Design of an Integrated Arrhythmia Detection Model using Connectivity Features and Multivariate Time Series Classification

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Abstract: - Cardiac arrhythmia, characterized by irregular heart rhythms, represents a widespread concern within the realm of cardiology. It encompasses a range of rhythm irregularities, with some being benign and others carrying substantial health risks. Therefore, the timely detection of arrhythmia holds considerable importance. Existing methods to detect arrhythmia mainly utilize either the traditional machine learning classifiers like SVM, and random forest or the recent deep learning-based models like CNN, LSTM, and RNN for the classification while few other methods use the classical signal processing-based transforms to extract the discriminating features. This paper proposes a novel integrated approach to classify the ECG signals for arrhythmia detection. Unlike existing methods, it considers the multivariate time series nature of the input along with the interrelationships among different ECG leads. The approach utilizes multivariate time series features extracted using ROCKET (RandOM Convolutional KErnal Transform) and introduces new connectivity-based features such as correlation and coherence for improved ECG signal classification. The state-of-the-art classification performance of the proposed integrated model on the PTB-XL PhysioNet dataset attested to the efficacy of the same.

Key-Words: - Arrhythmia detection, cardiovascular disease, disease diagnosis, electrocardiogram, multivariate times series classification, ROCKET, connectivity, feature extraction.

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1 Introduction

Cardiac arrhythmia, which refers to irregular heart rhythms, is a prevalent concern in the field of cardiology. It encompasses a spectrum of rhythm abnormalities, some of which are harmless while others could pose serious threats to health. As a result, the prompt identification of arrhythmia holds significant clinical significance and has the potential to be life-saving, [1], [2]. In cardiology, the most widely employed approach to identify cardiac arrhythmia involves the use of the electrocardiogram (ECG). This diagnostic method captures the heart's electrical activity. The standard procedure records a 12-lead ECG, which is gathered over a duration of 10 seconds. The diagnosis of cardiac arrhythmia involves inspection of these 12 lead ECG signals by an expert doctor which introduces the possibility of human error and observer bias, [2], [3]. To mitigate these challenges, various methods have been proposed in the literature to automatically identify cardiac arrhythmia from ECG signals using the concepts of signal processing, machine learning, and more recently deep learning, [4], [5], [6], [7], [8], [9], [10], [11]. While conventional signal processing and machine learning-based approaches typically necessitate the creation of manually crafted features, deep learning-based algorithms, on the other hand, can be used to automate feature extraction. From the detailed investigation of the work devoted to address the arrhythmia detection problem, [4], [5], [6], [7], [8], [9], [10], [11], it can be concluded that the cutting-edge approaches predominantly employ deep learning-based methods, specifically, convolutional neural networks (CNN) and recurrent neural networks (RNN). To have more insights into the same, we next discuss some representative existing state-of-the-art methods for arrhythmia detection.

Starting with an interesting work in [4], the authors here put forth a modified U-net model to distinguish between five distinct beat categories. Their model achieved an impressive accuracy of 97.3%, making use of a dataset of 83,648 beats from

47 subjects. In a separate investigation, [5], the authors utilized the discrete wavelet transform (DWT) to extract features, combined with a support vector machine (SVM) as the classifier, resulting in an accuracy of approximately 95.9%. [6], introduced a convolutional neural network model for the purpose of categorizing 17 different cardiac rhythms. Their reported accuracy stood at 91.3%, derived from the analysis of 1,000 ECG fragments. In their another work, the authors took a different approach, utilizing both convolutional layers and long short-term memory (LSTM) units to simultaneously address representation and sequence learning tasks that led to an accuracy of about 92.2%, [7]. Authors in [8], leveraged specific ECG features, such as peak-to-peak interval (R-R interval), beats per minute (BPM), and P wave to QRS peak interval, in conjunction with an SVM classifier, resulting in a classification accuracy of 91.0%. Meanwhile, [9], introduced a novel deep-learning methodology involving the transformation of 1-D ECG signals into 2-D time–frequency spectrograms using a superlet transform (SLT). This innovative approach yielded an impressive overall accuracy of 96.2%. [10], used an LSTM model to identify 12 different heart rhythm categories. This was achieved by analyzing a dataset consisting of 65,932 digital 12-lead ECG signals obtained from 38,899 patients and got an accuracy of around 90.0%. [11], proposed an attention-based time-incremental convolutional neural network (ATICNN), a deep neural network model achieving both spatial and temporal fusion of information from ECG signals and was able to get an accuracy of about 81.2%.

So, although serious efforts have been made to solve the arrhythmia detection problem, none of these existing methods take into consideration the multivariate time series nature of the input multi-lead ECG signal and the interrelationship among these leads. To circumvent these limitations of the existing approaches, in this paper, we propose an innovative approach to classify the ECG signals using multivariate time series features extracted using ROCKET (RandOM Convolutional KErnal Transform), [12] and the novel connectivity-based features such as correlation and coherence. Traditional methods for classifying time series typically use specific aspects like shape, frequency, or variance as representations. The ROCKET's convolutional kernels replace the need for manually crafting these representations with a single mechanism that can capture similar features effectively. Furthermore, unlike the existing state-of-the-art methods, here for the first time, we exploited the relational information among different leads of the ECG for arrhythmia detection. Having verified the efficacy of the multivariate time series-based approach and connectivity-based approach individually, finally, both approaches are integrated using feature concatenation to construct an integrated arrhythmia detection model. This integrated model essentially exploits both the multivariate time series-based features and the connectivity-based features simultaneously to improve the performance of the model further.

The remaining paper is organized as follows: Section II is devoted to basic preliminaries and related work required to appreciate the proposed work. A detailed explanation of the proposed arrhythmia detection model is presented in section III. Section IV consists of the performance analysis of the proposed model and its comparison with the existing methods. Section V concludes the paper by summarizing the proposed work and the possible future scope.

2 Basic Preliminaries and Related Work

2.1 Multivariate Time Series Classification

Multivariate time series classification is the process of predicting a class or categorical label for multiple concurrent series of sequential data points. Each data point in a multivariate time series is characterized by several variables or features. The data points in the multivariate time series are ordered by time. In other words, multivariate classification involves classifying a series of observations over a period of time wherein each observation is characterized by several attributes or measurements.

Conventionally, a variety of techniques have been employed to solve this multivariate time series classification problem, ranging from random forest, and support vector machines (SVM) to the recent convolutional neural networks (CNN), [13],[14]. While all these techniques consider the time series data as non-sequential wherein the order of data points does not matter, the more recent deep learning-based techniques like LSTM and other recurrent neural networks (RNNs) can be used to exploit the sequential nature of a time series, [13].

Multivariate time series classification finds application in various domains and contexts with some of the major applications as follows, [13], [15], [16]:

1) Healthcare: Time series classification can used to detect different diseases like arrhythmia with the help of ECG signals, epilepsy with the help of EEG, and diseases like Parkinson's. It can also be used to monitor vital signs like heart rate, blood pressure, and oxygen levels in blood.
2) Finance: It can be used to analyze the stock price of a particular company depending on the previously available stock market data.
3) Earthquake Warning Systems: Utilizing multivariate time series classification we can identify seismic activity patterns and offer early alerts for potential earthquakes.
4) Energy Management: Using the previously available data, time series classification can be used to forecast energy demand and optimize energy generation and distribution processes.
5) Environment Monitoring and Fault Detection: It can be used to analyze climate data to predict weather patterns and extreme events. It can also be used to determine the level of pollution and detect various faults with the help of proper sensors.

With this general overview of the multivariate time series classification, we next discuss ROCKET (RandOM Convolutional KErnal Transform), one of the best performing multivariate time series classifiers, which is used in our proposed arrhythmia detection model for classification purpose.

2.2 ROCKET (RandOM Convolutional KErnal Transform)

Typically, most of the state-of-the-art time series classification techniques focus on high accuracy but have complex computation requirements that are insufficient on small datasets and take a huge amount of time on large datasets. In contrast to this, ROCKET (RandOM Convolutional KErnal Transform), [12], achieves comparable accuracy levels while demanding considerably less time than competing state-of-the-art algorithms, including convolutional neural networks.

Due to its capacity to deliver high baseline findings on different time series classification benchmarks, ROCKET has gained popularity in a variety of applications, [12], [13]. It provides a novel method for feature engineering for time series data, which can be useful when working with huge datasets or when computational resources are few. The basic working principle of the ROCKET algorithm is described below.

As shown in Figure 1, the ROCKET algorithm first extracts features from the input multivariate time series using convolutional kernels and then passes these features to a linear classifier. It uses a large set of kernels, typically 10,000 and the reason for this is that computing convolutions is inexpensive due to the kernels having fixed weights and a single convolutional layer. These kernels are similar the those used in a CNN, the difference being each of these kernels has randomly allocated lengths, weights, bias, and dilation and it does not use nonlinear transforms such as Rectified Linear Unit (ReLU). Every individual kernel undergoes convolution with each time series, resulting in the creation of a feature map. Each kernel generates two features: the highest value and the proportion of positive values. So, a model with 10,000 kernels generates a total of 20,000 features. These features are then used to classify an input multivariate time series using different linear classifiers. Typically, a ridge regression classifier is used for a small dataset whereas logistic regression with stochastic gradient works well for the larger dataset, [12].

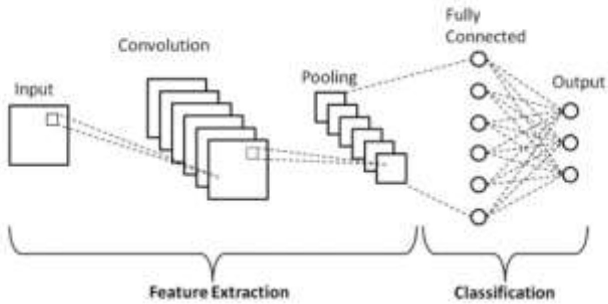

Fig. 1: Block diagram of the ROCKET multivariate time series classifier

2.3 Connectivity Features

Connectivity features of a time series are measures that describe how different variables in time series data are connected or interact with each other. In this work, we extracted the connectivity information from the ECG data using the following four widely used connectivity features, [17]:

1) Coherence: Coherence quantifies the similarity among the frequency components of two-time series signals. It indicates how well the phases and amplitudes of the signals' frequency components are correlated at different frequencies.
2) Correlation: Correlation examines the broader linear connection between two variables, without considering their frequency. It is frequently employed to quantify the degree of correlation between two time series and its value ranges between -1 to 1.
3) Phase-lag index: Phase-lag index (PLI) is a statistical metric employed to analyze the extent of phase synchronization or phase coupling between two time series signals. Its evaluation

includes the calculation of the instantaneous phase, followed by an examination of the stability and consistency of phase differences over time.

4) Phase-lag value: Phase-lag value (PLV) generally signifies the degree to which one signal is delayed compared to another with respect to their phase. It quantifies the time delay or difference in phase components between two signals at a particular frequency or over a specific time span.

Now, with this sufficient background about the multivariate time series classification and connectivity features, we discuss the details of our proposed arrhythmia detection models in the following section.

3 Proposed Arrhythmia Detection Models

In this section, we explain in detail the proposed multivariate time series-based arrhythmia detection model, followed by the connectivity-based model and finally discuss the integration of these two models. However, before that, a brief overview of the dataset and the preprocessing techniques is presented.

3.1 Dataset

In this work, we used PTB-XL Physionet dataset, [18], which consisted of 45,152 ECGs from various patients. The conversion rate from volts to A/D bits was 4.88, utilizing a 32-bit resolution A/D converter. The amplitude unit was measured in microvolts, with a maximum value of 32,767 and a minimum of -32,768. The study received ethical approval from the institutional review boards of Shaoxing People's Hospital and Ningbo First Hospital. Informed consent requirements were waived, and the data was permitted for public sharing following de-identification. From this dataset, we focused on atrial fibrillation patients, which represent the most common type of arrhythmia. In the given dataset there are 1780 patients of the type atrial fibrillation. We used another PTB-XL dataset to get the data of 5000 normal individuals. Both the datasets had the same time length of about 10 seconds and the sampling frequency of these datasets was also identical (500Hz).

3.2 Preprocessing

To assure the dataset's quality and suitability for analysis, a number of essential preprocessing activities were carried out throughout the data preprocessing phase. The first phase involves managing missing values, where imputation techniques are used to fill up dataset gaps. Detrending was employed to eliminate baseline wander, a low-frequency variation brought on by things like electrode movement. In order to focus more clearly on the signal's important components, the baseline wander was mathematically removed during this step. Last but not least, feature scaling was done to scale all features uniformly, preventing any feature from dominating others based on magnitude. Together, these preprocessing methods refined the unprocessed dataset, preserving its integrity and setting the stage for accurate and meaningful analyses. The sampling frequency of the data set is 500 Hz, and the total length of the signal is about 10 seconds, so we get about 5000 samples per time series. We then used the windowing technique to divide each time series into multiple parts to increase the data size and found that a window length of 2 seconds, which corresponds to 1000 samples, gives the highest accuracy. After performing these preprocessing steps, we applied three novel approaches to classify the 12-lead ECG data that are explained in detail below.

3.3 Multivariate Time Series-based Approach

In this approach, for the first time, the input 12-lead ECG signal was modeled as a multivariate time series signal. Once the input is modeled as a multivariate time series, the arrhythmia detection problem reduces to a multivariate time series classification problem which is then solved using the ROCKET algorithm. As described in the last section, the ROCKET (RandOM Convolutional Kernel Transform) algorithm extracts abstract features from the multivariate time series input, i.e., 12-lead ECG signals. These features are then used to train a logistic regression model using stochastic gradient descent as the optimization technique that determines the optimal set of parameters (weights and biases) to minimize the loss function and improve the accuracy of the predictions.

Here, we experimented with different numbers of kernels to generate different sets of features wherein each kernel contributes two different features. We also investigated different window lengths and found that a window size of 2 seconds gave the most accurate results. With this windowing technique, the ECG signal was divided into discrete 2-second intervals, each containing 1000 data samples. This balance between temporal resolution and computational efficiency was key to our methodology. To classify a particular patient, we used a majority decision strategy, wherein each subject was classified with a label of the majority segments. For each sample, the 12-lead ECG signal was divided into segments of 2-second length (consisting of 1000 samples), and the predominant class among all these segments was considered as the class for the given sample. This approach helped to mitigate potential fluctuations or anomalies within shorter segments and ensured reliable predictions.

Although this multivariate time series-based classification approach indirectly utilizes the interrelationship among different time series, to exploit this relational information further, we next propose a connectivity-based classifier that is discussed below.

3.4 Connectivity-based Approach

Typical machine learning models often consider every time series in a multivariate time series as an independent entity, thus neglecting the relational information amongst them, which can be exploited for classification purpose. In particular, as far as the multi-lead ECG signal is concerned, the neighboring ECG leads can share meaningful relational information, which can be quite useful for the present arrhythmia detection purpose. With this hypothesis, we propose here a detection model that extracts this relational information among different ECG leads and then use the same for classification purpose.

Fig. 2: Block diagram of the proposed connectivity-based arrhythmia detection model

In this proposed model, we first extract the connectivity information from the ECG time series using four widely used connectivity measures, viz., coherence, correlation, phase-lag index, and phase-lag value. Each of these characteristics generates a 12x12 matrix, representing distinct qualities related to each separate segment in the time series. Then we merge these matrices to create a comprehensive 24x24 matrix of the lead connectivity features. This matrix includes intricate connections and interdependencies among the segments, enhancing how the data is represented by offering a complete view of the sequential nature of the time series. To classify into classes from this feature matrix, we employed a convolutional neural network (CNN), [19], as shown in Figure 2.

In our experimentation, we explored various configurations of the CNN architecture. We tested different numbers of layers and neurons within each layer to determine the optimal structure. Our findings revealed that a neural network with three hidden layers yielded the most accurate results. Furthermore, we fine-tuned the number of neurons in each layer, settling on 256 neurons for the first (input layer), 10 for the second (hidden layer), and 1 for the third (output layer). This neural network's architecture comprised a convolutional layer as the initial processing step, extracting distinctive patterns from the feature space. Subsequently, a max pooling layer distilled the essential information, followed by a flattening step, which prepared the data for the final classification or prediction stage.

3.5 Integrated Approach

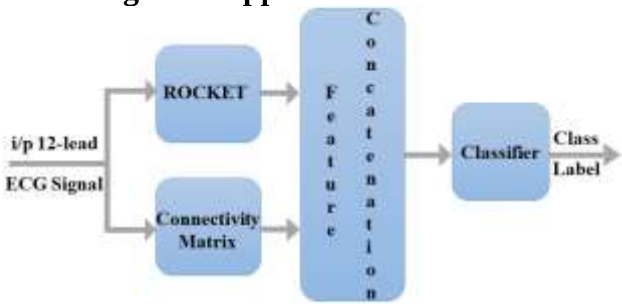

Fig. 3: Block diagram of the proposed integrated arrhythmia detection model

Having verified the efficacy of the multivariate time series-based approach and connectivity-based approach independently, inspired by similar applications, [20], we next integrate these approaches to enhance the detection performance further as indicated in Figure 3. In this integrated model, the multivariate time series-based features extracted from the ROCKET algorithm were concatenated with the comprehensive connectivity matrix to create a combined feature vector. This combined feature vector was then used as an input to a logistic regression classifier with a stochastic gradient descent optimizer. This integration aimed to harness the combined power of these features to produce a further comprehensive and robust model. The results of this concerted effort have indeed been promising. Through careful experimentation and analysis, it was found that the accuracy achieved with this model exceeded that of the first two models. This observation represents a tangible advance in our quest for more accurate and reliable predictions or classifications. The quantitative performance of these proposed models, along with the comparative analysis is presented in the next section.

4 Experimental Results and Discussion

In this section, we first present the classification performance of all three proposed models. Then we compare their performance with the performance of the existing arrhythmia detection methods. To quantify the classification performance of the detection model, we employed three performance measures, viz., accuracy, sensitivity, and specificity that are defined as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

where TP: True Positives represent cases where the model accurately forecasts the positive class,
TN: True Negatives occur when the model accurately predicts the negative class,
FP: False Positives happen when the model inaccurately forecasts the positive class despite the actual ground truth being negative, and
FN: False Negatives happen when the model incorrectly predicts the negative class when the actual ground truth is positive.

We used 5-fold cross-validation on all the above models to validate our results. By calculating the average performance over several folds, the fluctuation in the performance measurement is minimized, enhancing its reliability and hence providing a better estimate of how well a model is likely to perform on unseen data.

As far as the classification performance of the multivariate time series-based model is concerned, as the performance of the model depends on the number of kernels in ROCKET and the ECG window length, determining their optimal values becomes extremely important. So, to find the optimal values of the number of kernels N in ROCKET and the ECG time series window length w, we constructed the models with different values of N and w and examined the resulting performance (as shown in Figure 4).

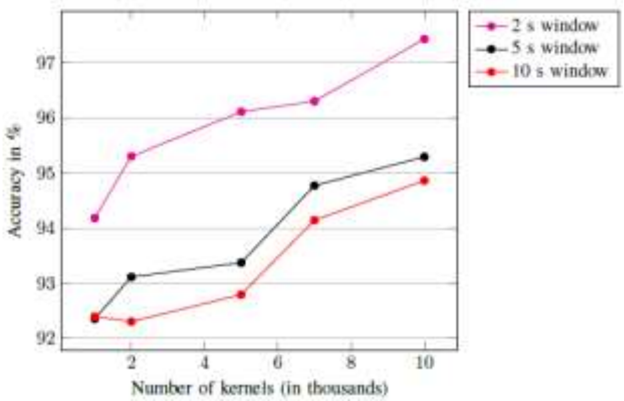

Fig. 4: Classification accuracy of the proposed multivariate time series-based arrhythmia detection model for different values of N and w

From the results in Figure 4, it can be observed that 10000 kernels and a window length of 2 s performs best and hence was selected in the final model. Having evaluated the performance of the multivariate time series-based approach, we next evaluate the performance of the connectivity-based approach.

In the connectivity-based model, as the input information to the classifier changes with the chosen measure of connectivity, the performance of the classifier is expected to depend on the connectivity measure, viz., coherence, correlation, phase-lag index, and phase-lag value. So, to obtain the optimal connectivity measure for the present application, we evaluated the performance of the same CNN classifier presented with different connectivity matrices. The results of the same are shown in Figure 5.

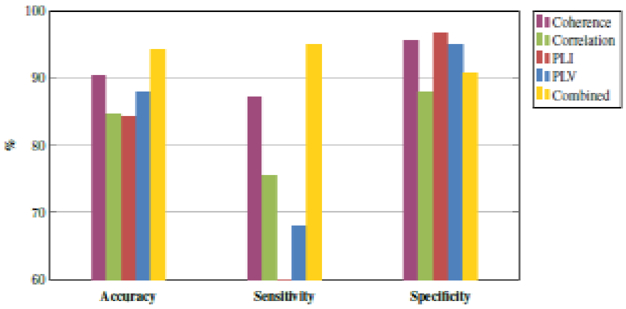

Fig. 5: Classification performance of the proposed connectivity-based arrhythmia detection model using different connectivity measures

From the results in Figure 5, it can be observed that coherence is the optimal connectivity measure for arrhythmia detection. Now, as each of the connectivity measures carries unique information, fusing the information from all should improve the model performance. To verify this hypothesis, we concatenated all four 12x12 connectivity matrices to construct a comprehensive 24x24 matrix and then used it as an input to the same CNN classifier. The superior performance of the combined feature matrix, as observed in Figure 5, verified our hypothesis.

Having validated the performance of the multivariate time series-based model and the connectivity-based model, we next validate the performance of our integrated arrhythmia detection model which exploits both the sequential and relational information of the ECG data. Classification performance of the integrated model and its comparison with our earlier proposed models is shown in Figure 6.

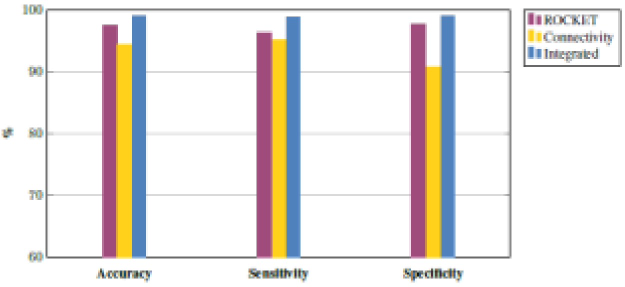

Fig. 6: Classification performance of the proposed arrhythmia detection models.

It is evident from Figure 6 that the proposed integrated model outperforms our proposed individual models, thus verifying its efficacy.

Finally, we compared the classification performance of our proposed integrated arrhythmia detection model with the existing state-of-the-art methods, the results of which are shown in Table 1.

Table 1. Classification accuracies of different arrhythmia detection methods.

Method	Classification Accuracy (%)
Mod U-Net [4]	97.32
SVM [5]	95.92
DNN [7]	92.24
Superlet-DNN [9]	96.20
LSTM [10]	90.00
Prop. Integrated Model	**98.96**

Results in Table 1 corroborates the superiority of our proposed integrated arrhythmia detection model which can be attributed to its unique capability to exploit both the sequential and the relational information in the multi-lead ECG data.

5 Conclusion and Future Scope

In this paper, we addressed an important problem of cardiac arrhythmia detection using ECG signals. The problem was first formulated as a novel multivariate time series classification problem which was then solved using state-of-the-art ROCKET multivariate time series classifier. To exploit the relational information among different ECG electrodes for detection purpose, the classification problem was then uniquely solved by extracting the different connectivity-based features. Finally, both the proposed models were integrated to design a novel integrated arrhythmia detection model that exploited both the sequential and the relational information of the ECG data simultaneously. Application of the proposed integrated model on PTB-XL PhysioNet dataset yielded state-of-the-art detection performance with reduced computational complexity and thus verified the applicability of the same.

Although our proposed integrated model equipped with the ROCKET algorithm achieved state-of-the-art detection performance, its performance may be improved further by employing other multivariate time series classifiers like multivariate DTW-NN, and InceptionTime, and hence can be an interesting extension of the present work. Also, the applicability of the proposed integrated approach can be extended in various other applications, e.g., Alzheimer's disease detection, Schizophrenia detection which also involve multivariate time series data as an input.

References:

[1] "What Is Arrhythmia?" National Heart, Lung, and Blood Institute. March 24, 2022, [Online]. https://www.nhlbi.nih.gov/health/arrhythmias (Accessed Date: September 3, 2023).

[2] C. Antzelevitch and A. Burashnikov, "Overview of basic mechanisms of cardiac arrhythmia," *Cardiac Electrophysiology Clinics*, vol. 3, no. 1, pp. 23–45, 2011. doi: 10.1016/j.ccep.2010.10.012.

[3] M. Behzadi, S. Joukar, and A. Beik, "Opioids and cardiac arrhythmia: A literature review," *Medical Principles and Practice*, vol. 27, no. 5, pp. 401–414, 2018. doi:10.1159/000492616.

[4] S. L. Oh, E. Y. K. Ng, R. S. Tan, and U. R. Acharya, "Automated beat-wise arrhythmia diagnosis using modified U-net on extended electrocardiographic recordings with heterogeneous arrhythmia types," *Computers*

in Biology and Medicine, vol. 105, pp. 92–101, 2019. doi: 10.1016/j.compbiomed.2018.12.012.

[5] Ch. Usha Kumari, A. Sampath Dakshina Murthy, B. Lakshmi Prasanna, M. Pala Prasad Reddy, and A. Kumar Panigrahy, "An automated detection of heart arrhythmias using machine learning technique: SVM," *Materials Today: Proceedings*, vol. 45, pp. 1393–1398, 2021. doi: 10.1016/j.matpr.2020.07.088.

[6] O. Yıldırım, P. Pławiak, R.-S. Tan, and U. R. Acharya, "Arrhythmia de-¨ tection using deep convolutional neural network with long duration ECG signals," *Computers in Biology and Medicine*, vol. 102, pp. 411–420, 2018. doi: 10.1016/j.compbiomed.2018.09.009.

[7] O. Yildirim, M. Talo, E. J. Ciaccio, R. S. Tan, and U. R. Acharya, "Accurate deep neural network model to detect cardiac arrhythmia on more than 10,000 individual subject ECG Records," *Computer Methods and Programs in Biomedicine*, vol. 197, p. 105740, 2020. doi: 10.1016/j.cmpb.2020.105740.

[8] K. Subramanian and N. K. Prakash, "Machine Learning based Cardiac Arrhythmia detection from ECG signal," *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tirunelveli, India, 2020, pp. 1137-1141, doi: 10.1109/ICSSIT48917.2020.9214077.

[9] P. M. Tripathi, A. Kumar, M. Kumar and R. Komaragiri, "Multilevel Classification and Detection of Cardiac Arrhythmias With High-Resolution Superlet Transform and Deep Convolution Neural Network," *in IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-13, 2022, Art no. 4006113, doi: 10.1109/TIM.2022.3186355.

[10] K.-C. Chang et al., "Usefulness of machine learning-based detection and classification of cardiac arrhythmias with 12-lead electrocardiograms," *Canadian Journal of Cardiology*, vol. 37, no. 1, pp. 94–104, 2021. doi:10.1016/j.cjca.2020.02.096.

[11] Q. Yao, R. Wang, X. Fan, J. Liu, and Y. Li, "Multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based timeincremental convolutional neural network," *Information Fusion*, vol. 53, pp. 174–182, 2020. doi:10.1016/j.inffus.2019.06.024.

[12] A. Dempster, F. Petitjean, and G. I. Webb, "Rocket: Exceptionally fast and accurate time series classification using random convolutional kernels," *Data Mining and Knowledge Discovery*, vol. 34, no. 5, pp. 1454–1495, 2020. doi: 10.1007/s10618-020-00701-z.

[13] A. P. Ruiz, M. Flynn, J. Large, M. Middlehurst, and A. Bagnall, "The great multivariate time series Classification bake off: A review and experimental evaluation of recent algorithmic advances," *Data Mining and Knowledge Discovery*, vol. 35, no. 2, pp. 401–449, 2020. doi: 10.1007/s10618-020-00727-3.

[14] H. Ismail Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P.-A. Muller, "Deep Learning for Time Series classification: A Review," *Data Mining and Knowledge Discovery*, vol. 33, no. 4, pp. 917–963, 2019. doi: 10.1007/s10618-019-00619-1.

[15] W. M. N. D. Kulasinghe, Maheshi B. Dissanayake, "A Novel LSTM-based Data Synthesis Approach for Performance Improvement in Detecting Epileptic Seizures," *WSEAS Transactions on Biology and Biomedicine*, vol. 20, pp. 132-139, 2023, https://doi.org/10.37394/23208.2023.20.13.

[16] Daehee Lee, Hyunseung Choo, Jongpil Jeong, "Anomaly Detection based on 1D-CNN-LSTM Auto-Encoder for Bearing Data," *WSEAS Transactions on Information Science and Applications*, vol. 20, pp. 16, 2023, https://doi.org/10.37394/23209.2023.20.1.

[17] G. Chiarion, L. Sparacino, Y. Antonacci, L. Faes, and L. Mesin, "Connectivity analysis in EEG DATA: A tutorial review of the state of the art and emerging trends," *Bioengineering*, vol. 10, no. 3, p. 372, 2023. doi: 10.3390/bioengineering10030372.

[18] P. Wagner et al., "PTB-XL, a large publicly available electrocardiography dataset," *Scientific Data*, vol. 7, no. 1, 2020. doi: 10.1038/s41597020-0495-6.

[19] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, "A survey of Convolutional Neural Networks: Analysis, applications, and prospects," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 12, pp. 6999–7019, 2022. doi: 10.1109/tnnls.2021.3084827.

[20] H. Padole, S. D. Joshi, and T. K. Gandhi, "Early detection of alzheimer's disease using graph signal processing and deep learning," *Intelligent Automation and Soft Computing*, vol. 31, no. 3, pp. 1655–1669, 2022. doi: 10.32604/iasc.2022.021310.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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The authors have no conflicts of interest to declare.