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WAVELET SCATTERING TRANSFORM FOR ECG CARDIOVASCULAR DISEASE CLASSIFICATION

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ABSTRACT

Classifying the ECG dataset is the main technique for diagnosing heart disease. However, the focus of this field is increasingly on prediction, with a growing dependence on machine learning techniques. This study aimed to enhance the accuracy of cardiovascular disease classification using data from the PhysioNet database by employing machine learning (ML). The study proposed several multi-class classification models that accurately identify patterns within three classes: heart failure rhythm (HFR), normal heart rhythm (NHR), and arrhythmia (ARR). This was accomplished by utilizing a database containing 162 ECG signals. The study employed a variety of techniques, including frequency-time domain analysis, spectral features, and wavelet scattering, to extract features and capture unique characteristics from the ECG dataset. The SVM model produced a training accuracy of 97.1% and a testing accuracy of 92%. This work provides a reliable, effective, and human error-free diagnostic tool for identifying heart disease. Furthermore, it could prove to be a valuable resource for future medical research projects aimed at improving the diagnosis and treatment of cardiovascular diseases.

KEYWORDS

Wavelet Scattering Transform, Cardiovascular Disease, SVM, ECG signal, Feature Extraction.

1. INTRODUCTION

Cardiovascular diseases (CVDs), the primary cause of the global death rate, impose a significant socioeconomic burden on society. According to both the American Heart Association (AHA) and the World Health Organization (WHO), approximately 31% of all fatalities are attributed to CVDs. A staggering 75% of these fatalities occur in countries with modest to moderate income levels. Additionally, it is projected that the number of CVD-related deaths will increase to 23.6 million by 2030[1].One of the most prominent tools for the classification of cardiovascular problems is the electrocardiogram (ECG). It refers to a diagnostic tool that is used to routinely assess the muscular functions and electrical activity of the heart[2]. Moreover, the ECG is a noninvasive method for monitoring CVD function by diagnosing the activity of cardiac muscles. Even though it is a relatively simple test to perform, the interpretation of ECG charts requires a considerable amount of training. Thus, manually examining ECG paper records can often be a time-consuming and daunting operation[1]. Furthermore, it offers cardiologists comprehensive information on CVD conditions, making ECG a valuable tool for detecting a wide range of cardiac disorders. Heart failure and arrhythmia are the main causes of CVD. Over 26 million adults worldwide suffer from congestive heart failure (HFR), a serious cardiac illness that accounts for 3.6 million new cases each year and significantly increases global mortality [3]. Another dangerous heart condition is arrhythmia (ARR), which results in abnormal heart rhythms. Cardiologists must undertake a time-consuming evaluation to ensure the accurate diagnosis of ARR and HFR. Diagnostic technologies are desperately needed to detect heart conditions, allowing cardiologists to diagnose patients with ECG recordings more quickly and accurately while also saving money. Machine learning-based diagnostic systems have been developed in recent decades to differentiate between different heart disorders[4].ML research identified diverse metrics effective in diagnosing NHR and distinguishing ARR based on heart rate variability. Some approaches have combined time-domain features with Renyi entropy exponents, achieving better NHR classification accuracy than using time-domain features alone[5].

The study's major contributions are:

1. Proposed a wavelet-based scattering transform method that can accurately separate several kinds of ECG classes of cardiovascular disease.
2: Extracted other features such as spectral features, time domain, and frequency-time domain.
3: Analyze the results of the proposed methods on multi-class signals.
4: compare the results with other work.

The remaining sections of the study are organized as follows: Section 2 covers related work and Section 3 presents the proposed work, including a description of the dataset, pre-processing, and feature extraction. Section 4 discusses the results and provides an analysis.

Finally, Section 5 limitations ,6 conclusion and outlines the future scope.

2. RELATED WORK

A significant amount of research on cardiovascular prediction has concentrated on predicting diseases based on variables such as age, gender, and diet. In contrast, our work focuses on disease prediction using the ECG database. The prediction approach is enhanced by employing appropriate classifiers and features. Diagnosing the ECG database from MIT-BIH ARR is challenging due to the high within-class variability in ECG signals. With its vast and complex data resources, machine learning offers flexible solutions for the classification of dependent variables from independent variables, especially in the healthcare field. Ismail, A.R., et al[6]. Introduced an ML model for the ECG prediction of five heart diseases using a 1D TCN architecture designed for cost-effective remote health monitoring. Their approach outperformed existing methods, achieving 91.33 an accuracy of approximately 96.12%.

Liu, F., et al[7]. These authors apply the wavelet scattering transform to acquire coefficients, which are subsequently expanded based on the wavelet scale dimension to derive features. Classification is carried out employing a support vector machine (SVM) along with the wavelet scale dimension voting strategy. Furthermore, the presented approach attains a precision of 92.23%, a sensitivity of 96.62%, a specificity of 90.65%, and an accuracy measure of 93.64% on the PhysioNet database. These outcomes illustrate the efficacy of the proposed method in accurately distinguishing between normal and abnormal heart sound samples.

Janani, K.S.et al[8]. focused on the classification of ECG signals using transfer learning and wavelet scattered features. Moreover, a comparative analysis shows that the classification performance based on the raw signals' scalogram achieves high accuracy at 98.02%. The ResNet18 achieves good performance metrics for wavelet scattered data, while the DenseNet model performs better for raw data. The study demonstrates the effectiveness of transfer learning and wavelet scattered features for ECG classification, providing a potential solution for accurate and efficient diagnosis of arrhythmia.

Ahmed, A.A., et al[9]. presented a deep-learning approach to classify arrhythmias from ECG signals using a 1D-CNN model. The model demonstrates superior accuracy compared to traditional machine learning methods, eliminating the need for feature engineering and achieving excellent performance on the MIT-BIH dataset.

Papadogiorgaki, M., et al.[10] Introduced novel methodologies for efficiently classifying cardiac rhythm using ECG signals. It employs traditional ML and deep learning techniques for feature extraction and evaluation. The paper showcases high statistical metrics, indicating the potential of deep learning for ECG signal classification.

N. O. Geng, Q., et al.[11] Suggested was a novel multi-task deep neural network for efficient arrhythmia detection in ECG feature sequences. The method combines low-level feature extraction with task-specific classification and leverages hierarchical class information. Testing on public datasets demonstrates its potential for early cardiovascular disease diagnosis.

O. Elbashir et al[12]. introduced ConvXGB, a model that integrates CNN and XGBoost for efficient ECG classification. The model simplifies the process by reducing parameters and avoiding weight readjustment during backpropagation. Evaluation on established datasets demonstrates its superiority over standalone CNN or XGBoost for ECG signal classification. The achieved scores in accuracy (0.9938), recall (0.9836), precision (0.9839), specificity (0.9911), and F1-score (0.9837) surpass expectations. This paper concludes that ConvXGB shows promise in monitoring patients and identifying various heart diseases and severe CVD syndromes, such as myocardial infarction and arrhythmia.

P. Ahmed et al[13]. Achieved accurate heartbeat classification using machine learning on enriched ECG datasets (PTB and MIT-BIH Arrhythmia Diagnostic ECG). They addressed class imbalance by assigning weights during training with LSTM and ANN. Comparative analysis showed high accuracy scores of 98.06% and 97.664% for MIT-BIH ARR in the ECG dataset. The paper discusses ensemble methods and LSTM for dataset analysis.

Q. Zhang, D., et al[14].introduced a CNN-based method for predicting ECG arrhythmia using MIT-BIH ARR signals. The optimized CNN model, similar to VGGNet, successfully classifies ECG signals into five beat types with a notable accuracy rate of 90.04%. Future work suggestions include employing data augmentation techniques and exploring deep-learning optimization methods for enhanced ARR classification. According to Nguyen et al[15]. presented a deep learning framework to improve CVD classification accuracy. Their approach involves kernel size calculation based on specific waves, wavelet transform, and convolutional layers, achieving a remarkable 99.4% classification accuracy for five different CVD.

Goharrizi et al[16].T propose a novel approach to classify heart diseases using multi-lead ECG signals. They employ the histogram of oriented gradients method, applying Fully Connected NN and SVM methods for prediction. The method achieves high accuracy in classifying 15 lead ECG databases.

The presented approaches have limitations. Existing ECG classification methods fall short, motivating the proposed method using wavelet scattering with SVM for a generalized and effective ECG class CVD classification model.

3. METHODOLOGY

In this study, the proposed approach for ECG multi-class classification consists of several stages. The first stage involves the ECG database, while the second stage preprocesses signals. The third stage involves feature extraction after splitting the dataset into training and testing sets. Finally, the study presents the classification and comparison results. The framework's structure is illustrated in Figure1.

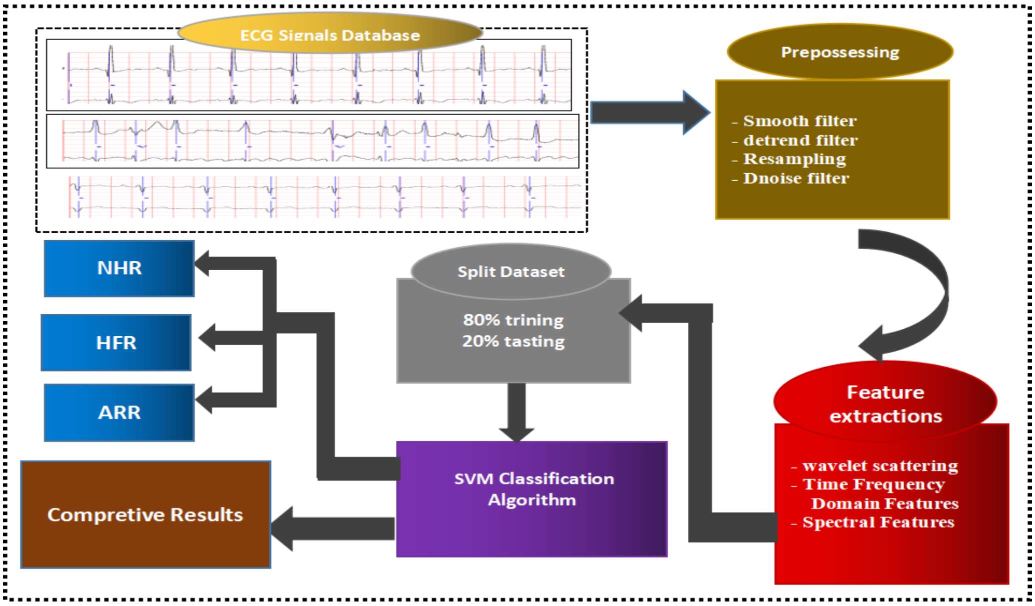

Figure 1. proposed approach of this study.

ECG Data Description and Processing

In this study, 162 ECG signals from lead II were assessed to evaluate the framework's efficiency (Figure 2). Signals were obtained from PhysioNet standard databases, featuring 96 Arrhythmia (ARR), 30 heart failure rhythms (HFR), and 36 normal heart rhythms (NHR) recordings. All signals were normalized and resampled to a constant 128 Hz frequency. To enhance classification efficiency, various filters were applied to remove unwanted artifacts and noise from the raw ECG signal while preserving essential characteristics. Post-preprocessing, the signal was segmented into 6 segments, each 10,000 samples long, totaling 972 signals. These signals underwent an 80% training and 20% testing split, with training consisting of 59.2308% ARR, 18.4615% HFR, and 22.3077% NHR, and testing comprising 59.3750% ARR, 18.7500% HFR, and 21.8750% NHR.

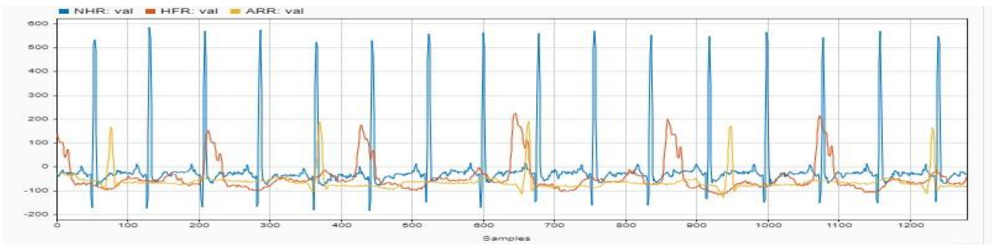

Figure 2. ECG signals(NHR,ARR,NHR)

The key parameters crucial for achieving good performance in a wavelet time scattering network are the number of wavelet coefficients, the scale of the time-invariant, and the number of wavelets per octave in every wavelet filter bank. These parameters play a vital role in classifying cardiovascular disease ECG signals using the WST and SVM models. The conversion of raw signals into a smaller set of attributes simplifies the problem of signal prediction, allowing for effective differentiation among several classes.

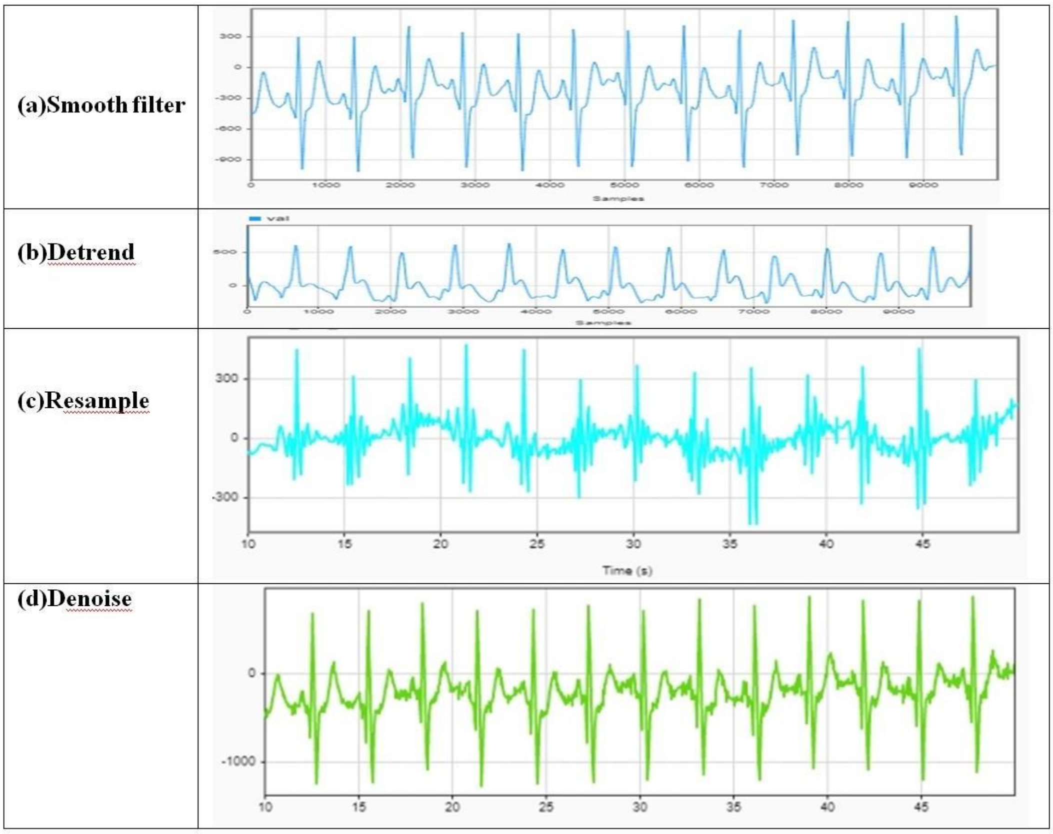

Figure 3. ECG prepossessing

This study utilizes preprocessed signals that include noise sources such as electromagnetic interference, power line interference, and baseline wander caused by patient movement and respiration activity. To mitigate these noises, the study employs a combination of a smooth filter, resampling, denoising, and detrending, which is crucial for minimizing potential information loss. The Signal Analyzer is employed for preprocessing, integrating various functions and actions, including a smooth filter, detrend, resampling, and denoise (Figure 3a). The smooth filter, applied with a window factor of 0.25, is complemented by detrending using linear methods (Figure 3b), resampling with an auto rate (Figure 3c), and denoising with a level of 8 using the Bayes method and fk wavelet (Figure 3d).

Feature Extraction

Wavelet Scattering Transform (WST)

In signal processing and data analysis, wavelet scattering is a mathematical transform used for signal analysis and processing. Based on wavelets, which are mathematical operations altering signal representation[1]. it employs a fixed, translation-invariant signal accuracy method. Effective for ECG signal prediction, it maintains class discriminability and deformation robustness. The WST summarizes signal characteristics through repeated wavelet decomposition, local averaging, and complex modulus. At each decomposition level, low-frequency features are recovered, the wavelet filter detects high-frequency components, and the scaling function records lower-frequency details. Fixed-frequency features are determined through local averages after calculating the modulus of high-frequency coefficients. Restoring lost detail due to local averaging, the high-frequency complex wavelet transform is calculated over time. A balance between discrimination and invariance is achieved by routing the signal through different scattering paths[2].

Let X(t) be the signal that has to be examined. The the low-pass filter Ø and wavelet function Ψ are considered to provide filters that cover every the signal frequencies. Let Øj(t), j ∈ N be the low pass filter that produce descriptions of X that are locally translation-in variant at a given scale T . The ʌk indicate the wavelet represent with an octave frequency resolution Qk. By dilating the wavelet, the multi-scale high pass filter-banks Ψ λK
can be created[1].

WST consist of the three steps: firstly convolution process by complex Wavelet transform,secondly nonlinear operation by methods process thirdly convolution average by scale function.

convolution operation by complex Wavelet of signal X is registered as follows:

$$x * T\lambda(\mathrm{t})=\mathrm{x}*T\lambda^{a}(\mathrm{t})+\mathrm{jx}*T\lambda^{b}(\mathrm{t}) \quad (1)$$

The wavelet modulus coefficients are structure by complex wavelet:

$$\mathrm{U}[\lambda]\mathrm{x} = |x(t) * T_{\lambda}| \quad (2)$$

nonlinear operation by methods operation complex wavelet transform and to obtain nonzero wavelet coefficient.

$$|x(t) * T_{\lambda}| = \sqrt{x * T\lambda^{a}(\mathrm{t}) + \mathrm{jx} * T\lambda^{b}(\mathrm{t})} \quad (3)$$

The third step amount to calculating the average convolution scale[8]. All that's required is an iterative combination of a Deep Convolution Network(DCN) with modulus operation, complex wavelet transform, and low-pass filter averaging[17]. Another way that WST operates for a particular time-domain signal, x, can be explained as follows:

1. To compute the WST, x is first convolved with the dilated mother wavelet ψ, whose center frequency is λ.

The formula for this operation is x*ψλ. In this case, the convolved signal's average, which fluctuates on a 2j scale, is zero.

2. To remove these oscillations, a nonlinear operator such as a modulus is then applied to the convolved signal such as |x*φλ|. By doubling the frequency, this process compensates for the information lost as a result of down sampling in the specified signal.

Lastly, the resulting absolute convolved signal, or |x*ψλ|*φ, is subjected to a low-pass filter φ.

Consequently, the average absolute amplitudes of wavelet coefficients over a half-overlapping time window of size 2j are used to calculate the first-order scattering coefficients for any scale (1≤j≤J). One way to write :

From equation 4 For each scale (1≤j≤J), first-order scattering coefficients are calculated as average absolute amplitudes of wavelet coefficients over a half-overlapping time window of size 2j.

$$S_{1X}(t,\lambda 1)=|X*\Psi\lambda 1|*\varnothing \tag{4}$$

The invariance decreases when restoring high-frequency components with the aforementioned approach. By repeating the steps on $|x*\psi\lambda 1|$, the second-order scattering coefficients can be calculated using equation (5):

$$S_{2X}(t,\lambda 1,\lambda 2)=||X*\Psi\lambda 1|*\Psi\lambda 2|*\varnothing \tag{5}$$

Higher-order wavelet scattering coefficients ($m \geq 2$) are computed by iterating the mentioned process, as shown in equation (6):

$$S_{mX}(t,\lambda 1,\lambda 2,\ldots,\lambda m)=||X*\Psi\lambda 1|*\Psi\lambda 2|\ldots\lambda m|*\varnothing \tag{6}$$

The resulting scattering coefficients, obtained by combining sets from the 0th to the mth order in the scattering transform, are expressed in Equation (7). The fundamental steps for calculating wavelet scattering coefficients up to level 2 are illustrated in Figure 4. The final feature matrix aggregates components from levels S0x, S1x, and S2x. Specifically, S0x denotes the zero-order scattering coefficients, assessing the local translation invariance of the input signal. Although high-frequency components are lost in each stage's averaging operation, they can be restored in the subsequent stage's convolution operation with the wavelet.

$$S_{X=\{S0x,S1x\ldots,Smx\}} \tag{7}$$

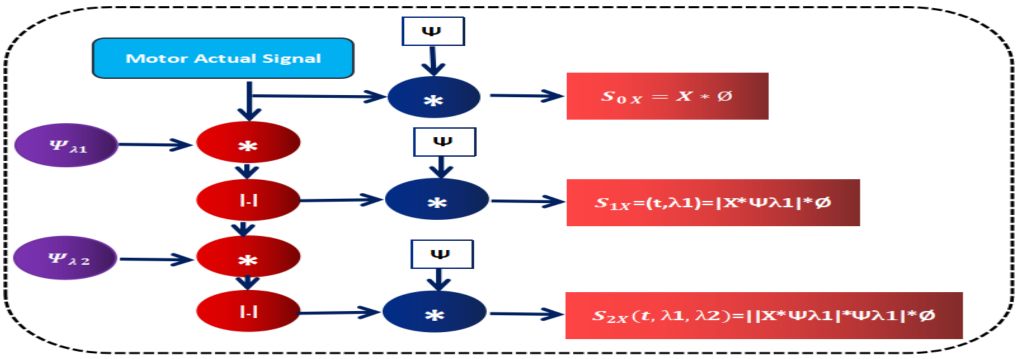

Figure 4. Feature extraction process schematic diagram of WST.

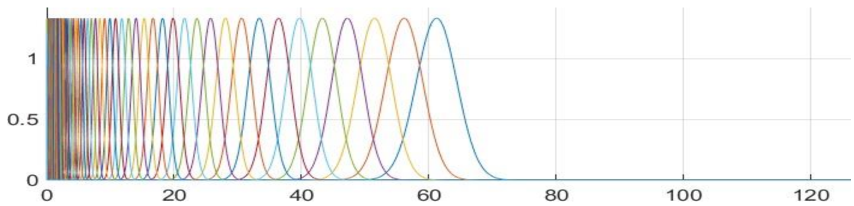

Figure 5. Wavelet filter first time

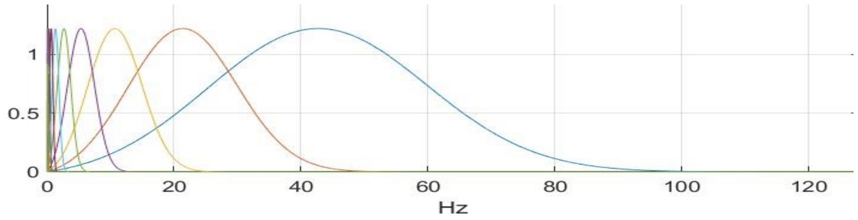

Figure 6. Wavelet filter second time

Figures 5 and 6 depict wavelet filters generated by wavelet scattering in the network. The sampling frequency is 200 Hz, and the invariance scale is one second. The default quality factor for the second filter bank is 1, while it is 8 for the first. The two filter banks have quality factors of 1 and 2, respectively, with six rotations each.

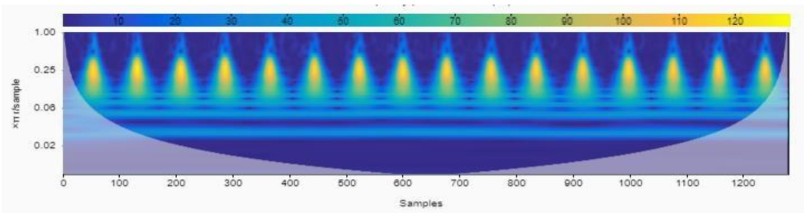

Figure 7. Spectrum of ECG database

In Figure 7, the frequency spectrum of an ECG signal is depicted, representing the distribution of various frequencies present in the signal [18]. The persistence spectrum refers to a representation that captures the persisting features or patterns in ECG signals over time. Analyzing the persistence spectrum could potentially offer insights into long-term trends or recurring patterns in the data.

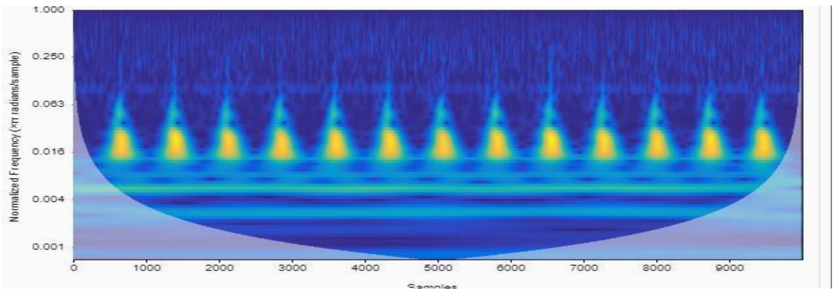

Figure 8. Scalogram of ECG database

A scalogram is a visual depiction of a signal, illustrating its frequency components at various time points. This graphical representation is frequently employed in signal processing and analysis, particularly within the realm of time-frequency analysis[18].

Time Domain features

In ECG signals reveal insights into cardiac activity. The wavelet transform, a stable and multi-scale time-frequency analysis tool, effectively extracts local features from signals, despite susceptibility to temporal changes and potential exclusion of significant features.

Table 1: Time Frequency Domain Features

FEATURS&CLASS	ARR	HFR	NHR
RMS	72.4779	84.2717	111.7525
Mean	-63.9844	-50.6324	-9.2469
Standard Deviation	34.0493	67.3787	111.4128
Shape Factor	1.0313	1.0861	1.9628
Crest Factor	2.6491	2.6937	5.2348
Peak Value	192	227	585
Impulse Factor	2.7321	2.9255	10.2747
Clearance Factor	2.7752	3.0654	13.825
SNR	-9.6401	5.296	-7.6421
SINAD	-10.4089	-4.5429	-8.2576
THD	2.5119	4.0698	-0.47474

Table 1 presents distinct characteristics and properties of ECG signals in different classes based on the measured values. The NHR class exhibits the highest values for RMS, Mean, Standard Deviation, Shape Factor, Peak Value,Crest Factor, Impulse Factor, SNR, Clearance Factor, and SINAD when compared to the HFR and NHR classes. Additionally, THD values for the ARR and HFR classes are positive, signifying the presence of harmonic distortion, while the THD value for the NHR class is negative, indicating the absence of harmonic distortion. These measurements provide insights into the different classes and can be utilized for further analysis and comparison.

Spectral Features

Spectral features encompass attributes and insights derived from examining the frequency domain representation of the signal. Analyzing the spectrum is essential for gaining an understanding of the frequency constituents within the ECG waveform.

Table 2: Spectral feature for ECG signals class

CLASS	ARR	HFR	NHR
Mean Frequency	0.055117	0.067744	0.52587
Median Frequency	0.0040038	0.039319	0.47635
Band Power	5406.0231	6503.6187	12679.3252
Occupied Bandwidth	0.43899	0.32229	1.1139
Power Bandwidth	0.0042349	0.0070078	0.029728

The values in the table represent the mean values for each parameter in each class. Mean frequency signifies the average frequency of a specific phenomenon. Median Frequency represents the mode or most common frequency of a certain phenomenon. Bandpower represents the power or intensity within a specific frequency band. Occupied bandwidth signifies the width or range of frequencies occupied by a certain phenomenon. Power Bandwidth represents the width or range of frequencies with significant power or intensity for a certain phenomenon.

Support Vector Machine (SVM)

The machine learning algorithm utilizes an effective separation method with a kernel-based approach for regression and classification datasets. The algorithm is generalized and advanced for nonlinear and multi class datasets, dividing them into a high-dimensional feature space with a kernel function. Moreover, SVM can overcome challenges posed by confused datasets and overfitting[19].

The most popular representation of the SVM equation

$f(X) = W^t Ø(X)+b$ (8)

Where Ø(X) is feature map, W belong to R^n, and b blongto R.

Confusion Metrics

To appreciate the performance of the suggested model, employed accuracy, Precision, and recall.

These are presented as follows:

Accuracy: It measures the proportion of correctly identified diseased signals and normal.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FN} + \text{TN} + \text{FP}) * 100\% \qquad (9)$$

Precision: It is the probability that the test outcome of a diseased signals truly reflects the condition[2]. additionally its a class of the number of correct positive results divided by the number of positive results. In other words, of all the records that the classifier assigns a given label, what proportion actually belong to the class

$$\text{Precision} = (\text{TP}/(\text{TP} + \text{FP})) * 100\% \qquad (10)$$

Recall: is defined as the number of correct class divided by the number of class for a given class.

$$\text{Recall} = (\text{TP}/(\text{TP} + \text{Fn})) * 100\ \% \qquad (11)$$

F1-score: It is indicated as the harmonic mean of recall and precision. its computed at the class, giving all classes the same weight[2].

$$\text{F1} - \text{score} = 2 * (\text{Precision} * \text{Recall})/(\text{Precision} * \text{Recall}) * 100 \qquad (12)$$

4. RESULTS

In this study, 162 ECG signals were categorized with multi-class information, allocating 80% for training and the rest for testing. We initially evaluated various parameters of the Wavelet Scattering Transform (WST) to determine the number of wavelets per octave, the necessary time windows, and the invariance scale for the proposed model. After transforming the data into feature vectors for each signal, we employed these vectors to classify the ECG signals using the Support Vector Machine (SVM) classifier. WST generated four time windows for each ECG signal, forming classes to accommodate the range of time windows. A plurality vote combined the selections from each time window to assign a class to the chosen ECG signal, with an additional preference for rule-breaking ties in case of encountering two fragments with the same class.

To assess performance, we estimated the misclassification rate using the entire dataset and generated a confusion matrix. The overall 5-fold classification error was 8.0247, achieving a correct classification rate of 91.98%. Misclassifications included two ARR classes as HFR, eight HFR classes as one each of NHR and ARR, and two NHR classes as ARR.

Table 3 and Figure 8 demonstrate good precision and recall for NHR and ARR, while precision and recall are notably lower for the HFR class. The HFR class achieved a higher accuracy of 97.143% compared to others in the training test.

Table 3: Training for ECG signals class

Class	Precision (%)	Recall(%)	F1_Score(%)	Accuracy(%)
NHR	97.143	94.444	95.775	97.143
ARR	90.291	96.875	93.467	90.291
HFR	91.667	73.333	81.481	91.667

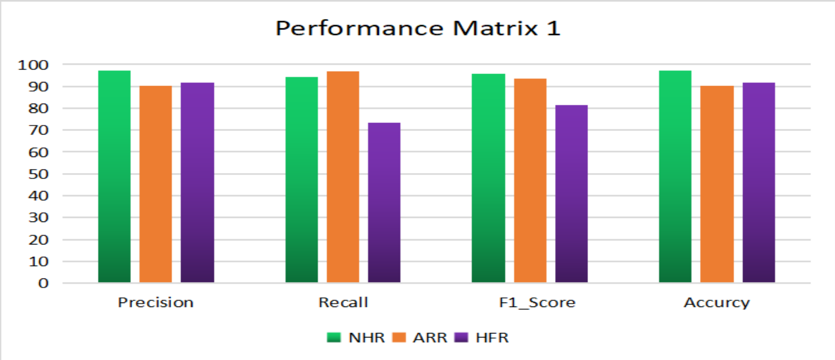

Figure9. Training ECG signals

Both precision of good for the NHR and ARR classes, but recall is significantly reduced for the HFR class.

Table 4: Tastingfor ECG signals class

Class	Precision (%)	Recall(%)	F1_Score(%)	Accuracy(%)
NHR	100	85.714	92.308	92.00
ARR	86.364	100	92.683	91.5
HFR	100	66.667	80	76.471

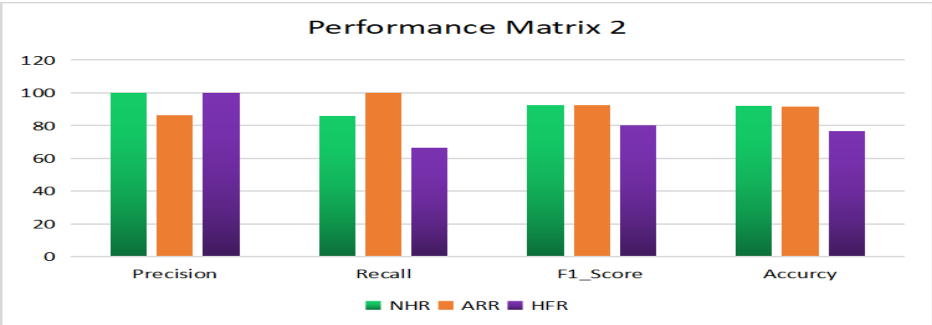

Figure10. Tasting ECG signals

In figure 10 and table 4 The model shows exceptional performance for the NHR and ARR classes, achieving perfect precision in both. However, there is room for improvement in the recall for HFR, indicating that the model misses some instances of this class. The overall accuracy of tasting NHR IS 92%. Table 5 shows that the proposed method, utilizing the PhysioNet dataset with three classes, processed 10-second ECG signals using the WST-SVM methodology, achieving 92% accuracy. This percentage reflects the effectiveness of the proposed method in ECG signal classification compared to other studies .

Table 5: Comparison of Performance Based on Accuracy for ECG Signal Classification

Author	**Dataset Used**	**No of Class**	**SignalLength**	**Methodology**	**Accuracy**
Erogul,et al[20].	MIT-BIH ARR	5	30 s	CNN	82.30%
Tsaiet, et al[21].	PhysioNet	2	2- hours	SVM	90.44%
Pałczyn ´ski et al[22].	PTB Dataset	2		CNN (1D)	90.04%
Jiaoet al[23].	MIT-BIH	5	10 s	LSTM-CNN	67.01%
Cheng et al[24].	MIT-BIH	5	-	FSL-SVM	79.00%
proposed	**PhysioNet**	**3**	**10 s**	**WST-SVM**	**92%**

5. LIMITATIONS

The research paper has Constrained by a dataset of only 162 ECG signals, the paper could benefit from the inclusion of larger and more diverse datasets. Future studies should delve into deep learning for improved Arrhythmia (ARR) classification, incorporating techniques like data augmentation and diverse architectures. Addressing noise and artifacts in ECG signal classification is crucial. Although the paper mentions the use of filters, further research should concentrate on advanced noise reduction techniques to enhance accuracy.

6. CONCLUSION

Our approach efficiently analyzes ECG signal fragments, providing simplicity, speed, and accuracy. By leveraging the deformation-invariant characteristics of WST, we minimize intra and inter-patient variation, achieving a training accuracy of 97.1% and a testing accuracy of 92% for three CVD types in 10-second ECG signals. WST demonstrates effectiveness across diverse signal classes, eliminating the need for feature engineering and QRS detection. The model excels in classifying ECG signals, offering valuable insights into time-varying data. Encouraging results prompt further research on scattering transform with alternative time-frequency representations. Future work can refine heart disorder classification by analyzing ECG fragments with multiple classes, assessing model efficacy with more fragments, and evaluating efficiency with other physiological signals. A proposed framework could integrate beat-level and fragment models for real-time ECG analysis, exploring a subject-oriented approach. Additionally, an attention-based RNN in the CNN model captures critical ECG features, emphasizing anomalous pattern locations for improved focus.

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