Comparative Analysis of ECG Signal Feature Extraction Techniques for Cardiac Dysfunction Classification Using CNN.

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***Abstract*—An advanced analysis of electrocardiogram signals, through feature extraction techniques such as Fourier transform (FFT), Hilbert-Huang (HHT), Discrete Wavelet Transform (DWT), and Mel Frequency Cepstral Coefficients (MFCCs), enables detailed characterization of the electrophysiological parameters associated with different cardiac dysfunctions. This paper compares these techniques to provide greater interpretability to the ECG-based prediction model. For this purpose, 197 signals extracted from the *PhysioNet* repository were used. The Convolutional Neural Network (CNN) model used a training set with 167 ECG signals. It had 30 ECG signals in the test set, which included 8 ARR, 7 MI, 10 NSR, and 5 CHF. The results indicated that the selection of the extraction technique should be guided by the particularities of the signal and the objectives of the application. Furthermore, the integration of these processing methodologies with machine learning algorithms has increased the accuracy of cardiac diagnoses and prognoses, consolidating it as a promising tool for clinical analysis.**

***Index Terms*—Electrocardiogram; Feature Extraction; Convolutional Neural Network; Cardiac Dysfunction; Machine Learning.**

I. Introduction

The heart is essential for homeostasis, distributing nutrients and oxygen through the circulatory system, and its pumping function is controlled by the autonomous bioelectrical activity of the myocardium. During each cardiac cycle, electrical potentials propagate through the thorax and, when recorded on the surface, give rise to electrocardiograms (ECGs) [1]. ECGs not only reflect the heart's electrical dynamics but also provide crucial diagnostic information for identifying arrhythmias, infarctions, insufficiencies, blocks, and ischemic changes [2].

Advanced signal analysis using techniques such as, Hilbert-Huang Transform (HHT), the Fourier Transform (FFT), Mel Frequency Cepstral Coefficients (MFCCs), and the Discrete Wavelet Transform (DWT), enables a detailed understanding of electrophysiological phenomena, contributing to the development of innovative medical technologies and personalized treatments [19]. In this context, feature extraction aims to reduce dimensionality and compress data while retaining essential information. It facilitates their use in machine learning and artificial intelligence models for applications such as classification and automated diagnosis [5]. So, despite the historical reliance on clinical expertise for ECG interpretation, the increasing adoption of computerized systems seeks to mitigate human limitations, enhancing the accuracy of the early identification of cardiac anomalies [6], [7] and [15].

The selection of the feature extraction method is directly linked to specific applications and the limitations of available resources. This study proposes a comparative evaluation of different ECG feature extraction techniques, including the HHT, FFT, MFCCs, and the DWT, while considering their applicability in interface with Convolutional Neural Network (CNN) models. For this purpose, a dataset comprising 197 ECG signals served as the basis. Of these, 55 were from cardiac arrhythmias (ARR), 55 from myocardial infarction (MI), 57 with normal sinus rhythm (NSR), and 30 from congestive heart failure (CHF). Additionally, the team used 167 ECG signals for the CNN model training set, and they selected 30 signals (8 ARR, 7 MI, 10 NSR, and 5 CHF) for the test set.

The comparative analysis of the transformation techniques for identifying transient events in ECG signals revealed distinct and complementary characteristics. In this sense, the choice of the most appropriate technique for analysis depends on the specific characteristics of the signal, the objectives of the analysis, and the available computational resources. Section II organizes the explanation of these aspects through a literature review, contextualizing the study. Next, Section III details the methods and characteristics of the ECG signals employed in the feature extraction techniques. In Section IV, the authors present and discuss the results obtained, comparing them with findings from similar studies and evaluating them using the confusion matrix generated when training and testing the CNN model, which allows for a more in-depth analysis of the proposed approach. Finally, Section V brings together the final considerations and suggests directions for future research.

II. Literature Review

The analysis of biomedical signals, particularly ECGs signals, is a widely studied area due to its critical role in the diagnosis and monitoring of cardiovascular diseases [8]. In this context, several signal processing methods have been developed to improve diagnostic accuracy and robustness against noise. Malmivuo and Plonsey [1] explored the fundamentals of bioelectromagnetism, emphasizing essential principles in the acquisition and analysis of biological electrical signals. The global impact of cardiovascular diseases on public health was comprehensively addressed by [2], highlighting the significant impact that these conditions represent worldwide. In Brazil, data from [3] highlight the high mortality rate associated with cardiovascular diseases.

In this perspective, numerous studies have focused on the development of automated ECG analysis systems to facilitate remote monitoring and improve diagnostic accuracy. The research [7] presented an ECG circuit with automated signal analysis, indicating notable technological advances in this domain. In line with the scope of the present research, Emanet highlights the importance of feature extraction strategies for ECG signals, combining techniques such as DWT, Principal Component Analysis (PCA), Autocorrelation and Variance to capture comprehensive signal information (frequency, time, morphology) before feeding it to the Random Forest classifier.

Taking a similar approach, the authors of [13], justify the use of DWT as an input feature vector for the Random Forest algorithm, given its effectiveness in processing non-stationary signals, such as ECG. On the other hand, some studies prioritize simplicity in the feature extraction phase by using raw signal segments directly as input to the model, aiming to automatically detect cardiac arrhythmias during hemodialysis procedures using the Random Forest classifier [14].

III. Methods Description

The Figure 1 illustrates the proposed system for identifying cardiac dysfunctions based on ECG signals, structured in two phases: Registration and Identification. In the Registration Phase, raw ECG signals are acquired and processed through sensing and noise filtering techniques to isolate relevant components, generating a training dataset. In the Identification Phase, now processed signals are further subjected to methods such as HHT, FFT, DWT, and MFCCs to extract key properties. These features are then used to train a neural network classifier for individual identification, ensuring a systematic ECG analysis through comprehensive preprocessing, feature extraction, and classification.

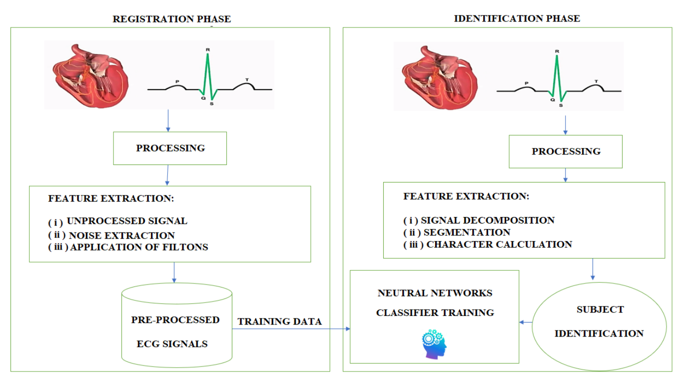

Fig. 1: Diagram represents the process of ECG feature extraction.

A. ECG Signal Characteristics (ARR, MI, NSR, and CHF)

Heart failure occurs when the heart is unable to pump blood effectively and efficiently. In the ECG, it can be identified by a low QRS complex amplitude, indicating reduced cardiac contractility and repolarization abnormalities, such as T wave inversion or flattening. Elevation or depression of ST segment deviation can indicate several causes, such as ischemic dysfunction or even the effects of gravity on the human body. These characteristics result from the lack of blood flow causing the inability of an organ or tissue to function properly [1].

Prolonged QT intervals may be associated with electrolyte disturbances or medication effects. Irregular rhythms and unevem distance between R-R peaks, such as atrial fibrillation, and axis deviation may indicate structural adaptations or ventricular hypertrophy [27]. Myocardial infarction occurs due to the interruption of blood flow to the myocardium. On the ECG, ST segment elevation (STEMI) is characteristic of acute infarctions. ST segment depression is associated with subendocardial ischemia, while T wave inversion indicates ischemia. A pathological Q wave, developing hours after the infarction, reflects myocardial necrosis and can be defined by a duration exceeding 0.04 seconds and an amplitude greater than 25% of the QRS complex. The ECG alterations vary depending on the infarction location and severity [18].

Table I presents a summary of the main electrocardiographic parameters in NSR and in clinical scenarios, including ARRs, CHFs, and MI signals:

- *General Parameters:* Heart rate is considered normal between 60-100 bpm but may vary in arrhythmia (tachycardia or bradycardia) and heart failure (normal or atrial fibrillation). In myocardial infarction, heart rate may be normal or tachycardic. Heart rhythm is typically regular but may become irregular in arrhythmia, heart failure, or infarction. The cardiac axis, normally between -30° and +90°, may present alterations in all clinical conditions.
- *Waves:* P wave amplitude is ≤ 2.5 mm under normal conditions, potentially absent or abnormal in arrhythmia. The T wave, typically ≤ 5 mm, may be absent in arrhythmias, flattened or inverted in heart failure, and inverted in infarction. The QRS complex, with an amplitude ≤ 20 mm, may be widened in arrhythmias, reduced in amplitude in heart failure, and morphologically altered in infarction (e.g., pathological Q wave).
- *Durations:* P wave duration (0.08-0.10 s) is generally maintained across conditions. The PR interval (0.12-0.20 s) and QT interval (<0.44 s) remain largely unchanged. The QRS complex duration (0.06-0.10 s) may be widened in arrhythmias and infarctions.

The accurate extraction of these characteristics using stochastic methods is essential for validating CNN inputs and ensuring reliability in clinical practice, as this heuristic approach aligns with the decision-making processes employed by health experts.

B. Feature Extraction Methods

With the advancement of technology and the increasing availability of devices capable of capturing biomedical signals, the generation of large datasets containing thousands of features has become common. This data proliferation is attributed to the ability to record physiological signals over long periods.

However, this data abundance also presents challenges, particularly regarding processing and feature extraction. Biomedical signals are often characterized as non-stationary, with statistical properties that vary over time; non-linear, due to the complexity of physiological systems that do not exhibit direct input-output relationships; non-Gaussian, as their distributions frequently deviate from the classical normal curve; and non-compact, as they contain information spread across different domains, such as time, frequency, and space [5].

Thus, the selection of features used in training significantly impacts the model's effectiveness, potentially enhancing or compromising its performance. Poorly selected or non-representative features can adversely affect the model's performance. Hence, it is prudent to choose application-specific features that robustly represent the signals of interest rather than relying on generic features [19], [25], and [26].

1) Hilbert-Huang Transform: The HHT is an adaptive technique for analyzing non-linear and non-stationary signals. It provides a time-frequency-based approach, effective in analyzing complex signals, such as biomedical, seismic, or financial signals. Initially, using Empirical Mode Decomposition (EMD), the signal is decomposed into several Intrinsic Mode Functions (IMFs), which are oscillatory functions derived directly from the original signal. These IMFs represent oscillatory components at distinct frequencies. Sequentially, the Hilbert Transform is applied, where each IMF is processed, converting the signal into an analytical form. This process extracts the amplitude envelope and the instantaneous frequency of each IMF, providing a time-frequency representation [9] and [10].

2) Fast Fourier Transform: The FFT is a widely used mathematical tool for signal and system analysis. It decomposes a time-domain signal into its frequency components, allowing for a detailed spectral analysis of its characteristics. It is extensively employed to handle large datasets due to its computational efficiency. By decomposing complex signals into constituent frequencies, FFT enables the identification of patterns, anomalies, and features that may be challenging to detect in the time domain [19].

3) Mel Frequency Cepstral Coefficients: MFCCs are commonly used in signal analysis, especially in speech, emotion detection and music analysis processing applications. They capture spectral features of a signal in a compact and representative form, approximating human auditory perception. The MFCCs are obtained by applying a series of mathematical transformations to the input signal. First, the time-domain signal is divided into small analysis windows, and the FFT is applied to obtain

TABLE I: ECG Parameters in Normal and Different Clinical Conditions. Adapted from [1].

Parameter	Normal	Arrhythmia	Heart Failure	Myocardial Infarction
Heart Rate (bpm)	60-100	Tachycardia or bradycardia	Normal or atrial fibrillation	Normal or tachycardia
Heart Rhythm	Regular	Irregular	Normal or irregular	Normal or irregular
Cardiac Axis	-30° to +90°	May be altered	Normal or altered	May be altered
Waves				
P Wave (amplitude)	$\leq$ 2.5 mm	Abnormal or absent	Normal	Normal
T Wave (amplitude)	$\leq$ 5 mm	Normal or absent	Flattened or inverted	Inverted
QRS Complex (amplitude)	$\leq$ 20 mm	Normal or widened	Low amplitude	Normal or with morphological changes (e.g., presence of pathological Q wave)
Durations				
P Wave	0.08-0.10 s	Normal	Normal	Normal
PR Interval	0.12-0.20 s	Normal	Normal	Normal
QRS Complex	0.06-0.10 s	Normal or widened	Normal	Normal or widened
QT Interval	¡ 0.44 s	Normal	Normal	Normal
ST Segment	Normal	Normal or altered	Deviation (mild to moderate)	Elevation or depression

the frequency spectrum. Then, the Mel scale is applied, mapping real frequencies to a perceptual scale, modeling how humans perceive frequency variations. Each Mel band is weighted by a triangular filter, and the sum of the energy values in each band provides the associated coefficients [20].

4) Discrete Wavelet Transform: DWT is a mathematical tool that decomposes a signal into different scale components, facilitating multi-resolution analysis. DWT effectively represents both high and low frequencies and is widely used in tasks such as image compression, denoising, and non-stationary signal analysis. The idea is to split the signal into components of different scales, each representing a specific frequency. The decomposition is performed at multiple levels, and each level comprises two main coefficients: the approximation coefficient (capturing low-frequency information) and the detail coefficient (capturing high-frequency information) [21]. Furthermore, DWT can be applied for noise reduction techniques by applying a thresholding operation on the detail coefficients, removing low-value coefficients that typically represent noise while preserving significant signal information. To ensure smoothness and preserve essential features, the chosen mother DWT was the level 5. This choice will be discussed in the results section.

C. Convolutional Neural Network and Dataset

After constructing the datasets obtained from the feature extraction methods, the data are submitted to the generic CNN for processing and classifying ECG signals. The implemented CNN is structured in several steps, starting with the installation of essential libraries, including *EMD-signal*, *pyhht*, *pywavelets* and *librosa* in the Colab environment that executes code in Python.

In the preprocessing step, the ECG signals are simulated to represent different cardiac conditions: ARR, MI, NSR, and CHF. The dataset consists of 197 ECG signals obtained from the *PhysioNet* repository and categorized into four classes: 55 ARR, 55 MI, 57 NSR, and 30 ECG signals of CHF. The dataset was divided into a training set consisting of 167 signals and a test set with 30 signals, distributed as follows: 8 ARR, 7 MI, 10 NSR, and 5 CHF. This pattern was maintained for each feature extraction method, thus forming a stratified sampling to maintain the class distribution. Therefore, each signal undergoes HHT, FFT, MFCCs, and DWT decomposition, and is stored together with its labels, which will serve as input for the convolutional neural network. The CNN architecture is designed with multiple convolutional and pooling layers, followed by fully connected layers and a softmax output layer. The model training and testing process includes the following main steps:

(i) *Data Augmentation:* To improve generalization, signals are generated using simulated variations in amplitude, phase, and noise levels, producing a diverse training dataset.
(ii) *Network Architecture:* The CNN comprises three convolutional layers with increasing filter sizes (32, 64, 128), each followed by max-pooling layers. Dropout is applied to the dense layers to mitigate overfitting.
(iii) *Optimization and Loss Function:* The model is compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function.
(iv) *Training Parameters:* The model is trained for 20 epochs using a batch size of 16, with test data comprising 20% of the dataset. Random seeds are fixed to ensure reproducibility.
(v) *Evaluation Metrics*: After training, the model is evaluated using accuracy, a confusion matrix, and a classification report. The confusion matrix is visualized to evaluate misclassifications between classes.

Upon completion, the trained model and the label encoder are saved for future inference. The confusion matrix and the classification report are stored in the specified directory for subsequent analysis.

IV. Results And Discussions

This section presents the results of the CNN model trained with the extracted features, evaluating the effectiveness of each technique in differentiating the four cardiac conditions. Confusion matrices and performance metrics are provided to illustrate the model's classification capabilities, facilitating a comparative evaluation of the feature extraction methods employed.

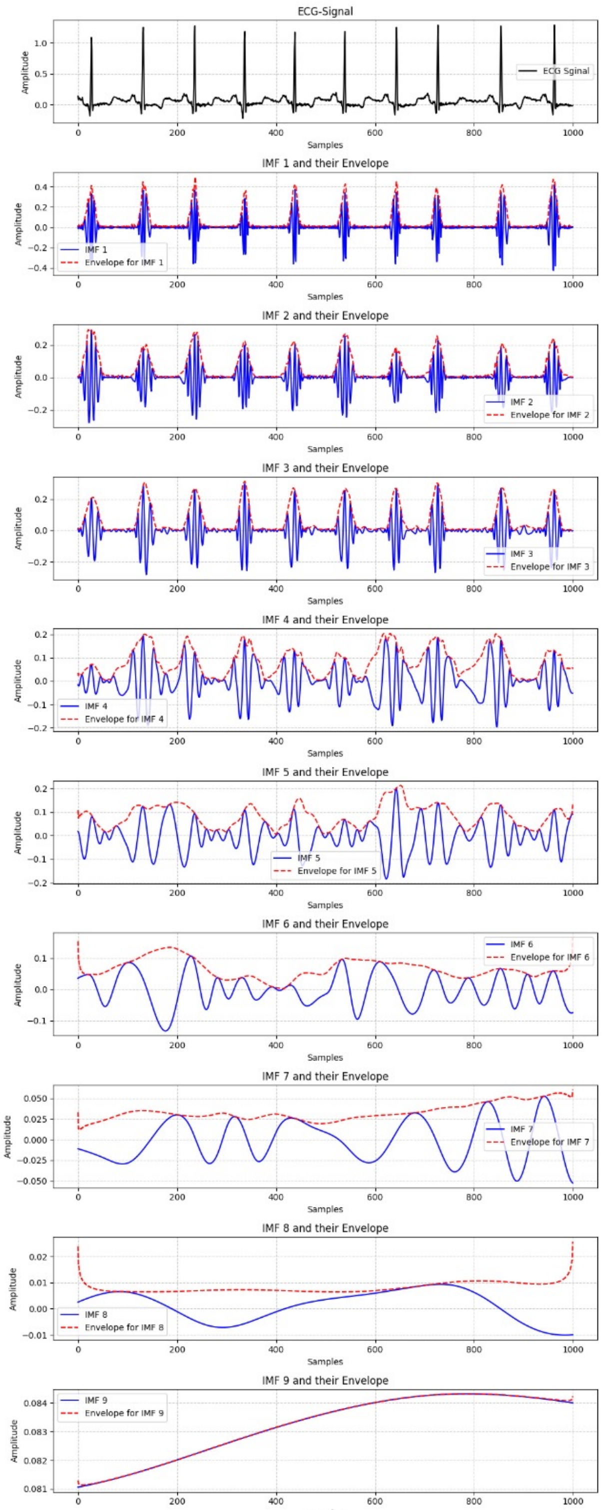

Fig. 2: Example of ECG signal with the first 1.000 points, diagnosed with ARR, applied HHT Transform with 5 IMFs and amplitude envelope.

The HHT approache introduces zero crossings associated with significant changes in signal behavior. These intersection points are often linked to peaks in their intrinsic mode functions (IMFs) and can be used to identify specific events, such as the QRS complex in ECG signals [10]. Thus, this feature manipulation approach can allow successful detection of abnormalities and efficient prognosis of cardiac disorders, such as RR, MI, and CHF (see Table II). However, the HHT transform has been reported to be sensitive to noise present in the ECG signal and computationally intensive, especially for processing long or real-time signals, due to the iterative process of localization and analysis. This may limit its applicability to systems with limited resources or that are quickly deactivated. That said, it is possible to state that the use of more than 5 IMFs in the training of the CNN model did not improve its performance. It becomes even more computationally expensive and may yield worse results due to significant noise at higher IMFs. Furthermore, Figure 2 illustrates the application of the HHT Transform to an RR-developed ECG signal.

Subsequently, the FFT allows the identification of frequency components associated with different cardiac conditions, frequently employed in ECG signal compression techniques, facilitating noise filtering. Furthermore, the Fourier series expansion can be used to separate ECG signal components, such as the QRS complex and T wave [22]. Yet, it is a challenging and computationally demanding process, as temporal information is lost and its dynamics for identifying short-term patterns, such as QRS complexes or P-R intervals, are essential for diagnosis. Furthermore, FFT assumes the signal is stationary throughout the analysis, leading to imprecise results. Consequently, simply using the Fast Fourier Transform to extract features from the ECG signal and train the CNN model was not effective in classifying these cardiac signals (see Table II). It is therefore necessary to manipulate the truncated expansion of the Fourier series in order to obtain meaningful results [22]. Figure 3 shows an ECG signal diagnosed with MI, processed using the Fourier Transform.

In sequence, since MFCCs are audio feature extraction techniques, they are generally used for classifying heart sounds and, when applied to ECG signals, are commonly associated with other feature extraction techniques such as DWT [23] and [20]. Furthermore, since MFCCs cannot effectively separate or distinguish the ECG components when extracting features, this technique may not be the best option for ECG classification (see Table II). Thus, they are typically used in machine learning algorithms, such as Neural Networks and SVMs (Support Vector Machines), to classify heart sounds as normal or abnormal [20]. In this sense, they can be used to distinguish specific types of arrhythmias, such as atrial fibrillation, ventricular tachycardia, premature ventricular contractions, and bradycardia. The Figure 4 shows the application of MFCCs to an ECG signal diagnosed as normal.

Finally, the DWT offers precise localization in the time and frequency domains, automatically segmenting ECG

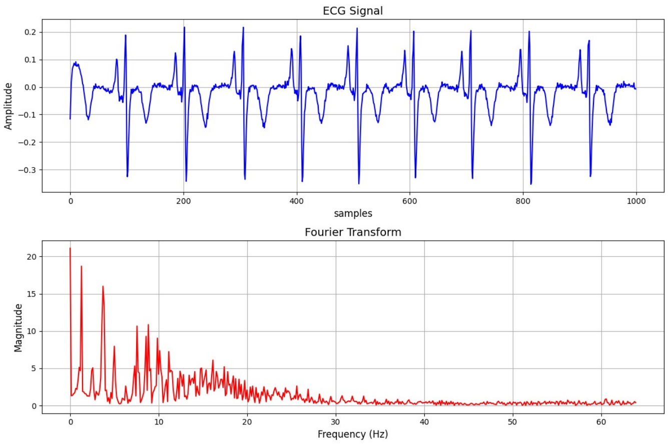

Fig. 3: Example of ECG signal with the first 1.000 points, diagnosed with MI, processed by the Fourier Transform.

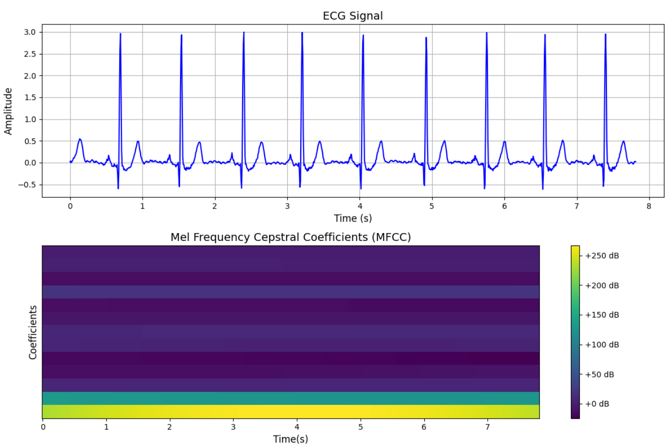

Fig. 4: Example of ECG signal with the first 1.000 points, diagnosed with NSR, applied MFCCs in a heatmap.

waves and enabling detailed analysis of each component. Through its multiscale decomposition, it highlights the energy of the QRS complex in specific bands, making it easier to identify abnormalities, although it requires greater computing power for in-depth processing [21] and [24]. Therefore, it can identify R points, as well as the start and end of P and T waves in noisy ECG signals. Consequently, it is an efficient approach to identifying and predicting ARR, MI, and CHF, proving to be the most robust among the techniques presented (see Table II). The Figure 5 shows the application of DWT in an ECG signal diagnosed with CHF.

The application of multi-level DWT in ECG signal processing demonstrates a systematic reduction in reconstruction error as additional DWT coefficients are incorporated, with error values decreasing from 4.39 at Level 1 to 2.57×10^{-12} at Level 5. Mathematically, the error quantifies the energy mismatch between the original signal $x_{\text{ECG Signal}}[k]$ and the reconstructed signal $x_{\text{reconstructed}}[k]$

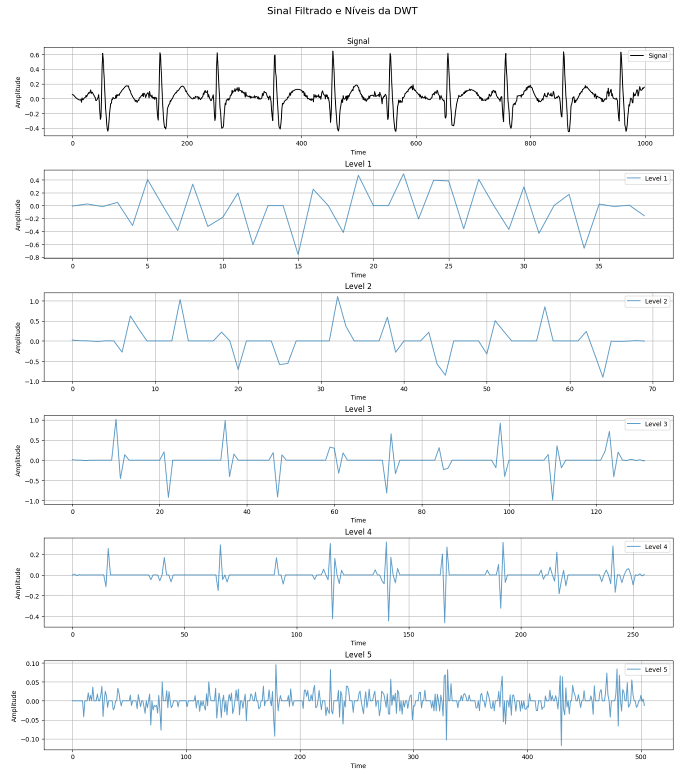

Fig. 5: Example of ECG signal with the first 1.000 points, diagnosed with CHF, applied DWT with 5 decomposition levels.

through the Euclidean norm:

$$\text{Error} = \sqrt{\sum_{k=1}^{N} \left(x_{\text{ECG Signal}}[k] - x_{\text{reconstructed}}[k] \right)^2} \quad (1)$$

The Figure 6 shows the cumulative reconstruction of an ECG signal at five DWT levels, showing a systematic reduction in reconstruction error as more coefficients are incorporated. At intermediate levels (2-3), the inclusion of mid-frequency coefficients reduces the error by around 50% by capturing critical components such as the harmonics of the QRS complex and transient artifacts. At levels 4-5, the reconstruction becomes virtually identical to the original signal, preserving the baseline and the morphology of the P and T waves, essential for clinical interpretation, and illustrating how multilevel DWT balances retention of diagnostic detail and computational efficiency.

Table II presents the classification report for the test set considering the different feature extraction techniques (HHT, FFT, MFCC, and DWT). Precision, recall, and F1-score values are reported for the four cardiac signal classes (ARR, MI, CHF, and NSR), along with the number of instances in each class. The last row shows the overall accuracy of the model for each technique, highlighting DWT (0.97) as the most effective, followed by HHT (0.90), while

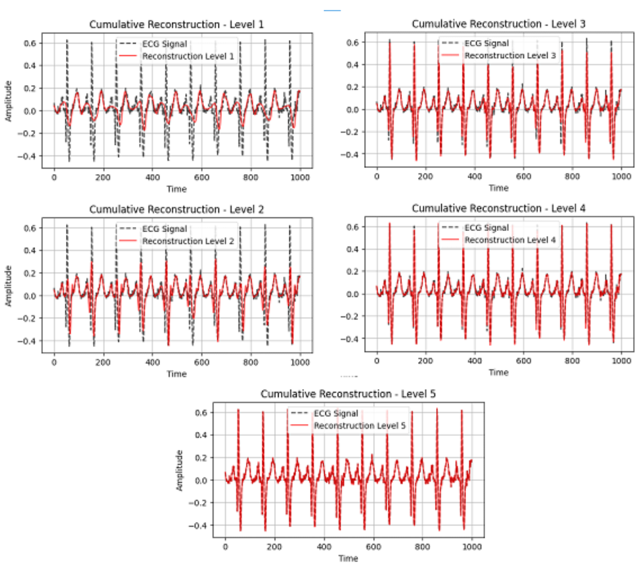

Fig. 6: Cumulative reconstruction of an ECG signal in five DWT levels (Levels 1 to 5).

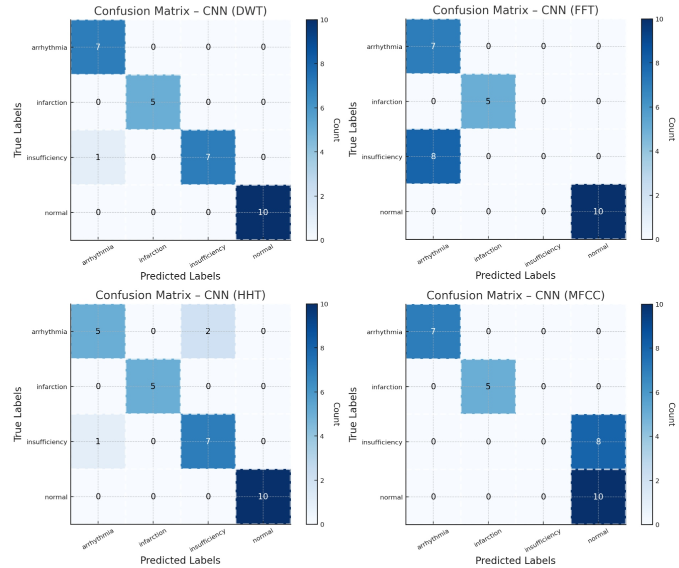

Fig. 7: Confusion Matrices for ECG Classification for Feature Extraction Methods.

FFT and MFCC showed similar performance (0.73). In addition, the Figure 7 provides a visual representation of the confusion matrices for each feature extraction method. They allow for comparing the actual and predicted classes, highlighting differences in the discrimination capability of the techniques.

TABLE II: Classification report of the test set for feature extraction methods.

Metric	HHT	FFT	MFCC	DWT
Arrhythmia				
Precision	0.83	0.47	1.00	0.88
Recall	0.71	1.00	1.00	1.00
F1-score	0.77	0.64	1.00	0.93
Instances	7	7	7	7
Myocardial Infarction				
Precision	1.00	1.00	1.00	1.00
Recall	1.00	1.00	1.00	1.00
F1-score	1.00	1.00	1.00	1.00
Instances	5	5	5	5
Heart Failure				
Precision	0.78	0.00	0.00	1.00
Recall	0.88	0.00	0.00	0.88
F1-score	0.82	0.00	0.00	0.93
Instances	8	8	8	8
Normal				
Precision	1.00	1.00	0.56	1.00
Recall	1.00	1.00	1.00	1.00
F1-score	1.00	1.00	0.71	1.00
Instances	10	10	10	10
Overall Metric				
Accuracy	0.90	0.73	0.73	0.97

The present study achieves similar accuracy to several studies that have employed DWT as a feature extraction method for the automatic classification of cardiac dysfunctions, with ECG signals extracted from the same PhysioNet database. For example, in [28], accuracy rates ranged from 95% to 99% using similar computational techniques for ECG analysis. Similarly, in [29], researchers achieved 90% accuracy in classifying ECG heartbeats for wearable devices. These studies highlight the effectiveness of DWT in capturing relevant features of the cardiac signal, although performance may vary depending on the characteristics of the data and the algorithmic approaches.

V. Conclusion

This study compared feature extraction techniques applied to ECGs signals (HHT, FFT, MFCCs, and DWT), highlighting their advantages and limitations. HHT proved effective for anomaly detection and efficient prognosis of cardiac disorders, achieving 90% accuracy in the CNN model but was sensitive to noise and computationally intensive. Additionally, FFT is effective in ECG signal compression techniques and noise filtering, but it is still limited in non-stationary signals, requiring more robust techniques for identifying and segmenting ECG components, reaching only 73% accuracy in the test set. In turn, MFCCs have limited application to ECGs and perform better in combination with other techniques, achieving only 73% accuracy in the CNN model, being recommended for heart sound classification. Furthermore, DWT stood out as the most robust, with 97% accuracy, providing good localization in time and frequency, facilitating the segmentation of components and constituting an efficient approach for identifying and predicting cardiac abnormalities. Thus, although this study demonstrated the potential of feature extraction techniques for ECG signal analysis, some gaps and possibilities for expansion remain. First, it is necessary to explore the impact of integrating different techniques in hybrid approaches, combining, for example, HHT and DWT to leverage the strengths of each method and mitigate their individual limitations. Furthermore, it is essential to assess the applicability of the proposed methods in real clinical datasets, considering practical challenges such as signal heterogeneity and the presence of artifacts.

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