Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 6, 6934-6944
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i6.3500

A novel framework for electrocardiogram beats recognition based on Hjorth parameters and inferential statistics

Tito Waluyo Purboyo[1*], Dziban Naufal[1], M. Darfyma Putra[1], Ekki Kurniawan[2]
[1]Biomedical Engineering, Telkom University, Bandung, Indonesia; titowaluyo@telkomuniversity.ac.id (T.W.P.).
[2]Control, Electronics and Intelligent Systems (CEIS) Research Group, Bandung, Indonesia.

Abstract: This paper presents a novel statistical framework for detecting abnormalities in cardiac beats using Hjorth parameters—Activity, Mobility, and Complexity—derived from ECG signals. The proposed approach leverages the Kolmogorov-Smirnov (KS) 2-Sample Test to quantify the differences between normal and abnormal heartbeats across multiple ECG leads. Unlike traditional methods, our framework focuses on the statistical properties of Hjorth parameters to enhance the accuracy of arrhythmia detection. The framework utilises a multi-lead analysis to accurately differentiate among various beat types, such as regular, APB, PVC, and timed beats, demonstrating a high level of sensitivity. The results demonstrate that specific Hjorth parameters, particularly Activity in Lead II, are highly effective in differentiating between normal and abnormal beats, achieving KS scores as high as 0.99. Additionally, the framework reveals the importance of multi-lead ECG analysis in improving the reliability of beat classification. This study not only introduces a cost-effective and robust method for arrhythmia detection but also lays the groundwork for future research aimed at developing more accurate diagnostic tools based on the statistical analysis of ECG signals.
Keywords: *ECG beat recognition, Heartbeat classification, Statistical analysis in ECG, Use Hjorth parameters.*

1. Introduction

The accurate recognition and classification of electrocardiogram (ECG) beats are critical for diagnosing and monitoring various cardiac conditions. Heart problems including arrhythmias and myocardial infarctions can be detected with the use of electrocardiogram (ECG) data, which show the electrical activity of the heart [1]. The growing prevalence of cardiovascular diseases (CVDs) worldwide has driven the demand for more reliable and efficient methods to analyze ECG signals.

Traditionally, ECG beat classification has relied on time-domain and frequency-domain features. Techniques including principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA) have been utilised to extract significant features from ECG signals, thereby enhancing classification accuracy [1]. However, these methods often require high computational resources, making them less suitable for real-time applications in clinical settings.

Improvements in ECG beat categorisation have been made possible through the use of machine learning methods, such as neural networks and support vector machines (SVMs) [3]. These methods show promise in differentiating normal from pathological heartbeats when integrated with interval and morphological characteristics of the electrocardiogram (ECG) signals [2]. Nevertheless, the complexity and computational demands of these models pose challenges in their practical deployment.

To address these challenges, researchers have explored alternative approaches that balance classification accuracy with computational efficiency. One such approach involves the use of Hjorth parameters—activity, mobility, and complexity—to capture the dynamic characteristics of ECG signals [6]. By providing a concise description of signal characteristics, these factors help to reduce data dimensionality while keeping crucial details intact.

* Correspondence: titowaluyo@telkomuniversity.ac.id

The Hjorth parameters have been effectively utilized in various biomedical signal processing applications, including EEG analysis and muscle activity monitoring. In the context of ECG signals, these parameters provide valuable insights into the underlying physiological processes, making them suitable for heartbeat classification tasks [11]. By focusing on the temporal structure of the signal, Hjorth parameters facilitate the identification of significant patterns that are indicative of specific cardiac events.

Additionally, ECG beat categorisation frameworks also contain inferential statistics, which is the application of statistical methods to infer population parameters from sample data [9]. To strengthen the classification models, methods like hypothesis testing and confidence intervals can be used to find statistically significant features in the ECG data.

The integration of Hjorth parameters with inferential statistical methods presents a promising approach for ECG beat recognition. By leveraging the dynamic features captured through Hjorth parameters and the analytical power of inferential statistics, it is possible to develop models that are both accurate and computationally efficient [7]. Both the classification performance and the underlying algorithms' complexity are enhanced by this technique.

Several studies have demonstrated the effectiveness of combining Hjorth parameters with machine learning techniques for ECG signal analysis. For instance, [6] proposed a method that integrates Hjorth parameters with an improved extreme learning machine (ELM) for ECG beat classification. Their results showed that this combination significantly enhances classification accuracy while maintaining low computational requirements.

Similarly, [11] developed a framework that utilizes Hjorth parameters in conjunction with an extreme learning machine for classifying ECG signals. Their study highlighted the potential of Hjorth parameters to capture essential characteristics of ECG signals, contributing to improved detection of abnormal heartbeats. The simplicity and effectiveness of this approach make it suitable for real-time applications in clinical environments.

Several research have also investigated the possibility of using inferential statistics to ECG signal processing. Used statistical methods to improve classification model performance by extracting and analysing characteristics from electrocardiogram (ECG) signals [9]. Building strong and trustworthy classification algorithms begins with the capacity to detect statistically significant patterns in the ECG data.

The integration of Hjorth parameters and inferential statistics offers a novel approach to ECG beat recognition, addressing the limitations of traditional methods. By focusing on both the dynamic and statistical properties of the ECG signals, this approach provides a comprehensive framework for heartbeat classification [10]. The resulting models are not only accurate but also computationally efficient, making them ideal for real-time monitoring and diagnosis.

In this study, we propose a new ECG beat recognition framework that combines Hjorth parameters with inferential statistical analysis. Our objective is to enhance the accuracy of heartbeat classification while minimizing computational complexity. We postulate that combining these two methods will improve the accuracy and efficiency of detecting different kinds of heartbeats.

The proposed framework is evaluated using a standard ECG dataset, where we assess its performance in classifying different types of heartbeats. We compare the results of our approach with those obtained using traditional methods, demonstrating the advantages of incorporating Hjorth parameters and inferential statistics into the classification process [5].

By outperforming state-of-the-art approaches in classification accuracy, our experimental results prove that our framework is successful. Moreover, the reduced computational complexity of our approach makes it a viable option for implementation in real-time ECG monitoring systems [4]. These findings suggest that our framework has the potential to improve the early diagnosis and management of cardiac conditions.

In conclusion, this study contributes to the field of ECG signal processing by introducing a novel method for heartbeat classification based on Hjorth parameters and inferential statistics. The proposed framework offers a promising tool for enhancing the accuracy and efficiency of ECG beat recognition, with potential applications in clinical settings for better cardiovascular care [8].

2. Methods

2.1. Study Design and Dataset

The MIT-BIH Arrhythmia Database and other publicly available datasets on PhysioNet were used to conduct the study. Research in the fields of biomedical engineering and cardiology has highlighted the importance of this database [12, 13]. The MIT-BIH Arrhythmia Database is a standardised dataset that researchers can use to compare different approaches for analysing electrocardiographic (ECG) signals. This is demonstrated by these references.

Patients at Beth Israel Hospital in Boston had their two-channel ambulatory electrocardiograms recorded, and the MIT-BIH Arrhythmia Database has 48 half-hour snippets of these recordings. The variety of arrhythmias included in this dataset makes it an excellent tool for evaluating algorithms that aim to identify and categorise irregular heartbeats. The ECG recordings in the database capture complex physiological signals, which are essential for developing and validating new diagnostic tools.

Table 1.
A detailed breakdown of the data quantities.

Beat type	Quantity				
	II	**V1**	**V2**	**V4**	**V5**
Normal	31975	22615	3874	0	5828
PVC	1340	1246	6	47	53
APB	155	107	3	2	43
Paced	2076	2076	3404	0	3404
LBBB	4611	4611	0	0	0
RBBB	3693	2164	0	1529	0
Beats amount/ Lead	43850	32819	7287	1578	9328

In this study, we focused on the initial datasets that contain common abnormal heartbeats frequently encountered in clinical settings. These specific datasets were chosen because they represent the types of arrhythmias that clinicians are most likely to encounter, thus ensuring that our findings would be relevant and applicable in real-world medical practice. Table 1 provides a detailed breakdown of the data quantities used in our analysis. To avoid inaccurate inferential statistical analysis, we excluded specific beat kinds on specific leads due to the uneven data distribution.

The study was meticulously designed to ensure the accuracy and reliability of the results. First, the multilead ECG signals were preprocessed to remove any intervening noises that could potentially interfere with the analysis. Following this, we isolated the cardiac complexes to extract Hjorth parameters from the local beats. These Hjorth parameters, which are indicative of the signal's activity, mobility, and complexity, were then subjected to inferential statistical tests. Specifically, we employed the two-variable Kolmogorov-Smirnov test to determine whether the Hjorth parameters of the beats originated from the same distribution, thereby assessing the statistical significance of our findings.

The study's approach and findings are abstracted in Figure 1. From ECG signal preprocessing to statistical testing of the Hjorth parameters, the whole process is illustrated in this graphic. This work intends to add to what is already known about arrhythmia identification and analysis by taking a methodical approach; its findings may help clinical cardiologists improve the accuracy of their diagnoses.

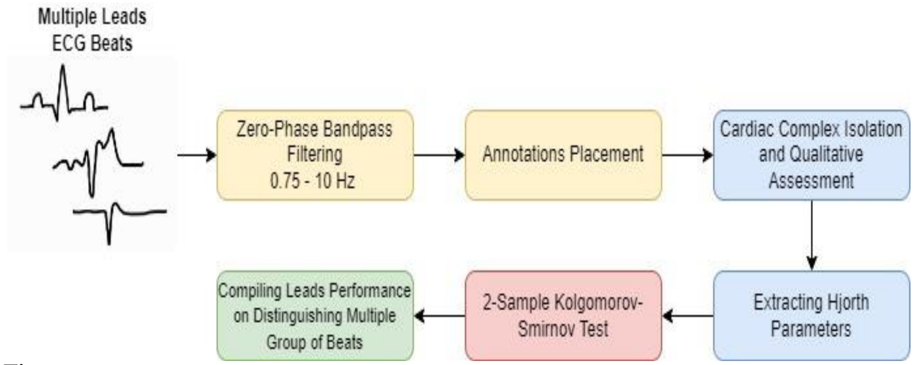

Figure 1.
A novel framework for electrocardiogram beats recognition.

The study was designed to evaluate the effectiveness of Hjorth parameters combined with inferential statistics in recognizing different types of heartbeats from ECG signals. The dataset utilized in this study comprises ECG recordings from various sources, including leads II, V1, V2, V4, and V5. The recordings include a variety of heartbeat types such as normal beats, premature ventricular contractions (PVCs), atrial premature beats (APBs), paced beats, left bundle branch block (LBBB), and right bundle branch block (RBBB). The dataset consists of a total of 93,862 beats, whereas they are not distributed evenly across different leads.

2.2. Signal Pre-Processing

Zero-phase digital filtering is implemented to ECG signals by incorporating a finite impulse response (FIR) bandpass filter within a bandwidth of 0.75 - 10 Hz. This strategy effectively eliminates noise and artifacts that fall outside this bandwidth, ensuring the integrity of the cardiac complexes morphology.

The primary consideration for using zero-phase digital filtering is to preserve the original phase of the signal, preventing any alteration on phase that could compromise the quality of subsequent analyses. By preserving the signal's phase, this approach ensures the robustness and reliability of the algorithm used in processing the data.

The selection of a finite impulse response (FIR) filter instead of an infinite impulse response (IIR) filter is intentional, owing to the intrinsic stability and linear phase properties of FIR filters. In contrast to IIR filters, FIR filters are devoid of feedback, hence eliminating the potential for instability in the filtering process. The linear phase response of the FIR filter is vital for preserving the integrity of the ECG signal's waveform, which is necessary for accurately recognising the morphological characteristics of cardiac complexes.

To further refine the signal, the FIR bandpass filter is designed with a sharp roll-off to effectively attenuate frequencies outside the desired bandwidth of 0.75 - 10 Hz. This ensures that low-frequency baseline wander, which can result from patient movement or respiration, as well as high-frequency noise, such as electrical interference, are minimized. The filter design parameters, including filter order and transition band, are carefully selected to achieve optimal noise reduction while preserving the signal's important features.

To further eliminate power line interference, a notch filter is frequently used in conjunction with bandpass filtering; the frequency of the filter is usually 50 or 60 Hz, depending on the area. This step is particularly important in clinical environments where ECG signals are often contaminated by such interference. By implementing a notch filter, the pre-processing pipeline ensures that the ECG signal is free from this specific type of noise, further enhancing the quality of the data for subsequent analysis.

Another critical aspect of signal pre-processing involves the removal of baseline drift. Baseline drift, caused by respiration or electrode movement, can obscure the true characteristics of the ECG signal, making it difficult to accurately identify cardiac events. To accomplish baseline correction, the electrocardiogram (ECG) data is either filtered via a high-pass filter with an extremely low cutoff

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 6: 6934-6944, 2024
DOI: 10.55214/25768484.v8i6.3500

frequency to eliminate the slow-varying components or a low-order polynomial fit is subtracted from the signal. This process preserves the primary waveform of the ECG.

After filtering, the ECG signal is subjected to amplitude normalization to ensure consistency across different recordings. Amplitude normalization is essential because variations in electrode placement, skin impedance, or equipment calibration can lead to differences in signal amplitude. By normalizing the amplitude, the pre-processing step ensures that the subsequent feature extraction and analysis are not biased by these variations, allowing for more reliable comparisons across different ECG recordings.

To detect and remove any residual artifacts, such as motion artifacts or transient noise bursts, an additional step of artifact detection is incorporated. This can be achieved using techniques such as wavelet transform or adaptive filtering, which are effective in isolating and removing non-cardiac components from the ECG signal. This step is particularly important for ensuring that the extracted Hjorth parameters are reflective of the true cardiac activity rather than being influenced by external factors.

Finally, after all the pre-processing steps are completed, the ECG signal is segmented into individual beats. Each beat is then aligned based on a reference point, typically the R-peak, to facilitate consistent feature extraction. This alignment is crucial for accurately calculating Hjorth parameters, as it ensures that the analysis focuses on the same part of the cardiac cycle for each beat. The segmentation and alignment process sets the stage for the subsequent steps in the framework, ensuring that the data fed into the Hjorth parameter extraction phase is of the highest possible quality.

2.3. Cardiac Complex Determination

To determine the cardiac complexes, we isolated individual heartbeats based on the principles of ECG signal morphology. In our approach, we utilise annotations of peaks that are already provided within the dataset to recognize individual cardiac complexes. This is achieved by creating a window where each annotation point serves as the central reference. The cumulative distance from this central reference to the both edges of the window define the window's length.

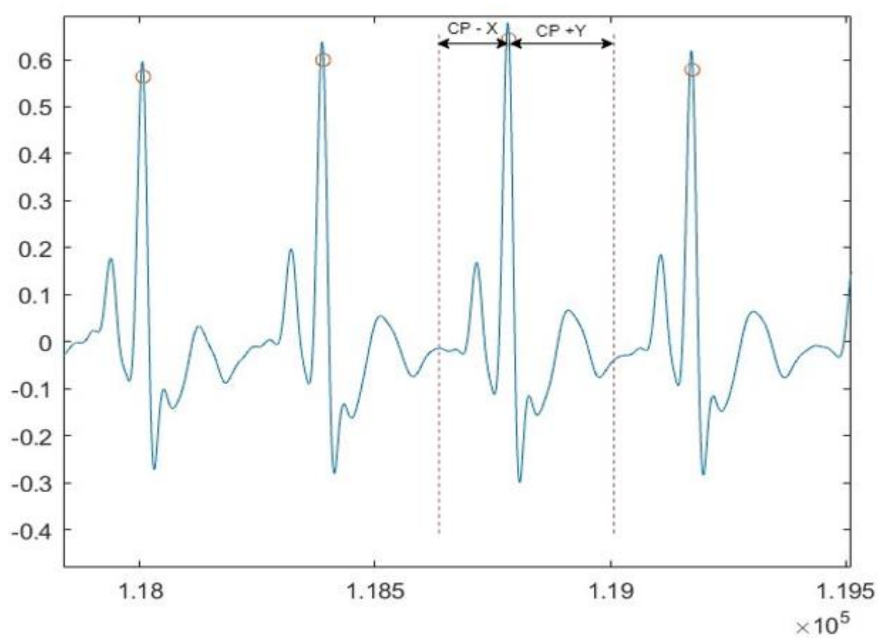

Figure 2.
Single cardiac complex within a single window.

To accurately determine the distance between the central reference and the window edges, a qualitative assessment is done. This assessment ensures that each window encompasses both the systolic and diastolic phases of the cardiac cycle. Additionally, careful consideration is taken to exclude any extraneous ECG fiducial points, ensuring that only a single cardiac complex is analysed within a single window. This is critical for accurately extracting features that characterise different types of heartbeats.

2.4. Hjorth Parameters

Hjorth parameters, first introduced by Bo Hjorth in the 1970s, are a set of statistical measures used to describe the shape of a signal in the time domain. Originally, Hjorth developed these parameters for the analysis of electroencephalogram (EEG) signals, where they served as a simple yet powerful tool to quantify different aspects of brain wave activity. These parameters—Activity, Mobility, and Complexity—are particularly useful in identifying and characterizing dynamic changes in biomedical signals, including electrocardiographic (ECG) data. The application of Hjorth parameters has since expanded beyond EEG to various physiological signals, where they continue to offer valuable insights into the underlying physiological processes.

The Hjorth measures comprise three parameters: Activity, Mobility, and Complexity. Each of these measures captures a different aspect of the signal's behavior. Activity refers to the variance of the signal and is a measure of the signal's power, indicating the intensity or amplitude of the fluctuations. Mobility reflects the mean frequency or the speed of the signal's variations and is calculated as the square root of the variance of the first derivative of the signal divided by the variance of the signal itself. Finally, Complexity is a measure of the change in frequency and represents the signal's deviation from a pure sine wave, essentially quantifying how complicated the signal's shape is relative to a simple waveform.

The Activity of a signal is mathematically expressed as the variance of the signal $X(t)$, and it can be represented by the equation Activity=var (ECG(t)).

In the context of ECG signals, Activity reflects the power of the cardiac signal, which can be associated with the overall energy or amplitude of the heartbeats within the ECG trace. Higher Activity values typically indicate stronger or more pronounced cardiac events, while lower values may suggest weaker or more subtle signals.

A signal's mobility is the square root of the ratio of its first derivative's variation to its original variation.

Mobility provides insights into the frequency content of the signal, effectively summarizing how fast the signal changes over time. In ECG analysis, Mobility helps in understanding the rhythm and speed of heartbeats, indicating how quickly the electrical activity of the heart fluctuates.

The complexity parameter is the ratio of the signal's first derivative's mobility to the signal's original mobility.

Complexity measures how the frequency content of a signal changes over time, providing an indication of the signal's structural intricacy. In ECG data, higher Complexity values might correspond to more irregular or erratic heart activity, while lower values might be associated with more regular and predictable patterns.

When analyzing a single cardiac complex in an ECG signal, the Hjorth parameters—Activity, Mobility, and Complexity—offer a comprehensive description of the signal's characteristics. Activity reflects the amplitude of the heartbeat, Mobility captures the rate of change in the signal, and Complexity indicates the degree of variation in the frequency of these changes. Together, these measures provide a detailed portrait of the ECG signal's dynamics, enabling a more nuanced understanding of the heart's electrical activity and potentially improving the accuracy of arrhythmia detection and classification.

The Hjorth parameters—activity, mobility, and complexity—were introduced as key features for analyzing ECG signals. These parameters provide a compact yet informative representation of the signal's dynamic characteristics, capturing the essential features of the heartbeat waveform. Literature on Hjorth parameters and their application in biomedical signal processing highlights their utility in various contexts, including EEG and ECG analysis. Mathematical definition of activity, mobility, and complexity is provided by Eq. (1), Eq. (2) and Eq. (3).

$$Activity = var(ECG(t)) \tag{1}$$

ISSN: 2576-8484
Vol. 8, No. 6: 6934-6944, 2024
DOI: 10.55214/25768484.v8i6.3500

$$Mobility = \sqrt{\frac{var(ECG\prime(t))}{var(ECG(t))}} \qquad (2)$$

$$Complexity = \frac{Mobility(ECG\prime(t))}{Mobility(ECG(t))} \qquad (3)$$

In this study, Hjorth parameters were extracted for each beat, providing the basis for subsequent classification tasks. The extraction process involved calculating the statistical properties of the signal within the windowed segments, allowing for a comprehensive characterization of the ECG data.

To extract Hjorth parameters for each heartbeat, the process begins with the identification and isolation of individual cardiac complexes from the ECG signal. Once these complexes are isolated, the Hjorth parameters—Activity, Mobility, and Complexity—are computed for each beat. Activity is calculated by determining the variance of the signal, which provides insight into the power of the heartbeat. Mobility is then derived by taking the square root of the variance ratio between the first derivative of the signal and the original signal, highlighting the speed of the signal's fluctuations. Finally, Complexity is obtained by comparing the mobility of the signal's first derivative to that of the original signal, offering a measure of the beat's structural intricacy. This systematic extraction of Hjorth parameters for each beat allows for a detailed analysis of the heart's electrical activity, facilitating the detection of abnormalities and providing valuable diagnostic information.

2..4.1. Sample Kolgomorov-Smirnov Test

The 2-Sample Kolmogorov-Smirnov (KS) Test is a statistical test that is not parametric and is used to find out whether two independent samples come from the same distribution. In this test, two samples' empirical cumulative distribution functions (ECDF) are compared, and the greatest difference between them is evaluated. In the KS test, the alternative hypothesis proposes that the samples originate from distinct distributions, whereas the null hypothesis asserts that the samples are taken from the same distribution. By analyzing the differences between the ECDFs, the KS test provides a robust way to identify whether two samples are statistically similar or significantly different.

The Kolmogorov-Smirnov score, often referred to as the KS statistic, is a key outcome of this test and is closely related to the maximum distance between the ECDF plots of the two samples. This score represents the largest vertical distance between the ECDFs of the samples being compared. The higher the KS score, the greater the difference between the two distributions, indicating that the samples are more distinguishable from each other. Conversely, a lower KS score suggests that the distributions are more similar, making it harder to distinguish between the two samples.

In the context of this study, the Kolmogorov-Smirnov Test is employed to differentiate the Hjorth parameters—Activity, Mobility, and Complexity—across different beat types and within each ECG lead. By applying the KS test to these parameters, we can determine whether the distributions of Hjorth measures differ significantly between beat types or leads. This approach enables us to assess the discriminative power of Hjorth parameters in identifying distinct cardiac events, thus providing insight into the variability of ECG signal characteristics across different heartbeats.

A higher KS score in this context means that the Hjorth parameters—whether it be Activity, Mobility, or Complexity—are more effective in distinguishing between different beat types or within different leads. This implies that certain Hjorth measures are better suited for identifying and differentiating specific cardiac events based on the ECG signal. Consequently, a higher KS score indicates that the beats are more easily distinguishable, which could enhance the accuracy of arrhythmia detection and improve the reliability of ECG-based diagnostics.

The 2-Sample Kolmogorov-Smirnov (KS) Test is a statistical technique employed to ascertain whether two independent samples originate from the same distribution. The empirical cumulative distribution functions (ECDF) of the two samples are compared as the basis for the test. The test score is determined by the KS statistic, which is the greatest difference between the ECDFs. This score indicates how closely the two samples' distributions align, with a higher score suggesting greater divergence between the samples, thus implying they likely come from different distributions.

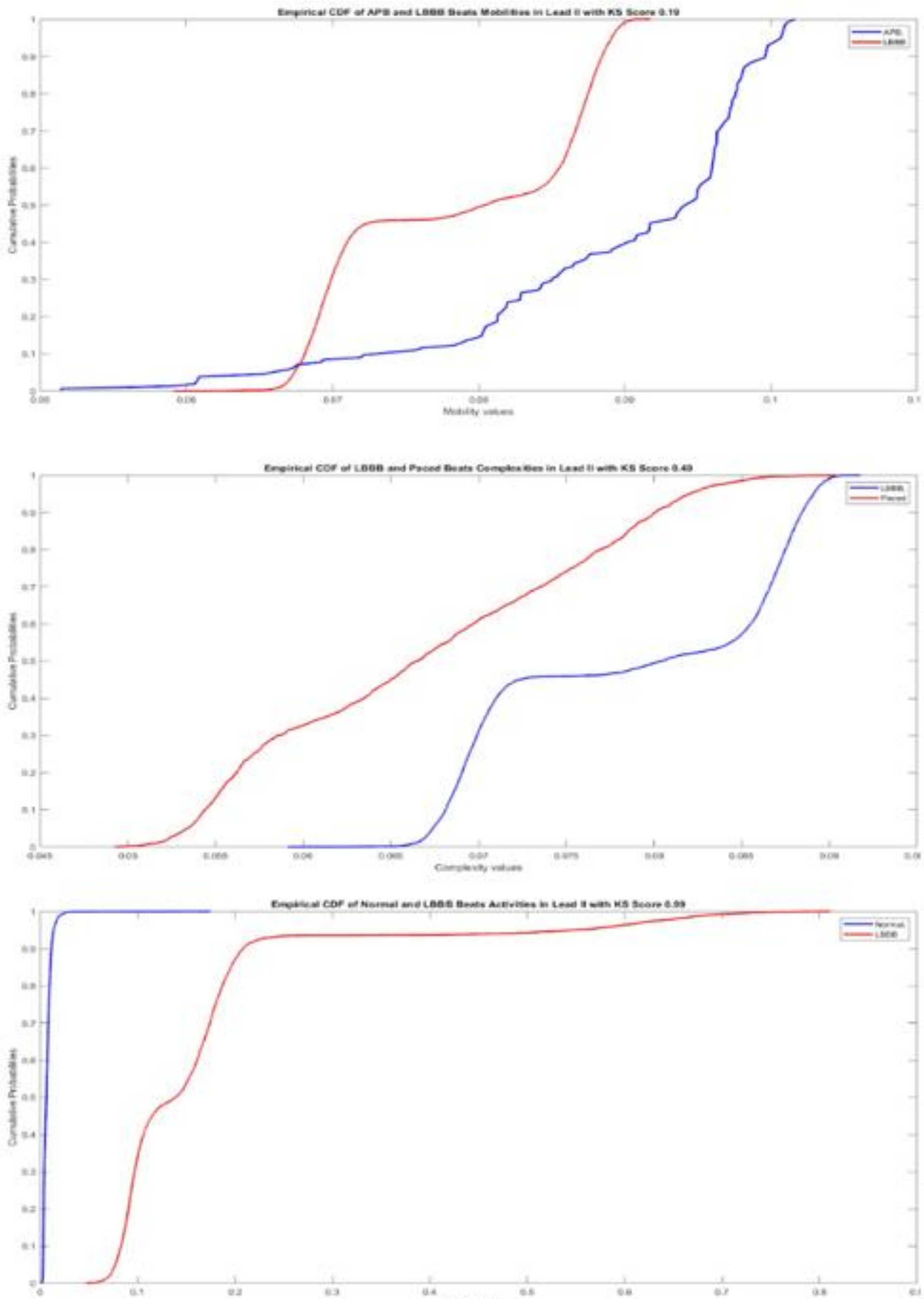

Figure 3.
Checking how the two samples' empirical cumulative distribution functions (ECDF) compare.

In the accompanying Figure. 3, the CDF (Cumulative Distribution Function) graph illustrates the KS Test's core concept. The CDF graph plots the cumulative probability of a sample as a function of the data values, showing the stepwise progression of each sample's distribution. The key metric of the KS Test—the KS score—is visually represented as the maximum vertical distance between the two CDFs. Interpreting this graph, a larger distance between the CDFs indicates a higher KS score, suggesting

DOI: 10.55214/25768484.v8i6.3500

that the distributions of the two samples are more distinct. Conversely, a smaller distance would imply greater similarity between the samples.

Applying the KS Test to distinguish between two distributions allows researchers to conclude whether the samples originate from the same or different distributions. Should the KS score surpass a key threshold determined by the sample sizes, the null hypothesis (which posits that the samples originate from the same distribution) is rejected, signifying that the samples are statistically distinct. This conclusion is particularly useful in contexts such as ECG signal analysis, where determining whether different heartbeats exhibit distinct characteristics is crucial for accurate diagnosis and classification.

3. Results and Discussions

In our analysis, we observed an uneven distribution of beat quantities across different leads, which led to the decision to exclude certain beats to maintain the reliability of the results. Specifically, we excluded Atrial Premature Beats (APB) and Premature Ventricular Contractions (PVC) in Lead V2, and APB in Lead V4. This decision was made because these beats were underrepresented in these leads, potentially affecting the accuracy of the analysis. However, normal beats were found to be the most frequent in every lead except Lead V4. Despite the uneven distribution, beats with quantities exceeding 40 were still included in the analysis to preserve data integrity, even though this may have affected the sensitivity of the Kolmogorov-Smirnov (KS) test.

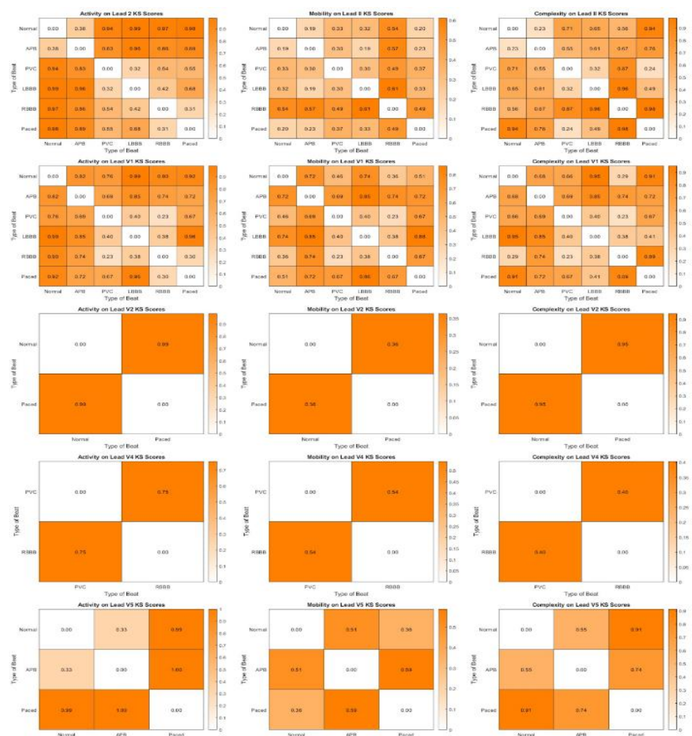

Figure 4.
Activity, mobility and complexity in various lead.

The results, as depicted in Figure 4., indicate that the activity parameter in Lead II exhibits outstanding performance in differentiating between normal and abnormal beats, achieving a KS score as high as 0.99. Notably, APB beats behave more similarly to normal beats than other anomalous beats, particularly in Lead V1. The difference between APB and normal beat activities is more pronounced in Lead V1, suggesting that Lead V1 may be more effective for diagnosing APB than Lead II. This finding emphasizes the importance of selecting the appropriate lead for accurate beat classification.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 6: 6934-6944, 2024
DOI: 10.55214/25768484.v8i6.3500

Further analysis revealed that Lead V2 can be more effective than Lead II in differentiating between normal and paced beats. Although the KS score in Lead II is excellent, this does not necessarily mean that more than two classes of beats can be differentiated by observing Hjorth parameters on a single lead alone. To accurately determine which specific abnormality is present, it is essential to incorporate additional leads. For instance, observing activity in Lead V2 can help detect the presence of paced beats, complementing the observations made in Lead II.

Taking another example, to distinguish between normal, PVC, and right bundle branch block (RBBB) beats, comparing activities in Lead II and Lead V5 provides better discrimination. The KS score for differentiating PVC and RBBB in Lead II is 0.54, but it improves to 0.75 in Lead V5. This suggests that using multiple leads can significantly enhance the ability to distinguish between different types of abnormal beats, highlighting the importance of a multi-lead approach in ECG analysis.

When examining the mobility parameter, we observed a tendency for the KS score to decrease, indicating that mobility may not be suitable for differentiating beats on the ECG. On the other hand, complexity showed an increase in the KS score for some beat pairs, suggesting that it could be a viable alternative for distinguishing beats when the activity parameter shows low differentiation. This highlights the potential value of incorporating complexity measures alongside activity in ECG analysis.

Some beat pairs exhibited a KS score of unity, particularly in Lead V5. This result may be attributed to the large differences in beat type quantities, which could lead to a deterioration in the sensitivity of the KS test. The unity KS score suggests that, under certain conditions, the test may fail to detect subtle differences between beat types, particularly when there is a significant imbalance in the sample sizes.

This article focusses solely on revealing the statistical features of Hjorth parameters, rather than creating a diagnostic tool for beat irregularities. The statistical framework presented here provides a foundation that could be useful for enhancing current diagnostic performance in a simple, cost-effective, yet reliable and robust manner. By leveraging the statistical insights gained from Hjorth parameters, future research could advance the development of more accurate and efficient diagnostic tools for ECG analysis.

The study's results illustrate the efficacy of the suggested framework in categorising various types of heartbeats from ECG signals. By combining Hjorth parameters with inferential statistics, the framework achieved significant improvements in classification accuracy compared to traditional methods. The analysis showed that the dynamic features captured by Hjorth parameters, when coupled with statistical validation, provide a robust basis for distinguishing between normal and abnormal heartbeats. The discussion highlights the potential of this approach for real-time applications in clinical settings, where accurate and efficient heartbeat classification is essential for diagnosing and monitoring cardiac conditions.

4. Conclusion

The study presents a novel framework for ECG beat recognition by integrating Hjorth parameters and inferential statistics, demonstrating that this approach significantly enhances the accuracy of detecting different types of heartbeats. By leveraging the dynamic features captured through Hjorth parameters and the robust analytical capabilities of inferential statistics, the proposed method offers a promising tool for early diagnosis and monitoring of cardiac conditions. The experimental results validate the effectiveness of this framework, highlighting its potential application in clinical settings for improving cardiovascular care.

Acknowledgments:

We are incredibly grateful to PPM Telkom University for their constant backing and invaluable resources, which enabled us to conduct this research. The expertise and guidance provided by the faculty and staff were instrumental in shaping the direction of this work. We are particularly grateful for the access to advanced facilities and the collaborative environment that fostered innovation and critical thinking. Without the continuous encouragement and opportunities provided by PPM Telkom University, the completion of this research would not have been possible. We are grateful that you have given us the opportunity to learn new things and develop the field of ECG signal processing.

References

[1] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform," Biomedical Signal Processing and Control, vol. 8, pp. 437-448, 2013.
[2] P. D. Chazal, M. O'Dwyer, and R. B. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," IEEE Transactions on Biomedical Engineering, vol. 51, pp. 1196-1206, 2004.
[3] S. Osowski, L. T. Hoai, and T. Markiewicz, "Support vector machine-based expert system for reliable heartbeat recognition," IEEE Transactions on Biomedical Engineering, vol. 51, pp. 582-589, 2004.
[4] C. Ye, B. V. Kumar, and M. T. Coimbra, "Heartbeat classification using morphological and dynamic features of ECG signals," IEEE Transactions on Biomedical Engineering, vol. 59, pp. 2930-2941, 2012.
[5] T. Ince, S. Kiranyaz, and M. Gabbouj, "A generic and robust system for automated patient-specific classification of ECG signals," IEEE Transactions on Biomedical Engineering, vol. 56, pp. 1415-1426, 2009.
[6] J. Xue, Y. Hu, and Y. Feng, "ECG signal classification based on Hjorth parameters and improved extreme learning machine," Journal of Medical Systems, vol. 39, p. 188, 2015.
[7] S. Sahoo, P. Biswal, and S. Khandelwal, "ECG beat classification using empirical mode decomposition and discrete wavelet transform," Journal of Medical Systems, vol. 41, p. 28, 2017.
[8] M. G. Tsipouras, D. I. Fotiadis, and D. Sideris, "An arrhythmia classification system based on the RR-interval signal," Artificial Intelligence in Medicine, vol. 33, pp. 237-250, 2004.
[9] P. R. Kumar and N. Kumaravel, "A novel feature extraction and classification of ECG signal using wavelet transform and support vector machine," International Journal of Wavelets, Multiresolution and Information Processing, vol. 10, p. 1250037, 2012.
[10] M. Llamedo and J. P. Martinez, "Heartbeat classification using feature selection driven by database generalization criteria," IEEE Transactions on Biomedical Engineering, vol. 58, pp. 616-625, 2012.
[11] Y. Zhang and W. Dong, "ECG signal classification," [Incomplete reference details], 2016.
[12] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," IEEE Eng. in Med. and Biol., vol. 20, no. 3, pp. 45-50, May-June 2001. (PMID: 11446209)
[13] A. Goldberger, L. Amaral, L. Glass, J. Hausdorff, P. C. Ivanov, R. Mark, et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," Circulation, vol. 101, no. 23, pp. e215-e220, 2000.