In this paper, we propose a novel adapted model named Attention-based Convolutional Factorization Machine (ACFM) for arrhythmia classification, which is formulated as:

$$y_n = \text{Softmax}(W \cdot [\text{bias} \cdot y_{\text{high-order}}] + b)$$

(1)

where \( m \) is the number of heartbeat type, \( b \) is the global bias, \( y_{\text{bias}} \) and \( y_{\text{high-order}} \) are the linear interaction and high-order interactions of features, respectively. \( a \) is the weight factor discriminating the importance of features’ interactions. The following figure illustrates the whole structure of ACFM that mainly consists of an Embedding Layer, a Feature Interaction Part, an Attention Layer and a hierarchical Rule-based Switch.

The ACFM captures linear interactions through linear regression. For high order interaction, we first correlates each pair of embedded features as a feature map through outer product, then we concatenate all feature maps as a 3D tensor \( T \) like an "image". In this way, a Convolutional Neural Network is introduced to acquire more expressive features.

In order to classify heartbeats more accurately, the most relevant feature interactions should be assigned of greater importance. Therefore, an attention mechanism is implemented in the Attention Layer. Finally, since individual difference introduced by the inter-patient paradigm may decrease the model’s output accuracy, we add a rule-based switch according to ratio of Pre-Avg RR intervals in the end when testing.

To evaluate the performance of the proposed method, three measures are adopted: Sensitivity (Se), Positive predictive value (P) and Specificity (Spec). The following table presents the performance comparison between our proposed method and several typical state-of-the-arts, where our method ACFM has achieved the best overall performance in the sensitivity classes in N and S. Top 1 and that of class V ranks No.2.

To more explicitly validate our model’s robust performance on samples with missing waves, we designed the following experiment. We randomly select 10%, 20%, 60%, 50% samples of the N, S, V, F classes, respectively in the training and testing sets and remove their P waves. Then we train the ACFM using the same strategy. The corresponding results are summarized below, where an overall accuracy of 87.6% is achieved.

Acknowledgements

The paper is supported by the National Natural Science Foundation of China (NSFC) under Grant No. 61672498 and the National Key Research and Development Program of China under Grant No. 2016YFC0302900.

Results

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To comprehensively understand the functionalities of components and mechanisms proposed in our model, we further carry out several ablation experiments. The results are demonstrated in the table below.

Experiment

In our experiment, we aim to classify heartbeats into AAMI heartbeat classes of Non-ectopic beats(N), Supra-ventricular ectopic beats(S), Ventricular ectopic beats(V) and Fusion beats(F). We adopt the inter-patient paradigm which means there is no individual overlap between training and testing sets. In detail, 44 records in MIT-BIH arrhythmia database are split into two subsets, DS1 and DS2. Each subset consists of the following records. DS1 = {101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230} DS2 = {100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234} During training, a focal loss which is formulated as: focal loss = -α \( 1 - \text{Softmax}(y_{\text{true}}) \) log \( \text{Softmax}(y_{\text{true}}) \) is introduced where we assign \( α \) as 0.5, 0.9, 0.6, 1.0 for class N, S, V, F, respectively. γ is valued 2.0.

EasiECG: A Novel Inter-Patient Arrhythmia Classification Method using ECG Waves

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Background

The electrocardiogram, known as ECG, is used to measure and record the electrical activities of heart, and has been widely used as the standard tool in the detection of cardiac abnormalities. In ECG record, a normal heartbeat waveform usually contains a P wave, a QRS complex, and a T wave that correspond to the atrial depolarization, ventricular depolarization and ventricular repolarization, respectively. In the past few decades, automatic classification of arrhythmias relying on Artificial Intelligence have been extensively studied. In this paper, we propose a medical experience-oriented arrhythmia classification method named EasiECG which takes advantage of the above mentioned P.Q.R.S,T waves. The RR intervals, which are the time intervals between two consecutive R waves, are also introduced as input features. Compared with other multi-stage methods, our EasiECG requires simple feature engineering and achieves higher accuracy.