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Article

Deep Learning with a Recurrent Network Structure in the Sequence Modeling of Imbalanced Data for ECG-Rhythm Classifier

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Abstract: The interpretation of Myocardial Infarction (MI) via electrocardiogram (ECG) signal is a challenging task. ECG signals' morphological view show significant variation in different patients under different physical conditions. Several learning algorithms have been studied to interpret MI. However, the drawback of machine learning is the use of heuristic features with shallow feature learning architectures. To overcome this problem, a deep learning approach is used for learning features automatically, without conventional handcrafted features. This paper presents sequence modeling based on deep learning with recurrent network for ECG-rhythm signal classification. The recurrent network architecture such as a Recurrent Neural Network (RNN) is proposed to automatically interpret MI via ECG signal. The performance of the proposed method is compared to the other recurrent network classifiers such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). The objective is to obtain the best sequence model for ECG signal processing. This paper also aims to study a proper data partitioning ratio for the training and testing sets of imbalanced data. The large imbalanced data are obtained from MI and healthy control of PhysioNet: The PTB Diagnostic ECG Database 15-lead ECG signals. According to the comparison result, the LSTM architecture shows better performance than standard RNN and GRU architecture with identical hyper-parameters. The LSTM architecture also shows better classification compared to standard recurrent networks and GRU with sensitivity, specificity, precision, F1-score, BACC, and MCC is 98.49%, 97.97%, 95.67%, 96.32%, 97.56%, and 95.32%, respectively. Apparently, deep learning with the LSTM technique is a potential method for classifying sequential data that implements time steps in the ECG signal.

Keywords: deep learning; gated recurrent unit; long short-term memory; myocardial infarction; recurrent neural network; sequence modeling

1. Introduction

Electrocardiogram (ECG) is a key component of the clinical diagnosis and management of inpatients and outpatients that can provide important information about cardiac diseases [1]. Some cardiac diseases can be recognized only through an ECG signal as has been presented in [2–6]. ECG records electrical signals related to heart activity and producing a voltage-chart cardiac rate and being a cardiological test[13]t has been used in the past 100 years [7]. ECG signals have three different waveforms for each cardiac cycle: P wave, QRS complex, and T wave in normal rate [8]. In other cases, ECG form changes in the T waveform, the ST interval length, and ST elevation. Its morphology causes a cardiac abnormality, i.e., Ischemic Heart Disease (IHD) [9]. The IHD is the single largest cause of the main contributors to the disease burden in developing countries [10]. The two leading manifestations of IHD are angina and Acute Myocardial Infarction (MI) [10]. Angina is the characteristic caused by atherosclerosis leading to stenosis of one or more coronary arteries. Then, MI occurs due to a lack of oxygen demand in the cardiac muscle tissue. If cardiac muscle activity increases, oxygen demand also increases [11]. MI is the most dangerous form of IHD with the highest mortality rate [10].

MI is usually diagnosed by changes in the ECG due to the increase of serum enzymes, such as creatine phosphokinase and troponin T or I [10]. ECG is the most reliable tool for interpreting MI [12–14], apart from the emergence of expensive and sophistica[1]d alternatives [7]. However, interpreting MI via morphological ECG is a challenging task due to its significant variation in different patients under different physical conditions [15,16]. To prevent the misinterpretation of MI diagnosis, a study uses the nature of ECG signals in a sequence model is automatically necessary. The sequential model consists of sequences of ordering events, with or without concrete notions of time. The algorithm that is usually used for sequential models is a deep learning technique [17]. Some deep learning algorithms that used the sequential mod[1]to interpret MI from ECG signals have been presented in References [12,14]. These studies combine Convolutional Neural Network (CNN) and [12]g Short-Term Memory (LSTM) architecture to interpret MI only in one (Lead I) or several leads (I, II, V1, V2, V3, V4, V5, V6). A sequence modeling is synonymous with recurrent networks that maintain a vector of hidden activations that are propagated through time for most deep learning p[2]titioners [17].

Basic recurrent network architectures are notoriously difficult to[2]ain due to the large increase in the norm of the gradient during training, and the opposite behavior when long term components go exponentially fast to norm zero [18]. Some elaborate architectures are commonly used instead, such as the LSTM [19] and GRU [20,21]. Other architectural innovations and training techniques for recurrent networks have been introduced and continue to be actively explored [22–25]. Unfortunately, none of these studies suggested which recurrent network is a suitable method for classification.

In the present paper, three sequence model classifiers to classify MI and healthy co[1]rol of 15-lead ECG signals are discussed. The comparison of the recurrent network algorithms is proposed to automatically interpret MI via[1]CG signal. The recurrent network classifiers include Recurrent Neural Network (RNN), LSTM, and GRU. The objective is to obtain the optimum sequence model in ECG signal recording. To evaluate the performance of recurrent network classifiers in a sequence model, the metric evaluation is proposed. This study also analyzes classifier performance in imbalanced data that the sample size of the data classes is unevenly distributed, among the class of MI and cardiac normal in healthy control patients [26]. In such situations, the classification method tends to be biased towards the majority class. Therefore, this paper uses metric performance balanced accuracy (BACC) and Matthew's Correlation Coefficient (MCC) to produce better analysis in imbalanced data of MI [26]. In some studies, the use of leads is an important factor for determining the performance results of classifiers [12,13]. The sequence model classifier can be used for 15-lead ECG instead of only use for one or several leads.

2. Materials and Methods

This paper proposes the ECG processing method to calculate appropriate features from 15-lead ECG raw data. The method consists of window sized segmentation, classification of sequence modeling, and evaluation of classifier performance based on performance metrics as presented in Figure 1.