International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 1s,2025
https://theaspd.com/index.php

Biomedical Signal Processing For Medical Diagnosis

Naina Bhoyar[1], Jharna Maiti[2], Rachna Kathuria[3]
[1]Assistant Professor, Department of Pharmacy, Kalinga University, Raipur, India.
ku.nainabhoyar@kalingauniversity.ac.in,0009-0000-0999-8741
[2]Assistant Professor, Department of Biochemistry, Kalinga University, Raipur, India.
[3]Assistant Professor, New Delhi Institute of Management, New Delhi, India., E-mail:
rachna.kathuria@ndimdelhi.org, https://orcid.org/0000-0002-7773-0269

Abstract
A classification system utilizing the nearest neighbor (NN) method has been created to screen for Antero Septal Myocardial Infarction (ASMI). In this approach, we extract QRS amplitude and T height features—both of which are crucial for diagnosis—from leads V1 to V4. To combine the effects of these four leads, we employ a scoring method. Interestingly, both Euclidean and Mahalanobis distance metrics are applied in the NN classifier, with the latter showing better performance. Additionally, time-plane ECG feature-based classification methods rely on explicit time-plane features, resulting in a large set of features. By applying a carefully crafted mathematical formula, we can extract key parameters from the wavelet cross spectrum and wavelet coherence to identify both normal and abnormal cardiac patterns, like Inferior MI. To ensure our approach is reliable, we conducted empirical tests that yielded an impressive accuracy rate of 97.6% when tested on our database.
Keywords: *Biomedical, mathematical, Signal Processing, ECG*

INTRODUCTION

A signal is essentially a function that can depend on one or more variables and carries valuable information. When we talk about a biological signal, we mean one that's recorded from a living organism and provides insights into that organism's state or behavior. It's important to note that a signal can include both relevant information and some that might not be directly related to what we're interested in [1]. What we consider "information of interest" really hinges on the specific context. Take the electrocardiogram (ECG) from a volunteer, for instance; it can often pick up interference from the electrical activity of muscles, known as electromyogram (EMG). Depending on what we need to analyze, we might extract the EMG signal from the ECG or just treat it as noise from muscle contractions[2]. The goal of signal processing is to filter out the irrelevant bits so that the information we care about is easier for either a human or a computer to access [9]. Remember, we can't add information to a signal; we can only remove what's unnecessary. Typically, analyzing biomedical signals involves five key stages: data acquisition, signal processing (or conditioning), feature extraction, hypothesis testing, and decision-making. The difference between feature extraction and signal conditioning is that both processes aim to filter out irrelevant information. However, the key distinction lies in how they handle the dimensionality of the signal. Typically, the outcome of signal conditioning maintains the same dimensionality as the original input, while feature extraction results in a much lower dimensionality [3]. This reduction is crucial for easier storage, processing, and visualization. Moreover, feature extraction techniques are often tailored to the specific signal being analyzed and its intended application, whereas signal analysis methods tend to be more general. In biomedical contexts, the final step after hypothesis testing is decision-making, which is especially vital in clinical settings where actions must be determined. A variety of statistical and feature extraction techniques are employed to support automatic decision-making. [13].

REVIEW OF LITERATURE

Electrocardiography plays a crucial role in assessing cardiovascular health. An ECG, or electrocardiogram, is essentially a visual representation of the electrical activity produced by the heart [4]. This electrical activity is captured using metal electrodes placed on the limbs and chest, which then send signals to an electrocardiograph that amplifies and records them. [5].

The photoplethysmogram (PPG) signal can also serve as a valuable tool for analyzing how well the heart is functioning. Heart rate variability (HRV) arises from the heart's rhythmic activity and reflects the combined effects of psychological changes. The PPG signal captures the influence of the central nervous system. In this study, PPG is explored as an alternative to ECG for HRV analysis. Before diving into any analysis, it's crucial to grasp the physiological basis of the ECG, understand the heart's anatomy, and familiarize oneself with the standard measurement conventions of ECG, as detailed in [11]. In conclusion, the literature review highlights some research gaps. While there are numerous algorithms available for detecting R peaks, accurately pinpointing and localizing these peaks remains a challenge due to various artifacts and the differences in ECG signal morphology among individuals. Additionally, it's essential to test these algorithms by introducing artificial noise to the signals, as real ECG signals often contain various artifacts. The algorithms should perform well even in the presence of higher noise levels [6].

MATERIALS AND METHODS

Cardiologists are well-versed in recognizing the shape and morphology of a typical healthy ECG [7]. They rely on their experience to visually inspect the signal's morphology and identify any clinical abnormalities. To create an automatic ECG analysis system, we first need to determine the best way to represent the signal itself. One straightforward approach is to use the raw time series data.

The presence of noise can really obscure the important features in a signal. Another key reason to avoid using raw time series data is that, in practice, this approach often results in poor performance during the crucial stage of extracting characteristic features—this holds true whether or not there's noise in the measured signal. Often, the original signal isn't in a format that allows the chosen model to perform well on the specific problem we're tackling. Because of this, we usually need to transform the signal into a different representation that highlights the key characteristics, making it easier to identify or characterize the relevant information. Take the ECG signal, for example; it's widely recognized that much of the important information is effectively captured in the frequency domain. Different waveform features, like the QRS complex and the T wave, tend to occupy distinct areas of the frequency spectrum. Therefore, a representation that can encode the spectral characteristics of the ECG signal is likely to provide significant advantages for analysis and classification.

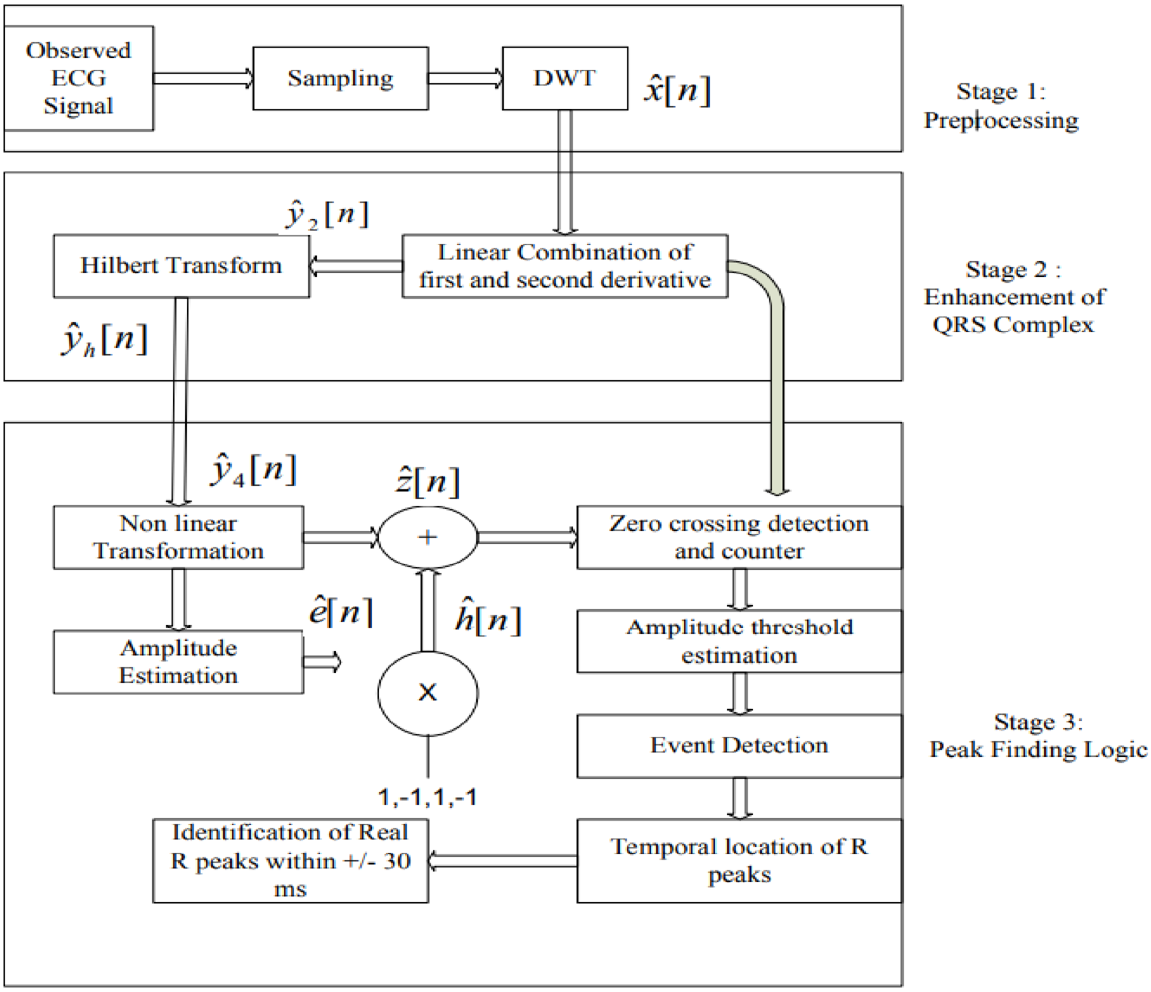

Figure 1: Proposed framework

Ideally, a thorough analysis of the ECG should merge the benefits of a spectral representation with the crucial temporal advantages of a time domain representation. This kind of signal description can be achieved through joint time-frequency transforms, such as the short-time Fourier transform and the wavelet transform. These methods are particularly well-suited for analyzing non-stationary signals like the ECG, whose properties change over time. This chapter offers a detailed review of the two main approaches to time-frequency analysis and discusses how each transform can be practically implemented [10].

RESULT AND DISCUSSION

Different medical conditions show up in the ECG signal in unique ways, particularly in the QT segment. We use clinically important leads along with specific features to classify the two different classes. Once the signals are cleaned up, the feature extraction module pulls out the key signatures from the ECG data that are clinically significant. [12].

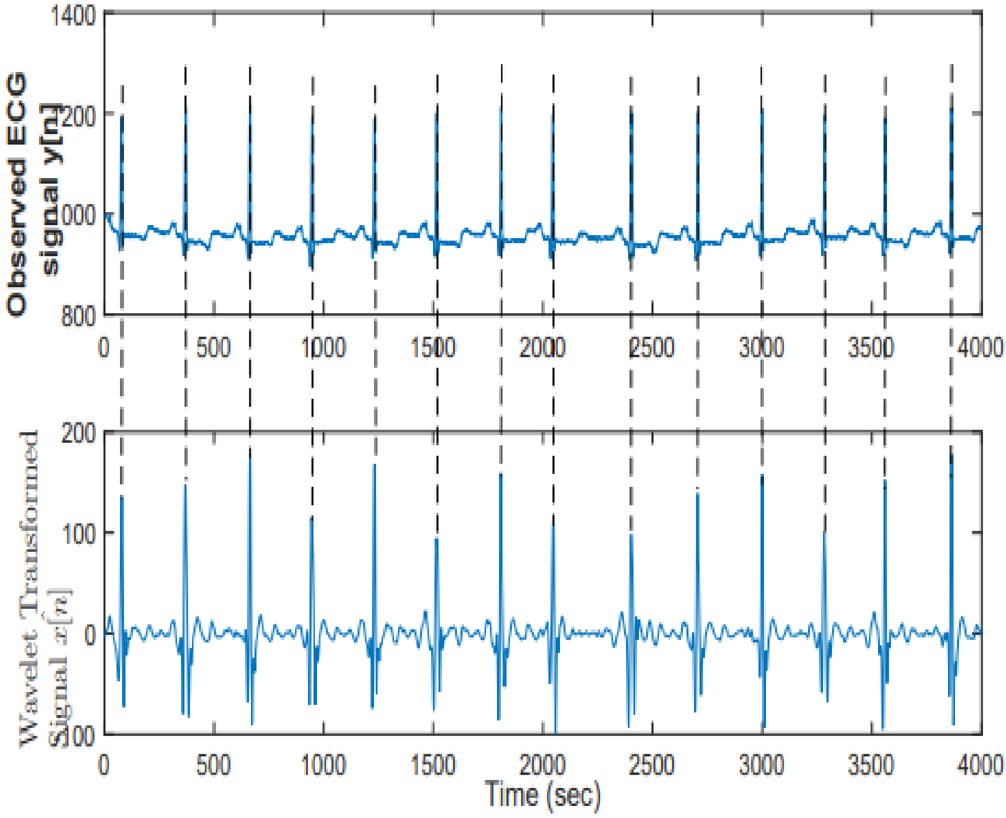

Figure 2: Observed ECG signal

The method we used for feature extraction is the same one mentioned earlier, where we pulled clinical signatures through multiresolution analysis.

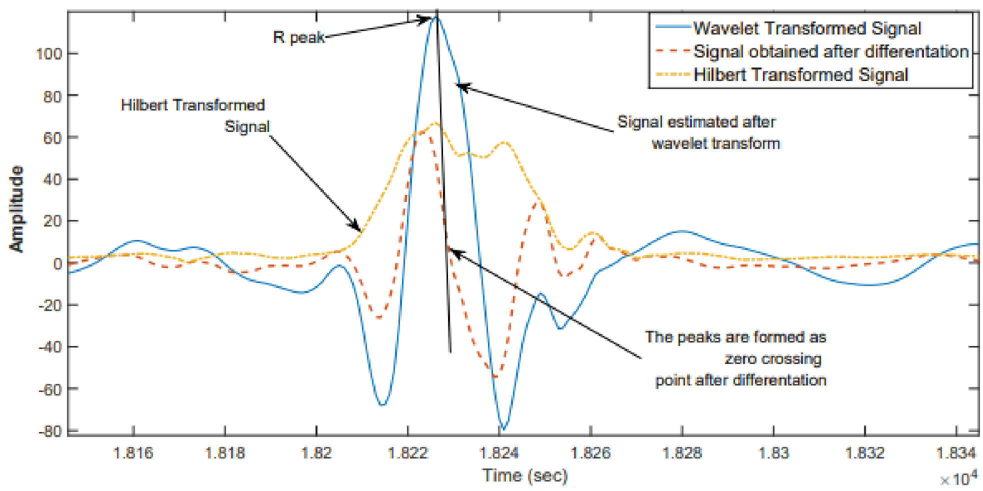

Figure 3: Signal obtained after various transform

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 1s,2025
https://theaspd.com/index.php

When it comes to classification, the key pathological features we've chosen to focus on are the height of the T wave and the amplitude of the QRS complex, which reflects how the ventricles activate or depolarize [8].

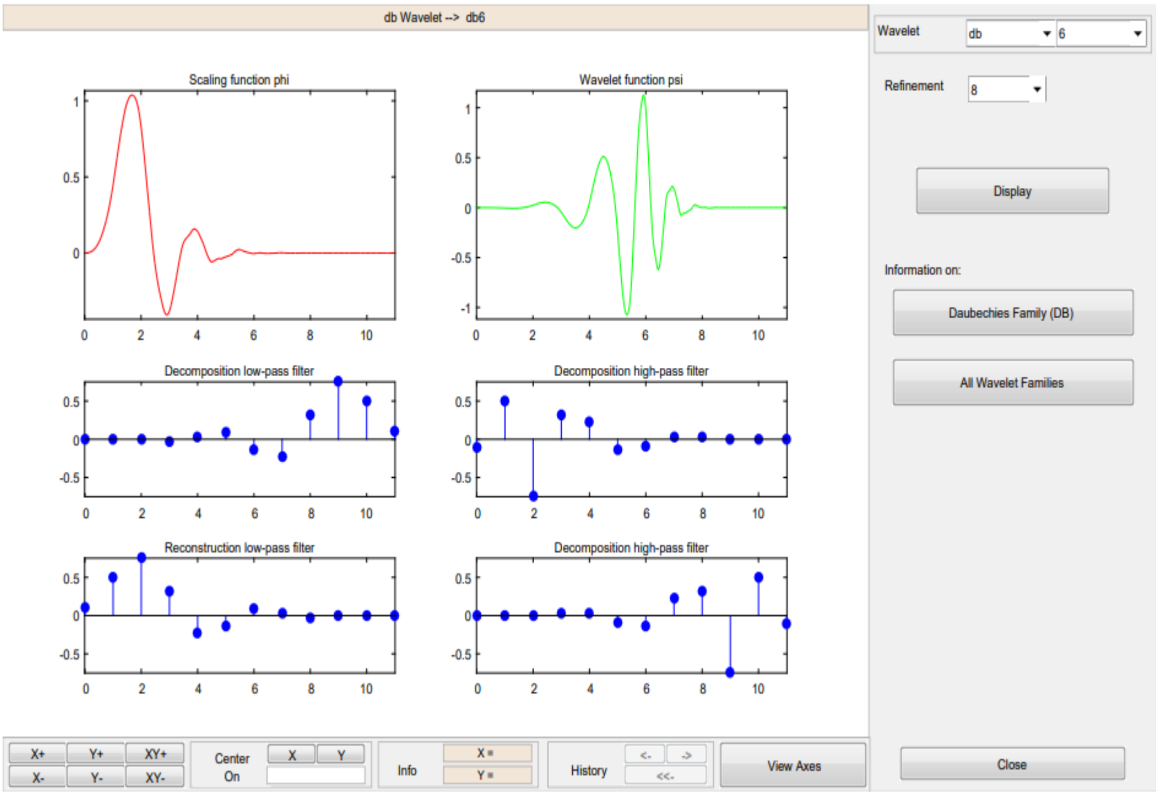

Figure 4: Mother wavelet

The Nearest Neighbour classification rule, often referred to as the NN rule, is a method used for classifying data. It relies on distance metrics like Mahalanobis and Euclidean distances to measure how far apart the clusters and data points are from each other [14].

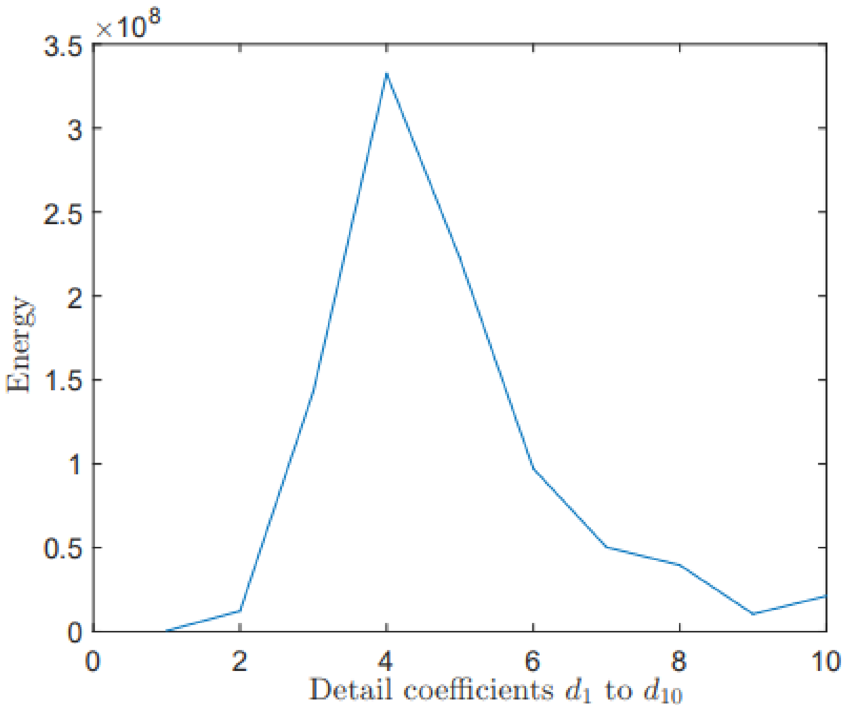

Figure 5: Energy distribution of detail coefficients

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 1s,2025
https://theaspd.com/index.php

First, we identify and select the relevant feature vectors to classify normal and abnormal subjects. To distinguish between ASMI and normal subjects, we use the K Nearest Neighbour (k-nn) estimation method [15]. For calculating cluster distances, we rely on both Euclidean distance and Mahalanobis distance metrics.

CONCLUSION

The heart is a powerful muscle that pumps blood throughout the body via the circulatory system's blood vessels. Over the past few decades, we've made remarkable strides in managing and treating cardiovascular diseases (CVDs). With the rise of W-ECG recorders, a vast amount of data is generated, making it quite challenging for analysts to sift through it all manually—there's always a risk of missing crucial information. That's why automated methods for analyzing ECG signals are becoming the go-to solution. Looking ahead, we can expect W-ECG to evolve into portable, battery-operated smart devices, like our mobile phones, which will be capable of real-time analysis and could provide immediate information to doctors or hospitals during emergencies. This makes it increasingly vital to develop more efficient computer algorithms for automatically identifying the various waves in ECG signals.

REFERENCES

1. Cerutti, Sergio. "Multivariate and multiscale analysis of biomedical signals: Towards a comprehensive approach to medical diagnosis." In *2012 25th IEEE International Symposium on Computer-Based Medical Systems (CBMS)*, pp. 1-5. IEEE, 2012.
2. Mohankumar, M., Balamurugan, K., Singaravel, G., & Menaka, S. R. (2024). A Dynamic Workflow Scheduling Method based on MCDM Optimization that Manages Priority Tasks for Fault Tolerance. International Academic Journal of Science and Engineering, 11(1), 09–14. https://doi.org/10.9756/IAJSE/V11I1/IAJSE1102
3. Sukumaran, Aswathi. "Predictors of Mental Well-being among Migrant Students during COVID-19 Pandemic." Holistic Pedagogical Approaches: 203..
4. Baggyalakshmi, N., Kanishka, J., & Revathi, R. (2024). Stationery Management System. International Academic Journal of Innovative Research, 11(1), 39–50. https://doi.org/10.9756/IAJIR/V11I1/IAJIR1105
5. Rafiee, J., M. A. Rafiee, N. Prause, and Marco P. Schoen. "Wavelet basis functions in biomedical signal processing." Expert systems with Applications 38, no. 5 (2011): 6190-6201.
6. Sharukes, K., Vasudevan, R., Sivabalan, G., & Nagarajan, G. (2023). Defect Tracking System. International Journal of Advances in Engineering and Emerging Technology, 14(1), 168–172.
7. AlHinai, N. (2020). Introduction to biomedical signal processing and artificial intelligence. In Biomedical signal processing and artificial intelligence in healthcare (pp. 1-28). Academic Press.
8. Vardhan, H., & Bhattacharya, R. (2025). The Impact of Sustainable Practices on Business Performance. International Journal of SDG's Prospects and Breakthroughs, 3(1), 15-21.
9. Foster, Kenneth R., Robert Koprowski, and Joseph D. Skufca. "Machine learning, medical diagnosis, and biomedical engineering research-commentary." Biomedical engineering online 13 (2014): 1-9.
10. Arvind, M., & Nair, A. (2025). Next-Generation Firewalls: Architecture and Effectiveness. In Essentials in Cyber Defence (pp. 35-55). Periodic Series in Multidisciplinary Studies.
11. Cerutti, Sergio, Maria Gabriella Baselli, Anna Maria Bianchi, Enrico Caiani, Davide Contini, Rinaldo Cubeddu, Fabio Dercole et al. "Biomedical signal and image processing." IEEE pulse 2, no. 3 (2011): 41-54.
12. Polat, Kemal, and Saban Öztürk, eds. Diagnostic biomedical signal and image processing applications with deep learning methods. Elsevier, 2023.
13. Moraes, Jermana L., Matheus X. Rocha, Glauber G. Vasconcelos, José E. Vasconcelos Filho, Victor Hugo C. De Albuquerque, and Auzuir R. Alexandria. "Advances in photopletysmography signal analysis for biomedical applications." Sensors 18, no. 6 (2018): 1894.
14. Yeonjin, K., Hee-Seob, K., Hyunjae, L., & Sungho, J. (2023). Venting the potential of wirelessly reconfigurable antennas: Innovations and future directions. National Journal of Antennas and Propagation, 5(2), 1–6.
15. Al-Yateem, N., Ismail, L., & Ahmad, M. (2024). A comprehensive analysis on semiconductor devices and circuits. Progress in Electronics and Communication Engineering, 2(1), 1–15. https://doi.org/10.31838/PECE/02.01.01.