Classification of Congestive Heart Failure Disease, Arrhythmias, And Normal Heart Rhythms Using Deep Learning

Nafiseh Batavani
Electrical Engineering Department
Najafabad Branch, Islamic Azad University
Najafabad, Iran
nafisehbatavani@gmail.com

* Mohammad Reza Yousefi
Electrical Engineering Department
Najafabad Branch, Islamic Azad University
Najafabad, Iran
mr-yousefi@iaun.ac.ir

2024 11th International Symposium on Telecommunications (IST) | 979-8-3503-5625-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/IST64061.2024.10843440

Abstract*—Cardiovascular diseases, regardless of their causes, are considered one of the most important causes of death worldwide. For this reason, the issue of time is critical in diagnosing cardiovascular diseases. If a heart disease is diagnosed in a patient by a doctor promptly and then the prescribed solution for treating the disease is properly implemented, not only will it prevent the end of life, but it will also greatly improve Quality of life for people who are facing this issue heart diseases. Given the limitations and challenges in diagnosing cardiac diseases from normal sinus rhythms, the presentation of automated machine learning methods is essential. This article aims to present an efficient method for classifying congestive heart failure disease, arrhythmias, and normal heart rhythms using a combined network of convolutional neural networks and gated recurrent unit networks (CNN+GRU). For this purpose, in the first stage, a dataset consisting of electrocardiogram (ECG) signals in three groups of normal sinus rhythm, congestive heart failure, and cardiac arrhythmias was extracted from the Physio-Net database, and preprocessing and noise removal of the signals was performed. In the second stage, continuous wavelet transform has been used to convert ECG signals into two-dimensional matrices. In the third stage, classification was performed using a combined model of convolutional neural networks and gated recurrent unit networks. Finally, the results obtained from two methods, Convolutional Neural Networks (CNN) and a combined approach of Convolutional Neural Networks and Gated Recurrent Unit (CNN+GRU), have been compared. The results have shown improvement, reduction of errors, and a significant increase in the accuracy of the proposed method in classifying congestive heart failure from other arrhythmias and normal heart rhythms.

Keywords— Deep learning, Convolutional neural network, Congestive heart failure, Cardiac arrhythmia, ECG signal.

I. INTRODUCTION

The heart is one of the vital and always active organs of the human body, whose life depends on its regular and continuous beat. Sometimes, due to various reasons, the heart is unable to perform its regular activities correctly. In these conditions, one of the cardiovascular diseases has occurred. According to the World Health Organization, these diseases are responsible for 31% of deaths worldwide. Arrhythmias are very common in this regard. Arrhythmias are abnormal heartbeats that lead to a significant decrease or increase in heart rate and ineffective pumping. Congestive heart failure (CHF) is a clinical syndrome in which, due to a disturbance in the structure and function of the heart, the heart cannot pump enough blood to meet the metabolic needs of the tissues. Heart failure impairs blood pumping, causing blood to back up and accumulate fluid in the lungs. Fluid accumulation in the lungs leads to shortness of breath and increased heart rate in the patient and can eventually impair vital organs such as the liver or kidneys over time. Since cardiac problems often affect the heart's electrical activity, cardiac patients can be monitored using cardiac signals. ECG is a painless and non-invasive procedure that records the electrical activity of the heart, leading to the rescue of many patients from death. For obtaining an electrocardiogram, Sensors are attached to the skin at specific points. The function of these sensors is to record the electrical signals generated by the heart. In the ECG signal, the normal heart rhythm in which there is no disturbance in the ECG signal is called normal sinus rhythm (NSR). Any disturbance in rhythm or changes in the pattern of morphology is an indication of irregularity that can be identified by analyzing the ECG. Generally, the accurate diagnosis and identification of cardiac arrhythmias from congestive heart failure and distinguishing them from normal sinus rhythms is a challenging, tiring, and experience-dependent process for physicians. Therefore, providing automated methods for identifying individuals at risk can be very helpful in reducing the complications of the disease[1], [2].

Deep learning, which is a part of machine learning, has made significant progress in the field of identifying and diagnosing various diseases in the last decade. One of the most widely used subfields of deep learning is convolutional neural networks. A convolutional neural network is a type of neural network with multiple layers that processes data through a network structure, extracts their important features, and then extracts their important features. Many deep networks, such as convolutional neural networks (CNNs), are classified as feedforward networks. In these networks, the signal moves in only one direction from the input layer to the hidden layers and then to the output layer, and the previous information is not stored in the memory[3], [4], [5], [6].

In [7], A classification method for arrhythmia based on the combination of convolutional neural networks (CNN) and long-term short-term memory (LSTM) is developed, which is designed to recognize eight types of ECG signals, including normal sinus rhythm. The advantage of this method is that it does not require feature extraction or noise removal from the ECG signal. Experimental results show that this method has a high performance in classification and in terms of accuracy, specificity and sensitivity, it has worked with percentages of 99.01, 99.57 and 97.67, respectively.

In [8], a deep learning approach has been proposed that combines Convolutional Neural Networks (CNN) and Long

Short-Term Memory networks (LSTM) for automatic identification of six types of ECG signals. Classification of natural sections (N) sinus rhythm, atrial fibrillation (AFIB), ventricular dyssynchrony (B), heartbeat rhythm (P), atrial flutter (AFL), and sinus bradycardia (SBR) ECG signals were performed with an accuracy of 99.32% and 97.15% for two databases.

In [9], an intelligent learning approach based on the Hidden Markov Model (HMM) with feature extraction from ECG signals has been proposed for arrhythmia analysis. HMM classification was able to classify the samples into five types of arrhythmia with 99.8% accuracy.

In [10], LSTM model is used to classify ECG signals. At first, the RR interval sequence was calculated from the ECG signals. Feature vectors were extracted from RR interval sequences by Fourier-Bessel expansion and then these vectors were classified using LSTM model. Finally, an accuracy of 90.07% was obtained in cross-validation.

In [11], The focus is on predicting the probability of a heart disease through a combination of advanced datasets available in the UCI repository and the use of Convolutional Neural Networks (CNN). The proposed model has achieved an overall accuracy of 97%. In [12], seven different neural network models have been used. These models belong to three main types of neural networks: simple neural networks, convolutional neural networks, and recurrent neural networks. In [13], In this method, diagonal wavelet transform and convolutional neural network have been used to classify ECG signals. An average sensitivity of 99.2% has been achieved. In [14], A deep learning-based classification system for arrhythmia detection is presented, which works by converting 1D ECG time series data into multidimensional representations in 2D images.

In [15], An approach for classifying ECG signals using machine learning and based on different characteristics of these signals is presented. Machine learning libraries and decision tree algorithms, random forests and gradient boosting trees (GBT) have been used for this classification. The results show that the GBD tree algorithm has achieved an overall accuracy of 96.75%, random forest has achieved an accuracy of 98.97%, and multi-class classification has achieved an accuracy of 98.03%.

In [16], a model for detecting heart arrhythmias has been proposed using three different machine learning methods. In [17], Transfer learning has been used in the definition and classification of four ECG patterns.In [18], the Support Vector Machine (SVM) algorithm has been proposed for classifying subgroups of arrhythmias. For multiclass classification using support vector machine, methods such as one-against-one (OAO), one-against-all (OAA) and error correcting code (ECC) were used to identify the presence or absence of arithmetic-based approaches. The performance of the classifiers was evaluated by accuracy, kappa statistic and root mean square error. The accuracy obtained was 92.07%.

In [19], An automatic system based on Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) has been introduced, which is designed to detect normal sinus rhythm, left bundle branch block (LBBB) and right bundle branch block (RBBB). The classification accuracy of this system, its sensitivity and its characteristics were equal to 98.10, 97.50 and 98.70% respectively. In [20], the CNN-LSTM method has been used for detecting normal and abnormal ECG (cardiac arrhythmia).

In [21], deep learning classification was developed using the Holdout method and 28 input features based on clinical data from patients at the Cleveland Clinic were trained and tested. Based on the results of the experiment, developed deep learning models. With an accuracy of 83.67 percent for diagnosing heart disease, the probability of misclassification error is 33.16 percent, and a sensitivity of 93.51 percent was achieved.

In [22], A method based on deep learning is presented for ECG classification of patients and automatic detection of arrhythmias. In this method, Alexnet is exploited as a feature extractor.

In [23], MLP (Multilayer Perceptron) and SVM (Support Vector Machine) techniques have been used to classify P, Q, R, S and T waves in ECG signals using machine learning techniques. In this study, BP (Back Propagation) algorithm with MLP classifier and K-A (Nuclear Adatron) algorithm with SVM classifier are used. Also, wavelet transform techniques such as DWT, discrete cosine transform (DCT) and continuous wavelet transform (CWT) have been used to improve classification accuracy.

In the following article, in the first section, data retrieval and data preprocessing are explained, and in the second section, wavelet transformation is described. In the third section, CNN+GRU classification is explained, and in the final section, the results are evaluated.

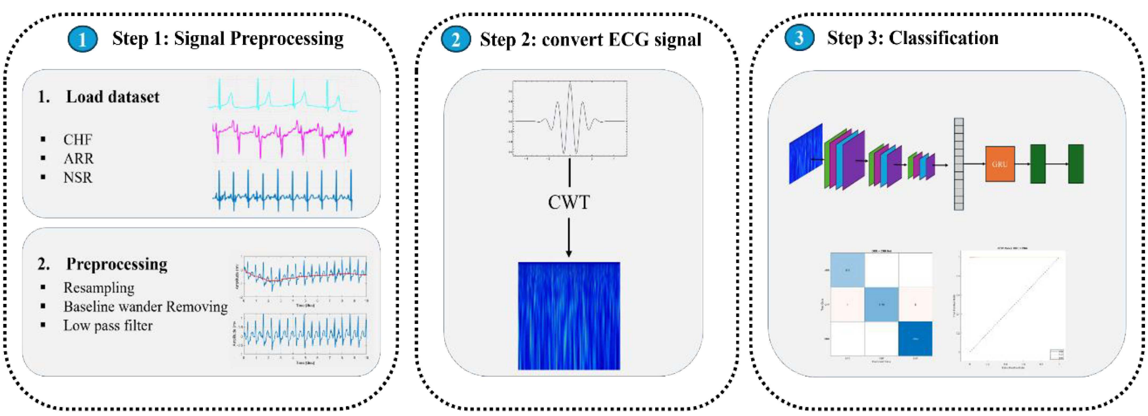

Fig. 1. Proposed Method Diagram

II. Proposed method based on a hybrid network CNN+GRU

The aim of this paper is to present a fully automated system to improve the diagnosis and classification of congestive heart failure from other arrhythmias and normal sinus rhythms. For this purpose, a convolutional neural network (CNN) along with a scalogram-based Gated Recurrent Unit (GRU) network has been used. The diagram of the proposed method in this paper is shown in Figure 1.

The proposed method shown in Figure 1 includes three steps. The first stage is dedicated to data collection and preprocessing. In this step, two low-pass and intermediate filters are used to remove unwanted noise from the raw ECG data and preserve all the important features of the ECG signal. The second stage is ECG signal transformation, which utilizes continuous wavelet transform (CWT) for this purpose. In the third stage, classification was performed using CNN+GRU.

A. *First step: Calling data and preprocessing*

To evaluate the effectiveness and performance of the proposed method, 162 ECG signal recordings related to cases with arrhythmia (ARR), congestive heart failure (CHF) and normal sinus rhythm (NSR) from three open access databases on the PhysioNet portal, including MIT-BIH ARR, BIDMC and MIT-BIH NSR, were used. Among 162 ECG recordings, 96 recordings belong to the ARR group, 30 recordings belong to the CHF group, and 36 recordings belong to the NSR group. All ECG recordings were measured from lead II and VI and analyzed and labeled by cardiologists. Figure 2 displays three samples of the original ECG recordings available in the database, each with a duration of 10 seconds, in three classes: ARR, CHF, and NSR.

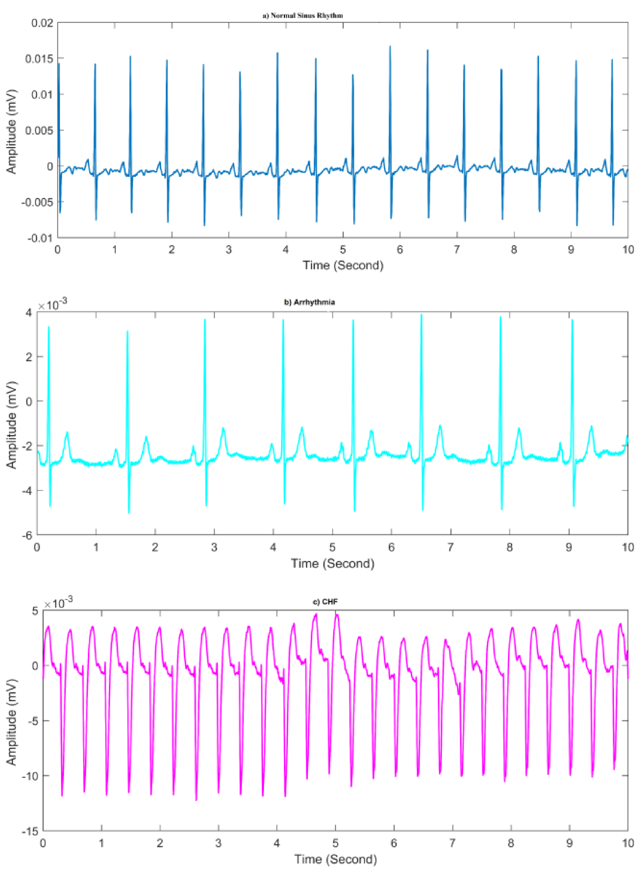

Fig. 2. Three samples of ECG recordings in three classes: a) NSR, b) ARR, c) CHF

Due to the difference of sampling frequency in three different categories, all signals were re-sampled at a rate of 128 Hz. ECG signals are usually affected by noise and various artifacts, which can reduce the accuracy of diagnosis. Therefore, in this study, two low-pass filters and one median filter are used to remove unwanted artifacts from raw ECG signals and preserve all its essential features. Because the valuable information of the ECG signal lies in low frequencies, a low-pass filter with a cut-off frequency of 53 Hz and order 2 was used to remove high-frequency noises. In addition, two median filters were applied to remove baseline instability. After removing the noise, all the signals were divided into 120 second pieces (15360 samples). Figure 3 shows the results of applying low-pass and median filters.

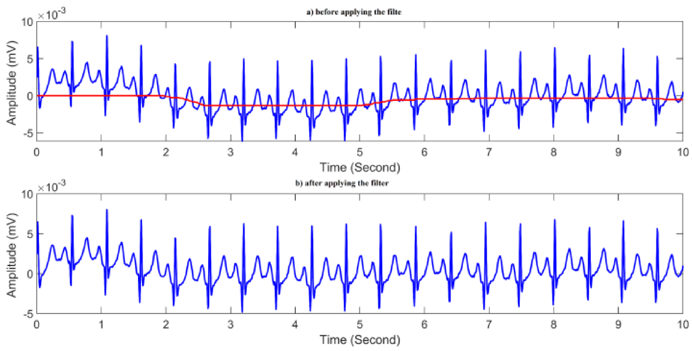

Fig. 3. Results of applying low-pass and median filters, a) before applying the filter, b) after applying the filter

B. *Second stage: ECG signal conversion*

With the advancement of signal processing and machine learning methods, several automated systems have been developed to detect cardiac diseases. Recently, deep learning has become one of the important subfields of machine learning in signal processing studies, especially in ECG analysis. The deep learning architecture is designed to automatically learn and select distinct features and then optimize the model weights and gradients using a backpropagation algorithm. One of the most effective architectures in signal processing applications is the Convolutional Neural Network (CNN). To use 2D-CNN, an image representation of a time series must be

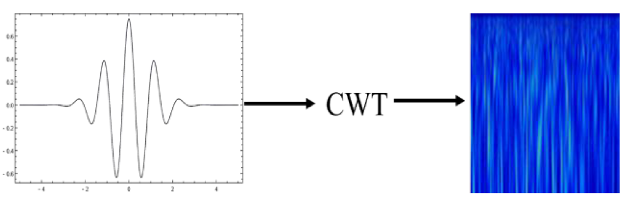

Fig. 4. Applying CWT and the Morse wavelet

generated. Various methods can be used to convert signals to images, such as spectrograms and scalograms. These methods focus on the spectral and frequency information of the signals. Therefore, the temporal information of signals and their analysis in different diagnoses is of great importance. In this thesis, Continuous Wavelet Transform (CWT) with the Morse wavelet has been used to transform ECG signals into two-dimensional matrices. The Morse wavelet figure is shown in Figure 4.

C. Stage 3: Classification using CNN-GRU

In this stage, a CNN+GRU network is used for classification. Initially, the data is divided into training, The

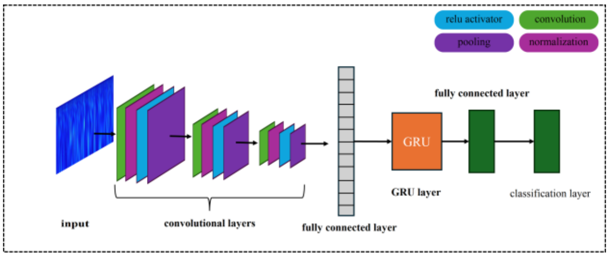

Fig. 5. Network Structure CNN+GRU

datasets for training, validation, and testing are allocated with ratios of 80, 10, and 10 percent, respectively. After dividing the data, the training process is performed on the training data and the performance of the model is measured using the test data. The structure of CNN+GRU network is depicted in Figure 5.

III. Simulation Results

As mentioned in the previous section, this article uses the combined CNN+GRU network method for classifying congestive heart failure (CHF) from other arrhythmias (ARR) and normal heart rhythms (NSR). After training the CNN-GRU model, the evaluation of this model is performed using test data. The average classification results for the three classes are shown in Table 1.

TABLE I. Classification Results

Performance metric	value
Accuracy	96.89
Error	3.11
Sensitivity	94.42
Specificity	98.77
Precision	84.32
f-score	87.96
kappa	92.99

According to Table 1, we can see that the accuracy of the proposed method is 96.89%, with an error of 3.11%. The sensitivity of this method is equal to 94.42% and its specificity is 98.77%.

The classification results for three different classes, CHF, ARR, and NSR, are shown in Table 2.

TABLE II. Classification results for three different classes of CHF, ARR, and NSR

Performance metric	CHF	ARR	NSR
Accuracy	97.07	97.47	98.23
Error	2.93	1.53	1.77
Sensitivity	88.89	97.32	97.05
Specificity	97.36	99.31	99.64
Precision	97.23	99.03	99.69
f-score	97.96	98.17	98.35

According to Table 2, the CHF class had the lowest accuracy and the ARR class had the highest accuracy. The error of the CHF class is greater than that of the ARR class.

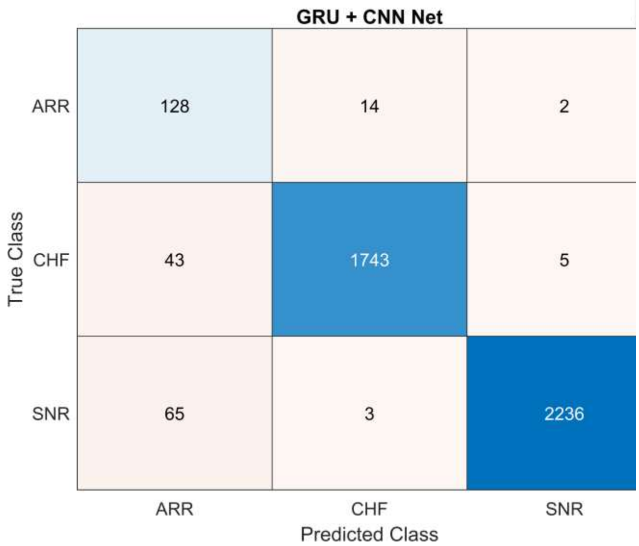

Fig. 6. Confusion matrix for test data

Therefore, the CHF class performs better than the other

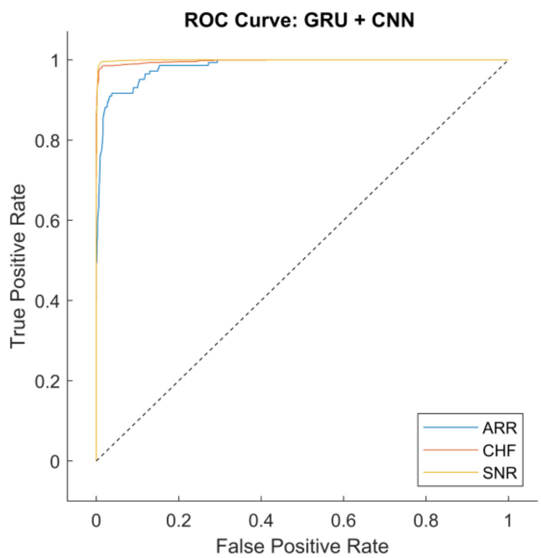

Fig.7. Curve ROC

classes. The confusion matrix for the test data in the CNN-GRU model is shown in Figure 6. Based on this figure, the confusion matrix shows low error rates and most of the data has been correctly classified.

The ROC curve obtained for the test data is shown in Figure 7. The ROC curve is obtained by plotting the sensitivity against 1-specificity. This curve has a main diameter, and the greater the distance of the ROC curve from the diameter or the larger the area under the curve, the better the performance of the model. On the contrary, if the curve is closer to the diameter or the area under the curve is smaller, it indicates a weaker performance of the model.

IV. Conclusion

In this article, a classification method for congestive heart failure disease is presented compared to other arrhythmias and normal heart rhythms. The combined CNN-GRU network method has been used. The advantage of using the GRU network is the presence of two update and reset gates. The table below compares the accuracy parameters of several references with the proposed method in this article.

TABLE III. Comparison of results with other studies

Reference	Year of publication	Accuracy
[4]	2020	90.07
[15]	2018	83.68
Proposed method	2024	96.89

Based on table 3, the proposed method's accuracy for classifying congestive heart failure disease has improved compared to previous studies in distinguishing it from other arrhythmias and normal heart rhythms.

References

[1] M. R. Yousefi, M. Khezri, R. Bagheri, and R. Jafari, "Automatic Detection of Premature Ventricular Contraction Based on Photoplethysmography Using Chaotic Features and High Order Statistics," *2018 IEEE Int. Symp. Med. Meas. Appl. Proc.*, Aug. 2018, doi: 10.1109/MEMEA.2018.8438697.

[2] K. D. habib abadi and M. Yousefi, "Improving the speed and accuracy of arrhythmia classification based on morphological features of ECG signal," *Majlesi J. Telecommun. Devices vol.*, vol. 36, no. 4, p. 0, Dec. 2020.

[3] M. R. Yousefi, A. Dehghani, and H. Taghaavifar, "Enhancing the accuracy of electroencephalogram-based emotion recognition through Long Short-Term Memory recurrent deep neural networks," *Front. Hum. Neurosci.*, vol. 17, p. 1174104, Oct. 2023, doi:10.3389/FNHUM.2023.1174104/BIBTEX.

[4] M. Seif, M. R. Yousefi, and N. Behzadfar, "EEG Spectral Power Analysis: A Comparison Between Heroin Dependent and Control Groups," *Clin. EEG Neurosci.*, vol. 53, no. 4, pp. 307–315, Jul. 2022, doi: 10.1177/15500594221089366.

[5] S. N. Monfared and MR Yousefi -, "Improving the Accuracy of Early Detection of Parkinson's Disease Using Brain Signals Based on Feature Selection in Machine Learning," Computational Intelligence in Electrical Engineering, in press, 2024, doi: 10.22108/ISEE.2024.139761.1665.

[6] M. R. Yousefi, A. Dehghani, S. Golnejad, and M. M. Hosseini, "Comparing EEG-Based Epilepsy Diagnosis Using Neural Networks and Wavelet Transform," *Appl. Sci. 2023,* vol. 13, no. 18, p. 10412, Sep. 2023, doi: 10.3390/APP131810412.

[7] Z. Zheng, Z. Chen, F. Hu, J. Zhu, Q. Tang, and Y. Liang, "An automatic diagnosis of arrhythmias using a combination of CNN and LSTM technology," *electronics*, 2020.

[8] C. Chen, Z. Hua, R. Zhang, G. Liu, and W. Wen, "Automated arrhythmia classification based on a combination network of CNN and LSTM," *Biomed. Signal Process. Control*, Mar. 2020, doi: 10.1016/j.bspc.2019.101819.

[9] A. K. Sangaiah, M. Arumugam, and G. Bin Bian, "An intelligent learning approach for improving ECG signal classification and arrhythmia analysis," *Artif. Intell. Med. Elsevier*, Mar. 2020, doi: 10.1016/J.ARTMED.2019.101788.

[10] A. Sharma, N. Garg, S. Patidar, R. San Tan, and U. R. Acharya, "Automated pre-screening of arrhythmia using hybrid combination of Fourier–Bessel expansion and LSTM," *Comput. Biol. Med. Elsevier*, May 2020, doi: 10.1016/J.COMPBIOMED.2020.103753.

[11] A. Mehmood *et al.*, "Prediction of Heart Disease Using Deep Convolutional Neural Networks," *Arab. J. Sci. Eng.*, Apr. 2021, doi: 10.1007/S13369-020-05105-1/METRICS.

[12] K. Çelebiler, "heart disease diagnosis using neural networks on electrocardiogram datasets," 2021, doi: 10.13140/RG.2.2.27247.15521.

[13] A. Pomprapa, W. Ahmed, A. Stollenwerk, S. Kowalewski, and S. Leonhardt, "Deep learning of arrhythmia analysis based on convolutional neural network," *Int. J. Bioelectromagn.*, 2019.

[14] A. Çınar and S. A. Tuncer, "Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks," *Comput. Methods Biomech. Biomed. Engin.*, 2021, doi: 10.1080/10255842.2020.1821192.

[15] F. I. Alarsan and M. Younes, "Analysis and classification of heart diseases using heartbeat features and machine learning algorithms," *J. Big Data*, Dec. 2019, doi: 10.1186/S40537-019-0244-X.

[16] N. Singh and P. Singh, "Cardiac arrhythmia classification using machine learning techniques," *Lect. Notes Electr. Eng.*, 2019, doi: 10.1007/978-981-13-1642-5_42.

[17] M. S. S. T. J. Yuan, "ECG arrhythmia classification using transfer learning from 2-dimensional deep CNN features," *IEEE Biomed. Circuits Syst.*, 2018.

[18] A. Mustaqeem, S. M. Anwar, and M. Majid, "Multiclass Classification of Cardiac Arrhythmia Using Improved Feature Selection and SVM Invariants," *Comput. Math. Methods Med.*, 2018, doi: 10.1155/2018/7310496.

[19] S. L. O. A, E. Y. K. N. B, R. S. T. C, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats," *Comput. Biol. Med.*, vol. 102, pp. 278–287, 2018, doi: 10.1016/j.compbiomed.2018.06.002.

[20] G. Swapna, K. Soman, and R. Vinayakumar, "Automated detection of cardiac arrhythmia using deep learning techniques," *Procedia Comput. Sci. Elsevier*, 2018.

[21] J. H. Miao, Kathleen H; Miao, "Coronary heart disease diagnosis using deep neural networks," *Int. J. Adv. Comput. Sci. Appl.*, 2018.

[22] A. Isin, S. O.-P. computer Science, and U. 2017, "Cardiac arrhythmia detection using deep learning," *Procedia Comput. Sci. Elsevier*, 2017.

[23] H. Bulbul, N. Usta, and M. Yildiz, "Classification of ECG arrhythmia with machine learning techniques," *2017 16th IEEE Int. Conf. Mach. Learn. Appl.*, 2017.