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A Time-Frequency Grounded ECG Feature Abstraction Systems based Advanced Design for Improvement of ANN for CA classification

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Abstract: Finding the aberrant waves of the ECG pattern allows for the majority of heart illnesses to be identified. Automated ECG feature extraction, in addition to the traditional human approach, is extremely important since it improves categorization. The extracted and selected features must be redundant and irrelevant in order to differentiate the classes to a significant level. The many different cardiac anomalies can be effectively classified with the help of a suitable feature extraction methodology. Hence, both the role of feature extraction and the categorization of patterns is crucial. The focus of this chapter is on extracting characteristics from several domains, including time, frequency, and time-frequency. The retrieved features are provided as inputs for an ANN that will classify the ECG arrhythmias. The de-noised ECG data undergo additional processing in order to extract features. Several domains, including Time, Frequency, and Time-Frequency (Wavelet) domains, are used to extract the characteristics. AR (Auto-regressive) constants are abstracted in the time domain. PSD (Power Spectral Density) values are convalesced in the frequency domain, and comparative wavelet energy at various disintegration levels is removed in the wavelet domain. In order to accurately classify arrhythmias, these features are used to create a fully connected Artificial Neural Network (ANN), with a performance evaluation of (96.85%) accuracy. The simulation findings reveal that compared to the other two ANN models, the one based on wavelet energy delivers better performance in terms of network complexity and accuracy in classifying cardiac arrhythmias. So, this model aids doctors in making the ultimate call in life-or-death circumstances.

Keywords*: ANN, ECG, PSD, AR.*

1. Introduction

Many different cardiac abnormalities can be effectively classified with the help of a suitable feature extraction methodology. Hence, both the role of feature extraction and the categorization of patterns is crucial. The main focus of this paper is on extracting characteristics from several domains, including time, frequency, and time-frequency. The retrieved features are provided as inputs for an ANN that will classify the ECG arrhythmias. The order of the chapters is as follows. The primary focus of this paper is on effective noise reduction filtering methods for ECG signals in various domains [1].

Features are distinguishing traits that can be determined from the signal. The most notable features are those that were extracted because they represent important signal properties [2]. The advantageous characteristics contribute to the precise identification of the signal's anomalies and aid in differentiating between distinct shape variations that correspond to abnormalities and arrhythmias. P, QRS, and T wave amplitudes as well as specific cardiac cycle intervals all point to an underlying heart condition. Finding the pertinent characteristics from the ECG pattern for the analysis of cardiac problems is the primary goal of the feature extraction method. A strong feature vector that can differentiate between multiple form changes that correlate to the anomaly is necessary for illness identification [3].

As the features are recovered from the raw ECG signal without being transformed into another domain, the time domain feature extraction approach is simpler to apply.

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Yet, the time domain has a drawback. While features are extracted with the assumption that the signal is stationary, the ECG signal's non-stationary nature causes statistical attributes to fluctuate over time. A linear prediction model called the AR predicts a signal's future value from a linear combination of its prior values. These methods perform more effectively than the base template methods. The process of extracting features from an AR model is frequently used in biological data like ECG and EEG. The AR approach can be used for telemedicine classification and diagnosis since it models the signal by taking into account some of the signal's prior data points [4].

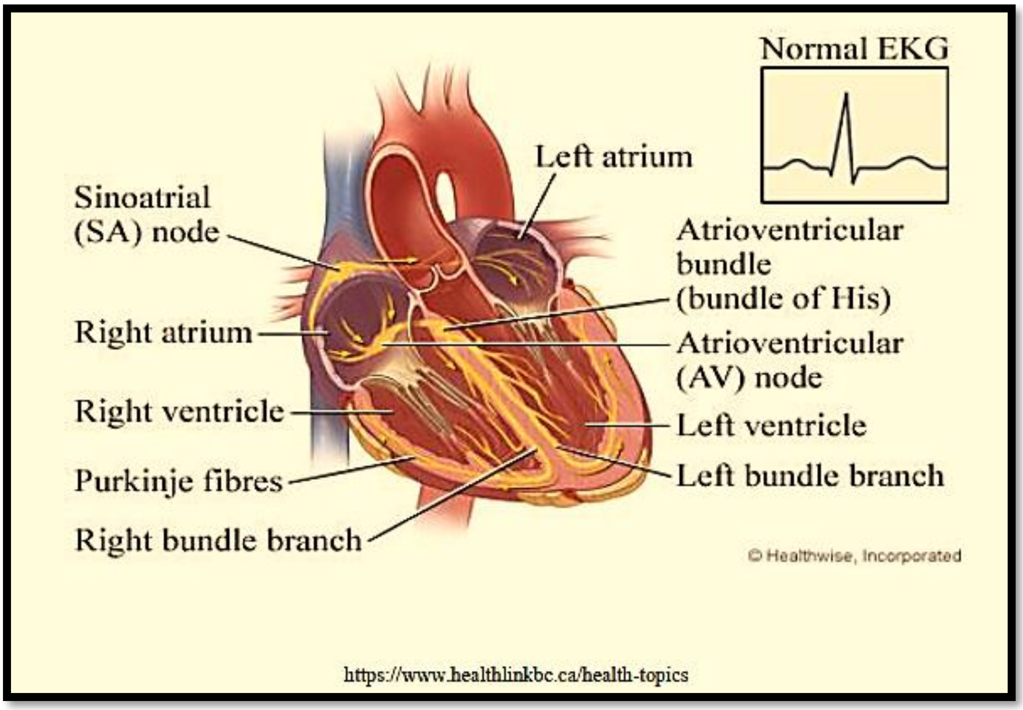

Fig I: Electrical Conduction system of the Heart.

The PSD, amplitudes of the maximum and lowest frequency components, and other characteristics are extracted from the time domain ECG signal using the Frequency Domain Feature Extraction (FDFE) method. This method computes the Power Spectral Density of various arrhythmia ECG beats and uses the results as characteristics for categorization. Using DWT, time-frequency domain-based feature extraction is performed. A strong technique for signal analysis, de-noising, compression, feature extraction, and classification is the wavelet transform. The wavelet transform's outstanding qualities, such as sparse representation, accurate approximation, redundancy, numerical stability, etc., made it the most widely used approach for signal analysis and representation across a variety of applications. It offers effective localization that is both time- and frequency-efficient (and scale). Characteristic features are then recovered from the decomposition levels [5].

An ANN, which stands for "artificial neural network," is a model of a biological neural network that is oversimplified significantly. The information processing unit is comprised of a large number of interconnected processing components that are referred to as neurons. These neurons work together to find answers to problems. As a consequence of learning, the weights that are assigned to the connections that are made between neurons need to be altered [6].

It is necessary for the ANN structure to be configured differently for each application. Using the trained data from an artificial neural network (ANN), which is used to learn information from data that may be complex or imprecise, an accurate classification output can be produced. The ANN unit is responsible for extracting patterns and identifying processes from data that may be complex enough to warrant the use of either human or machine training approaches. The Artificial Neural Networks (ANNs) are utilized quite commonly because to the several advantages that they offer [7], including fault tolerance, self-organization, real-time operations, and adaptive learning. ANNs are taught with previously collected data, regardless of how convoluted or erroneous that data may be, so that they can accurately classify newly collected data. During the training phase, it is the responsibility of the ANN component to identify and extract patterns from the data that may be too complicated to be detected by either human or automated methods. Because of the numerous benefits that ANNs offer, including adaptive learning, self-organization, real-time operations, and fault tolerance, they are frequently employed for the purpose of classification. The ANN makes use of the data that it has been trained on in the past in order to automatically organize the data and make predictions about the data that it has not been trained on. Because ANN has the ability to process data in parallel, it is now possible for it to function in real time. Moreover, specific hardware can be designed to make use of the capabilities that ANN offers. Another advantage of ANN is that it may keep producing results even in the face of considerable degradation in the underlying network.

2. Review of the literature

Seeing aberrant waves on an electrocardiogram (ECG) pattern is the initial step in diagnosing the vast majority of cardiac disorders. This is because an ECG pattern displays the heart's electrical activity. The traditional approach, which is carried out by humans, is of the utmost value; nevertheless, automated ECG feature extraction is of the utmost significance as well because it improves the classification process. It is necessary for the retrieved and selected characteristics to be repetitive and irrelevant in order to separate the classes to a significant degree. There are countless cardiac anomalies that may be identified in today's world, but all of them can be correctly categorized with the use of a suitable feature extraction technique. Because of this, both the process of extracting features and the process of classifying patterns play very essential roles [8].

The signal can be used to determine certain differentiating characteristics, which are referred to as features. The features that were retrieved because they represent essential signal attributes are the most notable ones to have been found. In signal processing, one method that may be used to reduce the number of dimensions is known as feature extraction. The researchers say that the technique for feature extraction takes the original signal and condenses it down to a lower-dimensional vector that nevertheless retains the majority of the information that was significant and relevant to the study of the original signal vector. In most cases, the retrieved traits are incorporated into the decision-making process [9-10]. The advantageous characteristics contribute to the accurate identification of the signal's abnormalities and help in distinguishing between distinct shape variations that correspond to abnormalities and arrhythmias. Additionally, the advantageous characteristics contribute to the accurate identification of the signal's abnormalities. An underlying heart problem can be inferred from the amplitudes of the P, QRS, and T waves, in addition to certain periods of the cardiac cycle. It is impossible to perform manual beat-by-beat readings of all characteristic spots in each lead during routine clinical practice, particularly for long-term ECGs. This is especially the case while the ECG is being recorded. Automated ECG feature extraction algorithms are therefore extremely relevant. In addition, some of the more minute elements of the signal are difficult to discern with the naked eye, and manually counting the intervals that separate each ECG pattern is a challenge in and of itself. Hence, computer-assisted analysis is required in order to provide medical professionals with the assistance they need in accurately diagnosing cardiac arrhythmias [11-12].

By using Wavelet and S-transforms to extract the pertinent features from time series databases, researchers described several signal processing algorithms that might be used to visually and automatically classify these time series databases. These methods have shown promising results in the fields of time series data mining and multiple pattern identification. Moreover, this method can be used with financial, medical, and other temporal data types. Applying such a method to the various parts of the large data set will reveal how similar the patterns in the data set are. In terms of accuracy and sensitivity, the novel strategy described in this work outperforms the other methods currently in use [13-14].

The FFT method is utilized in order to isolate significant shifts in both the simulated normal and noise-corrupted electrocardiogram signals. It has been observed that the FFT method is useful in detecting cardiac parameter abnormalities that may not be visible in the standard graphical presentations of ECG signals [15]. This has been confirmed to be the case. In order to evaluate the differences in the simulated normal and noise-corrupted ECG signals, both the frequency response and the pole-zero locations have been taken into consideration. And the distinctions between them are utilized in order to identify anomalies [16].

Research indicates that normalized auto-correlation and cross-correlation are simpler techniques for assessing and examining the parameters that can be retrieved from the lobe and shape of the correlation function. These findings were reached by comparing the correlation functions of two sets of data. When compared to the one-of-a-kind pattern of a normal ECG, the two types of cardiac illnesses that were investigated exhibited a distinct deviation in pattern [17]. The findings show that the normalized auto-correlation and cross-correlation techniques may represent and differentiate between normal and abnormal ECG signals based on the MNCC value [18].

A wavelet-based approach was built for the purpose of recognizing and categorizing the four distinct forms of ventricular arrhythmias that were investigated in the study, which was carried out by a small group of researchers. In the process of applying the procedure, four distinct wavelets were used, and the outcomes of each were examined and compared. According to what they found, a four-dimensional Daubechies wavelet was the most effective method for analyzing both the MIT-BIH arrhythmia dataset as well as the malignant ventricular arrhythmia dataset. Since it makes use of wavelet decomposition, the method can analyze more than 90 percent of the initial data with only a tenth of that amount being required. This is due to the fact that the original data is first wavelet-decomposed [19].

Both the sensitivity and specificity of the method (> 0.98) were high enough to allow it to correctly differentiate supra-ventricular rhythms from ventricular beats. A hardware implementation of the algorithm has been developed [20–23] for use on a business single-chip central processing unit.

3. The Main Aim of the research

In order to accurately analyze CAs, the following aims are achieved

1) Use of transform-based Time, Frequency, and algorithms to extract exact cardiac arrhythmia features.
2) Creation and use of an ANN classification model employing the features of cardiac arrhythmias that were extracted.
3) Use of transform-based time-frequency algorithms to extract the features of CA.

4. The Projected Work:

A single neuron does not have enough processing power to learn all the data sets. Two distinct types of ANNs are employed for data training. Both I Feed forward Artificial Neural Network (also called Multilayer Perception) and ii) Recurrent Neural Networks (RNNs) are examples of these types of systems.

The most popular type of artificial neural network (ANN) is a feedforward network. There is solely forward connectivity between the network's neurons, as the name suggests. Neurons in one layer of an ANN are coupled to those in the next layer via connections between the two layers. In order to analyze the data and recall the patterns, the ANN uses the popular Back propagation learning technique. When comparing feed forward ANNs to recurrent ANNs, the latter of which feature connections between neurons that form a directed cycle, it is clear that the former are more computationally efficient. The results for a given input are compared to the predicted results. The Back-propagation training process works backwards from the output layer to the input layer, adjusting the weights of the various layers based on the error calculated from the expected data.

There are three components to a typical Feed Forward Neural Network model: an input layer, a parallel hidden layer, and an output layer. Each node in the input layer is fed information, in the form of features. In the input layer, no calculations are done because it operates independently. Every hidden layer neuron receives input from all of the neurons in the input layer. The hidden layer is crucial to the Neural Network model's functioning. Each hidden node is a single neuron with its own processing power and decision surface. Each neuron in the output layer has made a determination about where in the decision space the input vector belongs.

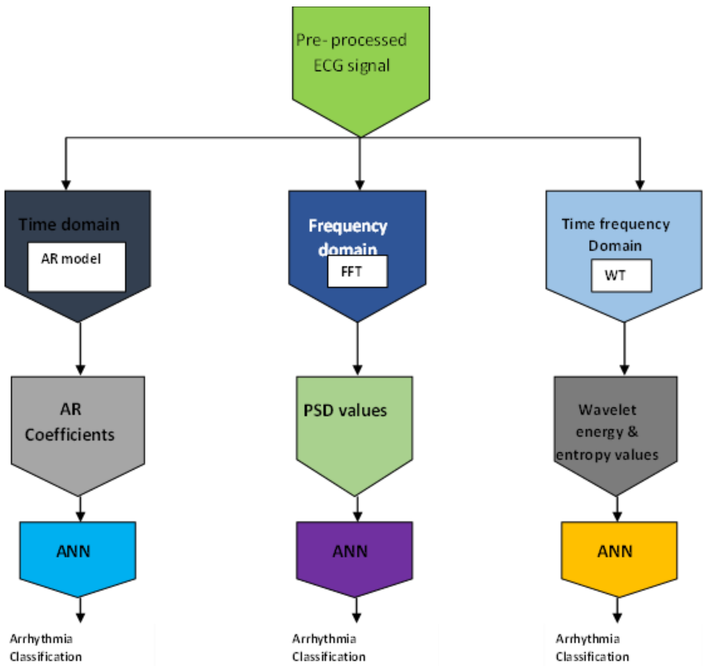

Fig II: Block diagram representation of feature extraction in various domains and classification

The technique for training consists of two distinct stages. The first step is to apply the input feature vector to the nodes in the input layer, and the second step is to have the values y for each output unit propagate outward from the network. Both of these steps are part of the input layer. Error signals are produced for each output unit whenever their actual value is compared to the target value. This comparison causes the error signals to be produced. As soon as a node in the network receives the error signal, it immediately makes any necessary adjustments to its weights.

5. Result and Discussion:

The NN classifier has been trained to improve its performance on each category of ECG signals. Below, we define precision, responsiveness, and selectivity.

The sensitivity of a test measures how well it can detect true positives. This is one of several factors considered when assessing a test's reliability. So, the likelihood that a test will detect the existence of disease in a person who has it is a measure of its sensitivity. The ill are the primary target audience for this parameter.

$$Senstivity = \frac{TP}{TP+FN} X100 \quad (1)$$

When evaluating a diagnostic tool, specificity measures how well it can distinguish Normal individuals from other groups. Conversely, specificity is a test's capacity to detect unfavorable outcomes. This is the likelihood that a test result of "not having" an illness corresponds to the patient's actual lack of that disease. If the test is sensitive enough, a positive result is likely to be correct. This term's calculation formula is

$$\text{Specificity} = \frac{TN}{TN+FP} X100 \quad (2)$$

Accuracy is defined as below:

$$\text{Accuracy} = \frac{TN+TP}{Total\ data\ Sample} X100 \quad (3)$$

After noise has been removed from an ECG recording, the data can be used for feature extraction and classification. Signals from detected R peaks in an electrocardiogram are sent into a window filter to create beats. The processes that are utilized to extract characteristics and classify ECG arrhythmias are illustrated by these images.

In a standard supervised artificial neural network architecture, an ANN consists of one input layer, one hidden layer, and one output layer. The ANN network is taught using a total of 112 different ECG patterns, some of which include NSR, AFIB, AFL, VT, and VFL beats. The input layer comprises five nodes, and it receives the five AR features (A2-A6) that are extracted from the AR model. These features are used as inputs to the input layer. The buried layer is comprised of twenty neurons, of which only five are used to classify the output.

In the next table, labelled "Table I," you will see a breakdown of the various ECG patterns together with the average values of the A2-A6 coefficients. This table demonstrates that the AR coefficients are distinct for each type of ECG pattern, which allows for the distinction between the groups to be made.

Table I: Average standards of AR constants of numerous ECG outlines.

	A2	**A3**	**A4**	**A5**	**A6**
NSR	-2.18	1.46	0.086	-0.45	0.14
AFL	-1.95	0.91	0.27	-0.24	0.036
AFIB	-1.75	0.29	0.52	0.20	-0.26
VT	-1.58	0.49	0.193	-0.33	0.24
VFL	-2.03	1.16	0.25	-0.43	0.09

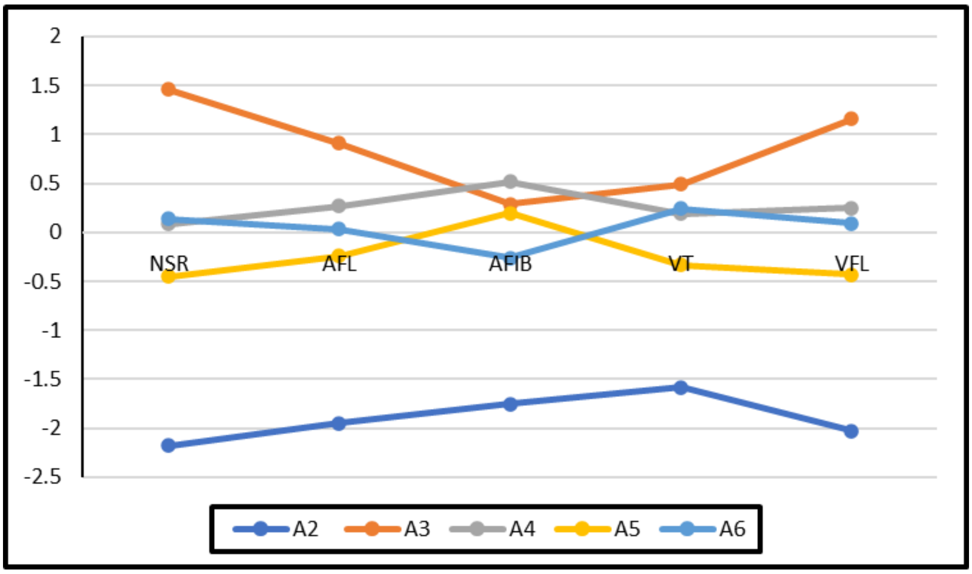

Fig III: Average standards of AR constants of numerous ECG outlines.

The efficiency of the network was determined by analyzing the test results for their degree of precision, responsiveness, and specificity. Overall, the accuracy of the classifier is 93.95%, while its sensitivity is 96.42% and its specificity is 98.89%.

FFT is utilized because it allows for the extraction of features from each ECG pulse. After putting each QRS complex through a Fourier transformation, we discovered spectral differences at frequencies lower than 20 Hz. The process of locating an appropriate window allows bins with frequencies ranging from 7 to 20 Hz while eliminating bins with frequencies outside of that range. Calculating the Power Spectral Density (PSD) for the frequency range of 7-20 Hz for the Fourier spectra.

Table II: Average standards of normalized PSD constants of different ECG patterns.

	NSR	**AFL**	**AFIB**	**VT**	**VFL**
7.0 Hz	0.31	0.18	0.64	0.56	0.71
9.0 Hz	0.38	0.31	0.78	0.12	0.092
12.5 Hz	0.34	0. 81	0.48	0.18	0.03
15.0 Hz	0.48	0.18	0.46	0.102	0.041
18.0 Hz	0.46	0.14	0.34	0.063	0.006

Network efficacy was calculated by measuring test results for precision, responsiveness, and specificity. The classifier has a sensitivity of 95.34% and a specificity of 98.89%, with a total accuracy of 94.73%.

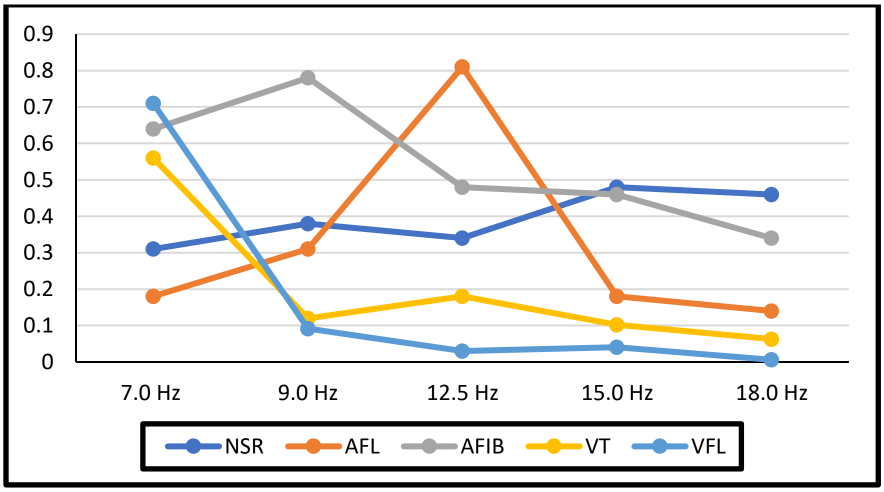

Fig IV: Average standards of normalised PSD constants of different ECG outlines.

There is one input layer, one hidden layer, and one output layer in a typical supervised ANN architecture. The ANN network is trained using a dataset consisting of 127 unique ECG patterns (including but not limited to NSR, AFIB, AFL, VT, and VFL beats). The four input nodes of the input layer get the normalized relative wavelet energy values from four different resolution levels (90-45 Hz, 45-11.25 Hz, 11.25-2.8 Hz, 2.8-0.5 Hz) through the WT decomposition approach. Twenty neurons make up the buried layer, and five are used to categorize the output.

Table III: Average standards of the normalized comparative wavelet energy standards.

	90-45 Hz	45-11.25 Hz	11.25-2.8 Hz	2.8-0.5 Hz
NSR	0.036	0.87	0.32	0.18
AFL	0.051	0.62	0.34	0.43
AFIB	0.012	0.18	0.67	0.12
VT	0.003	0.09	0.53	0.65
VFL	0.0031	0.025	0.498	0.514

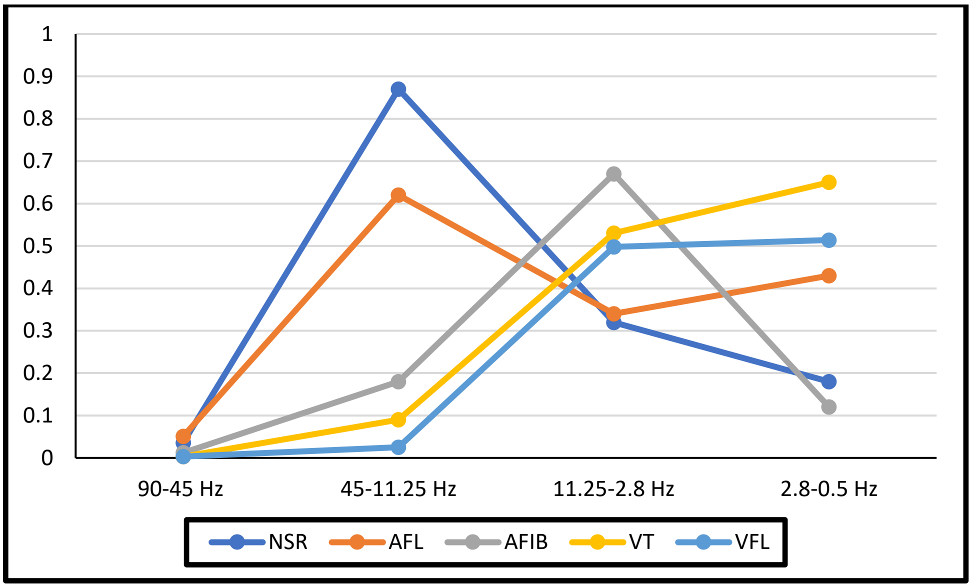

Fig V: Average standards of the normalized comparative wavelet energy standards.

Because wavelet coefficients are redundant, the normalized relative wavelet energy at each decomposition level is calculated to extract fine-grained characteristics. Classifying arrhythmias relies on these characteristics. The overall accuracy of the classifier is 97.25%, the sensitivity is 96.69%, and the specificity is 99.45%.

6. Conclusion:

It is essential to use both the traditional method, which is done by hand, and automated ECG feature extraction because the latter helps enhance categorization. In order to differentiate the classes to a significant degree, the characteristics that are retrieved and chosen must be redundant and irrelevant. The utilization of an appropriate method for feature extraction is required in order to correctly classify the various cardiac issues. Hence, important roles are played by the extraction of features and the classification of patterns. In this study, we investigate how to extract features from data that spans many domains, such as time, frequency, and time-frequency domains specifically. These qualities are similar to the essential signal parameters, and they are used in the development of individualized ANNs. Calculations of accuracy, specificity, and sensitivity are employed in the process of evaluating the performance of the created ANN. The newly designed ANN that makes use of AR coefficients achieves an accuracy of approximately 93.95%, as well as a sensitivity of 96.42% and a specificity of 98.89%. Because of the ANN that was built with PSD value inputs, we are able to achieve an accuracy of about 94.73%, a sensitivity of roughly 95.34%, and a specificity of approximately 98.89%. In contrast, the wavelet-energy-based ANN that was constructed for this function attained an accuracy of 97.25%, a sensitivity of 98.69%, and a specificity of 99.45%. These results speak for themselves. The results of the simulation show that when compared to the other two ANN models, the one that is based on wavelet energy provides superior performance in terms of the network complexity and accuracy it achieves while classifying cardiac arrhythmias. So, using this model can assist medical professionals in making the most important decision possible under extreme conditions.

Conflict of Interests:

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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