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Heart Rate Variability Analysis for Cardiovascular Disease Detection Using MIDNet 18 Architecture

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Abstract

Electrocardiogram (ECG) technology has grown as a crucial diagnostic method in the clinical cardiovascular field, helping doctors identify heart conditions and track the heart's electrical activity easily. The ECG identifies CVDs by detecting ventricular hypertrophy, arrhythmia, myocardial infarction, and atrial fibrillation. Recent studies explore transforming wireless patient data through IoT and MEMS devices, designing and integrating small, power-efficient ECG sensors for wearables, and automatically detecting heartbeats. The patient's special heart rhythm can be identified because advanced computers work together with a strong processor to gather health information. The wearable ECG denoising module for the multistage classification system was created by utilizing the Zynq7000 ZedBoard, an advanced and highly regarded platform in this research project. Preprocessing biosignals is essential for analysis because it affects both the data's quality and clinicians' decision-making abilities. It's crucial for how the bio-signals are classified in the system. An efficient digital filter, tailored for resource efficiency, is programmed onto an FPGA to reduce noise from an ECG signal.

Keywords: Cardiac Vascular Disease, Computer-Aided Diagnostic Systems, Deep Learning, MIDNet.

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1 Introduction

Myocardiocytes and cardiac pacemaker cells are the terms used to describe the approximately 300 billion muscle cells that comprise the heart muscle. Excitable cells include myocardiocytes, as well as skeletal and neuronal cells. These cells exhibit both resting and action potential electrical characteristics. The internal and external membranes of the myocardiocytes produce an electrical potential difference (Fang et al., 2020). The concentration differential between the internal and external membranes of cardiac cells causes a cardiac action potential. Purkinje fibers, the His Bundle, and the Atrioventricular (AV) node of cardiac pacemakers are located in the Sinoatrial (SA) node. The primary characteristic of pacemaker cells that sets them apart from myocardiocytes is their automaticity (Das & Kapoor, 2024). The pacemaker cell is responsible for generating electrical impulses that facilitate the development of an action potential in the myocardiocytes. The heart is kept pounding by this motion. An individual's heart rate is defined as the duration of a single action potential (Mejía-Mejía et al., 2020). An individual's heart is located at the centre of their cardiac system, which is composed of several components (Garis et al., 2023). The cardiovascular system is responsible for the entire body's blood circulation. Together, cardiovascular illnesses now rank among the world's leading causes of death. According to research by the Indian Council of Medical Research (ICMR), 25 percent of cardiac disease-related deaths occur in the age group of 25-69 years (Coutts et al., 2020). An electrical impulse train traversed the heart and was detected by the electrodes and leads affixed to the individual's body, resulting in a waveform known as the ECG (Ishaque et al., 2021). Each component of the ECG waveform is created by the repolarisation and depolarisation of various muscle tissues in response to an electrical impulse.

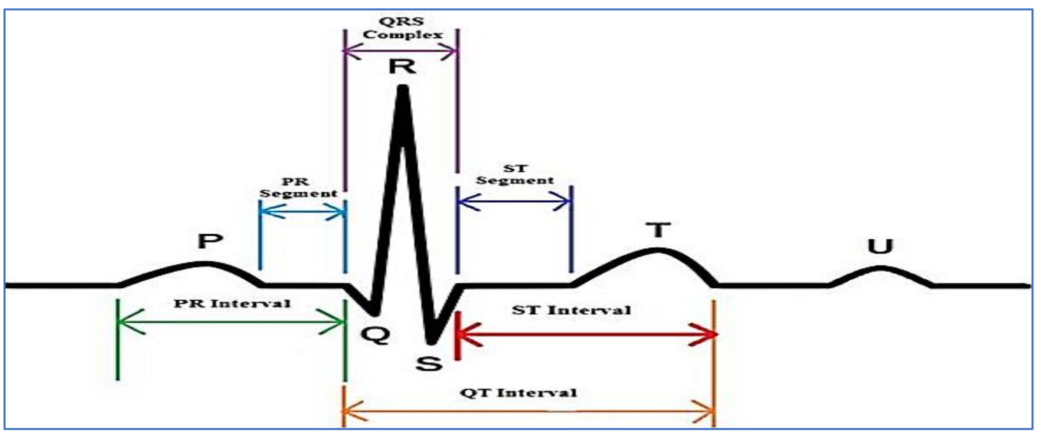

Figure 1: Waveform of the ECG signal and its elements

Section two offers an extensive analysis of ECG wave signal processing by examining various scholarly works. Section three presents HRV characteristics derived from diverse fields, selected based on their importance after statistical evaluation. Section four contrasts the effectiveness of our project with previous studies at the conclusion of the findings and analysis phase. Finally, section five discusses the advantages and disadvantages of this study (Figure 1).

2 Background Knowledge Related to CVD

The clinical ECG includes three limb leads, six chest leads, and three enhanced leads. The limb lead electrodes provide the signals for the augmented leads (aVR, aVF, and aVL) located in the frontal plane. Although heart activity can be seen from many angles, all 12 leads use the same set of electrodes. ECG sounds have caused significant changes in the heart's normal functioning rhythm. The ECG sounds have caused a significant change in the heart's normal functioning. These disruptions might cause doctors to misdiagnose CVD. The substantial impact that ECG sounds have on cardiovascular physiology has long been known (Gupta & Verma, 2025; Myoa et al., 2023; Sathyanarayanan & Murthy, 2024; Adeshina et al., 2025). The heart provides oxygenated blood to the entire body through myocytes or valves via various mechanisms, and cardiovascular diseases are triggered by any disruption in any of these systems (Swapna et al., 2012; Baevsky & Chernikova, 2017; Zhang et al., 2025). These illnesses result in a notable variance from the typical values of ECG characteristic values (Figure 2).

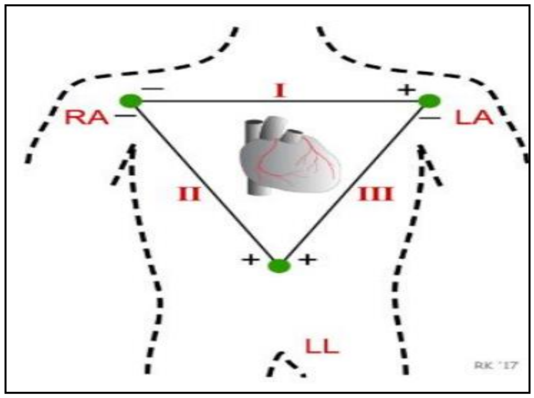

Figure 2: Einthoven's triangle

Three categories of cardiac rhythm abnormalities, sinus rhythm, superventricular tachycardia, and escape rhythm, were the focus of this study (Henje Blom et al., 2009). The sinus rhythm, which has a normal heart rate range of 60–100 beats per minute (bpm), is indicated by both slow and rapid heart rates (HR) on the ECG. Even when a patient is not exercising or in an active state, a condition in the heart known as Super Ventricular Tachycardia can induce an arrhythmia and cause the pulse to rise to more than 100 bpm (Gadde & Kalli, 2020; Oweis & Al-Tabbaa, 2014; Xhyheri et al., 2012; ChuDuc et al., 2013). When the heart rate is regulated by anything other than its primary source, the AV node or His-Purkinje fibers, an escape rhythm is produced (Xie et al., 2020). An irregular production of escape rhythms can cause atrial fibrillation.

Critical Synthesis and Positioning of MIDNet 18.

MIDNet 18 is a deep learning network specifically designed for analyzing heart rate variability (HRV) and ECG signals. It aims to automatically identify valuable patterns and categorize them as normal or abnormal heart conditions, enabling the accurate and non-invasive detection of cardiovascular diseases. Early HRV-based CVD detection pipelines rely on manual feature engineering and superficial classifiers (e.g., SVM, k-NN), which are sensitive to cross-patient variability, noise, and non-linear relationships between time/frequency/geometric HRV indices. Standard CNNs are better at learning features, but are usually trained on fixed 1D segments and tend to overfit in cases where class boundaries are weak (e.g., AF vs. other supraventricular rhythms), particularly when the data is asymmetrical. RNNs/ConvLSTMs capture temporal context but are vulnerable to long-term drift and require careful regularization; they tend to perform poorly when a distribution shift occurs or noisy ambulatory measurements are present. MIDNet 18 helps to overcome such limitations by: (i) converting HRV/ECG representations into multichannel inputs, preserving morphology and rhythm context; (ii) 14 lightweight 3x3 convolutional blocks with batch normalization and max pooling, to stabilize training and suppress noise; (iii) progressively reducing dense layers, to control capacity and reduce overfitting; and (iv) coupling statistical feature selection (t test/ANOVA) with deep feature representation. This design exhibits superior class separability and specificity, achieving 99% accuracy with 100% specificity/PPV, as well as 96.77% sensitivity, compared to a baseline CNN (93.4%) and RNN (73.77%) in this study. These gains are consistent with recent developments in deep learning for ECG analysis, which focus on strong hierarchies of features, regularized depth, and preprocessing that is resilient to noise.

3 Proposed Framework

This section explains the various ECG datasets and the suggested approach.

The data used in the research were obtained from the MIT-BIH Arrhythmia Database, which is accessible on PhysioNet. It is a collection of 1,000 annotated recordings of ECGs of 200 patients. Subjects were between 23 and 79 years old, and the sample of both sexes was relatively equal. Conditions such as normal sinus rhythm, arrhythmia, and atrial fibrillation are found in the clinical records. Each ECG recording is 30 minutes long and sampled at 360 Hz, and annotations are verified by expert cardiologists. This demographic and clinical diversity provides a suitable basis for assessing the MIDNet 18 architecture and enables the reproducibility of future research.

It includes selecting features, using machine learning techniques, and analyzing data with statistics for the proposed approach (Cygankiewicz & Zareba, 2013). Gathering HRV info involves collecting data from an online ECG database, applying digital FIR filters for noise reduction, detecting QRS complexes, extracting features, and analyzing them with t-tests, ANOVA, and deep learning techniques. Statistical analysis involves collecting data and analyzing it to identify patterns and trends. Numerous HRV assessments exist across time, frequency, and geometric dimensions; nonetheless, few significantly influence system efficiency. As a consequence, HRV value correlations reach up to 95% and 99%. (Schumann et al., 2002). The results of the t-test confirm that both the null hypothesis and the alternative hypothesis for the HRV characteristics sample data are true. (Goldenberg et al., 2019) (Figure 3).

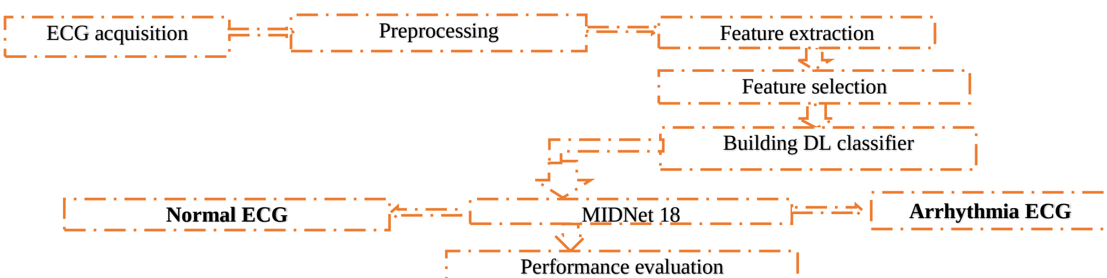

Figure 3: Overall architecture

MIDNet 18

Signal classification is the process of grouping signals according to the identified features. The statistical traits are more than sufficient for categorisation if the data is a direct number. However, there is feature ambiguity when the signals are used as classification input. As a result, the signals must be converted into data with a particular pattern. As a result, the suggested MIDNet18 model's input layer changes the chest CT input signal's size to 224 × 224 using three-channel representations of the signal pixel values (Dua et al., 2012). In conceptual terms, MIDNet 18 is a multi-layered filter which gradually extracts the most significant aspects of an ECG signal, including rhythm patterns and irregularities, whilst reducing noise. The model does not solely learn based on manual feature engineering, but learns which signal characteristics best represent the difference between normal and abnormal heart activity. The 14 convolutional layers of the suggested MIDNet18 model, each with a 3x3 kernel size and a ReLu activation function, are used to extract features from the input signal. The network can train more quickly thanks to the addition of seven (2x2) max pooling layers and twenty batch normalisation layers, which stabilise the learning process. The suggested architecture includes a softmax classifier in addition to four dense layers for signal classification. Fourteen convolutional layers make up the new MIDNet18 architecture that is being proposed. The input layer's sole purpose is to read the image. In this instance, the input layer does not learn any parameters. The first convolutional layer of the proposed model convolved the 16-filter input images, resulting in a 222 x 222 x 16-pixel output feature map. Throughout the model, the kernel or filter is three by 3 (Kim et al., 2016). Convolutional layers perform element-wise multiplication over the input image, updating the summation in a single feature map pixel. The feature maps for the input image are created by repeating the same procedure over the whole picture. Throughout the model, the convolutional layer's kernel size remains constant at 3 x 3. In the dense layer, the newly suggested MIDNet18 CNN takes advantage of backpropagation neural networks. The proposed model has four dense layers with different types of neurons. The fully connected layers translate the prior layers' activation volume into a class distribution that is computed using a class probability. Consequently, the output layer of the multilayer perceptron has output equal to the number of classes. As a result of the architecture's consideration of the temporal complexity of the network, the number of neurons in each subsequent dense layer decreases. The number of neurons connected by weight in each layer makes the model more complicated. The number of neurons in each dense layer was the subject of several experiments. As a result, the size of the neuron determines a high percentage of accuracy for binary and multiclass classification in less time and with less model complexity (Melillo et al., 2015). Stochastic gradient descent is an adaptive method for estimating first- and second-order moments in an Adam optimisation. Because of its efficiency and lower memory requirements, it works well for situations with massive datasets. The MIDNet18 model's learning rate was set at 0.001 due to its excellent test accuracy.

4 Experimental Results and Discussion

The various methods outlined here discuss their characteristics alongside performance metrics such as PPV, sensitivity, specificity, and accuracy. The percentage of overall accuracy increase due to statistical analysis methods is shown. To run a statistical test on a different HRV, start by adjusting the data set. The figure shows how the ECG was changed into an R-R interval pattern. The ECG recording is utilized to determine the next heartbeat's variation. Figure 4 illustrates how an ECG converts into an RR interval graph. This is a type of graph called a tachogram, which shows how your heart beats over time. It's like a line that moves up and down, showing when your heart beats faster or slower than usual. We use this line to see if your heartbeats change quickly from one moment to another. The numbers on the line tell us how many times your heart beats in a second, just like counting how many seconds pass by. The graphical and exact methods confirm the normality of the data distribution in the statistical study. Plots like box plot, Q-Q plot, and histogram plot help in easily seeing if data follows a normal distribution. To view how various heart rate measurements were adjusted, Figures 5, 6, and 7 depicted histograms, quantile-quantile plots, and box-and-whisker diagrams, respectively. The histogram shows that the intervals between RR and SDNN values are close to a normal distribution with respect to the subjects. Q-Q plot confirms that the data follows normality as the majority of the points of cardiac variability indicators fall along the diagonal reference line.

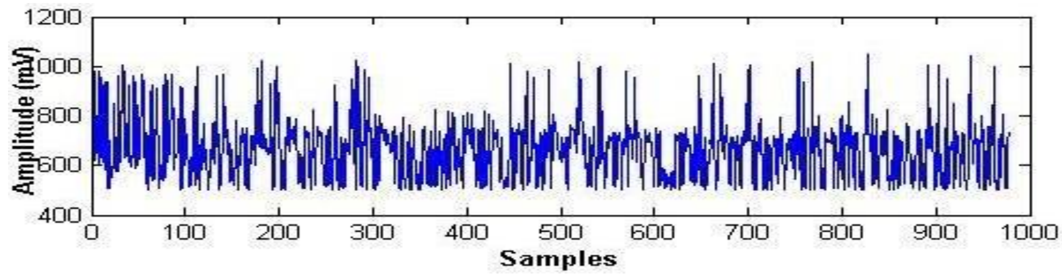

Figure 4: Beat-to-beat variation of R-R intervals (Tachogram)

The box plots indicate the dispersion and the central location of the HRV measurements, with wider dispersion in the arrhythmic cases than in the normal ECGs. It has been deduced from Figure 5 that the data is about regularly distributed. Figure 6 illustrates that the majority of the data are either closely spaced from or on a straight line, indicating a regularly distributed set of data. Figure 7 provides an explanation for the symmetrical nature of the variations in heart rhythm in relation to the mean, median, and center.

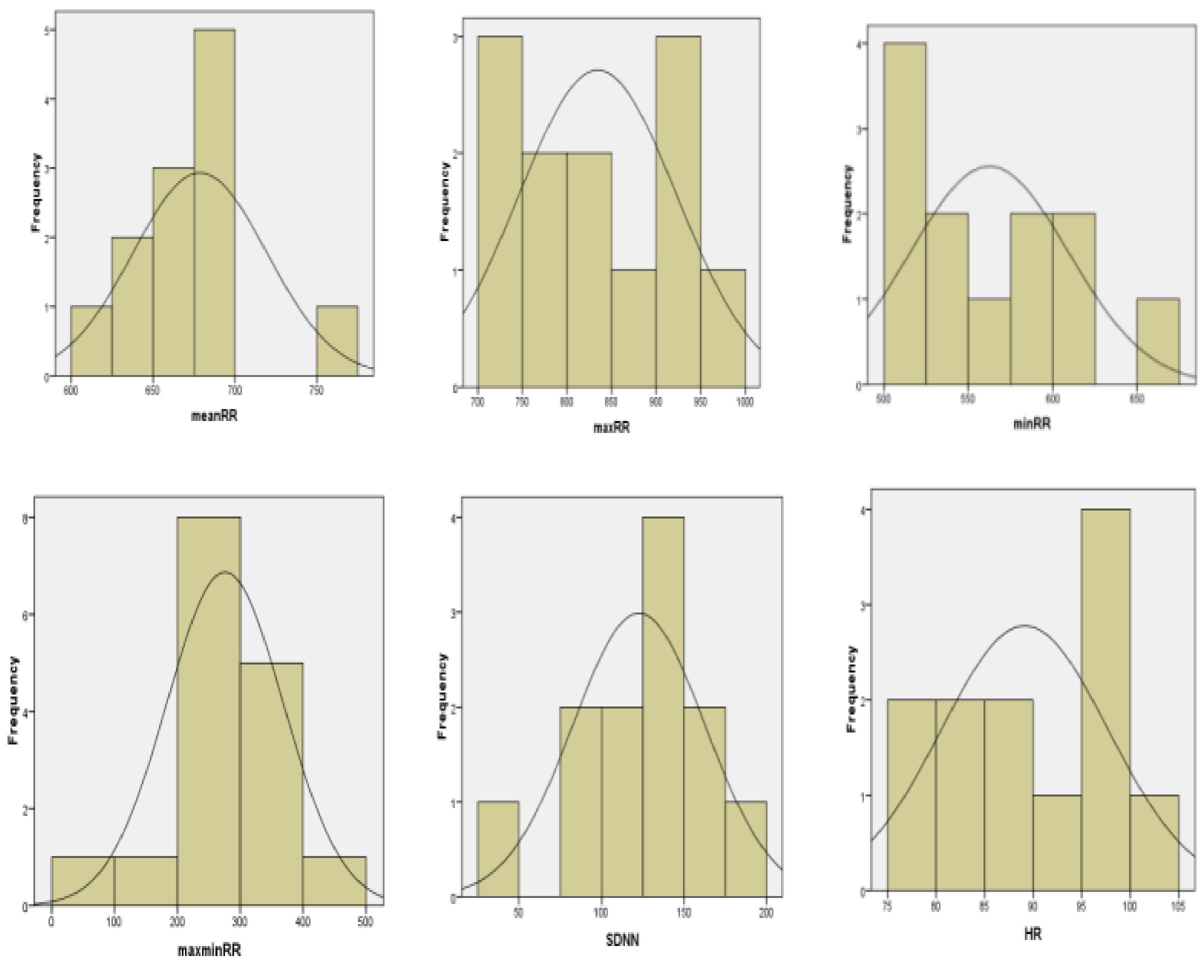

Figure 5: The distributional characteristics of normalized HRV features (e.g., RR interval, SDNN) of normal ECG and arrhythmic ECG signals indicate the distributional similarities between the two, and the similarity between their distributions is near-normal

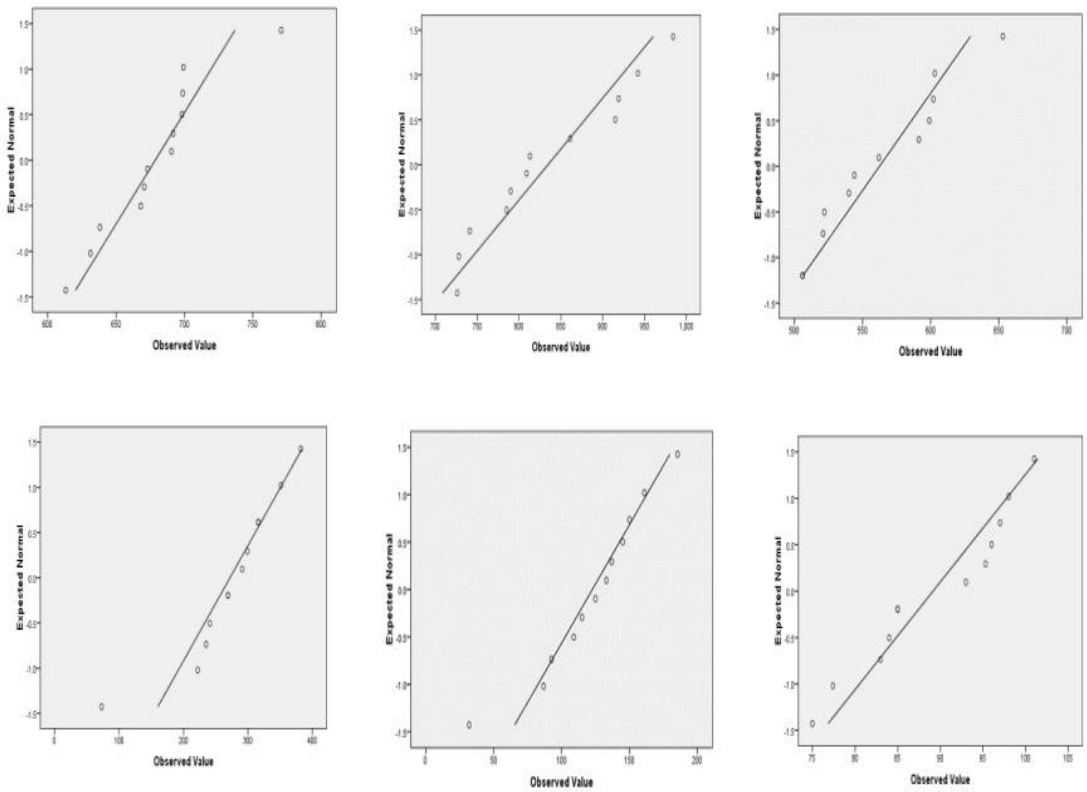

Figure 6: Q-Q plot of the HRV features (i.e., mean RR interval, heart rate variability measures) against A normal distribution, showing that the majority of the data points are close to the predicted line

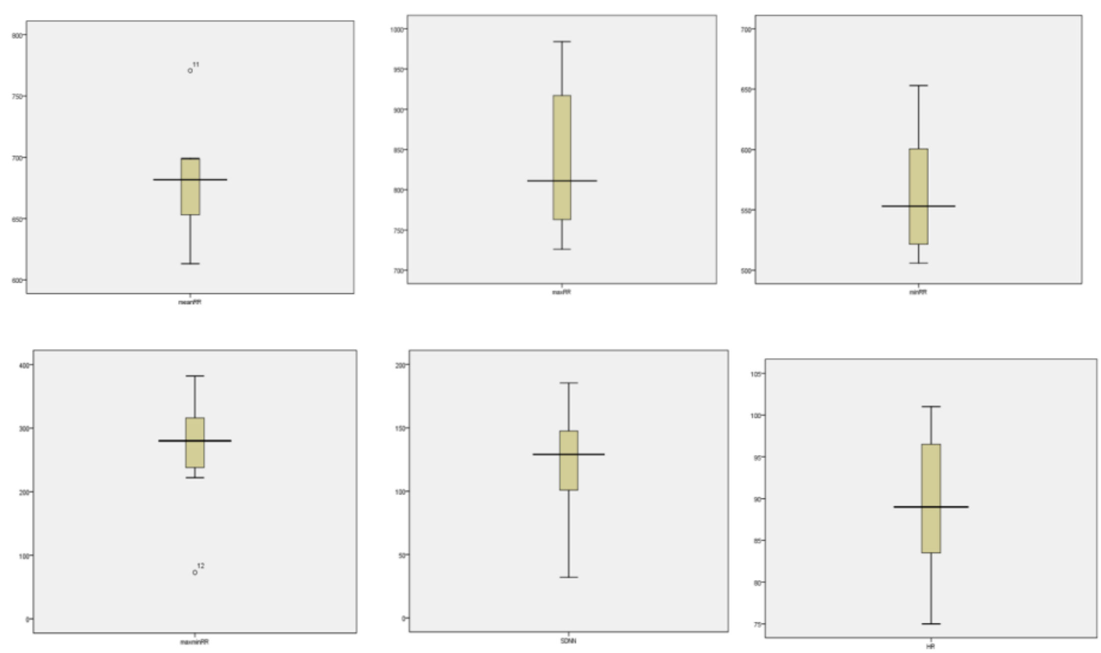

Figure 7: Boxplot of HRV characteristics (e.g., minRR, maxRR, SDNN) comparing normal and arrhythmic ECGs and showing the median, variability, and outliers

The Fast Fourier Transform (FFT) transforms the tachogram into a power spectrum by separating it into individual frequency components. Very low frequency waves, low frequency sounds, and high frequency signals are linked to many causes. The autonomic nervous system controls the heart's function, as depicted in Figure 8.

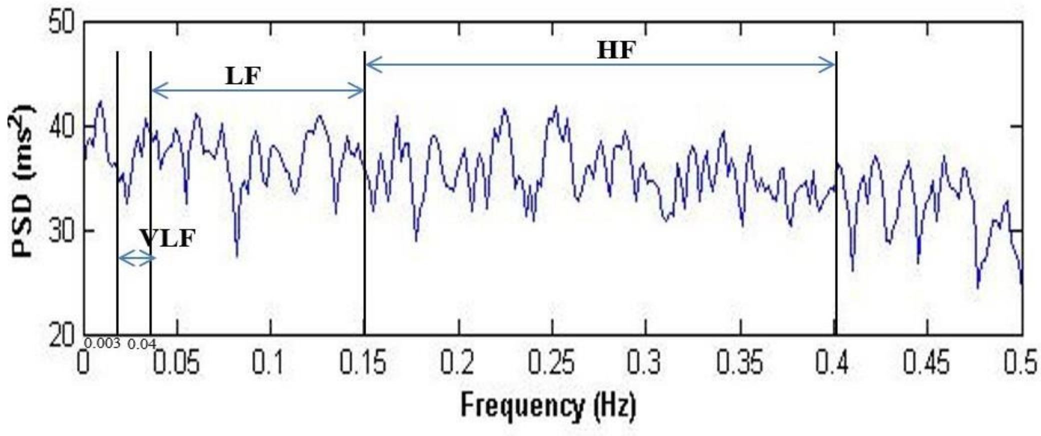

Figure 8: PSD for R-R interval

Table 1 shows that there have been significant changes in the mean RR and HR values. The remaining features, which include maxRR, minRR, maxminRR, and SDNN, have all seen substantial revisions. It indicates that a person is likely suffering from an arrhythmia condition if they have these kinds of fluctuations in their heart rhythm.

Table 1: Comparison between an arrhythmic and a normal ECG

HRV Features	**Normal ECG (sec)**	**Arrhythmia ECG (sec)**	**p value**
meanRR	666.58 ± 115.65	678.61 ± 40.88	p > 0.05
maxRR	666.83 ± 115.44	834.41 ± 88.22	p < 0.01
minRR	666.33 ± 115.874	562.41 ± 46.83	p < 0.01
maxminRR	0.5 ± 1.73	272 ± 78.48	p < 0.01
SDNN	0.35 ± 1.22	122.8 ± 40.07	p < 0.01
HR	93 ± 53	89 ± 9	p > 0.05

This is because, in contrast to a standard ECG signal, arrhythmia signals have a shorter RR interval when HR rises. The inverse relationship between the RR interval and the HR interval (60/RR sec) is to blame for this. According to the time-domain HRV feature's statistical analysis, four of the six features exhibit substantial significant changes, while the other two exhibit suggestive significant changes. These particular HRV properties can be used to classify the AR ECG and the NSR ECG. Various machine learning algorithms were used to classify ECG data in order to evaluate the efficacy of our suggested method. The use of t-tests for feature selection has been found to improve classification accuracy overall (Figure 9).

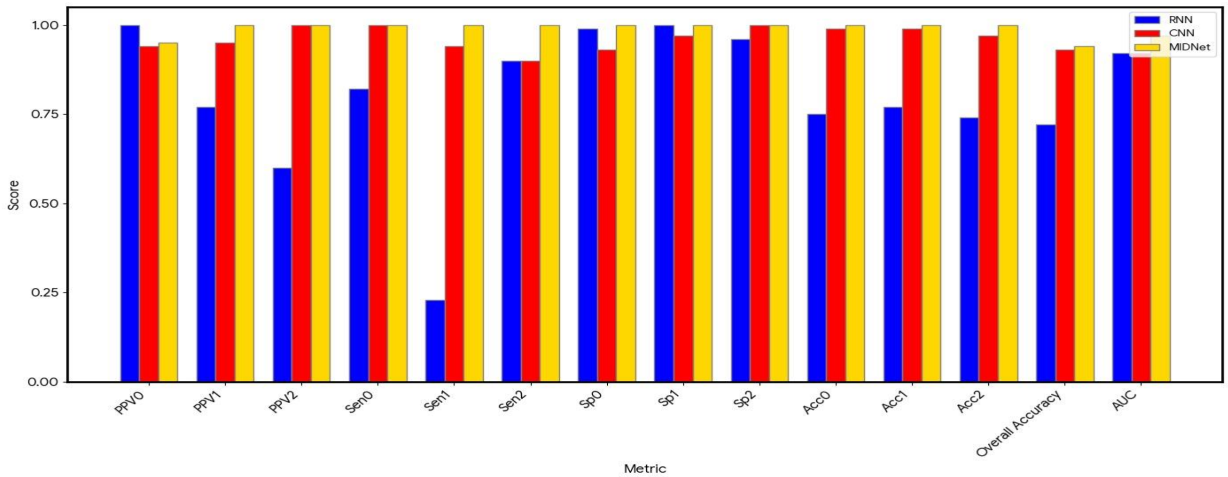

Figure 9: HRV statistical analysis, the three-stage categorization system's performance measure

Following statistical analysis, the features that distinguish between a normal and abnormal ECG yield classification accuracy of 73.77% when using an RNN classifier, 93.4% when using a CNN classifier, and 99% when using the MIDNet approach. MIDNet produced the best results, with 100% specificity, 100% PPV, and 96.77% sensitivity. It is evident that feature selection increased classification accuracy.

5 Conclusions

This chapter's primary goal is to identify the best HRV characteristics for atrial fibrillation, arrhythmia, and sinus rhythm illness classification. A digital filter is used to remove unnecessary noise, and the QRS detection algorithm is used to determine HR from the ECG waveform. The heart rate contributes to the computation of multiple HRV parameters, which are crucial in the classification of heart illness and the provision of an accurate non-invasive diagnosis. A range of ANS and PNS information is provided by all HRV measurements. By removing duplicate and unnecessary features from the heart rate metrics set, statistical analysis aids in the selection of these essential features. A smaller number of qualities have a significant impact on classification accuracy; MIDNet 18 approaches are suggested to improve classification by making use of these features. The proposed classifiers achieve an overall accuracy of up to 99%.

6 Future Directions

Even though the MIDNet 18 framework proposed a recorded high accuracy in the classification of cardiovascular conditions, there are prospects for future work. A key issue is to make the model work in real time on noisy ambulatory ECG data, frequently containing motion artifact and signal dropouts in wearable conditions. The addition of advanced denoising pipelines, adaptive filters, and edge computing deployments can be used to overcome this constraint. The other way is the multi-directional integration of multi-modality physiologic cues like blood pressure, oxygen saturation, and photoplethysmography (PPG) to add robustness to the diagnostics. Transfer learning and domain adaptation are methods that add to the generalizability when used with different patient groups and across different recording devices. Lastly, it should scale to remote telemedicine platforms and low-resource healthcare environments to impact and increase clinical adoption on a broader scale.

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