Journal of Advanced Zoology
ISSN: 0253-7214
Volume 44 Issue S-7 Year 2023 Page 889:894

A Method For Early Detection Of Cardiac Arrhythmias

Ibrahim Obied Ibrahim Ahmed[1]*, Dr. Fatima Rafique[2], Prof Dr. Anurag Rawat[3], Dr. Rimaa Mohammad Ibrahim Lafi[4], Narendar Kumar[5], Iftekhar Ahmed[6]

*[1]*Medical Department, Suwier Hospital, University of ElImam Elmahdi, Saudi Arabia, Email: ibrahimjubara6@gmail.com*
[2]Women Medical Officer, Radiology Department, District Health Quarter Teaching Hospital, Gujranwala, Pakistan, Email: Fatimarafique80@gmail.com
[3]Prof. Dr. Anurag Rawat , Department of Cardiology, Himalayan Institute of Medical Science, Dehradun, India, Email: anuragrwt@gmail.com
[4]General Practitioner in Purecare Medical Center and GP in Sawa Organization, Peoples' Friendship University of Russia (RUDN), Email: r.ere.1995@hotmail.com
[5]Medical Officer, Health Department of Government of Sindh, Pakistan, Email: kingkhan3497@gmail.com
[6]OST Graduate Student, Department of Pharmacy, University of Asia Pacific, Dhaka, Bangladesh, Email: cheeku2739@gmail.com

***Corresponding Author:** - Ibrahim Obied Ibrahim Ahmed*
**Medical Department, Suwier Hospital, University of ElImam Elmahdi, Saudi Arabia, Email: ibrahimjubara6@gmail.com*

Article History

Received: 19 October 2023
Revised: 28 November 2023
Accepted: 23 December 2023

Abstract

According to the WHO (World Health Organization), the beginning of specific cardiovascular illnesses is the leading cause of death worldwide. Cardiac arrhythmias, in particular, can develop into cardiovascular diseases like heart disease, so it's essential to figure out how to make an early diagnosis to stop the arrhythmia from developing into a condition that, in more advanced stages, wouldn't respond well to treatments. It was possible to extract typical heart electrophysiology patterns like the QRS complex, the P.R. segment, the Q.R. segment, the R.S. segment, and the S.T. segment by characterizing the signals picked up by external ambulatory monitors and using the T.W. (Wavelet Transform) for this type of signal analysis.
Digital filters were used in the filtering process, and the signal was then described, facilitating easier differentiation through a support vector machine-based classification method established by comparing the outcomes from the various methodologies. The research showed that it is possible to create an automatic tool for detecting cardiac issues as a decision support tool for sending patients for examination by a specialist doctor using the proposed model.

Keywords: Arrhythmias, SVM, Bayes, and wavy

INTRODUCTION:

According to the WHO (World Health Organization), the beginning of specific cardiovascular illnesses is the leading cause of death worldwide. Particularly, cardiac arrhythmias can potentially develop into cardiovascular diseases like heart disease. Early arrhythmias are relatively intermittent, which makes earlier diagnosis challenging. Abrupt ventricular arrhythmias are the leading cause of sudden death and are frequently brought on by short coronary events. Arrhythmias are a significant contributor to morbidity and mortality in cardiac disorders. These can manifest independently of structural heart disease or in individuals without heart disease (S. Sahoo, Dash, Behera, & Sabut, 2020).

It is crucial to find a way to make an early diagnosis to prevent the arrhythmia from developing into a heart condition that, in its mature stages, would not respond well to treatments. This underlines the significance of making a prompt diagnosis. The electrophysiological behaviour of the heart could be graphically established in this study by characterizing the signals picked up by external ambulatory monitors, which enable the recording and storage of the data produced by the electrocardiogram (ECG). T.W. (Wavelet Transform) was deemed an appropriate choice for analyzing this signal because the data received through monitoring are not stationary (Patro et al., 2022).

The QRS complex, P.R. segment, Q.R. segment, R.S. segment, and S.T. are only a few examples of the natural patterns inherent in the electrophysiology of the heart that may be extracted using the discrete wavelet transform (TDW), which carries out an adaptive time-frequency decomposition into a corresponding model. Filtering made it possible to eliminate undesirable signals that changed the behaviour pattern of the original movement since these patterns are modified by the noise coming from the ECG sample (T.-M. Chen, Huang, Shih, Hu, & Hwang, 2020).

After the signal was filtered and characterized, it was possible to distinguish it more efficiently using a classification method defined by comparing the results obtained from various classification techniques, including support vector machines, linear classifiers, and Bayesian classifiers, among others; comparing results obtained in other investigations from accessible arrhythmia databases, like the MIT-BIH Arrhythmia Database and population-generated databases, compiling data from the MIT-BIH Arrhythmia Database, and corresponding results obtained from further studies (He et al., 2020).

BACKGROUND:

The Database is described.

The MIT-BIH arrhythmia database was utilized to create the arrhythmia classification model in this paper. The Arrhythmia Laboratory at Beth Israel Hospital provided the more than 4,000 long-term Holter recordings that comprise the MIT-BIH Arrhythmia Database. 60% of the tapes came from patients treated in hospitals. The length of each Holter recording is roughly 30 minutes. There are two groups of records in the Database: the first contains 23 papers, and the second has 25 records. While the latter group includes ventricular, junctional, and supraventricular arrhythmias and conduction anomalies, the former group serves as a representative sample of the range of waveforms and artefacts an arrhythmia detector may encounter. Twenty-two women and 25 men, aged 23 to 89, made up the sample (Marinho et al., 2019).

Prior work

The authors demonstrate that, given that the QRS complex is the most prominent aspect of an ECG signal, automatic classification of heartbeats can sometimes be traced back to signal processing techniques for the QRS complex. The authors provide a summary of signal processing techniques proposed for filtering, feature extraction, and arrhythmia classification of an ECG signal from 1979 to 2014. These techniques include digital filtering, amplitude analysis, signal width, and using bandpass and digital filters in contrast to the Okada Method, dyadic wavelet transform, quadratic spline wavelet with fuzzy logic inference classification, Mexican hat wavelet, Morlet's complex wavelet function, neural networks, and quad (Samol et al., 2019).

FEATURE EXTRACTION:

The wavelet transform with the Sym and Daubechies functions was used in the current work to identify the ECG signals, from which the characteristic vectors of each movement were obtained. The signal was then passed through a model learning classification module constructed on the foundation of a support vector machine, which allowed it to classify the types of arrhythmia included in the project, namely the left bundle branch block and right bundle branch block (Mullens et al., 2020).

Wavelet transform

The wavelet transform is a mathematical tool with numerous uses in engineering and medicine, including symptomatic anomaly identification, process control, and signal processing. In the example, we'll use it as a separating factor to distinguish the signals originating from the heart rate. This transformation uses translation and dilation operations to create a signal's temporal and scale informational building blocks, which are produced by a single fixed function known as the mother wave ψ (t) (Terasaki et al., 2019).

$$\psi_{a,b} = \frac{w\left(\frac{x-b}{a}\right)}{\sqrt{|a|}}, a, b \in R, a \neq 0$$

The signal can expand and contract when both a and b are real scalars, and the signal's position can change over time when b is present. Localization with time-frequency adaptation is offered via the wavelet transform. Good time resolution can be achieved with low scale levels, whereas good frequency resolution can be achieved with significant scale levels. Using a wavelet relies on the application and the features to be retrieved; some of the families that make up wavelets are the Daubechies, Symlets, and Biortogonales (Wu, Lan, Yang, & Nie, 2019).

FILTERS:

Filters are devices built to transmit or block signals within a specific frequency range or ranges, allowing the differentiation of signals regarding their spectral composition. Thus, the pass band is the frequency range where signals pass without being impacted, and the reject band is the frequency range where signals are blocked. Filters may be entirely passive (made up only of resistors, capacitors, and inductors), actively operated (using op-amps), or digitally controlled (using digital circuitry or computer software). Within these systems are two primary divisions: analogy filters, which handle continuous signals across time, and digital filters, which hold discrete signals in the time domain. Digital filters such as Chebyshev and Notch were employed in this paper (Wang et al., 2021).

CLASSIFICATION:

The three phases of the approach are pre-processing, characterization, and classification, respectively. The supervised learning technique SVM, frequently used to resolve classification and logistic regression issues, was employed after the signal had been pre-processed and described. According to the author, the SVM algorithm's usage of vectors allowed for the adjustment of the decision bounds, decreasing the dimensionality of the data set's many associated factors (Samadova, 2023).

The author suggests principal component analysis (PCA) as a complement to linear discriminant analysis (LDA), generalized discriminant analysis (GDA), and other tools that go hand in hand with the SVM. Feature reduction and selection have played a significant role in removing redundancy without losing important information. The prototype's results match those from the implementation using the training dataset in MATLAB, which was done for the classification procedure of the ECG signals LBBB and RBBB displayed in Figure 1 (Santoso et al., 2020).

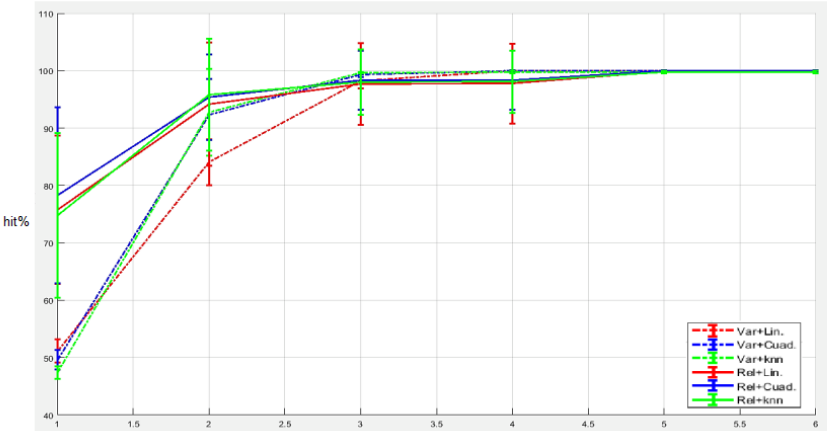

Figure 1: Classification outcomes

PCA

SVM and PCA were combined to extract features and reduce dimensionality. This is predicated on the idea that the directions along which the variances are highest hold most of the class information. PCA is most frequently derived in terms of a standardized linear projection that maximizes the variance in the projected space. Figure 2's three validation features, which correspond to the confusion matrix, demonstrate that the processes are not biased toward any particular class (J. P. Sahoo, Ari, & Patra, 2019).

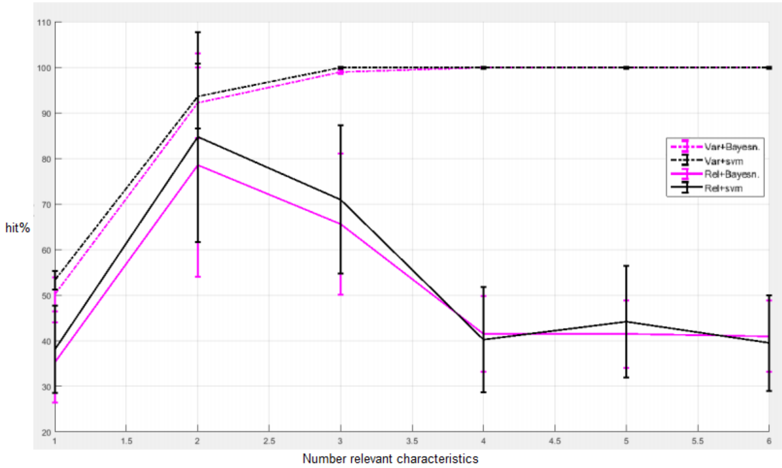

Figure 2: Classifier-based variation and PCA-based feature relevance

SVM-Based Classification

To distinguish between various sorts of classes, SVM builds a hyperplane. It then tends to maximize the margin and exclude any misclassified data points in this margin. Several kernel functions can be utilized, including polynomial kernels, radial basis function kernels, and sigmoid kernels; however, since the data in this case was not linearly separable, a Gaussian kernel was used. Quadratic and linear (C. Chen, Seo, Jun, & Zhao, 2022).

Bayes classification

The supervised classification issue, which may be solved using a Bayesian technique, entails placing an item defined by a set of attributes or characteristics, X1, X2,..., Xn, into one of the m possible classes, c1, c2,..., cm, while maximizing the probability that the class will be identified based on the attributes (Y. Chen, Wu, Zhao, Fan, & Shi, 2020):

$$\boldsymbol{Argc}[\boldsymbol{MaxP}(\boldsymbol{C}|\boldsymbol{X1},\boldsymbol{X2},\dots,\boldsymbol{Xn})]$$

The Bayes' rule (compact) is used in the construction of the Bayesian classifier to determine the posterior probability of the class given the attributes:

$$P(C|X) = P(C)P(X|C)/P(x)$$

Gaussian kernel SVM classification

Robust kernel-based techniques include support vector machines and Gaussian Bayesian processes. As a particular scenario for smooth lying the models, the connection between Bayesian Gaussian processes and support vector machines appears. The simplest way to express random processes is probably with Gaussian processes. Furthermore, nonparametric estimation has frequently employed Gaussian processes (Umlauft & Hirche, 2019).

Classification by K-Nearest Neighbor (KNN)

Rule-based machine learning algorithms are commonly used in medical applications to construct an expert medical system. In many contexts, the K-Nearest Neighbor (KNN) rule is widely accepted as a sample classification strategy (Zeni, 2020).

FINDINGS AND ANALYSIS:

The percentages are obtained in the confusion matrix below with three validation criteria in a way that allows us to show that the procedure is not biased towards one class (Jiwani, Gupta, & Whig, 2021).

Table 1 Confusion matrix

Table 1: Confusion matrix			
	N	**RBBB**	**LBBB**
N	98.26	0%	0.0174%
RBBB	0	91,30%	0.0870%
LBBB	0	5.22%	94.78%

CONCLUSIONS:

The results described in this article were obtained by extracting features from the data according to the clinician's criteria, as was indicated during this work. Medical standards and the wavelet transform together produce results that are acceptable when compared to the confusion matrix. The proposed procedure's code was written in MATLAB and evaluated using information directly taken from the MIT/BIH database entries.

REFERENCES:

1. Chen, C., Seo, H., Jun, C. H., & Zhao, Y. (2022). Pavement crack detection and classification based on fusion feature of LBP and PCA with SVM. *International Journal of Pavement Engineering, 23*(9), 3274-3283.
2. Chen, T.-M., Huang, C.-H., Shih, E. S., Hu, Y.-F., & Hwang, M.-J. (2020). Detection and classification of cardiac arrhythmias by a challenge-best deep learning neural network model. *Iscience, 23*(3).
3. Chen, Y., Wu, Z., Zhao, B., Fan, C., & Shi, S. (2020). Weed and corn seedling detection in field based on multi feature fusion and support vector machine. *Sensors, 21*(1), 212.
4. He, J., Rong, J., Sun, L., Wang, H., Zhang, Y., & Ma, J. (2020). A framework for cardiac arrhythmia detection from IoT-based ECGs. *World Wide Web, 23*, 2835-2850.
5. Jiwani, N., Gupta, K., & Whig, P. (2021). *Novel healthcare framework for cardiac arrest with the application of AI using ANN.* Paper presented at the 2021 5th international conference on information systems and computer networks (ISCON).
6. Marinho, L. B., de MM Nascimento, N., Souza, J. W. M., Gurgel, M. V., Rebouças Filho, P. P., & de Albuquerque, V. H. C. (2019). A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification. *Future Generation Computer Systems, 97*, 564-577.
7. Mullens, W., Auricchio, A., Martens, P., Witte, K., Cowie, M. R., Delgado, V., . . . Leyva, F. (2020). Optimized implementation of cardiac resynchronization therapy: a call for action for referral and

optimization of care: a joint position statement from the Heart Failure Association (HFA), European Heart Rhythm Association (EHRA), and European Association of Cardiovascular Imaging (EACVI) of the European Society of Cardiology. *European journal of heart failure, 22*(12), 2349-2369.

8. Patro, K. K., Prakash, A. J., Samantray, S., Pławiak, J., Tadeusiewicz, R., & Pławiak, P. (2022). A hybrid approach of a deep learning technique for real-time ECG beat detection. *International journal of applied mathematics and computer science, 32*(3).
9. Sahoo, J. P., Ari, S., & Patra, S. K. (2019). *Hand gesture recognition using PCA based deep CNN reduced features and SVM classifier*. Paper presented at the 2019 IEEE International Symposium on Smart Electronic Systems (iSES)(Formerly iNiS).
10. Sahoo, S., Dash, M., Behera, S., & Sabut, S. (2020). Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey. *Irbm, 41*(4), 185-194.
11. Samadova, S. (2023). ALGORITHM FOR AUTOMATIC RECOGNITION OF CARDIAC ARRHYTHMIAS. *Системи управління, навігації та зв'язку. Збірник наукових праць, 2*(72), 146-150.
12. Samol, A., Bischof, K., Luani, B., Pascut, D., Wiemer, M., & Kaese, S. (2019). Single-lead ECG recordings including Einthoven and Wilson leads by a smartwatch: a new era of patient directed early ECG differential diagnosis of cardiac diseases? *Sensors, 19*(20), 4377.
13. Santoso, F., Farhan, A., Castillo, A. L., Malhotra, N., Saputra, F., Kurnia, K. A., . . . Hsiao, C.-D. (2020). An overview of methods for cardiac rhythm detection in zebrafish. *Biomedicines, 8*(9), 329.
14. Terasaki, F., Azuma, A., Anzai, T., Ishizaka, N., Ishida, Y., Isobe, M., . . . Kitakaze, M. (2019). JCS 2016 guideline on diagnosis and treatment of cardiac sarcoidosis—digest version—. *Circulation Journal, 83*(11), 2329-2388.
15. Umlauft, J., & Hirche, S. (2019). Feedback linearization based on Gaussian processes with event-triggered online learning. *IEEE Transactions on Automatic Control, 65*(10), 4154-4169.
16. Wang, T., Lu, C., Sun, Y., Yang, M., Liu, C., & Ou, C. (2021). Automatic ECG classification using continuous wavelet transform and convolutional neural network. *Entropy, 23*(1), 119.
17. Wu, Z., Lan, T., Yang, C., & Nie, Z. (2019). A novel method to detect multiple arrhythmias based on time-frequency analysis and convolutional neural networks. *IEEE Access, 7*, 170820-170830.
18. Zeni, C. (2020). *Gaussian process regression for nonparametric force fields.* King's College London,