are sampled at a frequency of 500 Hz. This subset includes the entire set of ECGs corresponding to patients featured in the MIMIC-IV Clinical Database. We selected those ECG waveforms from MIMICS IV ECG matched subset whose corresponding clinical records suggested that the patient had normal or high levels of serum potassium. To ensure the relevance and accuracy of the correlation between potassium levels and ECG characteristics, only those ECG recordings were selected where the time difference between the associated potassium test and the ECG acquisition was less than 4 hours. However not all signals are of adequate quality for rigorous analysis. Several factors including noise, artifacts and other irregularities compromises the quality of the signals. Pre-processing techniques like filtering and outlier detection was employed to prepare the data for classification. After preprocessing 1790 patient samples were included for this study of which 895 are normal cases and 895 were cases of hyperkalemia. For cases of hyperkalemia only those patients were considered whose potassium values were >6.0 mEq/L.

2.2 Feature Extraction

ECG Signal is a time series representation of the electrical activity of the heart. It serves as a cornerstone in cardiovascular diagnostics, aiding clinicians in the detection and characterization of various cardiac abnormalities. One of the key challenges in ECG analysis lies in extracting informative features that capture essential aspects of the signal's structure and dynamics .Morphological features of the ECG signal encapsulate critical structural information, describing the shape, amplitude, and duration of its waveform components. Empirical Mode Decomposition (EMD) [15] is a data-driven signal processing technique used to decompose non-stationary and nonlinear signals into a finite set of Intrinsic Mode Functions (IMFs). Each IMF represents a narrowband oscillatory mode with a characteristic frequency. Features extracted using EMD capture spectral and temporal characteristics of the signal at different frequency scales. In this study, we propose a comprehensive approach that integrates morphological features with features extracted using EMD for ECG signal classification. By combining the structural insights offered by morphological features with the spectral and temporal dynamics captured through EMD, our methodology aims to enhance the discriminative power and diagnostic accuracy of ECG-based classification tasks.

A. Morphological Feature Extraction

The alterations in the ECG waveform due to hyperkalemia commence with tall, peaked T-waves, followed by a prolongation of the PR interval and flattening of the P-wave. As hyperkalaemia advances, the QRS complex broadens, and in severe cases, it may even merge with the T-wave, resulting in a sine-wave pattern [16]. These changes are gradual, aligning with the severity of hyperkalemia; the more elevated the potassium levels, the more distinct the ECG alterations become.

Five morphological features, specifically the amplitude of the P wave and T wave, length of QRS segment, length of PR segment and ST depression, were extracted to capture the distinctive characteristics associated with ECG changes resulting from hyperkalemia. Figure 2 shows the steps involved in the feature extraction algorithm used to extract the features. The algorithm was implemented using MATLAB.

The following are the steps to determine the five features

1) ***Preprocessing:***

The raw signals extracted from the MIMICS IV database contained power line interference noise, muscle noise and baseline wander. We applied a 3^{rd} order Butterworth filter to effectively eliminate the high-frequency noise. Additionally, we employed a 4^{th} order Butterworth filter to remove baseline wander from the signals. To ensure consistency and facilitate accurate feature extraction, the signals were normalized before feature extraction

2) ***R-Peak Detection:***

Locate R-peaks using the following steps:

a) Apply the findpeaks function in MATLAB to identify peaks in the signal with a minimum distance constraint of 0.6.

b) Calculate the initial minpeakheight by setting it to the mean of the signal minus 0.6 times the standard deviation of the signal.

c) Rerun the findpeaks function on the signal, this time with minpeakheight set to the mean of all previously detected peaks plus 0.2 times the standard deviation of the signal. This step ensures that all peaks detected are R peaks. For each R peak detected, q point is obtained by locating the lowest signal value in the interval of 20ms before R peak and S point is obtained by locating the lowest signal value in the interval of 20ms after R peak.

3) ***Q, R, and S Peak Detection:***

For each detected R-peak, obtain the Q point by locating the lowest signal value in the 25ms interval before the R-peak. Similarly, obtain the S point by locating the lowest signal value in the 25ms interval after the R-peak.

4) ***QRS Interval:***

Calculate the QRS interval by subtracting the S point from the Q point.

5) ***P peak and PR Interval:***

Obtain the P peak point by locating the highest peak 25ms before the Q point. Calculate the PR interval as the difference between the R peak and the P peak point.

6) ***T Peak and ST Depression:*** *The following are the steps to calculate ST Depression*

a) Locate the T point by finding the highest signal value 37ms after the S point.

b) Calculate the ST depression by taking the mean of values between the S point and the T point where values are less than 0 as shown is Fig 3.

7)Calculate the Feature values from the PQRST points detected as follows :

P Interval = Pend – Pstart (1)

PR Interval = RPeak – P start (2)

QRS Interval = S point – Q start (3)

T Interval = Tend – T start (4)

ST Depression (5)

8)For each signal, take the mean values of all the extracted features.

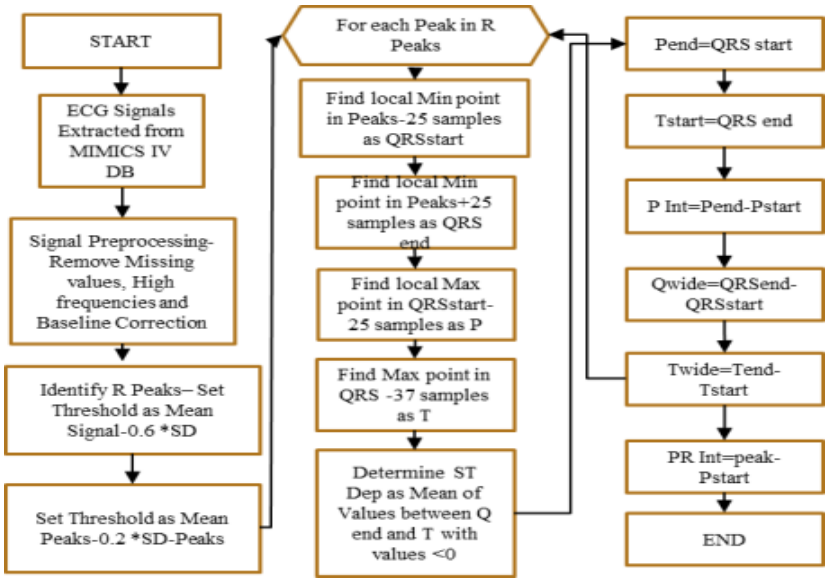

Figure 2. Feature Extraction Flowchart

Figure 4 shows the plot highlighting the P, QRS, and T peaks and Pwave and Twave detected using the proposed algorithm. The five features extracted using the algorithm are P Interval, PR Interval, QRS Interval, T interval and ST Depression

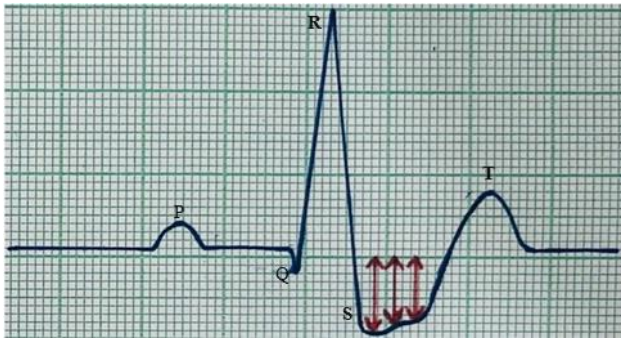

Figure 3. ST Depression

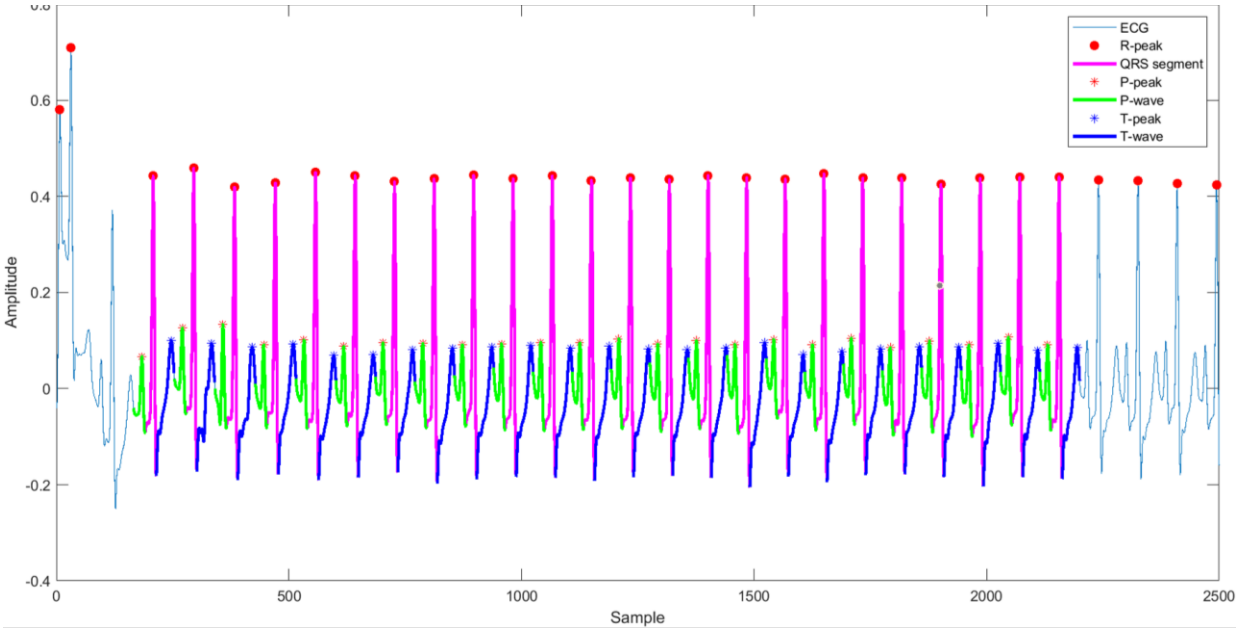

Figure 4: ECG Signal with Extracted Features

B. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is a technique used in signal processing which decomposes non-stationary and nonlinear signals into a limited set of Intrinsic Mode Functions (IMFs). This method is particularly effective for analyzing complex signals such as electrocardiogram (ECG) recordings. EMD iteratively sifts through the signal, extracting IMFs that represent narrowband oscillatory modes with characteristic frequencies. IMFs possess two key properties: (1) the number of extrema and zero-crossings must either be equal or differ by at most one, and (2) the mean value of the envelopes defined by local maxima and minima must be zero. These properties ensure that IMFs

effectively capture the inherent oscillatory modes present in the signal. Figure 5 shows the IMFs obtained from EMD. Among the IMFs extracted through EMD, IMF 2 is particularly well-suited for ECG analysis due to its relevance to the characteristic frequency range of ECG waveforms. IMF 2 often captures the fundamental oscillatory component corresponding to the heart rate frequency, making it highly informative for cardiac signal analysis. Additionally, IMF 2 tends to exhibit prominent features related to the main cardiac events, such as the P-wave, QRS complex, and T-wave, making it a valuable source of information for characterizing ECG morphology and dynamics. From IMF 2 obtained through EMD, we extracted the following features:

a) Total Power: This represents the overall energy content of the signal across all frequency bands. High total power may indicate increased signal variability or complexity, potentially reflecting underlying physiological abnormalities. It is calculated as :

$$\text{Total Power} = \sum_{i=1}^{N} x_i{}^2 \quad (6)$$

Where x_i represents the individual data points of the IMF and N is the total number of data points.

b) Spectral Entropy: Spectral entropy was computed using Welch's method, a commonly used technique for estimating power spectral density (PSD) from a time series signal. Welch's method divides the signal into overlapping segments, computes the periodograms of these segments, and averages them to obtain a smoothed estimate of the PSD. The formula for the periodogram is:

$$P_{xx}(f) = \frac{1}{N} \left| \sum_{n=0}^{N-1} x_w[n] e^{j2\pi f n} \right|^2) \quad (7)$$

where $P_{xx}(f)$ is the estimate of power spectral density at frequency f, and N is the number of samples, $x_w[n]$ is the windowed segment and f is the frequency. Then, the Welch spectrum estimate $P_{Welch}(f)$ is calculated as:

$$P_{Welch}(f) = \frac{1}{N_s} \sum_{k=0}^{N_s-1} P_K(f) \quad (8)$$

Where $P_{Welch}(f)$ is the Welch spectrum estimate at frequency f, $P_k(f)$ is the periodogram for the k-th segment.

N_s is the number of segments. [18]

c) Variance: Variance is a statistical measure that measures the dispersion or spread of data points around the mean. Higher variance values suggest greater variability in signal amplitude, which may be indicative of pathological conditions or irregular cardiac activity. Variance is calculated as

$$\text{Variance} = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2 \quad (9)$$

Where x_i represents the individual data points of the IMF, μ is the mean of the IMF, and N is the total number of data points.

d) Skewness: Skewness quantifies the asymmetry of the signal distribution around its mean. Skewed distributions may indicate non-normal or abnormal signal patterns, with positive skewness indicating a longer tail towards higher values and negative skewness towards lower values. Skewness is calculated as

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^3}{\sigma^3} \quad (10)$$

Where xi represents the individual data points of the IMF, μ is the mean of the IMF, and σ is the standard deviation of the IMF, and N is the total number of data points.

e) Singular Values:Singular values derived from the Singular Value Decomposition (SVD) of IMF2 capture information about the energy distribution and dominant frequency components of the signal. Singular values offer a spectral perspective on signal dynamics, complementing morphological features with frequency-domain information extracted from EMD.

$$A = U\Sigma V^T \quad (11)$$

Where A is an m × n data matrix, U is an m × m orthogonal matrix, And V is an n × n orthogonal matrix.

$$\Sigma = \text{diagonal}\ (\sigma 1,\ \sigma 2,\ \sigma 3\ldots..\ \sigma r) \quad (12)$$

where $\sigma 1 \geqslant \sigma 2 \geqslant \ldots. \geqslant \sigma r \geqslant 0$.

Σ is an m × n matrix whose i^{th} diagonal entry equals the i^{th} singular value σi for i = 1…r All other entries of Σ are zero. The first four singular values are extracted as features for this study.

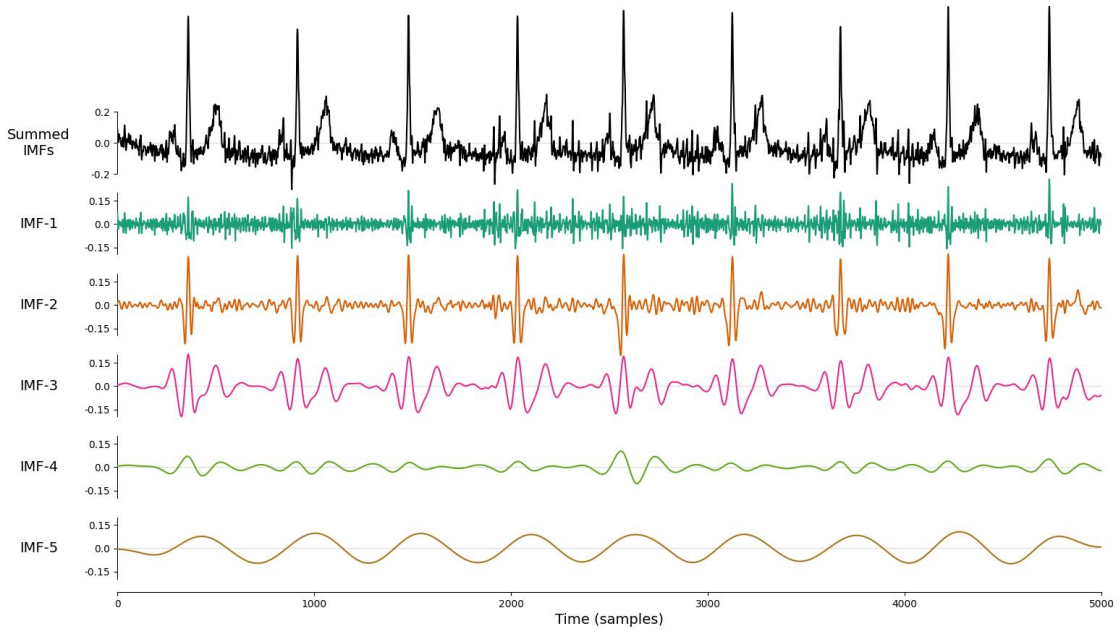

Figure 5: IMFs obtained from EMD

C. Classification

In this study, our primary objective is to classify ECG signals into Normal or Hyperkalemic Class. After extracting the thirteen features from the data, outlier detection using z-score method was performed to detect and remove outliers. By deducing the mean and dividing by the standard deviation the Z-score standardizes the data and produces a distribution with a mean of 0 and a standard deviation of 1. In our analysis, we employed three classifiers to train on the features extracted from the ECG signals. We utilized the following classifiers:

*1)***Kernel Naïve Bayes Classifier (KNB)** [17]**:** An improvement on the classic Naive Bayes classifier, the Kernel Naive Bayes (KNB) uses kernel techniques to manage non-linear feature relations. Unlike the standard Naive Bayes classifier, which assumes feature independence, KNB uses the kernel trick to implicitly translate the input features into a high-dimensional space where they may become linearly separable, in contrast to the tradition Naïve Bayes classifier which assumes feature independence. ECG signals with their subtle variations between 'Normal' and 'Hyperkalemic' patterns, can exhibit complex non-linear characteristics. KNB's ability to implicitly map features into a higher-dimensional space using kernel methods allows it to capture and represent the intricate patterns present in ECG signals more effectively than traditional linear classifiers.

*2)***AdaBoost Ensemble Classifier** [18]: The Adaboost Ensemble classifier boosts classification performance by combining several weak classifiers into a robust ensemble model. Through iterative adjustments of training instance weights, the Adaboost algorithm prioritizes challenging-to-classify examples, thus enhancing the accuracy of the classifier. This approach is particularly advantageous for ECG signal classification tasks where the distinction between normal and abnormal patterns can be subtle and challenging. By using the collective decision-making of an ensemble of classifiers, Adaboost enhances the robustness and generalization capabilities of the model, leading to more accurate and reliable hyperkalemia detection from ECG signals.

*3)***Neural Networks (NN)** [19]: A multi-layer perceptron model can capture complex non-linear relationships in the data. A wide NN architecture was used for classification as it effectively models feature interactions inherent in temporal ECG data and offers a rich set of transformations for nuanced differentiation

Each classifier was trained using the same dataset to ensure consistency in the evaluation of their performance. 5 fold cross validation was used and 10% of the data was set aside for testing.

3. IMPLEMENTATION & RESULTS

All the experiments in this study were carried out in MATLAB. The dataset extracted from MIMICS IV ECG: Diagnostic Electrocardiogram matched subset database were of 10 seconds sampled at 500 Hertz. Noise and Baseline wander was removed by applying Butterworth filter. Min- Max Scaling was used for normalizing the signals. After pre-processing 895 normal, 895 hyperkalemic ECG signals were obtained. The feature set contained 5 morphological features and eight spectral features extracted from IMF 2 obtained after Empirical Mode Decomposition. Outlier Detection using Z-score was employed to detect and remove outliers from the extracted features. Then we compared the performance of three classifiers on the reduced feature set. To ensure robust model evaluation, 20% of the dataset was held out as a separate test set, while the remaining 80% was used for training and cross-validation. . A 5-fold cross-validation approach was employed for all classification task. This required dividing the training data into five subgroups, with each iteration using four of the subgroups for training and the remaining subgroup for validation. Each subgroup was used as validation set exactly once during the five iterations of the procedure. This allowed for comprehensive assessment of model performance and minimized the risk of overfitting or biased evaluation

For the first experiment 895 normal signals and 895 hyperkalemic signals were classified based on the morphological features alone Table III presents the classification results. For the second experiment both morphological and EMD features were considered for classification

TABLE III Results

	Normal vs Hyperkalaemia					
	Morphological Features			**Morphology +EMD Features**		
Models	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
Kernel Naïve Bayes	89.01	93.9	91.3	94.32	96.47	95.4
AdaBoost	96.43	93.02	**94.7**	97.7	98.84	**98.3**
Neural Network	94.05	94.19	94.1	97.67	97.7	97.7

4. DISCUSSION

Table III presents the results of the classification. The evaluation metrics considered were Sensitivity, Specificity and Accuracy. Across all three models, using only morphological features achieves reasonably high accuracy, sensitivity, and specificity. Kernel Naïve Bayes achieves the lowest accuracy but still performs reasonably well. Neural Network and AdaBoost exhibit higher accuracy, sensitivity, and specificity compared to Kernel Naïve Bayes, indicating their effectiveness in capturing the discriminatory information present in morphological features. The addition of features

extracted using EMD enhances the performance of all three models significantly across all metrics. AdaBoost consistently demonstrates the highest accuracy, sensitivity, and specificity among the models, followed closely by the Neural Network. Kernel Naïve Bayes also benefits from the addition of EMD features, showing notable improvements in accuracy, sensitivity, and specificity compared to its performance with morphological features alone. These results indicate that features extracted using EMD provide complementary information to morphological features, effectively capturing additional spectral and temporal characteristics of ECG signals.

5. CONCLUSION

In this study, we explored the effectiveness of different feature sets and classification models for ECG classification into Normal vs. Hyperkalemia classes. Initially, we evaluated the performance of classification models using Morphological Features alone. Our findings indicate that morphological features alone achieve reasonably high accuracy, sensitivity, and specificity across all models tested. This underscores the importance of waveform characteristics in distinguishing between normal and hyperkalemic ECG signals. The inclusion of EMD features significantly improved the classification performance of all models, with notable enhancements observed in accuracy, sensitivity, and specificity. This highlights the complementary nature of morphological and EMD features, which capture both structural and spectral-temporal characteristics of ECG signals. Among the classification models evaluated, AdaBoost emerged as the top-performing model, consistently achieving the highest accuracy, sensitivity, and specificity with the combined Morphology + EMD Features. This underscores the effectiveness of ensemble learning techniques in leveraging the diverse information encapsulated within different feature sets. Future studies will incorporate a broader dataset and explore a more diverse set of features to enhance the detection and interpretation of hyperkalaemia in ECG signals. This ongoing research aims to advance the development of automated diagnostic tools for hyperkalemia detection, ultimately contributing to improved patient care and clinical outcomes in cardiology.

Acknowledgments

The researcher would like to thank Rashtrasant Tukadoji Maharaj Nagpur University, Nagpur, India, for granting the funds to carry out this research.

Funding

This research was supported by Rajiv Gandhi Science and Technology Commission Scheme of Rashrasant Tukadoji Maharaj Nagpur University, Nagpur (CR-99/171)

Conflicts of Interest

The authors declare no conflict of interest.

Data Availability

Data used in this study is available at http://www.physionet.org/

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