International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 11 Issue 5 ǁ May 2023 ǁ PP. 100-104

Meta Structural Learning Algorithm with Interpretable Convolutional Neural Networks for Arrhythmia Detection of Multisession ECG

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Abstract
Due to the recent advances in the area of deep learning, it has been demonstrated that a deep neural network, can recognize cardiac arrhythmias better than cardiologists. Moreover, traditionally feature extraction was considered an integral part of ECG pattern recognition. However, recent findings have shown that deep neural networks can carry out the task of feature extraction directly from the data itself. Then, the identification and classification of the ECG patterns are done by the machine learning perspective. It is demonstrated that feature maps learned in a deep neural network trained on great amounts of generic input images can be used as general descriptors for the ECG signal spectrograms and result in features that enable classification of arrhythmias.
Keywords: *Arrhythmia detection, convolutional neural network, deep features representation, meta learning, multi-session ECG.*

Date of Submission: 19-04-2023 Date of acceptance: 03-05-2023

I. Introduction

Computer-aided diagnosis (CAD_x), are systems that help physicians to interpret medical images and signals. ECG recording techniques, X-ray, MRI, and ultrasound systems create a lot of information and a professional radiologist or physician has to analyze and assess them in a quite short period of time[1] . CAD systems process the digital signals and images and highlight the suspicious parts such as possible diseases to facilitate the physician's decision-making process. These assistants can help physicians to reduce the human error caused due to fatigue[2].

One of these diagnosis systems, which is quite developed is the system for automatic diagnosis of cardiac diseases using ECG signals. The electrical signals generated by various activities of upper and lower heart muscles are measured with electrocardiograms (ECGs). However, sometimes the performance of each muscle is affected by external factors such as excessive blood fat, which can cause arrhythmia in the electrical performance of the heart. For instance, a heart problem on the walls of the ventricles can be considered a cause of arrhythmia[3]. Moreover, the supraventricular on the upper walls of the ventricles in a region called atria is another complication leading to arrhythmia in the electrical signals of the heart. According to the statistics, heart complications account for one-third of the mortality rate in the adults aged 35–90 years old[4].

Meta-learning is defined as an emerging method for developing the ability to deal with new conditions in machine learning model[17].Meta-learning emphasizes the preparation of guidance for machine learning models so that they can make the best decision in new conditions including unseen samples. Moreover, meta-learning seeks a way towards learning to learn. Thus, it plays a key role in resolving the problem of arrhythmia classification in multi-session ECG signals[18]. In recent years, numerous methods have been proposed to develop a model for the demonstration of the same behavior while handling the signals recorded in various sessions, numerous algorithms are introduced for meta-learning including reinforcement learning, transfer learning, and active learning.

II. Literature Review

The ECG signals include various arrhythmia, among which 11 types were mentioned in the previous section. The methods are divided into different classes with respect to the number of arrhythmias classified in various investigations. Besides, it should be noted that all investigations introduced for diagnosing arrhythmia were assumed to be carried out based on single-session ECG signals[2]. Among all methods introduced up to now, deep learning is one of the top algorithms in the field of the classification of ECG signals.

The methods introduced are CNN-based deep learning models, which have classified various arrhythmia in ECG signals. The majority of these methods use 1D filters in CNN since the ECG signal in the MITBIH dataset is 1D as well. Here several CNN-based methods are explained. In [14], a CNN model with 8 convolution layers, 4 pooling layers, and one fully connected layer is used, which obtained the accuracy of 93.1% for 22 patients and 109449 accurate pulses.

In [16], a deep learning method enjoying the U-Net architectural standard, which comprised thirty-two 1D residual layers, was introduced to classify 5 types of arrhythmia. The results suggested that this method calculated accuracy of 98.5%. In a CNN model including 12 convolution layers was used for the classification of 44 records.

ECG-based multi-class arrhythmia detection using spatiotemporal attention -based convolutional recurrent neural network[18], This paper shows spatial and temporal attention mechanisms assigning weights for channels and temporal segments of feature map, respectively. The purpose is to emphasize the informative feature and suppress unimportant ones along two principal dimensions: spatial and temporal axes. Comparing with the state-of-the-art works, this further improves the performance of arrhythmia classification.

Heart electrical activity as reflected in Electrocardiograms (ECG) have been analyzed and diagnosed using various techniques. [16]. Among them complexity measure, nonlinearity, disorder and unpredictability play a vital role due to nonlinear interconnection between functional and anatomical subsystem emerged in healthy state and during various diseases. There are many social and economic issues of alcoholic abuse as memory weakness, decision making, impairments and concentrations etc. Alcoholism not only defect the heart but also associated with emotional, behavior and cognitive impairments damaging the white and gray heart matters.

III. Methodology

3.1. Data Set

The ECG dataset used in this paper, was collected from Chapman University and Shaoxing People’s Hospital (Chapman ECG in short) the numerical details of the dataset. The ECG signals for each person were recorded within several days and during different sessions. In this dataset, the 12-lead ECG signals were recorded from 10646 people with a frequency higher than 500Hz. Each ECG signal in 12-lead is a 10-second strip. In addition, an initial pre-processing stage was applied to this dataset in order to smooth the ECG signals using the Butterworth filter and the Non-Local Means technique.

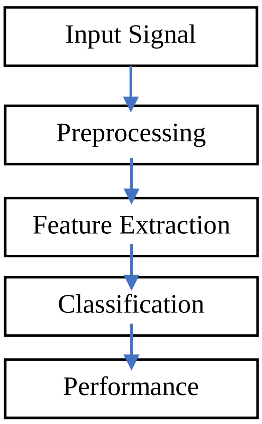

Figure-1 Modules Description of the number of the samples of the arrhythmia classes in the chapman ECG dataset.

3.2.Input Signal

Electrophysiological monitoring method to record electrical activity of the heart. It is typically non-invasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used in specific applications. ECG measures voltage fluctuations resulting from ionic current within the neurons of the heart. In clinical contexts, ECG refers to the recording of the heart's spontaneous electrical activity over a period of time.

Diagnostic applications generally focus on the spectral content of ECG, that is, the type of neural oscillations (popularly called "heart waves") that can be observed in ECG signals.

3.2 Pre-processing

3.2.1Butterworth Filter

The process or device used for filtering a signal from unwanted component is termed as a filter and is also called as a signal processing filter. To reduce the background noise and suppress the interfering signals by removing some frequencies is called as filtering. The Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the pass band. It is also referred to as a maximally flat magnitude filter. There are various types of Butterworth filters such as low pass Butterworth filter and digital Butterworth filter.

3.1.Feature Extraction

3.3.1Q-R-S Detection

The QRS complex is a combination of three of the graphic deflection seen on a typical ECG. This study proposes a real-time QRS detection and R point recognition method with low computational complexity while maintaining a high accuracy.

The enhancement of QRS segments and restraining of P and T waves are carried out by the proposed ECG signal transformation, which also leads to the elimination of baseline wandering.

Subsequently, the R point can be recognized based on four QRS waveform templates and preliminary heart rhythm classification can also be achieved at the same time.

3.4 Classification

In deep learning, a convolutional neural network (CNN, or Conv Net) is a class of artificial neural network, most commonly applied to analyse visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation equivariant responses known as feature maps.

Counter-intuitively, most convolutional neural networks are only equivariant, as opposed to invariant, to translation. They have applications in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series.

3.5 Performance Estimations

The performance of the process is measured in terms of performance metrics like Accuracy, Sensitivity, Specificity and time consumption.

TP is the total number of correctly classified foreground (true positives). TN is the total number of wrongly classified foreground (true negatives).

FN is the total number of false negatives, which accounts for the incorrect number of foreground pixels classified as background (false negatives).

FP is the total number of false positives, which means the pixels are incorrectly classified as foreground (false positives). The performance values were calculated for each frames of the input video based on the metrics described above.

IV. Result & Discussion

The experimental results section evaluates the performance of the proposed model for the classification of samples in the Chapman ECG dataset. It is clear that a sufficient number of samples are required as inputs to construct a classification model. However, in the Chapman dataset, some of the 11 classes have a very small number of samples to train the deep learning model.

The number of these classes like Atrial Tachycardia=121, Atrioventricular Node Re-entrant Tachycardia=16, Atrioventricular Re-entrant Tachycardia=8, Sinus Atrium to Atrial Wandering Rhythm=7 signal samples, which is quite small. Therefore, in these tests merely seven classes of arrhythmia with a sufficient number of samples are used. As reported earlier the only method for the comprehensive and accurate evaluation of a model for classification of ECG signals is a model in which the signals of the training and testing parts are recorded during different sessions and within several days. This is the only acceptable modality to test the model. Consequently, all evaluations carried out in this section are performed on the basis of configuration.

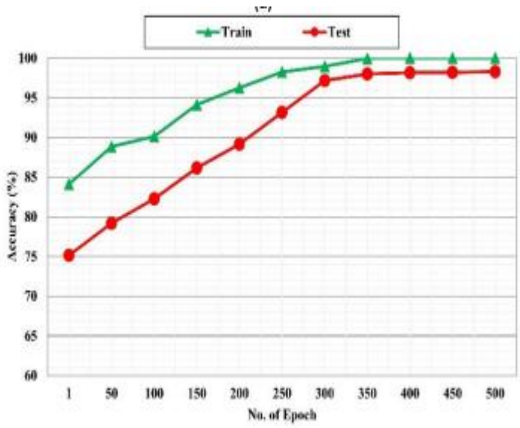

Figure-2 Its convergence rate curve.

The above figure demonstrates the superiority of the proposed model over other available methods of diagnosing arrhythmia of ECG signal by manifesting the numerical results and necessary comparisons. This subsection counts several crucial reasons and required justifications for this superiority. Deep learning models are statistical models that are dependent on data distribution. These models perform well merely when faced with data distribution that they are trained with. For instance, in this method, the model obtained an F-measure of almost 99% for training and testing data, however, in experiments carried out in the study it was observed that it retrieves the F-measure of 82% for the Chapman dataset. In light of that, the generalization of a statistical model is directly dependent on the sample distribution. In the proposed method, the statistical model was trained based on data distribution, and this distribution does not necessarily exist in the testing data section. As already mentioned in the latent medical variable cannot be directly achieved in the medical data.

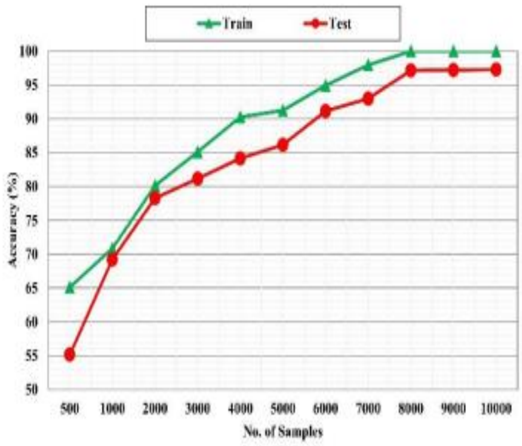

Figure-3 Accuracy of the classification model by increasing the number of samples constructed concerning 12-lead ECG.

Methods such as frequency analysis can express these variables. In the proposed method special frequencies were used in the ECG signal, which helped to extract the functional dependency in the ECG leads. Methods such as Big-ECG of their performance are directly dependent on specifying the stroke. It reduces the flexibility of the model since, in some types of arrhythmia, the QRS peak undergoes changes and is quite difficult to specify. In general, these are several justifications that can be stated to improve the proposed method in comparison to other previous methods.

Methods	Value
Accuracy	97.5681%
Sensitivity	97.1117%
Specificity	99.204%

Figure-4 Classification Result.

V. Conclusion

In this Paper, the authors proposed an Interpretable Meta Structural Learning algorithm regarding the challenging problems to classify various arrhythmia of ECG signals recorded in several sessions for each person. Therefore, a compound loss function was provided that included a structural feature extraction fault and a space label fault with GUMBEL-SOFTMAX distribution in the CNN models. The collaboration was carried out between models to create the learning to learn feature in these models via transferring the knowledge among them when dealing with unseen samples. This Paper encoded the models in the form of evolutionary trees of the GP algorithm to create the interpretability feature for CNN models. These trees learn the process of extracting deep structural features in the course of the evolution of the GP algorithm. The experimental results suggested that the proposed classification model enjoys an accuracy of 98% for the classification of 7 types of arrhythmia in the samples of the Chapman ECG dataset on 10646 patients, which were recorded in different sessions. Finally, the comparisons demonstrated the competitive performance of the proposed model through state-of-the-art methods based on the big learning models.

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