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PAPER

Deep Learning Approach for Detecting Cardiovascular Arrhythmias in Seven Lead ECG Signal from Holter

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ABSTRACT

Cardiac arrhythmias are abnormalities caused by irregularities in the heart's electrical conduction system. Cardiovascular diseases (CVD) have been identified as the leading cause of death worldwide. Premature ventricular contraction (PVC) is one of these diseases. It is an arrhythmia that can be linked to a several heart diseases that affect between 40% and 75% of the population. Ventricular bigeminy occurs when one or two premature beats are detected on an electrocardiogram when there is ventricular contraction between two normal heartbeats or trigeminy. The appearance of ventricular bigeminy or trigeminy rhythms is related to angina. Myocardial infarction, hypertension, and congestive heart failure are also possible conditions. Based on deep learning, this paper proposes creating a robust approach for automatically detecting and classifying cardiovascular arrhythmias in long-term electrocardiogram (ECG) recordings from halters based on deep learning (DL). We present a convolutional neural network (CNN) and long-short-time memory (LSTM) model that identifies cardiovascular arrhythmias. We have designed and implemented the proposed model using Python. The model was trained and validated on a database that includes a total of 17 long-recorded ECG signals (24 h) from 17 subjects, which were obtained from Yfa Hospital. The signals were recorded with seven leads holter. The CNN classifier achieved an accuracy of 91.14% as a final result, validated through a 10-fold cross-validation. Moreover, the proposed model was found to be capable of analyzing ECG recordings to classify multiple cardiovascular arrhythmias in the ECG record signals efficiently.

KEYWORDS

bigeminy, trigeminy, ECG signal, deep learning (DL), convolution neural network (CNN)

1 INTRODUCTION

Cardiovascular diseases (CVD) are a leading cause of death worldwide. There is a wide range of well-known CVDs, including congenital heart disease, coronary heart disease, supraventricular single extrasystole, peripheral arterial disease,

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rheumatic heart disease, and cerebrovascular disease. According to the World Health Organization (WHO), approximately 17.9 million people die every year due to heart-related complications and heart disease. An effective way to prevent unexpected and premature deaths is to identify individuals at high risk of CDs early and provide them with appropriate treatment [1]. Ventricular bigeminy occurs when two extra or ectopic beats from the bottom of your heart combine. Because these occur early in the cardiac cycle, patients may experience extra thumping or forceful beats in the chest, as well as a sensation of their heart stopping. Trigeminy occurs when these events happen in groups of three. Premature ventricular contraction (PVC) is more common in people who are at a higher risk of coronary heart disease [2]. It is associated with structural heart disease and increases the risk of CVD and sudden death [3,4]. Although. Some studies have mentioned that PVC can cause cardiomyopathy in people who do not have structural heart disease regardless of whether PVC can appear in healthy subjects. Using 24-hour or 48-hour holter monitoring has shown that 40% to 75% of the general population have this arrhythmia [4]. ECGs are the most commonly used tool for diagnosing various types of arrhythmia. Researchers are paying close attention to ECG analysis in order to accurately and effectively diagnose arrhythmias and critical cardiac conditions. Traditional diagnosis entails bedside ECG recording and the presence of a physician in order to analyze and diagnose a condition. Such methods, however, take time, and in most severe cardiac cases, time is critical in diagnosing such a condition [5]. Multiple processes are used in monitoring systems to analyze and classify ECGs [6]. For deep learning (DL) approaches, these processes can be divided into three steps: data acquisition, preprocessing, feature extraction, and classification. This study proposes one such approach [7]. Deep neural networks (DNN) are a more recent technique in neural networks that utilize multiple layers to extract both higher-level and lower-level information from various types of input, such as images, categorical values, signals, and numerical values. Some of the most well-known DL architectures include convolutional neutral networks (CNN), reinforcement learning, and recurrent neutral networks (RNN) [8]. The RNN is the most fundamental DL algorithm, with artificial neurons serving as the neural network's very essence. The neurons are connected by weights, and the weighted sum is calculated after data is transmitted to the input layer. Each neuron's bias is then added to the weighted sum of inputs. The activation function governs neuron activation. When a neuron is activated, it sends information to other neurons in the subsequent layers until it reaches the penultimate layer. When a neuron in the output layer tallies with the input digit, the weights and biases are constantly adjusted to ensure that the network is well-trained [8]. In this study, we aim to detect cardiovascular arrhythmias, especially bigeminy (ANZA) and trigeminy (ANZB), support decision-making in the diagnosis process. The model is based on convolutional (CNN) and long-short time memory (LSTM) neural networks and trained on ECG signals with a notated database. This model can be used for monitoring systems that use holter devices.

2 RELATED WORK

Researchers have proposed methods for detecting cardiac rhythms. Machine learning (ML) and DL algorithms have recently sparked interest due to their ability to detect heart disease. For example, [9] developed an automated method for identifying various types of arrhythmias using traditional ML models, such as support vector machines and binary decision trees. They used temporal and frequency representations with non-linear analysis as well as an image-based phase plot. The accuracy, sensitivity, and specificity were 95.1%, 94.5%, and 94.2%, respectively, in the balanced dataset. Miao and Miao et al. [10], based on a multiclass morphologic pattern, presented a DL-based method for fetal cardiac topographic health diagnosis. The developed method is used to distinguish and classify the morphologic pattern of people who are having difficulty conceiving. Their preliminary computational results show that this model was evaluated on a small number of patients, with 88.02% accuracy, 85.01% precision, and an F-score of 0.85%. A small selection of patients was used to test this model. In [11], to address overfitting issues, they employed a variety of dropout strategies. They used a set of datasets compiled from various sources. The proposed HMANN model, which stands for heterogeneous modified artificial neural network, achieved an 87%. Peimankar [12] proposed a real-time methodology that uses RR intervals as a feature to classify ECG periods as either atrial fibrillation (AF) or normal rhythm. Their method extracts features directly from the RR interval period. The results achieved were 98.98% and 96.95% for sensitivity and specificity, respectively, across three datasets with a total of 89 subjects. Another work [13] demonstrated a platform consisting of two convolutional networks for detecting and classifying heartbeats and rhythms. The first network recognizes and categorizes rhythms, while the second network detects heartbeats and classifies them as artifacts and pause annotations. In the detection stage, they achieved 99.84% and 99.78% for sensitivity and positive predictive, respectively, and in the classification stage, the network performed 89.4% for recognizing ventricular ectopic beats with a sensitivity of 97.85%. In [14], in a single-lead ECG, they used a convolutional network from 13 layers to distinguish between AF, normal, and other rhythms. This model consists of different layers, such as dilated convolution layers, max pooling layers, ReLU activation functions, batch normalization, and dropout layers. The average precision, recall, and accuracy scores were 84%, 85%, and 88%, respectively. The authors in [15] proposed a method for developing software models based on dynamic properties such as blood volume, pressure in various parts of the body, blood vessels, blood flow in the chambers of the human circulatory system, and statistical data. And, before calculating the model, the process of model individualization and identification is carried out. The values of the parameters of the circulatory system are determined separately for each patient. Then they use a Simulink interactive environment as hardware to simulate the monitoring of the cardiovascular system. However, using the digital twins for optimal therapy options requires a mechanistic understanding that links all levels, from genetic and molecular traces to the pathophysiology, lifestyle, and environment of the patient. There is still a need for more research and adjustments to be made in healthcare because the study focuses on monitoring the cardiovascular system and predicting treatment for some conditions using medical equipment that is not always available, such as for measuring pressure (pneumatic cuffs) and for measuring blood flow (phase-contrast magnetic resonance angiography). 4D-flow magnetic resonance imaging, two-dimensional echocardiography and Doppler echocardiography. Also, the variety measurements were used to get about 52 parameters that should be adjusted carefully by specialists who know the correct position for each non-invasive diagnostic tool before using the method for prediction. A hybrid CNN-LSTM model was created by Lui et al. [16] and Lih et al. [17] for the identification of normal and other CVDs, respectively. [16] obtained an accuracy of 98.5% for small data, while [15] applied the sample shuffling technique but did not disclose the classification accuracy. In a different way, other research has concentrated on early rhythm prediction. [18] proposed artificial neural networks (ANN) that depends on back propagation learning and a perceptron structure to predict ventricular tachycardia one hour before it occurs. Depending on heart rate variability (HRV) and respiratory rate variability, they obtained up to 14 parameters. The performance was 88% sensitivity, 82% specificity, and 93% ACC. In [19], a model for predicting early ventricular tachyarrhythmias using features from HRV, 120 seconds, and QRS complex shape was presented. This technique detects ventricular fibrillation before 30 seconds of its appearance using two ANN. Using 10-fold cross validation, the accuracy of the 11 HRV features was 72%, while the accuracy increased to 98.6% by using four QRS complex features. To train the model with less time complexity, Shakib et al. [20] used Gabor filters together with a convolutional network model. They reported that Gabor filters were able to save a significant amount of time during the training. Additionally, in another study, Alekseev et al. [21] reported that CNN models with Gabor layers outperformed the conventional model on several datasets (a 6% improvement in accuracy). As a result of the two studies, it is clear that the CNN model with Gabor filters performs well in terms of accuracy while also reducing computational complexity. In this study, the Gabor filter used the ECG signals to classify normal, myocardial infarction, and CVDs. In [8], a literature review gave details about the wide range of techniques that have been used from 2012 to 2021, focusing on the most recent techniques that have been used in CVDs and heart arrhythmia diagnosis. For this purpose, we used convolution (CN) and LSTM networks to enhance decision-making. The proposed techniques investigated using the ECG signal to detect and classify cardiovascular arrhythmias using different numbers of leads. Some techniques focus on using one or two leads to reduce cost and increase the availability, while others rely heavily on using a larger number of leads for better information and to build a more reliable detection and classification model that can be used more efficiently in the diagnosis process and enhance the decision-making by the cardiologist. Most of the state-of-the art techniques that have high accuracy results use well-known and highly annotated databases such as MIT-BIH and long-term AF from the PhysioNet repository [22,23]. In fact, such techniques will be less adaptable to be used for multiple databases, and training such techniques using low-annotated databases is challenging. For these reasons, in our proposed work, we used a database from Yfa Hospital with some annotations about abnormalities noted by four cardiologists. We used special techniques to overcome these challenges. Our model classifies several arrhythmias, especially bigeminy and trigeminy. The reason for using these types of neural networks is because the classifiers in CNN networks have high accuracy, and are less complex than other networks.

3 METHODOLOGY

3.1 Training data

Actual database from Yfa Hospital in Russia were used for the study. The initial database was for solving the problem of detecting arrhythmias of the bigeminy. During holter monitoring, devices were connected to several patients for about 24 hours. The database consists of 17 folders with daily ECG data in which episodes of bigeminy occur in significant numbers. Each folder contains two files: file ECG.txt and file dataset.xlsx.

- File ECG.txt contains the values of the ECG signal recorded in a line for seven leads, separated by a space in this order: (I, II, V5, III, aVL, aVR, aVF). In each subsequent line, the values of the leads are recorded in the same order with a frequency of 266 Hz.
- File dataset.xlsx contains a table with information on decoding data from the ECG file, which carries the time of the recorded complex in milliseconds from the beginning of the day; the time of the recorded complex in milliseconds from the start of recording; line number in the ECG file with values corresponding to the recorded complex; type of the found complex: S-supraventricular; V#-ventricular; a brief description of the recorded arrhythmia; name of the arrhythmia. There are 16 arrhythmias mentioned, some of them presented in the ECG signals, and are annotated. While other arrhythmias did not appear in the recorded ECG signals. Table 1 give the details about the short and full name of the mentioned arrhythmias. The database does not contain information about heart beats waves and complexes, such as T wave, P wave, QRS complex, PQ interval, QT interval, and RR intervals.

Table 1. Details of the short and full name of the mentioned arrhythmias

	Arrhythmia Code	Arrhythmia Full Name
1	ANVEDM	ventricular paired monomorphic extrasystole
2	ANVEDP	ventricular paired polymorphic extrasystole
3	AVES1	ventricular single extrasystole type 1
4	ANVES2	ventricular single extrasystole type 2
5	ANVES3	ventricular single extrasystole type 3
6	ANVES4	ventricular single extrasystole type 4
7	ANVSS1	ventricular single slip type 1
8	ANVSS2	ventricular single slip type 2
9	ANSES	supraventricular single extrasystole
10	ANSED	supraventricular paired extrasystole
11	ANSRT	supraventricular tachycardia
12	ANVRTM	ventricular monomorphic tachycardia
13	ANVRTP	ventricular polymorphic tachycardia
14	ANVIR	idioventricular rhythm
15	ANZA	bigeminy
16	ANZB	trigeminy

To facilitate the implementation of the model and the reading of the ECG signals, we renamed the lead as (L1, L2, L3, L4, L5, L6, L7). Figures 1 and 2 represent examples of random time intervals of the original signals.

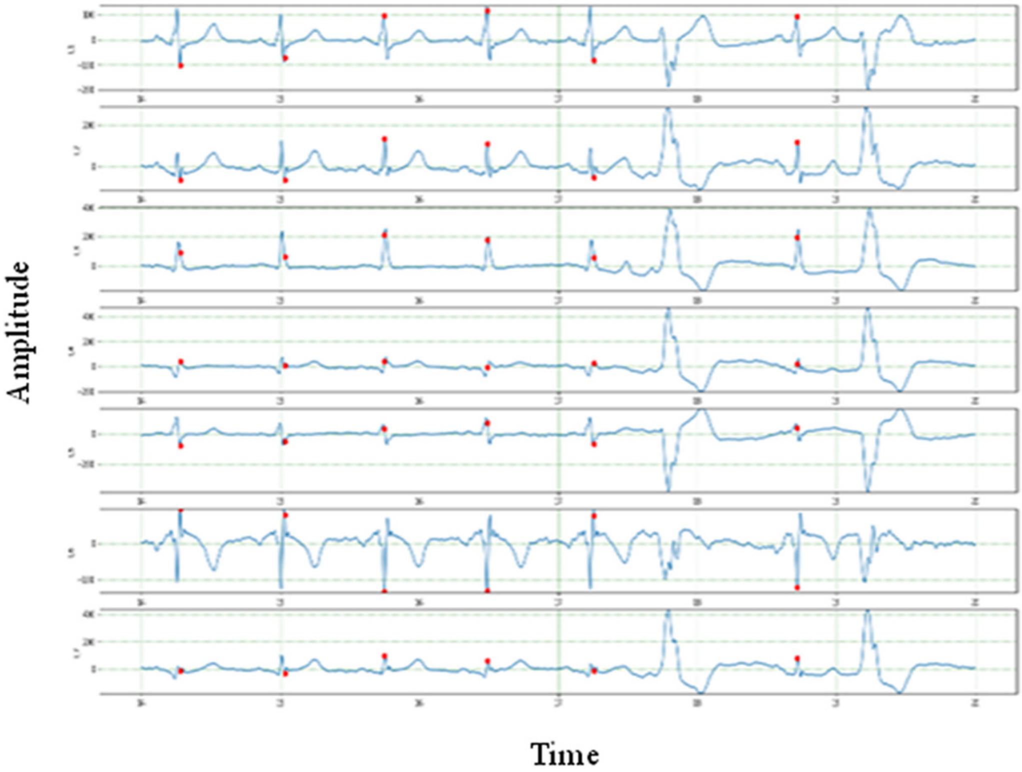

Fig. 1. Example 1 of random time intervals of the original signals

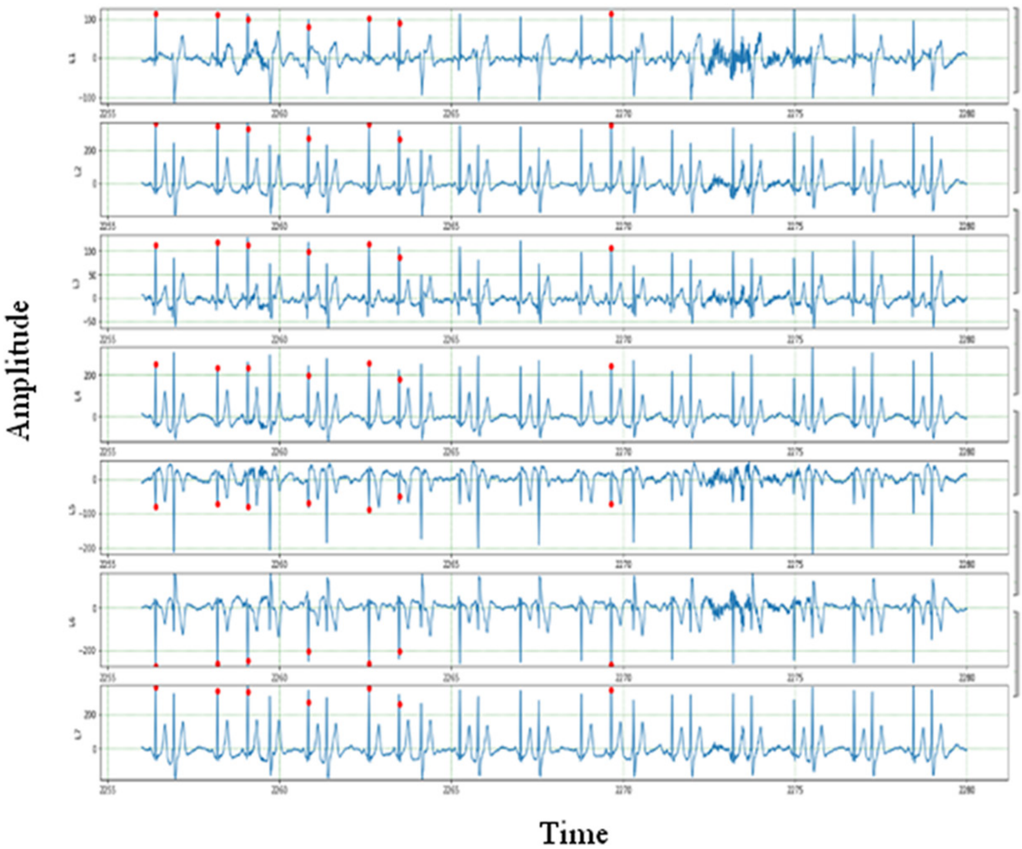

Fig. 2. Example 1 of random time intervals of the original signals

3.2 Deep learning model

CNN model. Typical CNN models use filters that are trained to extract features from input data and represent their location on a feature map. Then use the feature map as input to subsequent layers, which employ new filters to generate a new feature map, and so on. This process is repeated in successive layers as the extracted features become more complex and capable of making predictions. The extracted features are then used to classify the signals using the output feature map. The back propagation algorithm is used to train the CNN model; this algorithm collects gradient values for weight coefficients on various layers repeatedly. The weights are then updated using various stochastic gradient descent techniques [24].

CNN-LSTM model. To implement the work, we used the Python programming language to build 11 CNN-LSTM. A dropout rate of 0.2 was applied to layers 8 and 10 to enhance feature generalization. Batch sizes of 0–20 epochs were used. The convolution layers do not have bias, and to counter the class imbalance, weighted loss was employed. After the signals were input to the convolution layers in every instance, max pooling was employed after the convolution layers to extract the optimal features for classification. First, we used 80% of the original database for training and 20% for validation. Because the original database does not contain information about the heartbeats, waves, and complexes, the accuracy of the model was 82.2%. To increase the accuracy of the model, we used the neighborhood technique to find more features (annotations) from the original signals to overcome the leak of annotations. We considered delaying the signal and reconstructing it to get 23 new annotations: seven from lead left, seven from lead center, seven from lead right, one from the distance between left and center, and one from the distance between center and right. Table 2 explains in detail of the layer architecture that has been used in our model. It gives information about the number of layers, type of layers, output shape in Python, kernel size, the activation function, the parameter numbers that have been used, and the parameter numbers.

Table 2. CNN-LSTM model layers architecture

Layer Number	Layer Type	Output Shape	Kernel Size	Activation Fn.	Parameters Number
1	Conv1D	(301961, 1, 192)	16*1	linear	70848
2	MaxPooling1D	(301961, 1, 192)	–	–	0
3	Conv1D	(301961, 1, 128)	8*1	sigmoid	196736
4	MaxPooling1D	(301961, 1, 128)	–	–	0
5	Conv1D	(301961, 1, 64)	8*1	linear	65600
6	MaxPooling1D	(301961, 1, 64)	–	–	0
7	LSTM	(301961, 128)	–	–	98816
8	Dropout	(301961, 128)	–	–	0
9	Dense	(301961, 32)	–	relu	4128
10	Dropout	(301961, 32)	–	–	0
11	Dense	(301961, 16)	–	sigmoid	528

4 RESULT

As a result of using our proposed model, the total number of parameters was 436,656. The trainable parameters were 436,656, and the non-trainable parameters were 0. The model was trained using 20 epochs, and the classifier optimizer is Adam. The accuracy of the classification increased to 90.85%. Figure 3 shows the changes in the loss value of the network in terms of the loss against epoch numbers during the training process, and Figure 4 is the representation of classifying the CVDs. We considered all the 16 arrhythmias mentioned in the database regarding the appearance of the arrhythmia in the recorded signal to make our model more robust to learn the features of the absent arrhythmias in case they appear in other holter records.

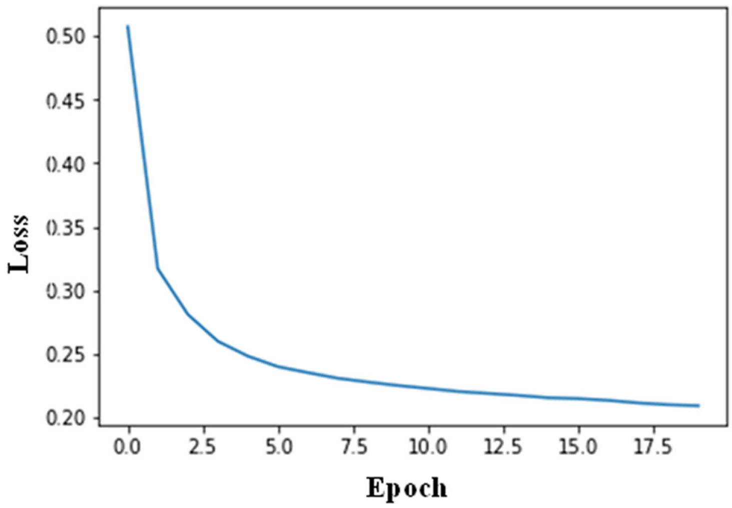

Fig. 3. Loss against varying epoch in CNN-LSTM model

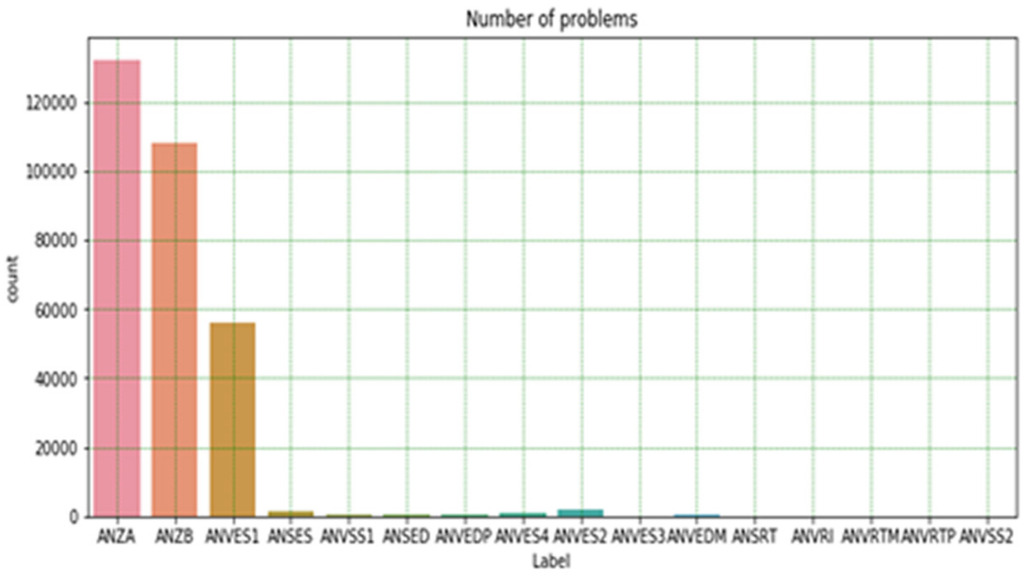

Fig. 4. Classification of the cardiovascular annotated arrhythmias in the database

5 CONCLUSION

Considering about 17.9 million deaths a year, CVDs are the primary cause of death globally. Thus, early detection of CADs is important to provide timely treatment and helps the cardiologist make the right decision during the diagnosis. The proposed model, a combination of CNN-LSTM DNNs, aims to classify some of the important arrhythmias in the holter ECG signals with high accuracy. Compared to the state-of-the-art models that used ECG signals, our proposed model produced better performance in detecting cardiovascular arrhythmias in a low-annotated database and was more flexible to be used with other databases because of its ability to generate features from the original data signals. Moreover, since the model learns features directly from the data, it does not need intensive feature extraction or modification.

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