Poster: DeePTOP: Personalized Tachycardia Onset Prediction Using Bi-directional LSTM in Wearable Embedded Systems

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Abstract

Monitoring tachycardia and early intervention can reduce the occurrence of heart failure, cardiac arrest, death, etc. In this paper, we propose a novel personalized Bidirectional Long Short-Term Memory (BLSTM) model for early individualized tachycardia diagnosis. It leverages continuous monitored vital sign including heart rate (HR), respiratory rate (RR), and blood oxygen saturation (SpO_2), which are feasibly acquired by wearable embedded systems, as well as the admission information. The Area Under the Curve (AUC) of our model in our clinical experiments achieves 0.82 when predicting the onset of tachycardia 6 hours (6h) in advance, which precedes several baseline models.

1 Introduction

Tachycardia, a type of clinical event, is usually defined as over 100 beats per minute of HR for adults at rest [3]. Sinus tachycardia occurring in the intensive care unit might cause serious diseases such as delirium, organ hypoperfusion and disfunction, and even cause death [3]. Many continuous monitoring physiological status studies have indicated the deterioration of vital signs occurs before serious adverse events above 6$\sim$12h [5]. Therefore, early detection enables clinicians perform the active treatment.

In this paper, we propose our model, DeePTOP (Personalized Tachycardia Onset Prediction using BLSTM Networks Model), which is the first work that applies the deep learning method for the personalized tachycardia prediction. It leverages the patients' admission information and three raw vital signs of HR, RR, and SpO_2, conveniently acquired by wearable embedded systems and feasible to be continuously monitored, and then applies BLSTM to early detect tachycardia. How the models in previous works [1, 3] describe the complex multiple temporal information and represent the long-term dependence of sequences were not well studied in previous studies. Meanwhile, those models focused on the population characteristic without the consideration of the individual information.

2 Algorithm Design

Recurrent Neural Network (RNN) with the hidden units of LSTM is widely adopted in clinical medical data analysis during recent years, especially for processing multivariate time series with long-term relevance [4]. BLSTM with two hidden layers which are separately used to learn both of past and future states. The main idea of DeePTOP is that according the basic admission information, patients will be clustered into *m* subgroups adopting K-means algorithm and the early prediction model will be learned using Bidirectional LSTM algorithm in each subgroup cohort. Fig. 1 presents the model of DeePTOP with the detailed process as follows:

(1) Based on cohort admission information of age, gender, admission type, first care unit of staying in Intensive Care Unit (ICU), and the medical history of the circulatory system, the K-means algorithm will be used to determine which subgroup an individual belongs to. The clustering center indicates the subgroup characteristics of admitting ICU.

(2) We then leverage the data in an observing window with a predicting gap before the tachycardia onset. In observing windows, the raw time-series vital sign signals are input into the model at first. Additionally inspired by the model of Convolutional-LSTM, the statistic features extracted from the raw time-series signals are also fed into the model, which are merged with the processed data of backward and forward

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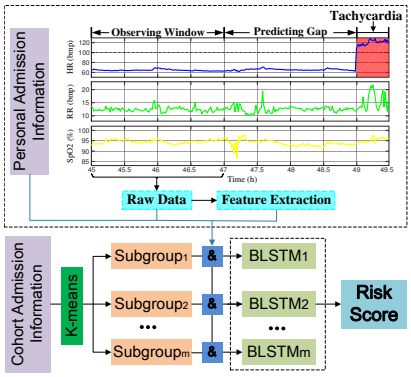

Figure 1. Model of DeePTOP

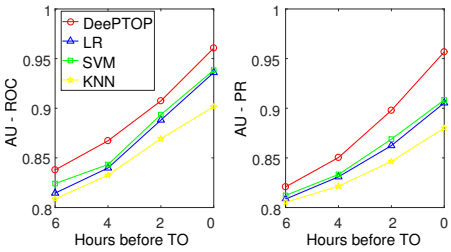

Figure 2. DeePTOP's performance of AU-ROC and AU-PR with the number of hours before the tachycardia onset (TO)

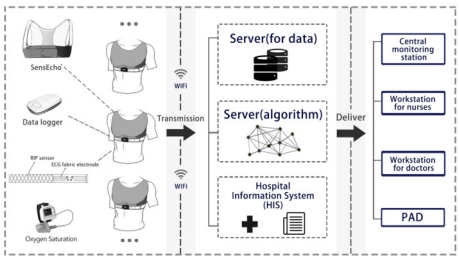

Figure 3. Overview of the SensEcho system

layer before the full connection layer.

(3) A specific patient with admission information is determined of subgroup, and all of raw data and the constructed feature sets will be jointly into a specific predicting model corresponding to the subgroup. The risk score real-timely evaluates the individual probability of tachycardia onset and can be used for early warning.

3 Preliminary Evaluations

We leverage MIMIC-III Waveform Database [2] to construct our model, and evaluate the data collected in Chinese PLA General Hospital. A tachycardia event is defined as the time interval in which any of the following requirements is recognized: (i) the duration of HR above 100 beats per minute (bpm) lasts at least 30min; (ii) the duration of HR above 130bpm lasts at least 20min; (iii) the duration of HR above 150bpm lasts at least 5min. This definition is jointly confirmed by the clinicians from the Departments of Emergency, General Ward, and Surgical ICU. The proposed observation windows and predicting gap sizes are 2h, and 0∼6h (with the step interval of 2h), respectively. MIMIC-III includes 22,221 numeric records of high-resolution time-series vital signs of 10,267 ICU patients, which are collected by bedside monitor. MIMIC-III also can be matched with the clinical database records by the same index of 'subject_id'. The screening criteria are age over 18, admitting hospital and ICU for the first time, recording time longer than 14h, existing HR, RR and SpO_2 synchronously and missing ratio of each vital sign not exceeding 30% in 2h observation window. The negative samples are acquired by extracting vital signs in a 2h observation window with the 1h sliding step from the patients without occurring tachycardia. The positive samples are constructed by selecting vital signs in 2h observation window with a predicting gap before tachycardia onset. In order to balance the ratio of positive and negative samples, we retain extracting data extended for 5min after the tachycardia onset (for target replication). Finally, the number of positive and negative samples are 2,222 and 64,589, respectively. We randomly select 2,300 negative samples combining all of positive samples with 25 times for further analysis.

We use K-means clustering algorithm with the Bayesian information criterion (BIC) to select the number of subgroups. Four subgroups are selected in this paper. In each observing window, 21 statistics features are extracted. Data fusion of process data with features extracted set are input into the output layer. The model's each layer has 32 units with two BLSTM layers. The fully connected layer has 8 units before the 2-unit output layers. We use 70% of the data for training, 20% to tune the hyper-parameters and 10% to validate the model's performance. Fig. 2 presents the predicting results before tachycardia onset of 0∼6h. Our model are consistently superior to the baseline models of logistic regression (LR), support vector machine (SVM) and K-nearest neighbors (KNN) in each early prediction time.

Table 1. Validation results for 6h in advance on our data

Method	AU-ROC	AU-PR	Sensitivity	Specificity	Accuracy
LR	0.70	0.69	0.70	0.68	0.66
SVM	0.72	0.71	0.73	0.67	0.67
KNN	0.78	0.73	0.67	0.77	0.70
DeePTOP	**0.82**	**0.80**	**0.78**	**0.80**	**0.77**

We are currently using a novel wireless wearable multi-sensor monitoring system, *SensEcho* [6, 7], to collect actual patient data in Chinese PLA General Hospital (PLAGH). Fig. 3 displays an overview of the SensEcho system, consisted by three parts of a wearable multi-senor system unit, a wireless network and data transmission unit, and a central monitoring system. Continuous monitored vital signs of HR, RR and SpO_2 are real-timely transmitted to data and algorithm servers via WiFi. Till our actual experiments, we have collected above 210 patients' monitoring data. 30 tachycardia events are captured by our system. Table 1 shows a specific performance parameters of DeePTOP and baseline models for 6h in advance. As we can see, our model performance outperforms the rest. Thus far, we keep collecting more data to evaluate the robustness of DeePTOP.

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