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A Novel Personalized Incremental Arrhythmias Classification Method for ECG Monitoring

Zhiyuan LI[a], Yuanyuan TIAN[a], Yanrui JIN[a,1], Xiaoyang WEI[a], Mengxiao WANG[a], Chengliang LIU[a,2] Liqun ZHAO[b] and Xiaoxue YANG[c]

[a]State Key Laboratory of Mechanical System and Vibration, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China
[b]Department of cardiology, Shanghai First People's Hospital Affiliated to Shanghai Jiao Tong University, Shanghai 200080, China
[c]Shanghai University of Finance and Economics, Shanghai200433, China

Abstract. With the development of smart healthcare, ECG monitoring has become an integral part of remote health care and plays a crucial role in diagnosing arrhythmias. However, the current mainstream ECG automatic diagnosis models lack research on incremental learning with accumulated personal data. Therefore, this paper proposes a personalized incremental learning method for diagnosing arrhythmias to facilitate the development of individualized models for personal users. Initially, the individual's ECG signals are encoded through ECG feature extractor composed of ResBlock, and Bi-LSTM. Subsequently, ECG diagnosis is performed using a personalized classifier tailored to the individual. As the personal data accumulates to a sufficient quantity, the personalized classifier is fine-tuned by incorporating the individual sample dataset with an arrhythmias-priority examplars based on herding, thus enabling the model to adapt to the individual domain. The experimental results demonstrate that the proposed model achieves an accuracy of 87.08% on the CPSC2018 dataset. Moreover, upon personalized incremental fine-tuning on the CPSC2020 dataset, the model's performance improves by over 13% compared to the initial model. Hence, the proposed personalized incremental learning method is effective.

Keywords. ECG, arrhythmias classification, incremental learning, deep learning

[1] Corresponding Author, Yanrui JIN, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China; E-mail: jinyanrui@sjtu.edu.cn.
[2] Corresponding Author, Chengliang LIU, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China; E-mail: chlliu@sjtu.edu.cn.

1. Introduction

According to statistics from the World Health Organization (WHO) [1], cardiovascular diseases account for 31% of the global total deaths each year, making it the most significant threat to people's health and lives. Arrhythmia is an important disease within the cardiovascular field, and its diagnosis often requires the aid of electrocardiography to observe the cardiac function. However, interpreting an electrocardiogram (ECG) is a time-consuming and highly specialized task, particularly when it comes to interpreting Holter monitors. This process can often take several days, significantly depleting medical resources and delaying the diagnosis of diseases.

In recent years, research focus has shifted towards methods for automated diagnosis of electrocardiograms (ECG), making it a hot topic of study. Ma [2] developed an end-to-end multi-scale convolutional neural network (CNN) with a Seq-to-Seq architecture to achieve beat-level arrhythmia classification. Hong [3] combined diagnostic knowledge of ECG with a fusion of beat-level and rhythm-level features, constructing a multi-level attention network for atrial fibrillation classification. Awni [4] introduced a 34-layer deep neural network-based single-lead ECG diagnostic model, which was trained and validated on a self-constructed clinical dataset consisting of 53,549 patients and the performance of this model demonstrated clinical cardiologists-level performance.

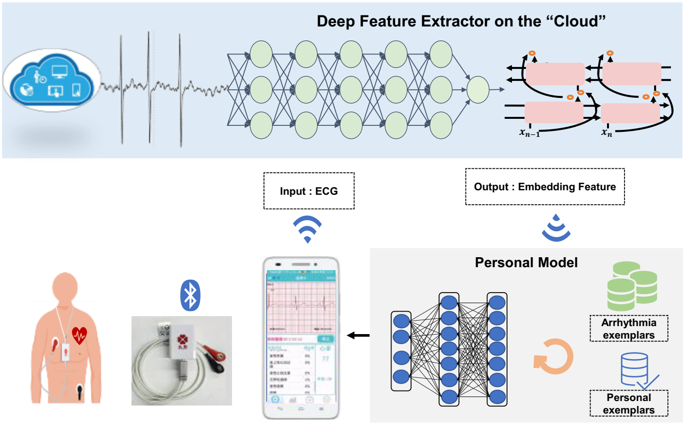


Figure 1. the proposed incremental framework for individual ECG monitoring.

Meanwhile, with the development of smart healthcare and wearable devices, some ECG medical products targeting individual applications have been developed, such as Heart Guardian by LEPU [5] and Apple Watch. These products often adopt a "hardware + cloud" architecture, where ECG data is collected through wearable devices, and automatic diagnosis is performed on the cloud with a diagnostic report returned. Mary [6] designed an IoT system based on ECG classification, deploying adaptive deep neural networks on the cloud for real-time ECG monitoring. S. Karthiga [7] designed an ECG classification framework based on an IoT system and researched the diagnostic performance of SVM, ANN, and CNN in such systems. In this IoT-based system, the models are typically deployed on cloud servers, lacking the adaptive ability to accommodate the varied distribution of ECG signals accumulated from individual users. As a result, personalized updates and accuracy improvement of the models cannot be achieved.

Based on the above issues, this paper proposes a personalized incremental learning approach for the diagnosis of arrhythmias, as shown in Figure 1. The proposed approach consists of three main components: 1) an ECG feature representation module, which provides a reliable representation of ECG based on clinical electrocardiographic data, enabling highly accurate classification of cardiac arrhythmias; 2) a prioritized exemplar selection module, which stores important samples within the model's classification range and personalizes the samples; and 3) a personalized classifier, which is a dedicated classifier for each patient and maps the unified ECG representation to their individual disease domain, achieving adaptive classification.

The main contributions of this paper are as follows:

1) Considering the lack of research on incremental learning in ECG intelligent monitoring systems, we design an ECG monitoring incremental learning approach based on residual convolutional-bidirectional long short-term memory (RCB-LSTM) networks, prioritized exemplars selection and personalized classifiers, which enables proactive optimization and incremental updates of personalized ECG diagnostic models.

2) The prioritized exemplar selection strategy, which combines herding and random strategies, is used to establish both a disease sample set and an individual incremental sample set. This strategy effectively alleviates catastrophic forgetting caused by sample imbalance during the incremental process.

3) The results demonstrate that, for the classification and diagnosis of AF, PAC, and PVC rhythm disorders, this method achieves an accuracy of 87.08% on the CPSC2018 dataset [8], showing significant improvement over existing methods. In terms of incremental learning, with the application of personalized incremental methods, the diagnostic accuracy of the model on the CPSC2020 [9] dataset increases by an average of 13%.

The structure of the paper for the following sections is as follows: the materials and methods are described in Section II. Section III provides a detailed explanation of the experimental setup, results, and analysis. Section IV serves as the conclusion.

2. Material and Method

2.1. Data Preprocessing

Dataset 1 CPSC2018: This dataset was collected from 11 hospitals and consists of 6,877 12-lead ECG records of 10 different diseases (3,178 records from females and 3,699 records from males). Each record has a sampling frequency of 500 Hz and varies in length from 6 to 60 seconds.

Dataset 2 CPSC2020: This dataset includes 10 long-term ECG records from patients with cardiac arrhythmias. Each record has duration of approximately 24 hours and a sampling frequency of 400 Hz. The corresponding PVC and SPB annotation files are provided.

We resample the above dataset to a uniform sampling frequency of 400 Hz and applied a finite impulse response (FIR) bandpass filter to remove noise from the ECG signals. Considering the requirements of wearable monitoring scenarios, we only utilize single-lead (lead II) data [16]. For dataset 1, we align the data length for each record by zero-padding records with fewer than 4,096 points and truncating records with excessive points. For dataset 2, we use a sliding window of length 4,096 with a stride of 5 seconds to extract the data.

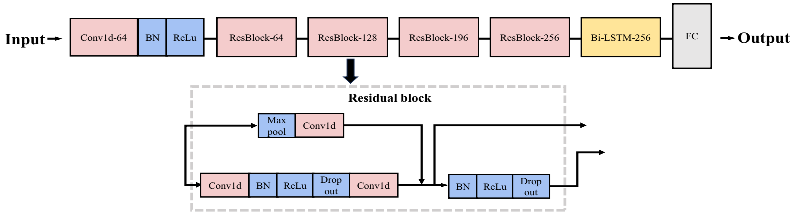


Figure 2. the proposed RCB-LSTM model structure.

2.2. Arrhythmia Classification Model (RCB-LSTM)

The structure of the RCB-LSTM model is shown in Figure 2, which includes a convolutional layer based Res-block [10], as well as a bidirectional LSTM attention layer [11], to achieve feature extraction of the ECG.

2.2.1 Residual Neural Network and Bi-LSTM

Considering the disease characteristics for classification, it is necessary to extract fine-grained semantic features such as P-wave, RR interval, and QRS complex. Therefore, we choose utilize a residual convolutional structure for automatic feature extraction from the cardiac signals. Besides, we employ bidirectional long-short term memory (Bi-LSTM) to model the features extracted by convolutional layers. This approach allows the features to capture both the contextual information and waveform characteristics over time.

2.2.2 Prior Sample Selection Strategy

For the typical disease sample set, we employ a priority sample selection strategy based on herding. For the personal labeled sample set, we use a random sample selection strategy and sample labeling to complete the construction of this sample set.

(a) Herding-based prioritized exemplar selection

Inspired by the work [12], we utilize a priority sample selection strategy based on herding to construct a sample set of typical diseases. This data set will be used to mitigate model catastrophic forgetting when constructing individual incremental models. Firstly, we compute the features of all available samples using a trained model. Then, we calculate the average of each class's data in the sample set. In the third step, *m* prioritized samples are obtained for each class by traversing according to formula (1).

$$p_k^i \leftarrow \underset{x \in X^i}{\operatorname{argmin}} \left\| \mu^i - \frac{1}{k}\left[F(x) + \sum_{j=1}^{k-1} F\left(p_j^i\right) \right] \right\| \tag{1}$$

(b) Personal Sample Selection and Re-labeling

After accumulating a sufficient amount of personal ECG data, we randomly select a small number of samples from the accumulated personal data. We then query and obtain their corresponding true labels (sample labeling) and store them in the personal priority sample set for personalized model incremental training.

2.3. Personalized Model Training

Once the ECG classification model training is completed, we employ a method of constructing an incremental learning model for personalized ECG monitoring scenarios. In the initial stage t_0, the personalized classifier is initialized with the classifier weights of the initial model. As data is gradually collected, in stage t_1, sample selection and labeling are performed from a large amount of unlabeled ECG records following, resulting in the personal sample set Mp_1. Subsequently, Mp_1 is merged with the disease sample set M, which is used to optimize the classifier. During the training process, we only optimize the classifier using an Adam optimizer with a learning rate of *1e-4* and a batch size of 8 for 5 epochs, allowing the classifier to better adapt to the individual signal distribution.

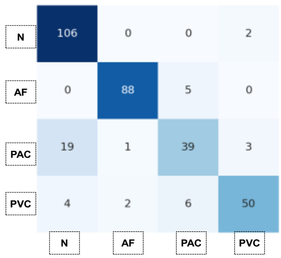
3. Experimental Results and Discussion

3.1. Experimental Setup

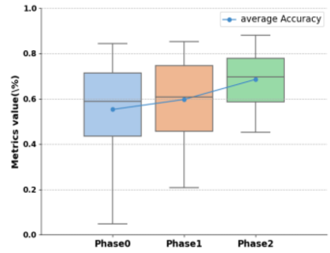
In this section, we conduct two experiments to validate the effectiveness of the proposed arrhythmia classification model and personalized incremental learning method for ECG monitoring. In Experiment 1, we train, validate, and test the RCB-LSTM using a total of 3,244 ECG samples from four categories: Normal, AF, PVC, and PAC, collected from the CPSC2018 dataset. We compare the performance of our model with existing cardiac arrhythmia diagnosis methods. In Experiment 2, we obtain the ECG representation model and initial personalized classifier from the model trained in Experiment 1. We use each record from dataset 2 as individual user data, where the first 50% of each Holter record is selected as the gradually collected personal dataset, while the remaining 50% is used as the individual test set.

Table 1. Comparison classification results on the Test set (CPSC2018).

Model	*Acc*	*Specificity*	*Sensitivity*	*F1 score*	*MCC*
ResNet [14]	72.62%	*90.22%*	*66.41%*	*70.59%*	*0.6327*
VGG [15]	28.62%	*75.00%*	*25.00%*	*12.73%*	*0.000*
ATI-CNN [13]	81.20%	-	-	81.20%	-
Our's	**87.08%**	***95.51%***	***84.08%***	**86.69%**	***0.8256***



(a) the confusion matrix on the CPSC2018



(b) the incremental performance on the CPSC2020.

Figure 3. the experiment results.

3.2. Experiment 1 – RCB-LSTM Classification Results

We divide the dataset into a training set, validation set, and test set in a ratio of 8:1:1. The model is trained for 30 epochs with a batch size of 16 and a learning rate of 0.001. The confusion matrix results on the test set are shown in Figure 3a. Table 1 compares the performance of our model with several existing models, demonstrating that our model achieves better performance. The overall accuracy is 87.08%, with F1 scores of 85.05% for the overall performance. For the four categories, the F1 scores are 89.45%, 95.65%, 69.64%, and 85.47% respectively. Our model outperforms common models by 16.41% Acc and 10.03% F1. Besides, our model outperforms these models in terms of sensitivity, specificity, and Matthews correlation coefficient (MCC).

3.3. Experiment 2 - Personalized Incremental Learning Results

In this experiment, we obtain a well-trained RCB-LSTM based on Experiment 1. We use a herding-based priority sample selection strategy on the CPSC2018 dataset to construct a typical disease sample set for individual incremental updates. For each patient's data in CPSC2020, we perform two-stage incremental learning on the training set. First, we construct the personal dataset using the training set data and conduct the second phase of incremental learning, optimizing the personalized classifier. Then, we test the incremental results on the test set. The specific experimental results are shown in Figure 3b. The "phase0" represents the diagnosis results of the model before personalized incremental learning. After two rounds of incremental learning (“phase 1”, “phase 2”), the average ACC of the model diagnosis increased by 13.3%, demonstrating significant improvement in the incremental learning effect.

4. Conclusion

In this paper, we propose a personalized incremental learning method for automatic arrhythmia diagnosis, which achieves improved model performance in the context of ECG monitoring. This method consists of three main modules: 1) ECG feature extractor based on RCB-LSTM, 2) herding-based typical disease sample selection strategy and personal sample set, and 3) personalized classifier. The experimental results demonstrate that the proposed classification method achieve an accuracy of 87.07% and an F1 score of 86.69% on the CPSC2018 dataset. Furthermore, using the incremental method on the CPSC2020 dataset results in a 13% improvement in individual ECG monitoring.

Acknowledgements

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