A Novel Approach to Visualize Arrhythmia Classification Using 1D CNN

Madhumita Mishra(✉), T. L Sharath Kumar, and U. M Ashwinkumar

REVA University, Bengaluru, India
madhumita.mish@reva.edu.in

Abstract. Cardiac-related disorders have been one of the major concerns in recent decades. The electrocardiogram, an extensively utilized medical instrument, records the electrical activity of the heart as a wave. Cardiac arrhythmia is a condition of having an irregular heartbeat. Manually identifying irregularities in an ECG wave is a complicated and challenging task. The current work focuses on computationally identifying the ECG wave fluctuations to determine the abnormality in the heartbeat. We propose to use a 1-Dimensional Convolutional Neural Network (CNN) that analyses a given ECG signal data to identify irregularities in the functioning of the heart and represent the associated risks using graphics interchange format (GIF) files of a 3-dimensional heart. We obtained an accuracy score of 96.72% in classifying given ECG data into five different arrhythmia classes. Automated detection and visual representation of cardiac conditions can help medical associates easily interpret ECG signals and determine arrhythmia early.

Keywords: Electrocardiogram · Cardiac Arrhythmia · 1-Dimensional CNN · Graphics interchange format

1 Introduction

The heart is an essential structure of living beings which pumps blood across the entire body through a network of blood vessels and related pathways of the circulatory system. The circulatory system is essential for human life because it is responsible for transporting blood, oxygen, and other vital materials to all the different parts of our body. Cardiovascular diseases (CVDs) are a class of ailments of heart and related blood vessels, which can comprise cardiac arrhythmia, coronary heart disease, rheumatic heart disease and other heart related conditions. Diseases related to the heart and associated cardiac systems are among the leading causes of mortality today. The most prevalent cause for mortality globally is cardiovascular diseases which approximately claims 18 million lives each year [6]. Amongst the significant causing CVDs, cardiac arrhythmias are a primary illness type where the normal functioning of the heart is affected. Normal heartbeats indicate regular functioning of the heart, but an arrhythmia is a condition where the heart has an abnormal beating pattern. Automatic identification of such paradigms

P. Pareek et al. (Eds.): IC4S 2023, LNICST 536, pp. 198–209, 2024.
https://doi.org/10.1007/978-3-031-48888-7_17

can be of great help in the medical field for dealing with cardiac disorders. A few known characteristics of the cardiac system require expert clinical knowledge to identify any heart ailments.

An electrocardiogram is a standard and painless test that medical practitioners use to measure the electrical variations in the heart's rhythmic functioning. Cardiologists try to analyze ECG signals to determine any irregularities in the functioning of the heart before suggesting a specific treatment. Manual analysis of ECG is a time-consuming and difficult job for doctors that demands great expertise to examine the data extensively because of the large amount and varying complexity of ECG data. To overcome these challenges faced by traditional manual practices of ECG data analysis, automated computer-aided diagnostic methods have been devised to analyze and interpret ECG signals effectively. Much research has been carried out in this area by applying several popular machine learning algorithms and other computer science-based principles to analyze ECG signals practically. It is a demanding task because of the varied wave morphologies between patients and redundant noise that can be present in the input data. The algorithm must be capable of implicitly identifying the distinct wave patterns and their underlying dependencies.

Considerable amounts of research work have already been done in automated ECG analysis. All these works focus on different techniques that can be applied to analyze ECG data and detect the corresponding heart-related conditions. Interest in this area has been analyzing ECG-related data to detect and classify cardiac arrhythmias. Many algorithms have shown promising results in analyzing ECG data and seeing arrhythmic conditions. Also, automated analysis can be very efficient and less time-consuming compared to traditional manual ECG signal analysis done by cardiologists.

J. Ferretti et al. [1] presented a novel approach employing a 1D-CNN to analyze and classify an ECG dataset into 16 different arrhythmia conditions. They implemented a 1D convolutional neural network, tested four different network architectures, and compared their results.

In [2], Amin Ullah *et al.* have implemented a 2-D CNN to classify ECG signals into different arrhythmic types automatically. They used a short-time Fourier transform to convert simple 1-dimensional ECG time series signals into more refined 2- dimensional spectrograms. 2-D spectral images were input to a 2-D CNN model to classify the dataset into eight kinds of arrhythmia.

In a paper titled "Cardiac Arrhythmia Classification based on 3D Recurrence plot analysis and deep learning", Hua Zhang *et al.* [3] implemented an advanced deep learning algorithm based on three-dimensional recurrence plots to analyze ECG and VCG signals and detect four different types of arrhythmic cardiac conditions. The 3D RP maps were constructed to train and test a 3D CNN model. This method provided a better visual representation of the outputs and achieved an efficient average F1 score of 93.50 in classifying cardiac arrhythmia.

Elena Merdjanovska *et al.* [4], in their paper titled "Comprehensive survey of computational ECG analysis: Databases, methods and applications", provide a complete survey of 45 various ECG records along with different computational methods applied for their analysis. They present a summary of machine learning algorithms and multiple tools used for data analysis in machine learning. They have explained the recent works in heart disease detection using machine learning algorithms and concluded that choosing the proper techniques for cleaning the data with productive algorithms is beneficial to develop enhanced accuracy prediction systems.

The traditional machine learning approach uses efficient ML algorithms such as decision trees (DTs), random forest (RF), support vector machine (SVM), and other algorithms to classify cardiac arrhythmia. Automated analysis and classification of ECG signals have been carried out using various techniques, including ML algorithms, artificial neural networks (ANNs) [10, 13], frequency analysis [12], wavelet transform [9], statistical methods [15] and various other approaches.

We implemented a 1-dimensional convolutional neural network to train on an ECG dataset to detect cardiac arrhythmia and then visualize the output through a 3-D model of the heart in GIFs. The beneficial advantage of 1D CNN lies in its simplicity, and it is also computationally less expensive when compared to other complex models. Automated processing and analysis of ECG using neural networks can be very beneficial. Representation of associated arrhythmic conditions using GIFs of 3-dimensional heart models can help everyone better interpret the ECG signals.

2 Methodology

Electrocardiogram (ECG) can be considered as a visual representation of the rhythmic activity of the heart, depicted as wave-like signals, commonly used to diagnose cardiovascular diseases. In our proposed project work, we implement a 1-dimensional convolutional neural network to analyze ECG signals from an ECG dataset and classify the related arrhythmic conditions into one of five classes of heart arrhythmia. We then visualize the predicted arrhythmic class using graphics interchange format (GIF) files of heart to represent the associated arrhythmic condition as the output. The different types of arrhythmias combined into five major categories are presented in Fig. 1.

Figure 2 depicts the basic flow of our proposed work.

2.1 Dataset Collection

We use a processed version of the popularly used PhysioNet's MIT-BIH Arrhythmia ECG—databases with labelled ECG records [5]. The processed version of the dataset that we are using has the ECG lead II recordings re-sampled to 125Hz. This dataset we are using has multiple groups of heartbeats, represented symbolically as N, S, V, F, and Q, that are numerically stored using these indices- 0, 1, 2, 3, and 4, respectively. Of these character symbols, 'N' means Normal heartbeats, 'S' means Supraventricular ectopic beats, 'V' means Ventricular ectopic beats, 'F' means Fusion beats, and 'Q' means Unknown beats.

The input dataset includes two.csv files, one with samples for training the neural network and the second has sample data for testing the model. The "train.csv" file consists of 87,554 samples, while the "test.csv" file has 21,892 samples. This selected input set of data is loaded and prepared using appropriate Python modules.

ARRHYTHMIA CLASS	TYPES CONSOLIDATED
N (Normal Beat)	• Normal • Left/Right bundle branch block • Atrial escape • Nodal escape
S (Supraventricular Ectopic Beats)	• Atrial premature • Aberrant atrial premature • Nodal premature • Supra-ventricular premature
V (Ventricular Ectopic Beats)	• Premature ventricular contraction • Ventricular escape
F (Fusion Beats)	• Fusion of ventricular and normal
Q (Unknown Beats)	• Paced • Fusion of paced and normal • Unclassifiable

Fig. 1. Major arrhythmic classes and their types in the input ECG dataset (Ref: Liu, Fan, et al. 2019)..

2.2 Data Pre-processing

Since the processed ECG dataset is very imbalanced, we must adequately balance the dataset for efficient application of the CNN model. We process and segregate the data into five distinct groups, each with samples corresponding to five different arrhythmic classes. Each data set is later resampled to obtain 50000 examples of every arrhythmic type. These five distinct classes of records are then combined to procure a balanced input dataset containing a total of 250000 samples of records. This dataset is further pre-processed by adding white Gaussian noise (AWGN), and the class labels are then processed using one-hot encoding.

2.3 Model Implementation

We have implemented a classifier that can classify the given ECG signal data into 5 major arrhythmic classes: Normal beats, Supraventricular Ectopic beats, Ventricular ectopic beats, Fusion beats, and Unknown beats.

A 1D CNN model is implemented using "tensorflow.keras.models", and the different layers for the model are imported from "tensorflow.keras.layers" modules of Python. The model has three pairs of 1D Convolution and 1D MaxPooling layers as initial layers. These are then accompanied by a single flattening layer that lessens the input values into one-dimensional ones. It is then followed by three Dense layers, of which two of the dense layers have a ReLU function to activate neurons. The last third thick layer

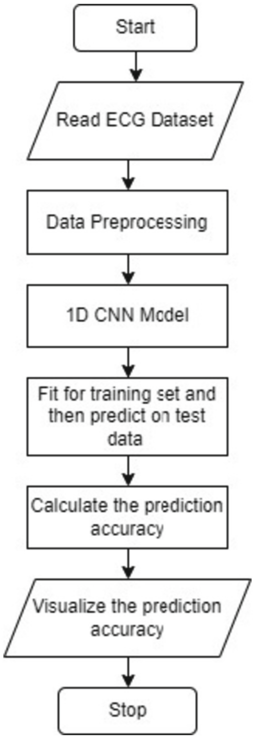

Fig. 2. The basic flow of the arrhythmia classification used in the proposed work.

employs a SoftMax activation function giving out five probabilistic outputs associated with five different output categories of arrhythmia.

Activation functions are mathematical functions that transform the inputs given into the required output within a specific range. Neurons are activated only when the work reaches a set threshold value of the function. Rectified linear activation function (ReLU) is a non-linear activation function that is a simple and effective function that returns zero as output for any negative input while returning the input value directly as the output if it is positive.

Mathematically ReLU output for any given input value 'A' is written as:

$$f(A) = \max(0, A) \tag{1}$$

SoftMax activation is a function used to convert a vector of numbers into a vector of probabilities. So, these are usually used in the final layer of a neural network to obtain chances of each output value vector

The structural design of proposed model is presented in Fig. 3.

The implemented CNN algorithm is then fitted to the training dataset and later tested on the test dataset. We have executed our CNN model for 13 epochs with a batch size of 32. The configuration of the implemented CNN model is shown in Fig. 4.

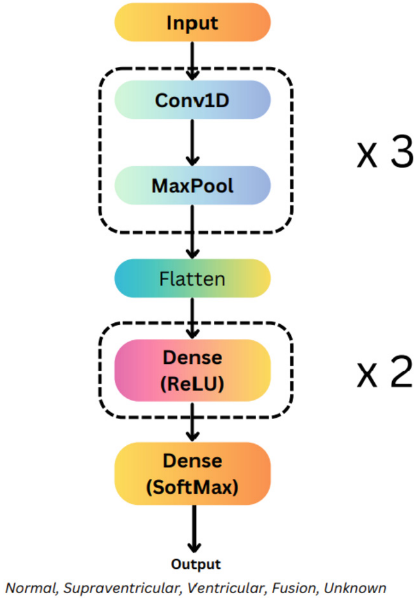

Fig. 3. The proposed 1-dimensional CNN model.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_3 (Conv1D)           (None, 182, 64)           448

 max_pooling1d_3 (MaxPooling  (None, 90, 64)           0
 1D)

 conv1d_4 (Conv1D)           (None, 85, 64)            24640

 max_pooling1d_4 (MaxPooling  (None, 42, 64)           0
 1D)

 conv1d_5 (Conv1D)           (None, 37, 64)            24640

 max_pooling1d_5 (MaxPooling  (None, 18, 64)           0
 1D)
  flatten_1 (Flatten)         (None, 1152)              0

  dense_3 (Dense)             (None, 64)                73792

  dense_4 (Dense)             (None, 32)                2080

  dense_5 (Dense)             (None, 5)                 165

=================================================================
Total params: 125,765
Trainable params: 125,765
Non-trainable params: 0
```

Fig. 4. Network configuration of the implemented 1-dimensional CNN model in jupyter.

The functionality of the achieved model is assessed in terms of accuracy percentage and precision score. Other evaluation metrics such as F1 score, recall value and support values are also calculated. These comparison metrics are beneficial in evaluating the performance of the model in the multi-class classification of arrhythmia.

3 Results

This section shows the resultant outcomes we have collected by applying the proposed method to detect cardiac arrhythmia. A brief analysis of the results obtained from the 1D CNN model is also given.

3.1 Experimental Setup

We implemented our proposed 1D CNN model using a computer system having an AMD Ryzen 7 5800H processor with a clock speed of 3.20 GHz and 16 Gb of RAM. The python code was executed on Jupyter Notebook software to implement the model and visualize the results. Libraries like pandas, sklearn, matplotlib, seaborn, tensorflow and other advanced python libraries were used in the implementation of the proposed model.

3.2 Results

After successfully training our CNN model using Adam optimizer on the training dataset, we apply it to the test dataset to predict the arrhythmia condition. The prediction result with the accuracy score and other performance metrics is calculated and displayed as the final prediction result in a classification report.

The performance of the proposed 1D CNN classifier is evaluated using performance metrics such as accuracy, precision, recall and F1 score. These metrics are mathematically explained in Eqs. (2)– (5), respectively.

Accuracy and precision score of the model are found from the confusion matrix using the following formulae:

$$Acccuracy = \frac{(TP + TN)}{(\mathrm{TN} + \mathrm{TP} + \mathrm{FN} + \mathrm{FP})} \tag{2}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

$$Recall = \frac{TP}{(TP + FPN)} \tag{4}$$

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{5}$$

where,

- TP indicates the number of cases that are correctly classified as arrhythmia.

- FP indicates the non-arrhythmic cases classified as arrhythmic.
- TN indicates the non-arrhythmic cases classified as non-arrhythmic.
- FN indicates the arrhythmic cases classified as non- arrhythmic.

The prediction result with the accuracy score and other performance metrics is calculated and displayed as the final prediction result in the form of a classification report as shown in Fig. 5.

Our 1D CNN model has given an accuracy score of 96.72% with a F1 score of 85.08% to detect and classify cardiac arrhythmic condition from the test dataset.

	precision	recall	f1-score	support
0	0.99	0.97	0.98	18118
1	0.64	0.83	0.72	556
2	0.92	0.95	0.93	1448
3	0.53	0.84	0.65	162
4	0.96	0.99	0.97	1608
accuracy			0.97	21892
macro avg	0.81	0.91	0.85	21892
weighted avg	0.97	0.97	0.97	21892

```
0.9672483098848894
F1_score =  0.8508205226765082
```

Fig. 5. Classification report of the CNN model that depicts the evaluation of the proposed model in detecting 5 different classes of arrhythmia.

The prediction outputs attained after applying our CNN model are analyzed using accuracy percentage and other evaluation metrics to measure the model's efficiency. Evaluation metrics are utilized to visualize the results using various functional Python modules. The performance of the model is analyzed with respect to five classes of the output using a confusion matrix as shown in Fig. 6.

The output prediction of the different arrhythmic classes is represented using GIF files that indicate the corresponding arrhythmic condition. A GIF file of the heart is shown as output for the inputs corresponding to the heart's regular beats.

The Fig. 8 presents the output GIF shown in case of supraventricular heart beats.

Supraventricular beats include various arrhythmic conditions that affect atrial parts of the heart. Functioning of the atrium is affected resulting in abnormal heartbeats.

Figure 9 depicts the output GIF file that will be shown when the input data corresponds to ventricular arrhythmic condition.

Ventricular beats include cardiac conditions associated with ventricular part of the heart. Functioning of the ventricle is affected resulting in abnormal heartbeats.

Figure 10 shows the output GIF file that will be displayed in the case of input data being a fusion beat.

Fusion beats include the combination of ventricular and normal beats.

The classification results of the proposed model are analyzed by doing a comparative analysis of relevant works that have achieved promising results in the task of arrhythmia classification.

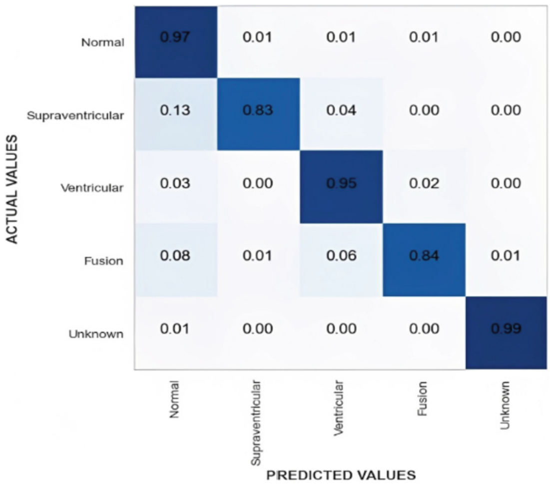

Fig. 6. Proposed model's performance is visualized through a confusion matrix.

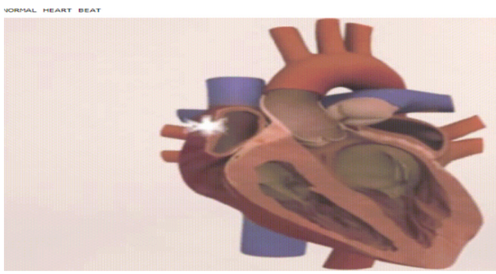

Fig. 7. Representation of normal heart beats.

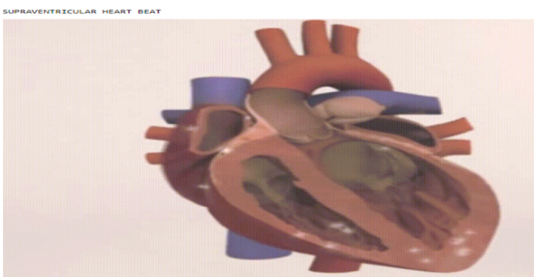

Fig. 8. Representation of supraventricular heart beats.

In terms of accuracy percentage, Table 1 depicts a comparison of similar works with the proposed model.

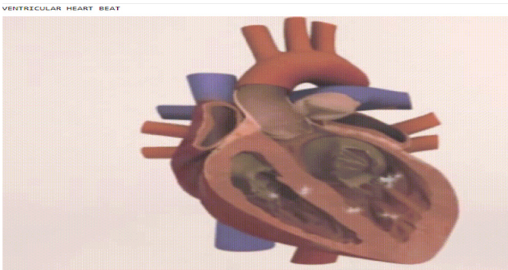

Fig. 9. Representation of ventricular heart beats.

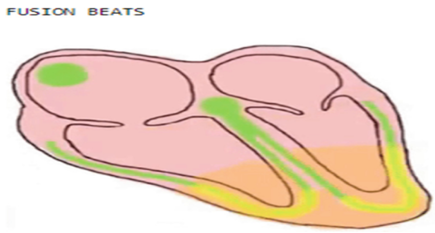

Fig. 10. Representation of fusion beats.

Table 1. Comparison of classification results of relevant works.

Work	Approach	Accuracy (%)
Proposed Work	**1D CNN**	**96.72**
J. Ferretti *et al.* [1]	1D CNN	95
Acharya *et al.* [16]	CNN + Augmentation	93.5
Singh S *et al.* [17]	RNN	87.1
Martis *et al.* [18]	SVM + DWT	93.8

This analysis helps us to compare the performance efficiency of different approaches that have been used in automated classification of cardiac arrhythmia. The output results obtained from the proposed model show better efficiency and accuracy.

4 Conclusion.

In our proposed project work, we are using a 1-dimensional CNN model to analyze a given ECG dataset and automatically detect and classify a given set of heartbeats from ECG data, which can be very beneficial in the precise and early diagnosis of cardiac diseases. Arrhythmic condition detected by the model is further represented as a visual output using GIF files of the heart that help in easy understanding of the corresponding arrhythmic condition. Our model achieved a satisfactory classification with an accuracy of 96.72% and a F1 measure of 85.08%. This paper explores a simple classification method to analyze and categorize ECG data and visualize the arrhythmic output class. In future works, we would like to consider more straightforward and productive techniques to optimize convolution neural networks and obtain improved detection results. And we would also like to implement advanced models like 2D CNN to get more efficient results. We will use deep learning algorithms and learn more about medical data analysis that can help us in our future work.

References

1. Ferretti, J., Randazzo, V., Cirrincione, G., Pasero, E.: 1-D Convolutional Neural Network for ECG Arrhythmia Classification. In: Esposito, A., Faundez-Zanuy, M., Morabito, F.C., Pasero, E. (eds.) Progresses in Artificial Intelligence and Neural Systems. SIST, vol. 184, pp. 269–279. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-5093-5_25
2. Ullah, A., Anwar, S.M., Bilal, M., Mehmood, R.M.: Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sens. **12**(10), 1685 (2020). https://doi.org/10.3390/rs12101685
3. Zhang H., et al.: Cardiac Arrhythmia classification based on 3D recurrence plot analysis and deep learning. Front Physiol. Jul 22;13:956320. doi: https://doi.org/10.3389/fphys.2022.956320. PMID: 35936913; PMCID: PMC9352947,(2022)https://doi.org/10.3389/fphys.2022.956320
4. Merdjanovska, E., Rashkovska, A.: Comprehensive survey of computational ECG analysis: databases, methods and applications. Expert Syst. Appl. **203**, 117206 (2022). https://doi.org/10.1016/j.eswa.2022.117206
5. Dataset: https://www.kaggle.com/datasets/shayanfazeli/heartbeat
6. WHO Cardiovascular diseases "https://www.who.int/newsroom/factsheets/detail/cardiovascular-diseases-(cvds)"
7. Ahmed, A.A., Ali, W., Abdullah, T.A.A., Malebary, S.J.: Classifying cardiac arrhythmia from ECG signal using 1D CNN deep learning model. Mathematics **11**, 562 (2023). https://doi.org/10.3390/math11030562
8. Subramanian, K., Prakash, N.K.: Machine learning based cardiac arrhythmia detection from ECG signal. In: Third International Conference on Smart Systems and Inventive Technology (ICSSIT), (2020)
9. Wang, T., Changhua, L., Sun, Y., Yang, M., Liu, C., Chunsheng, O.: Automatic ECG classification using continuous wavelet transform and convolutional neural network. Entropy **23**(1), 119 (2021). https://doi.org/10.3390/e23010119
10. Coast, D.A., Stern, R.M.M., Cano, G.G., Briller, S.A.: An approach to cardiac arrhythmia analysis using hidden markov models. IEEE Trans. Biomed. Eng. **37**, 826–836 (1990)
11. Mustaqeem, A., Anwar, S.M., Majid, M.: Multiclass classification of cardiac arrhythmia using improved feature selection and SVM invariants. Comput. Math. Methods Med, (2018)
12. Minami, K.I., Nakajima, H., Toyoshima, T.: Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network. IEEE Trans. Biomed. Eng. **46**, 179–185 (1999)
13. Hu, Y.H., Tompkins, W.J., Urrusti, J.L., Afonso, V.X.: Applications of artificial neural networks for ECG signal detection and classification. J. Electrocardiol. **26**, 66–73 (1993)
14. Osowski, S., Hoai, L.T., Markiewicz, T.: Support vector machine based expert system for reliable heartbeat recognition. IEEE Trans. Biomed. Eng. **51**, 582–589 (2004)
15. Willems, J.L., Lesaffre, E.: Comparison of multigroup logistic and linear discriminant ECG and VCG classification. J. Electrocardiol. **20**, 83–92 (1987)

16. Acharya, U.R., et al.: A deep convolutional neural network model to classify heartbeats. Comput. Biol. Med. **89**, 389–396 (2017)
17. Singh, S., Pandey, S.K., Pawar, U., Janghel, R.R.: Classification of ECG arrhythmia using recurrent neural networks. Procedia Comput. Sci. **132**, 1290–1297 (2018)
18. martis, R., et al.: Application of higher order cumulant features for cardiac health diagnosis using ECG signals. Int. J. Neural Syst. **23**(04), 1350014 (2013). https://doi.org/10.1142/S0129065713500147
19. M. Kachuee, S. Fazeli and M. Sarrafzadeh,: ECG heartbeat classification: a deep transferable representation, In: IEEE International Conference on Healthcare Informatics (ICHI), New York, NY, USA, pp. 443–444, doi: https://doi.org/10.1109/ICHI.2018.00092, (2018)
20. Strodthoff, N., Wagner, P., Schaeffter, T., Samek, W.: Deep learning for ECG analysis: benchmarks and insights from PTB-XL. IEEE J. Biomed. Health Inform. **25**(5), 1519–1528 (2021). https://doi.org/10.1109/JBHI.2020.3022989
21. Essa, E., Xie, X.: An ensemble of deep learning-based multi-model for ECG heartbeats arrhythmia classification. IEEE Access **9**, 103452–103464 (2021)
22. De Santana, J. R. G. Costa, M. G. F. Costa Filho. C. F. F.: A new approach to classify cardiac arrythmias using 2D convolutional neural networks. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), (2021)
23. Chourasia, M., Thakur, A., Gupta, S., Singh, A.: ECG heartbeat classification using CNN In: IEEE 7th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), (2020)
24. Liu, Fan, et al.: Arrhythmias classification by integrating stacked bidirectional LSTM and two-dimensional CNN. Advances in Knowledge Discovery and Data Mining: 23rd Pacific-Asia Conference, PAKDD 2019, Macau, China, April 14–17, 2019, Proceedings, Part II 23. Springer International Publishing, (2019)