
Analysis of Electrocardiogram Dynamic Features for Arrhythmia Classification

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ABSTRACT

Arrhythmia is a deviation from the normal heart rate pattern. Arrhythmias are usually harmless, but they can cause heart problems. Some types of arrhythmias include Atrial Fibrillation (AF), Premature Atrial Contractions (PAC), and Premature Ventricular Contractions (PVC). Many studies have been conducted to identify the dynamic characteristics of electrocardiogram (ECG) irregular waves in the detection of arrhythmias. However, the accuracy obtained in these studies is less than optimal. This study aims to solve the problem by evaluating three main features of arrhythmias using ECG signals: RR interval, PR interval, and QRS complex. Experiments were conducted rigorously on these three features. The accuracy achieved was 98.21%, with a specificity of 98.65% and a sensitivity of 97.37%.

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1. INTRODUCTION

Heart disease is still a threat in Indonesia and even in the world. Director of Prevention and Control of Non-Communicable Diseases said that based on Sample Registrasion System (SRS) heart disease is the second most common cause of death after stroke. In addition, the result of this disease is that the country suffers economic losses [1]. Early detection of heart disease is possible by identifying irregularities in the heart rhythm, known as arrhythmias, which can occur within the human body. Arrhythmia refers to abnormal frequency or rhythm in a person's heartbeat, although most arrhythmias do not pose a significant risk to overall health. Nonetheless, irregular heartbeats can result in more pronounced manifestations of cardiac ailments and anomalies, including conditions like Premature Ventricular Contractions (PVC), Atrial Fibrillation (AF), and Premature Atrial Contractions (PAC) [2]. AF is recognized as a cardiac irregularity marked by a rapid and irregular heart rhythm. This condition leads to the buildup and the formation of blood clots within the heart increases the likelihood of developing heart disease and experiencing a heart attack, encountering heart failure, and suffering from a stroke [3]. Nevertheless, PAC and PVC frequently responsible for rhythmic disturbances, can imitate the irregular heartbeat pattern that is typical of Atrial Fibrillation. PAC arises when an atrial source outside the usual sinoatrial node triggers atrial activation prior to the standard node activation, whereas PVCs happen when a comparable mechanism takes place within the ventricles [4].

According to Alagarsamy, Manjunathan et.al, [5] Clinical indications for arrhythmias involve recognizing specific abnormal conditions in the pumping of the heart, which can be identified by monitoring the conduction of electrical impulses or by facilitating the passage of a small electrical current through electrodes, thereby affecting the conductivity of the cardiac muscle. Electrocardiogram

is the term used for a device that records the electrical activity of the heart via electrical wires. Research on electrocardiogram (ECG) dynamic feature analysis for arrhythmia classification, there are several examples of research related to feature extraction analysis for arrhythmia classification, such as [6]-[17]. In a study conducted by Tao, Wang et al. [6], innovative approach for the automated detection of arrhythmia, a critical factor in preventing cardiovascular disease-related deaths. The conventional method of diagnosing arrhythmia by manually analyzing electrocardiogram (ECG) readings is time-consuming. In this research, A new technique is introduced that merges CWT and CNN for the purpose of ECG classification. The focus of the approach is on analyzing RR intervals, the intervals between R peaks in the ECG signal, which are informative in diagnosing arrhythmias. The strategy involves extracting four features from RR intervals and combining them with features derived from CNN. This amalgamated feature set is then inputted into a fully connected layer for the final classification of ECG signals. When tested on MITDB, this study demonstrates noteworthy performance outcomes. Specifically, the method achieves performance rates of accuracy (70.75%), sensitivity (67.47%), F1-score (68.76%), and positive predictive value (98.74%).

Chen, Hua et.al, [2] Performed a hybrid investigation involving the utilization of both CNN and LSTM for the classification of automatic arrhythmias categorized by tissue type. The architecture introduced in this research integrates multiple inputs, examining 10-second segments of ECG signals along with their corresponding RR intervals. These ECG signals are sourced from the MITDB. By employing a five-fold cross-validation strategy, the implementation is carried out, this network achieves an impressive accuracy of 99.32%. Duan, Junbo et.al, [8] A research study was conducted to accurately detect atrial fibrillation events by analyzing the RR intervals of electrocardiogram (ECG) signals. Unlike previous approaches that utilized specific numerical characteristics or combinations of characteristics as input features (such as entropy, mean, median, square root mean, variance, quantile, etc.), this study employed probability density as an input feature. By incorporating the entire statistical information in a natural, comprehensive, easy-to-calculate, and efficient manner, and utilizing the RR interval feature, the study achieved results of 96.97% accuracy, 95.24% sensitivity, and 99.94% specificity.

Shrikanth Rao, S.K. and Martis, Roshan Joy, [9] An investigation was conducted to create a decision support system utilizing machine learning or ML techniques aimed at identifying AF through the analysis of electrocardiogram (ECG) data. The study analyzed a total of 5,052 normal signals, 759 signals with atrial fibrillation (AF), and an additional 2,498 signals with different rhythm patterns. The Pan Tompkins algorithm was employed to identify QRS peaks in the signals. The study achieved an overall accuracy of 85.1%, with the normal class achieving 83.1% accuracy, the AF class achieving 87.5% accuracy, and the remaining classes achieving 84.8% accuracy.

Dev Sharma, Lakhan et.al [10] The study also emphasizes the identification of bundle branch block through the utilization of statistical features extracted from the QRS complex, combined with the k-nearest neighbors' algorithm. Five statistical features derived from the QRS region were employed to classify normal beats, R-BBB (right bundle branch block), and L-BBB (left bundle branch block). The achieved outcomes demonstrated an accuracy rate of 99.05%, sensitivity of 98.48%, and specificity of 99.30%. Solikhah, Mar'Atus et al, [11] A research investigation was carried out to identify irregular heart rhythms in electrocardiograms by integrating the features of QRS Interval, R-wave gradient, and RR Interval. The identified arrhythmia categories within the research included PVC, PAC and LBBB. The most optimal outcomes were obtained through the amalgamation of the three features (RR Interval, QRS Interval, and R-wave gradient), showcasing commendable results in sensitivity, specificity, and accuracy, registering rates of 94.63%, 93.94%, and 94.49% correspondingly.

After discussing several studies concerning feature extraction, there exists a similar study to the researcher's work that employs three different approaches to feature extraction, as indicated in the study [11]. It can be observed that the researcher employed feature extraction using RR Interval, QRS Interval, and R-wave gradient. However, the study yielded suboptimal accuracy results. Therefore, the aim of this research is to achieve improved accuracy outcomes by employing features like RR Interval, QRS Complex, and PR Interval through dynamic feature extraction methods. Furthermore, a performance analysis is conducted on the RR Interval, QRS Complex, and PR Interval features to select the most effective feature extraction method based on sensitivity, specificity, and accuracy in the classification of arrhythmia categories like AF, PVC, and PAC.

2. METHOD

The approach employed to conduct this study is illustrated in the provided Figure 1:

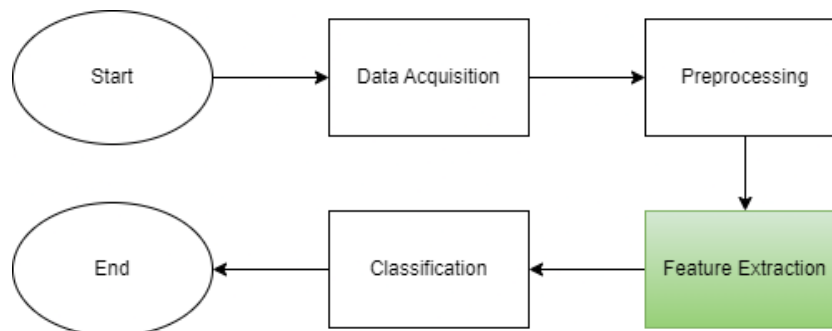


Figure 1. Research Stages

The primary emphasis of this study is directed exclusively towards the process of feature extraction denoted by the green region highlighted in Figure 1. The elucidation of the aforementioned research phases is elaborated as follows:

a. Data acquisition

The study utilized two databases, namely the MIT-BIH Arrhythmia Database (MITDB) and the MIT-BIH Atrial Fibrillation Database (AFDB)[18]. AFDB comprises 23 records, whereas MITDB contains 48 records. In total, 71 data records were employed for the detection of PVC, AF, and PAC.

b. Pre-processing

After the data collection process is completed, the next step is data preprocessing, which aims to enhance data quality and tailor the data to match the analytical methods to be employed. The methods utilized encompass data normalization, data resampling, bandpass filtering, and wavelet-based denoising. Data normalization involves scaling the data to achieve a standard deviation of one and a mean value of zero. This normalization facilitates further analysis by standardizing the signal. Data resampling entails altering the data's sampling rate. Subsequently, the signal data undergoes bandpass filtering using a Butterworth filter to eliminate frequencies beyond the desired range. The final step involves wavelet-based denoising, where minor disruptions in the signal data are eliminated based on a specified threshold after discrete wavelet transformation. By adhering to these steps, the initial signal is successfully normalized, resampled, bandpass-filtered, and denoised using wavelets. This process significantly enhances signal quality by standardizing it, adjusting frequencies, and removing noise, enabling more comprehensive subsequent analysis.

c. Feature Extraction

Upon progressing to the subsequent pre-processing phase, known as the feature extraction stage, an essential step in the classification process, considerable emphasis has been placed on this aspect in previous studies. Typically, conventional methods predominantly depend on time-domain characteristics, such as intervals between heartbeats, durations of specific components (QRS, QT, PR, etc.), and amplitudes. Nonetheless, the intricacy of ECG waveforms and their vulnerability to interference make pure time-domain feature extraction less accurate, thereby leading to classification inaccuracies [20]. So, at this point in the process, three types of feature extractions are employed: the RR interval, PR interval, and QRS complex. To identify the RR Interval feature using the SciPy library, it is necessary to first locate all the R peaks, as depicted in Figure 2. Once all the R peaks have been identified, the time interval between each R peak and the subsequent one is calculated.

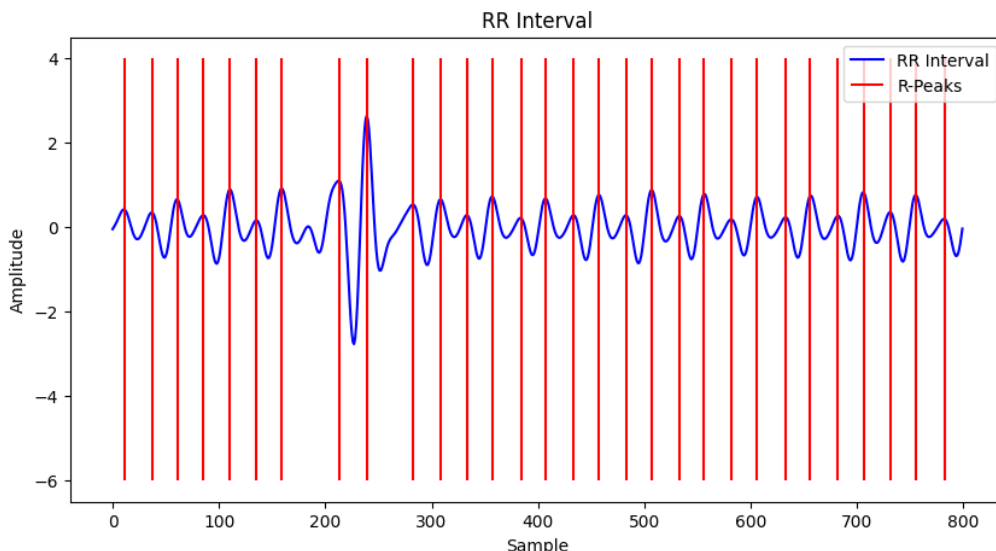


Figure 2. RR Interval

To identify the PR Interval feature, the SciPy library is utilized. Detecting the PR Interval feature requires knowledge of the P peak, R peak, and the starting point of the QRS Complex, as depicted in Figure 3. Once the P peak, R peak, and the starting point of the QRS Complex are determined, the calculation can be performed.

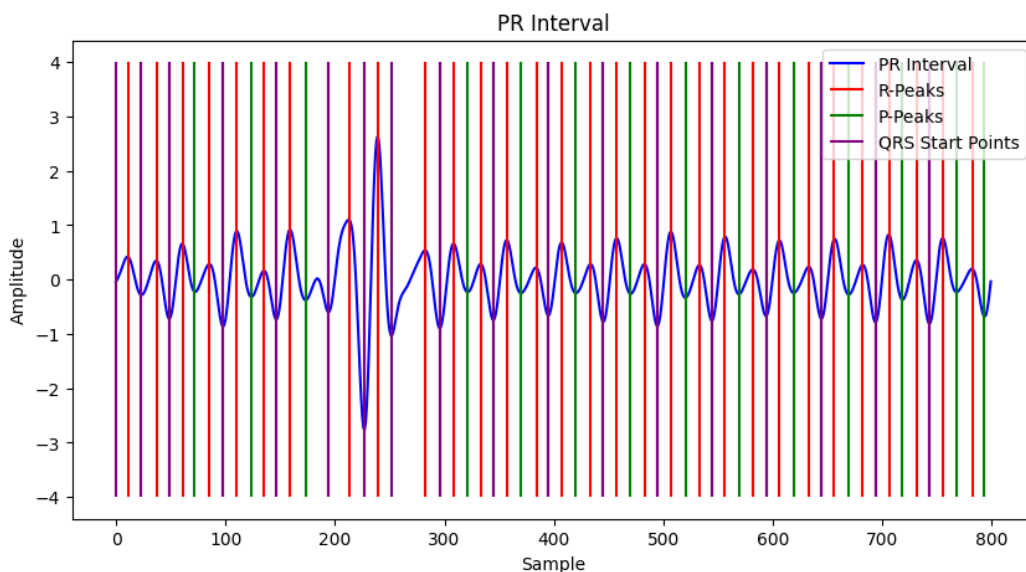


Figure 3. PR Interval

To detect the QRS Complex feature, the SciPy library is utilized. It is essential to identify the Q wave, R peak, and S wave by utilizing the library. Once the Q wave, R peak, and S wave are obtained, as depicted in Figure 4, the calculation for the detection of the QRS complex is then carried out.

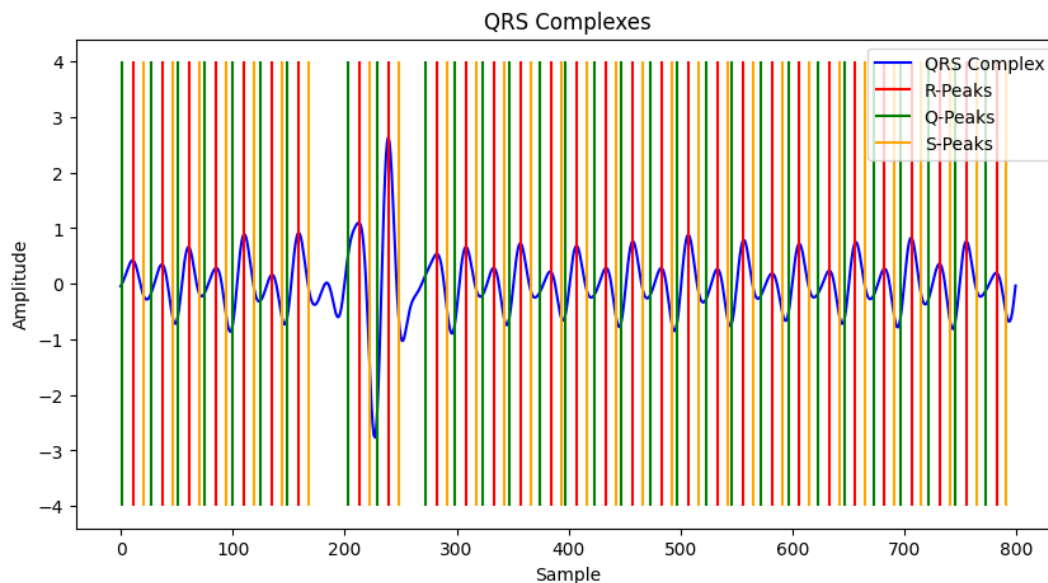


Figure 4. QRS Complex

d. Classification

The study employs Convolutional Neural Networks (CNN) as the algorithm of choice. CNNs have proven to be a more efficient and accurate method for representing ECG signals, eliminating the need for complex rules in identifying waveform boundaries compared to traditional ECG signal processing techniques. CNNs possess the exceptional capability in extracting features or signals from medical images or bio-signals by employing diverse filters. [21]. After selecting the data to be used, then after going through the pre-processing and feature extraction stages, the next step is to create AF, PVC, and PAC disease symbols on the electrocardiogram (ECG) signal to be used as abnormal data. category. In the early stages the model uses K-Fold Cross Validation to divide the data into folds and provides an index for each fold, then Standardize and Reshape Input Features which are useful in improving model performance by eliminating scale differences between features that will be used later to become the CNN Model. In building the CNN model, Sequential is used which is useful for adding layers sequentially one by one, in the layer itself there is a Conv1D layer which is used to extract features, MaxPooling1D is used to reduce dimensions, Dense is used to classify, and on each layer, the Rectified Linear activation function is applied. Unit (ReLU) so that the model can identify important features in the data effectively and can carry out an accurate classification of existing abnormal categories. Then in the training model, Early Stopping is employed to prevent overfitting. During the training of the model, it is configured with a loss function named 'categorical_crossentropy', the optimizer employs 'adam', and the metric utilized is 'accuracy'. Then, the model is trained using the fit() method with training data and validation with the specified number of epochs and batch_size, the greater the number of epochs, the better the prediction, but it will take longer to compile. After training is complete, the model will be evaluated on test data using the evaluate() method. The loss and evaluation accuracy is stored for use in further analysis. After going through all the folds, the average accuracy and average confusion matrix are calculated. Then, report_classification is used to generate a classification report which includes the sensitivity and specificity calculated for each abnormal class. The test metric that will be used in this study is the multi-class confusion matrix test metric. Selection of test metrics because the number of classes is more than two, this test metric shows the proportion of the actual predicted results for each heart rhythm [22].

Accuracy equation:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Specificity equation:

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

Sensitivity equation:

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

In the given context, TP stands for true-positive, signifying the tally of accurately recognized atrial fibrillation (AF) beats. Conversely, TN corresponds to true-negative, denoting the quantity of precisely identified normal beats. FP, or false-positive, quantifies the instances of normal beats that are inaccurately flagged as AF, while FN, or false-negative, indicates the number of AF beats mistakenly categorized as normal.

3. RESULT AND DISCUSSION

Here are the results of feature extraction analysis using RR Interval, PR Interval, and QRS Complex, followed by classification using CNN, to achieve the best results considering accuracy, specificity, and sensitivity values.

3.1. Testing 3 Features

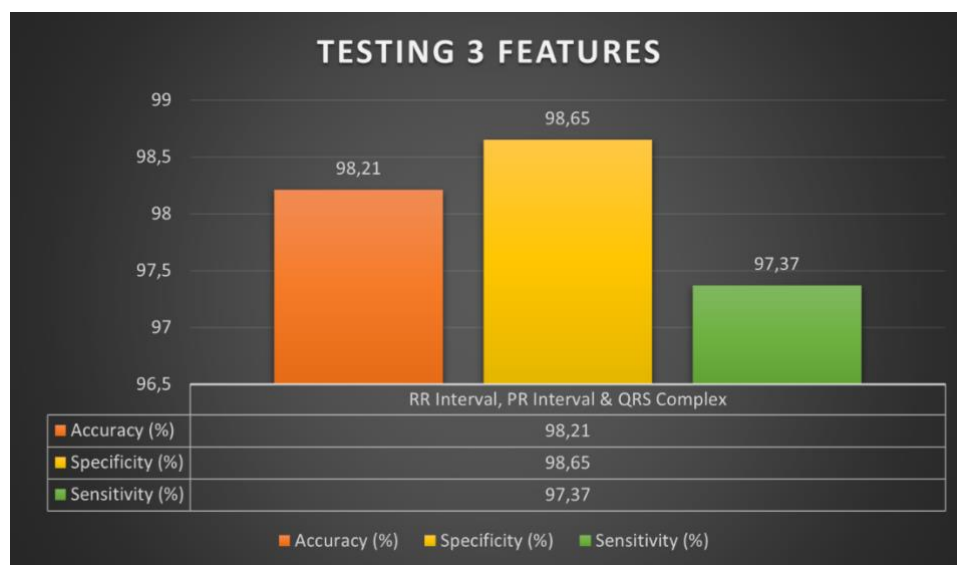


Figure 5. Testing 3 Features

In Figure 5, it can be observed that utilizing a combination of three key cardiac features: RR Interval, PR Interval, and QRS Complex, resulted in sensitivity (97.37%), specificity (98.65%), and accuracy (98.21%). This analysis presents a noteworthy insight into the effectiveness of the employed model or methodology, focusing on the assessment of sensitivity, specificity, and accuracy. Sensitivity, which gauges the system's ability to correctly identify true positives out of the total actual positive cases, exhibited a remarkable value of 97.37%. This indicates the model's proficiency in recognizing genuine positive instances.

High sensitivity values, particularly in a medical context, are crucial to ensure that cases requiring clinical attention are not overlooked. On the other hand, specificity plays a pivotal role in evaluating a model's performance. In this context, the specificity value reached 98.65%. This value suggests that the model possesses a strong capability to correctly identify true negatives from the total actual negative cases. In essence, the model minimizes the occurrence of false positive results, which can alleviate unnecessary anxiety and doubt for patients.

Furthermore, the achieved accuracy of 98.21% portrays the extent to which the model approximates overall correctness. High accuracy is a primary goal in various data analysis applications, including medical contexts such as this one. An accuracy value approaching 100% signifies that the model maintains a high level of congruence between predicted outcomes and actual truths. Overall, the outcomes derived from this analysis underscore that the utilization of three pivotal features: RR Interval, PR Interval, and QRS Complex, resulted in a robust model for the classification of arrhythmias AF, PVC and PAC.

3.2. Discussion

The findings presented in Figure 5 shed light on a compelling analysis involving the integration of three fundamental extraction features: RR Interval, PR Interval, and QRS Complex. The results demonstrate that this amalgamation yields impressive sensitivity (97.37%), specificity (98.65%), and accuracy (98.21%) rates. This analysis is particularly insightful as it delves into the efficacy of the adopted model or methodology, with a specific focus on evaluating sensitivity, specificity, and accuracy – three key parameters crucial in medical diagnostics. Sensitivity, a metric gauging the model's capability to accurately detect true positives among all actual positive cases, stands out remarkably at 97.37%. This remarkable figure underscores the model's adeptness in correctly identifying genuine positive instances.

Such a high sensitivity rate, especially within the medical domain, holds immense importance in ensuring that cases necessitating clinical intervention are not missed. Conversely, specificity's role in assessing model performance is pivotal. In this study, the specificity value reaches an impressive 98.65%. This indicates the model's robust ability to accurately classify true negatives from all actual negative cases. Essentially, the model significantly curtails false positive outcomes, a factor that can substantially reduce unnecessary anxiety and uncertainty among patients. The achieved accuracy rate of 98.21% further accentuates the model's ability to approximate overall correctness. The pursuit of high accuracy is a primary objective across various data analysis applications, notably in the realm of medical diagnostics. A nearly perfect accuracy rate signifies the model's capacity to maintain a strong alignment between predicted outcomes and actual realities.

The author subsequently contrasts these findings with those from other Advanced Studies employing diverse feature extraction variations, as illustrated in Table 1.

Table 1. Comparison of Extraction Feature Variation Results with Previous Research

Writers	Feature	Sensitivity (%)	Specificity (%)	Accuracy (%)
Duan, Junbo et al. [8]	RR Interval	95.24%	99.94%	96.97%
Solikhah, Mar'Atus et al. [11]	RR Interval, QRS Interval, and R-wave Gradient	94.63%	93.94%	94.49%
Tao, Wang et al. [6]	RR Interval	67.47%	68.76%	70.75%
Current Study	RR Interval, QRS Complex, and PR Interval	97.37%	98.65%	98.21%

Considering the outcomes presented in Table 1, the application of diverse feature extraction methods in this investigation achieved a higher level of performance compared to their utilization in previous research endeavors. Nevertheless, it's important to note that this study fell short in matching the specificity value achieved in [8], exhibiting a disparity of 1.29%, and for comparison with the combination of 3 variations of feature extraction from [11], this study managed to outperform 2.74% sensitivity, then for specificity this research managed to outperform 4.71%, and for accuracy this study also managed to outperform 3.72%. This proves that the combination of 3 variations of feature extraction RR Interval, QRS Complex, and PR Interval is better than the RR Interval, QRS Interval, and R-wave gradient in terms of arrhythmia classification to obtain more optimal results.

4. CONCLUSION

From the explanation above, the analysis depicted in Figure 5 reveals a compelling integration of three core extraction features: RR Interval, PR Interval, and QRS Complex. The combined approach yielded remarkable sensitivity (97.37%), specificity (98.65%), and accuracy (98.21%) rates, showcasing the model's proficiency in sensitivity, specificity, and accuracy assessment—key parameters essential for medical diagnostics. The high sensitivity underscores the model's ability to accurately detect true

positive cases, ensuring critical instances are not overlooked. The pivotal role of specificity is evident with an impressive 98.65% value, indicating the model's competence in accurately identifying true negatives and minimizing false positives. The achieved accuracy rate of 98.21% highlights the model's ability to approximate correctness effectively. Moreover, when compared to three variations of feature extraction from [11], this study showcased improvements of 2.74% in sensitivity, 4.71% in specificity, and 3.72% in accuracy, affirming the superiority of the RR Interval, QRS Complex, and PR Interval combination in arrhythmia classification. For future research, variations in signal and other algorithms can be utilized to extract features from electrocardiogram (ECG) signals.

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