MINA: Multilevel Knowledge-Guided Attention for Modelling Electrocardiography Signals
(Reimplementation by K. Anjali Sreeja)

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Abstract

Electrocardiography produces a voltage versus time graph of the electrical activity of the heart called a electrocardiogram(ECG). ECG signals used to detect cardiac abnormalities. Through this paper, the authors suggested a robust attention guided mechanism, MINA, for modelling these ECG signals in order to classify atrial fibrillation(AF) patients. MINA is implemented using PyTorch, and the reimplementation can be found here.

1. Introduction

Electrocardiography is the most common, non-invasive diagnostic tool to record electrical activities of the heart. Heart diseases are one of the leading causes of death around the world [2] and deciphering ECG signals can help detect atrial fibrillation(AF), myocardial infraction and other heart diseases [10].

As shown in figure 1, normal patients' ECG and AF patients' ECG show different patterns at different levels, namely, *1) beat level, 2) rhythm level. and 3) frequency level*. Each of these levels represent anomalous activities of the heart. These patterns provide great insights to support diagnoses [4][7].

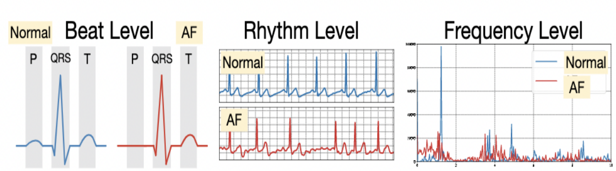

Figure 1. Normal ECG signals and ECG signals with AF show different patterns at different levels.

In real world usage, not only is accurate classification given importance, but also the interpretability of the classification is necessary. Also, not all heart diseases pose abnormal ECG constantly [2], especially during the early stage of the disease, whereas, if the disease is diagnosed at this stage, it could be less fatal. For all these reasons, interpretability of the results, especially highlighting diagnosis related parts of the data is really important for early diagnosis.

Recently deep learning models showed good performance in modelling ECG data. Convolutional neural networks (CNN) were used to capture beat level patterns [1]. Rhythm features were captured using recurrent neural networks (RNN) [6][5]. Even attention mechanism was used to extract interpretable rhythm pattenrs [6]. Inspite of this progress, the results from these models could not be used in real time due to the models being black-box or highlighting only one type of patterns (like in [6]).

Through this paper, the authors proposed MINA, MultI-level kNowledge-guided Attention for modelling ECG singals, which learns from different features which align with medical knowledge. Detailed explanation of MINA is given in section 3. When tested on AF prediction, MINA achieved PR-AUC score of 0.9475, which outperforms the best baseline model by over 5

2. Description of MINA

MINA's architecture, shown in figure 2, is described below.

2.1. Signal Transformation and Segmentation

Each single ECG signal, x, is transformed into different channels, each of different frequency bands, in order to extract and use frequency-domain information. For this transformation, Finite Impulse Response bandpass filter is used. $X = [x^{(1)}, x^{(2)},....,x^{(F)}]$. Then, for each channel, $x^{(i)}$ is split into M equal segments. For segmentation, sliding window protocol is used instead of segmenting using the QRS complex [6].

2.2. Beat Level Attentive Convolutional Layer

To locate abnormal wave shapes and edges, 1-D convolution is performed on each of the *M* segments. Here, instead of traditional average pooling, knowledge-guided attention is proposed, i.e., beat level attention, $o = \sum_{j=1}^{N} \alpha_j l^j$, is used so that the important signal locations can be focused on.

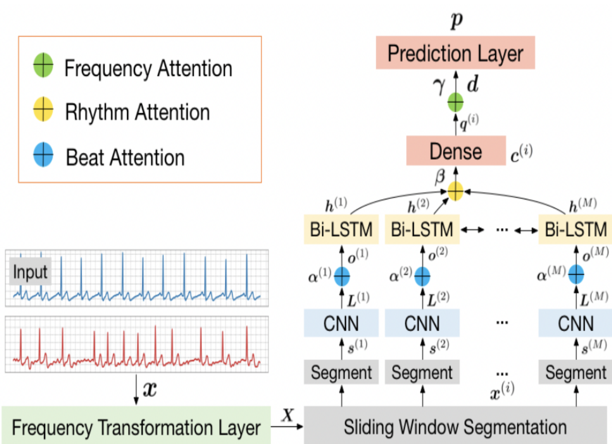

Figure 2. MINA architecture

2.3. Rhythm Level Attentive Recurrent Layer

Abnormal rhythm variation is captured from beat sequences using bidirectional Long Shorted-Term Memory (Bi-LSTM) [8] which is denoted as $h^{(k)}$ = *BiLSTM*($o^{(1)}$,...,$o^{(k)}$). The forward and backward outputs of the Bi-LSTM are concatenated to get the rhythm level feature *H* = [$h^{(1)}$,...,$h^{(M)}$]. Here, knowledge-guided attention is used with rhythm level knowledge to output the rhythm level attention $c = \sum_{k=1}^{M} \beta_k h^k$.

2.4. Fusion and Prediction

After learning rhythm level features, fully connected transformation is performed. [Q = $W_c{}^T$ C] where *C* = [$c^{(1)}$,...,$c^{(F)}$]. Frequency level attention, *d*, is calculated using $q^{(i)}$ and weight of $q^{(i)}$ where, $d = \sum_{i=1}^{F} \gamma_i q^i$. Now, we make a prediction, *p* = softmax(W^T d + b). Weighted cross entropy loss, *CE(p)* $= -\sum_{c=1}^{C} \Pi(z_c = 1) w_c log p_c$, where *C*, *z*, *w*, and Π are the number of classes, ground truth, weight vector, and indication function respectively. *w* is a tuned in order to handle the common issue of class imbalance.

2.5. Knowledge Guided Attention of MINA

The attention mechanism is MINA is a two layer neural network. In the first layer the scores for computing weights are calculated based on the multilevel outputs *L*,*H*, and *Q* as well as on beat level K_α, rhythm level K_β, and frequency level K_γ domain knowledge features. Model outputs and knowledge features are concatenated to compute scores and attention weights. $\alpha = softmax(V_\alpha{}^T (W_\alpha{}^T \binom{L}{K_\alpha} \oplus b_\alpha))$, $\beta = softmax(V_\beta{}^T (W_\beta{}^T \binom{L}{K_\beta} \oplus b_\beta))$, $\gamma = softmax(V_\gamma{}^T (W_\gamma{}^T \binom{L}{K_\gamma} \oplus b_\gamma))$, where W_α,W_β,and W_γ are the weights and biases in the first layer and V_α,V_β,and V_γ represent weights in second layer.

3. Implementation

3.1. Dataset

The dataset used for both implementation and reimplementation is the ECG data from PhysioNet Challenge 2017 databases [3]. The dataset contains 8,528 ECG recordings sampled at 300Hz by the AliveCor device where 738 are from AF patients. The data is divided into 75%, 10%, 15% training, validation, and testing data respectively. The data is then preprocessed to get equal ECG length of n = 3000.

3.2. Reimplementation Details

Two baseline models used for comparison are CNN [9] and CRNN [5]. CNN, CRNN and MINA have one convolutional later, number of filters is 64, filter size is 32 and stride is 2. In MINA, pooling is replaced by the attention mechanism. In the recurrent layers of CRNN and MINA, hidden units in each LSTM is set to 32. Dropout rate in the fully connected layer is 0.5. In MINA, for sliding window segmentation, stride, T = 50. Optimizer used was Adam and learning rate was 0.003. The reimplementation was in PyTorch version 1.9.0 on a 32GB RAM system with Nvidia GeForce RTX 3060 as well as on a 16GB unified memory 8 core CPU, and 8 core GPU MacBook Air with M1 processor.

3.3. Results

MINA outperforms the baseline models by approximately 5%.

PERFORMANCE COMPARISON			
	ROC-AUC	**PR-AUC**	**F1**
CNN	0.8711	0.8669	0.7914
CRNN	0.9040	0.8943	0.8262
MINA(Authors)	**0.9488**	0.9436	0.8352
MINA(Reimplementation)	0.9475	**0.9523**	**0.8414**

Table 1. Performance comparison on AF prediction

3.4. Issues Faced

The paper consists of a lot of mathematical annotations, so it took considerable amount of time to understand it all. The code given by the authors is not very clear. It is not mentioned about whether the interpretability aspect of this paper was specifically for cardiologists, which it is. Due to this uncertainty, I spend quite a lot of time in trying to figure out how to check the interpretability. Also had issues with running my model on DNA as it was throwing a Memory Error. Once that was fixed, DNA was down. Due to this, I trained the model on my own laptop and PC. I only trained 10 epochs on my laptop which took about 2 hours. 100 epochs on my PC took approximately 47 hours.

4. Conclusion

The authors of this paper not only focused on classification of AF patients, but also gave a great emphasis on how this classification is done. If this model predicts AF, it is because of the beat level, rhythm level, and frequency level attention that were extracted. This makes this model less black-box and more interpretability, which I believe will enable its clinical usage. This paper furthers great research scope in interoperability of various medical-domain deep learning models.

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