

Detection of Healthy and Unhealthy ECG Signal Using Optimized Convolutional Neural Network

Mohammad Hosein Fatehi ¹, Mehdi KHajooee², Nahid Adlband ², Mohammad Mahdi Moradi ²

¹Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran

²Department of Biomedical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran

Email: MH.Fatehi@iau.ac.ir (Corresponding author), mehdi.kh856@yahoo.com, nahid_adlband@yahoo.com, moradi.m.mahdi@gmail.com

Receive Date: 10 September 2022, Revise Date: 6 October 2022, Accept Date:20 November 2022

Abstract

According to the information of the World Health Organization, today heart diseases are considered the most important threat to humans and are the first cause of death in the world. According to the latest global statistics, 46% of deaths are related to the heart. According to reports and research, a large number of causes of death are caused by heart diseases, while 25% of cases are reversible. Correct and timely diagnosis of patients with acute heart problems can largely prevent sudden death and further problems. Due to the fact that recording an electrocardiogram is inexpensive and fruitful, the use of an electrocardiogram can help a lot in many heart diseases and other diseases. Deep learning is one of the new methods with high accuracy in diagnosis and classification, which is based on the convolutional neural network. Convolutional neural networks have a very high processing and training time, which can be optimized and reduced in order to reduce the time, so that acceptable results can be obtained with high accuracy. In this article, using the optimized convolutional neural network, the healthy and unhealthy signal was obtained with 99.9% accuracy and 99.7% sensitivity with 10-fold cross-validation. According to the obtained results, it can be said that the proposed method has the ability to separate healthy and unhealthy signals with acceptable accuracy.

Keywords: ECG signal, deep learning, heart diseases, optimized convolutional neural network.

1. Introduction

Heart-related diseases are one of the most important diseases that threaten human life. According to the World Health Organization (WHO), deaths from cardiovascular diseases are the first cause of death. Nearly 20 million people with cardiovascular diseases, which is about 31% of other cases. More than 75% of these deaths occurred in developing countries. In addition, the prevalence and mortality of cardiovascular diseases are always growing [1]. Therefore, regular monitoring of the heart has become increasingly important and necessary for the investigation and

prevention of cardiovascular diseases. Arrhythmia is an important group of diseases in cardiovascular disease. Arrhythmias can occur alone or with other cardiovascular diseases. Arrhythmia diagnosis mainly depends on electrocardiogram.

ECG (electrocardiogram) is an important modern medical tool that records the process of excitability, conduction and recovery of the heart. Automatic detection of irregular heart rhythm from ECG signals is an important task for automatic diagnosis of cardiovascular disease.

2. Related works

Traditionally, the classification of

electrocardiogram signals usually needs to be divided into two stages, for example, feature extraction and pattern classification, studies on the focus of diagnosis in the problem of heart rate determination in electrocardiogram data, and some technologies It has been applied in heart rate detection, including threshold-based methods [2], digital filter-based methods [3] and wavelet transform. Used the QRS complex extraction technique to classify and distinguish between normal heart rate and abnormal heart rate.

Classification of the detected electrocardiogram signal pattern is another step. Wavelet transform is one of the common methods to obtain the characteristics of electrocardiogram signals. Li used the wavelet transform decomposition (WPD) technique to obtain representational features for detecting different types of heartbeats and calculated the entropy from the WPD-decomposed coefficients. It has also used other features such as wavelet and entropy and wavelet entropy and variance, etc. has also separated [4].

In the research, the results of the classifier were calculated with two FCM methods, the fuzzy method and the SVM method, and the SVM method had better results than the fuzzy method [5,17]

Recently, deep learning methods based on deep neural network have had good results in separation and processing. For this reason, much attention has been paid to ECG classification studies based on deep learning. Many researchers have made great efforts to diagnose heart diseases based on deep learning. Salom et al proposed a new and practical solution for cardiac signal based authentication using recurrent neural

networks (RNN) [6].

Zhang et al presented an electrocardiogram classification algorithm for specific patients based on neural networks (RNN) using cardiac signal and heart rate correlation and obtained favorable results [7]. Based on the proposed one-dimensional convolutional neural network, which can be used exclusively for the electrocardiogram signal. Lee et al proposed a method based on convolutional neural network to detect 5 types of arrhythmia [9]. In this research, arrhythmias were separated using convolutional neural network with 4096 deep features obtained without manual intervention.

June et al proposed a new and efficient electrocardiogram arrhythmia classification method using two-dimensional convolutional neural network. In general, it showed outstanding performance in the field of pattern recognition. In this research, convolutional neural network has been used to achieve the goal of detecting arrhythmias, and the obtained results have an acceptable accuracy of 97.84%[10].

The studies mentioned above show that the convolutional neural network can automatically classify and identify diseases and images. But deep learning methods have high processing time, which are not suitable for real time processing. Here, to overcome this task, the optimized convolutional neural network has been used to reduce the calculation load for the diagnosis of existing diseases.

3. Materials and methods

Database

In this research, tagged electrocardiography signals from the Arrhythmia-BIH-MIT database have been used. This database contains 48 two-channel ECG recordings

obtained from 47 study cases in BIH Arrhythmia Laboratory between 1975 and 1979. The recordings were recorded with a frequency of 360 samples per second and with an accuracy of eleven bits in the range of ten millivolts. Each record has been marked by two or more heart specialists independently and differences in opinions have been resolved in the best way. This database is considered one of the most reliable sources for analyzing heart diseases in the world.

Here, two groups of signals, including normal signal and abnormal signal (with arrhythmia) are used.

Signal processing

To use the convolutional neural network, the input of the network must be images, for this purpose, the two-dimensional image of the signal based on the spectrogram is used in this article.

Time-frequency image of signal based on spectrogram

Vital signals are non-static, and uniformity and stability in them means non-existence, and for this reason, analyzing and analyzing them with other common methods cannot extract important features from the signal and achieve good results. Investigating and studying such signals in the time domain or in the frequency domain alone is useless and does not give good results and is not enough. In the simultaneous analysis and investigation of time-frequency, useful information can be obtained from the behavior of the signal, which is very useful and important.[15]

To construct the time-frequency image of the proposed signal, the ECG signals in the time domain are first converted into a two-dimensional time-frequency spectrum using the short-time Fourier transform

(STFT).

STFT is an advanced mathematical equation derived from Discrete Fourier Transform (DFT), to discover the frequency and instantaneous amplitude of waves, whose similarity equation is shown in formula 1 [11].

Its energy is assumed to be the spectrogram of the signal mentioned in equation number 2.

$$\text{STFT} = \sum_{m=-\infty}^{\infty} \omega(m)X(n+m) e^{\frac{-j2\pi}{Nmk}}$$

The STFT energy form is called a spectrogram. Define as below:

$$\text{SPEC}(t,\omega) = |\text{STFT}(t,\omega)|^2$$

The results obtained using STFT can obtain information about the temporal evolution of the signal frequency change, because the complete time interval is divided into a number of small time intervals and then they are analyzed alone using the Fourier transform [16].

Optimized convolutional neural network

Convolution neural networks are similar to artificial neural networks to a great extent. These types of networks consist of neurons with a large number and with learnable weights and biases.

Convolutional neural networks have different architectures that have been used in different researches, and AlexNet is the most common architecture that has been used. In this article, the optimized architecture based on AlexNet is used. In this architecture, the convolutional neural network layers have been merged together and the layers have been reduced from 25 to 8 layers.

At the end of the architecture, the classifier is placed. Figure 1 shows the structure of the optimized convolutional neural network based on AlexNet.

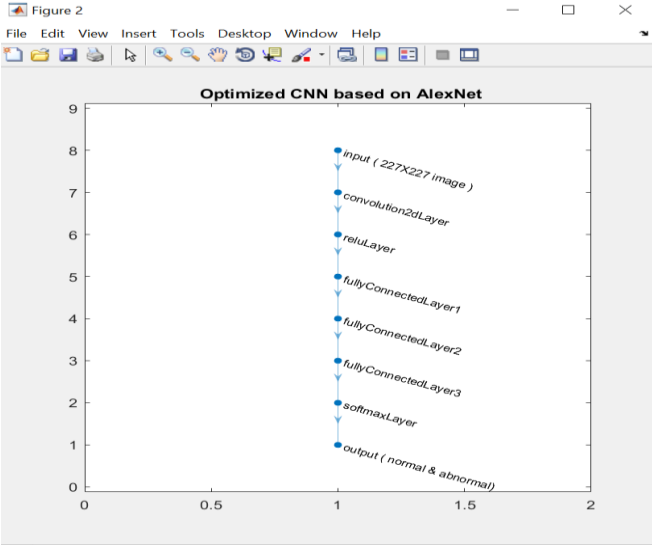


Fig.1. The structure of optimized convolutional neural network based on AlexNet

Figure 2 shows the flowchart of the proposed method

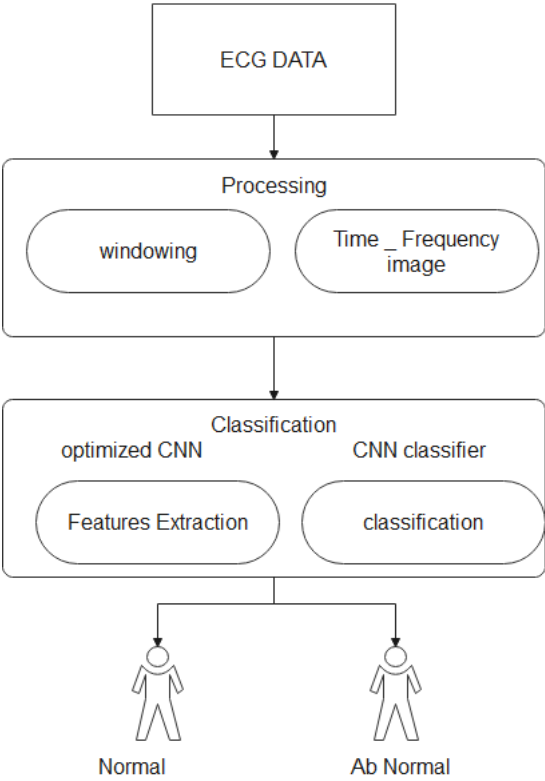


Fig.2. The flowchart of the proposed method

4. Results

The data were downloaded and studied from the Phizionet site according to the research needs. 4000 ECG signal samples in

two groups, healthy and with arrhythmia, have been used in this research. In Figure 3, you can see an example of a healthy signal.

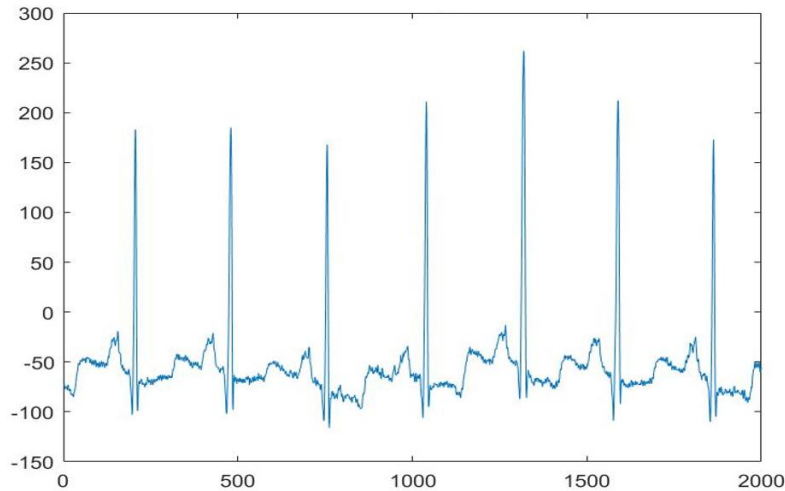


Fig. 3. Example of a healthy heart signal

In Figure 4, you can see an example of a signal with arrhythmia.

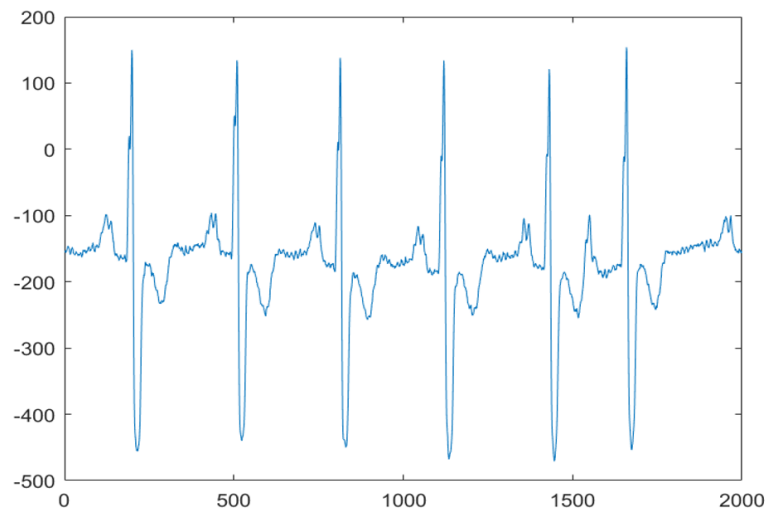


Fig.4. Example of heart signal with arrhythmia

5. Signal spectrogram

A spectrogram is a representation of the frequency spectrum of a signal over time. A spectrogram is a color map that is displayed in terms of time and frequency and helps to understand how the frequency spectrum of

a signal changes over time. In the analysis of vital signals, spectrograms are used a lot. In Figure 5, you can see the time-frequency image of a normal signal, and in Figure 6, you can see an arrhythmic signal using a spectrogram.

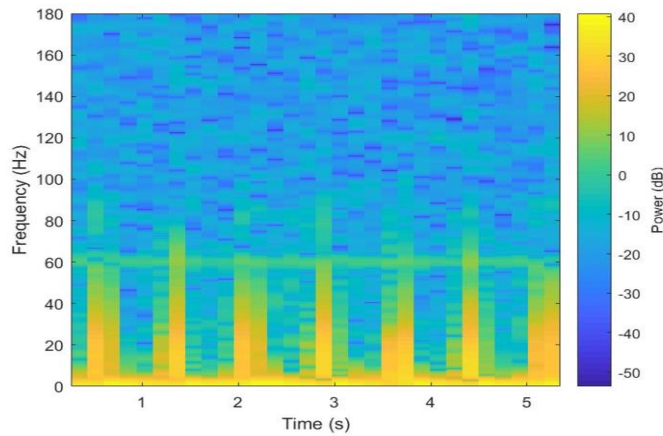


Fig.5: Spectrogram of healthy heart signal

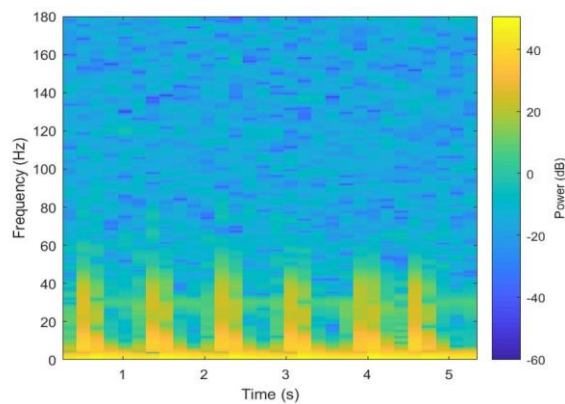


Fig. 6. Spectrogram of cardiac signal with arrhythmia

As mentioned before, in this research, the images were entered into the optimized convolutional neural network and then the two groups were separated.

Here, the results have been calculated

using the confusion matrix according to Table 1 and the accuracy, precision and sensitivity of the classifier using equations 3, 4 and 5, also with 10-fold validation.

Table 1 confusion matrix

		prodect	
		normal	Ab normal
target	Ab normal	TP	FP
	Ab normal	FN	FP

The method of calculating accuracy, sensitivity and precision of each class is calculated using the following equations.

$$\text{accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{FN} + \text{TP}}$$

$$\text{precision} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

In Tables 2, 3, and 4, you can see the accuracy, precision, and average sensitivity results of the classifier

Table 2. Average accuracy results of the classifier

average accuracy	classifier
99.5	Alexnet convolutional neural network
99.9	Optimized convolutional neural network

Table 3. Average precision results of the classifier

avrage precision	classifier
99.6	Alexnet convolutional neural network
99.7	Optimized convolutional neural network

Table 4. Average sensitivity results of the classifier

average sensitivity	classifier
99.4	Alexnet convolutional neural network
99.7	Optimized convolutional neural network

In Figure 7, you can see the confusion matrix for one of the 10 modes.

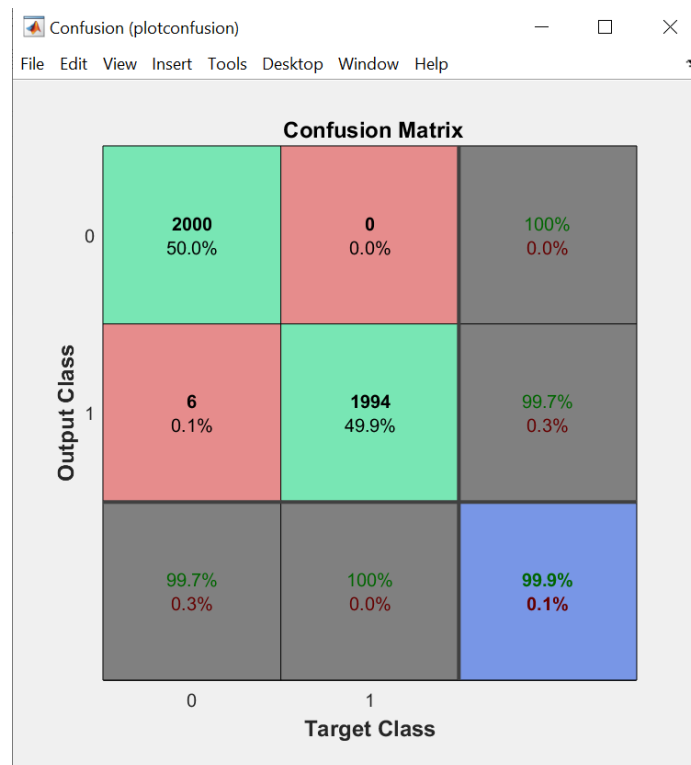


Fig.7. Confusion matrix

Discussion

In this thesis, healthy signals with arrhythmias were downloaded from the Physionet site, which has arrhythmias with a valid label made by a specialist doctor. Then, the single-channel signal was converted into an image to enter the convolutional neural network. This work is done on the basis of spectrogram.

To reduce the calculation load, an

optimized convolutional neural network based on Alexnet architecture was used, and the layers were reduced from 25 layers to 8 layers.

Then the results were calculated based on the confusion matrix with 10-fold cross-validation. The results are compared with other similar articles in Table 5.

Table 5 Comparison of the proposed method with other articles

Ref.	accuracy
[11]	92,3
[10]	98
[13]	98,82
[9]	95.5
[12]	97
[14]	99
My method	99.9

According to the reports and results, it can be concluded that the proposed method for detecting a healthy signal with arrhythmias has reliability and can be chosen.

References

- [1] Eduardo Jose da S. Luza, William Robson Schwartzb, Guillermo Cámara-Cháveza, David MenottiacECG- based heartbeat classification for arrhythmia detection: a survey,journal of Computer Methods and Programs in Biomedicine, 127 (April 2016), pp. 144-164.
- [2] G. Sannino, G. De Pietro, A deep learning approach for ECG-based heartbeat classification for arrhythmia detection, journal of Future Generation Computer Systems ELSEVIER (2018), pp. 446-455.
- [3] Shalin Savalia, Vahid Emamian, Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks, MPDIbioeng., 5 (2018).
- [4] G. Smaoui, A. Young, M. Abid, Single scale CWT algorithm for ECG beat detection for a portable monitoring system, J. Med. Biol.Eng, 37 (1) (2017), pp. 132-139.
- [5] S.H. Jambukia, V.K. Dabhi, H.B. Prajapati, Classification of ECG signals using machine learning techniques: a survey, International Conference on Advances in Computer Engineering and Applications, IEEE (2015), pp. 714-721.
- [6] M. Alfaras, M.C. Soriano, S. Ortín, A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection, Front. Physiol., 7 (2019), p. 103
- [7] M. Padmanabhan, P. Yuan, G. Chada, H.V. Nguyen, Physician-friendly machine learning: a case study with cardiovascular disease risk, prediction, J. Clin. Med., 8 (2019), p. 1050.
- [8] A. H, M.H. Ribeiro, G.M.M. Paixão, *et al.*, Automatic diagnosis of the 12-lead ECG using a deep neural network,Nat. Commun., 11 (2020), p. 1760.
- [9] Bhekumuzi M. Mathunjwa, Yin-Tsong Lin, Chien-Hung Lin, ECG recurrence

- plot-based arrhythmia classification using two-dimensional deep residual CNN features, *Sensors*, 22 (2022), p. 1660.
- [10] Sraitih Mohamed, Younes Jabrane, Amir Hajjam El Hassani, An automated system for ECG arrhythmia detection using machine learning techniques, *J. Clin. Med.*, 10 (2021), p. 5450.
- [11] Wusat Ullah, Imran Siddique, Rana Muhammad Zulqarnain, Classification of arrhythmia in heartbeat detection using deep learning, *Hindawi , Computational Intelligence and Neuroscience* (2021), p. 13.
- [12] Saira Aziz, Sajid Ahmed, Mohamed-Slim Alouini, ECG-based machine-learning algorithms for heartbeat classification, *Sci. Rep.*, 11 (2021), Article 18738.
- [13] Mengze Wu, Yongdi Lu, Wenli Yang and Shen Yuong Wong , “A study on arrhythmia via ECG signal classification using the convolutional neural network “, *Front. Comput. Neurosci.* 14.
- [14] Fajr Ibrahim Alarsan, Mamoon Younes, Analysis and classification of heart diseases using heartbeat features and machine learning algorithms, *J. Big Data* (2019), 10.1186.
- [15] Moradi, M., Fatehi, M., Masoumi, H., Taghizadeh, M. Deep neural network method for classification of sleep stages using spectrogram of signal based on transfer learning with different domain data. *Scientia Iranica*, 2022; 29(4): 1898-1903.
- [16] Moradi, M., Fatehi, M., Masoumi, H., Taghizadeh, M. Deep Learning Method for Sleep Stages Classification by Time-Frequency Image. *Signal Processing and Renewable Energy*, 2021; 5(3): 67-83.
- [17] Moradi MM, Fatehi MH, Masoumi H, Taghizadeh M. Adaptive neuro-fuzzy method for sleep stages detection by PPG signal. *Journal of Advanced Pharmacy Education & Research* | Jan-Mar. 2020; 10(S1).