Transformer Embedded with Learnable Filters for Heart Murmur Detection

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Abstract

Aim: Heart murmur detection can provide a preliminary diagnosis of heart disease, and has become increasingly important in assisting clinical diagnosis and treatment in recent years. The purpose of this study is to construct an automatic detection system for heart murmurs.

Methods: We build a learnable filter-based transformer architecture. The learnable filter is embedded between the embedding layer and the encoder layer of the transformer. The parameters of the filter are optimized by Adam to adaptively represent any filter in the frequency domain, thereby achieving the effect of adaptive noise reduction. Then, the transformer encoder module captures the long-term dependencies of the heart sound signal, allowing the network to learn more effective features from the input signal. Finally, the final classification result will be obtained according to the voting rules we set.

Results: Our (Bear_FH) method is trained and validated on public datasets proposed by the challenge. In the formal phase of the challenge, testing the trained algorithm with a hidden test set, we achieved challenge metric scores (weight accuracy and cost) of 0.402 and 24406 on the murmur detection task. Our final ranking is 39th. We achieved a challenge metric scores (weight accuracy and cost) of 0.5 and 15982 on the clinical outcome identification task. Our final ranking is 35th.

1. Introduction

Cardiovascular disease (CVD) is the leading cause of death worldwide [1]. Currently, 17.7 million people worldwide die from cardiovascular disease every year. The study of heart sound signals has very important clinical value for the early diagnosis of cardiovascular disease. At present, the automatic analysis of heart sounds based on biological signal processing and artificial intelligence technology is becoming a popular research direction.

In the past few years, a large number of automatic heart sound classification algorithms based on machine learning [2–4] and deep learning [5, 6] have been proposed. Among them, deep learning methods usually use short-time Fourier transform and wavelet transform [7] to extract the effective features of heart sound signals, and subsequent classification models often use CNN and RNN [8]. At the same time, Transformer, as an attention-based method, has an excellent performance in time series forecasting, analysis of medical physiological signals [9], etc.

The goal of the George B. Moody PhysioNet Challenge 2022 is to identify the presence of murmurs, as well as to detect the clinical outcomes from heart sound recordings collected from multiple auscultation locations on the body using a digital stethoscope [10]. In this paper, we adopt the transformer as the basic framework to classify clinical heart sound recordings according to their corresponding temporal features, and our method is described in detail below.

2. Methods

In this section, we first briefly describe the basic information of the dataset and then introduce the implementation details about our method. The process design of the entire framework is shown in Figure 1. The first is the preprocessing stage, which is divided into 3-second segments by sliding the heart sound recording between windows and normalized. Then, the deep neural network proposed in this paper is used to extract the features of heart sound segments. Finally, the final patient-level results are obtained through a decision-making strategy based on the majority voting rule.

2.1. Datasets

We will conduct experiments on the PhysioNet Challenge 2022 dataset[11]. For clarity, we summarize the basic information of this dataset in Figure 2. The PhysioNet Challenge 2022 data was primarily collected from the pediatric population (21 years or younger). The dataset contains a total of 1568 patients with one or more heart sound recordings (5192 heart sound recordings in total), of which 3162 records from 942 patients are publicly shared as training set, and 2030 records from 626 patients are used as validation set and test set set for private reservation.

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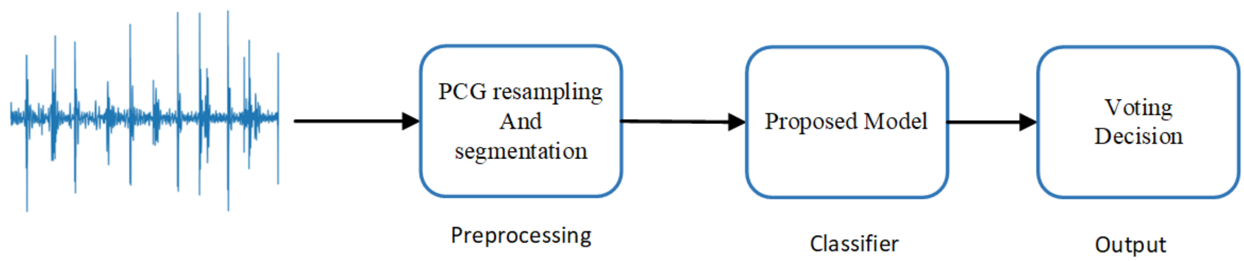

Figure 1. The flowchart of the proposed method.

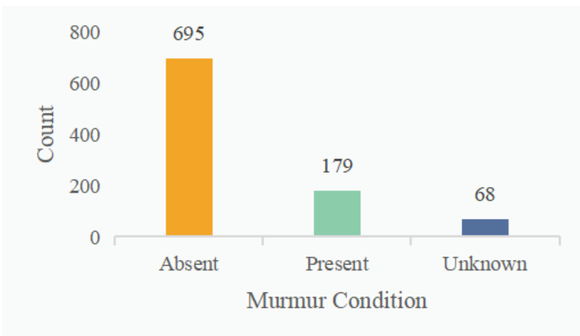

Figure 2. The PCG samples category distribution chart.

2.2. Data Pre-processing

When data is collected, each PCG record is naturally different due to differences in individuals and collection environments. In order to make the model training have better results, we adopted the following data preprocessing techniques. First, all heart sound recordings were resampled to a frequency of 2000 Hz. Second, normalize each heart sound recording to be between -1 and 1. Third, in order to ensure that the length of the data input to the deep learning model is fixed, each heart sound recording is cut into 3-second segments through a sliding window. Note that a 3-second heart sound recording is longer than a full cardiac cycle. Fourth, after data statistics, it is found that there is a serious data imbalance problem, so we use two data enhancement methods: random shift signal and random addition of Gaussian noise to the signal.

2.3. Model Overview

Our learnable filter-based transformer model consists of three main components: 1) A basic CNN for learning shared low-level features. 2) The learnable filtering layer uses learnable filters to adaptively reduce noise information in the frequency domain and capture periodic features. 3) The transformer encoder layer captures the global dependencies of the heart sound signal. Figure 3 shows the overall framework of our proposed network.

2.3.1. Convolution Layer

We mainly use multi-layer convolution to replace the embedding layer in the transformer. The original PCG waveform can obtain the shallow features of the heart sound signal through a series of convolution operations. At the same time, the original waveform is down-sampled by a factor of about 30, which reduces the number of model parameters. The obtained shallow features are then summed together with the positional encoding, and the obtained result is finally fed into the learnable filtering layer.

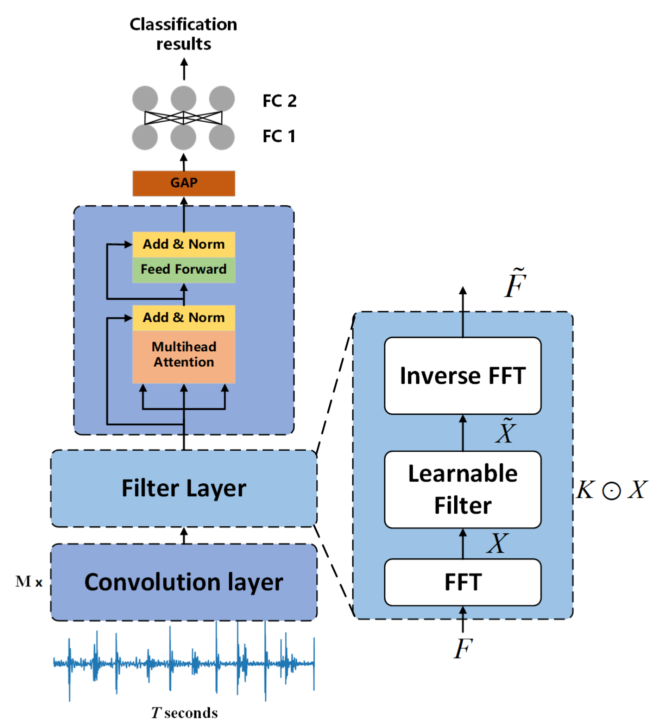

Figure 3. Illustration of our deep neural network.

2.3.2. The Learnable Filtering Layer

In this module, we mainly realize the adaptive reduction of data frequency domain noise information and the capture of data periodic characteristics. First, we perform a Fast Fourier Transform (FFT) along the item dimension to transform the input information from the time domain to the frequency domain:

$$\text{X} = FFT(F) \in C^{n\times d}, \tag{1}$$

where $FFT(\cdot)$ denotes the one-dimensioal FFT. X is a complex tensor and represents the spectrum of F,and n,d denotes the length of feature sequence and the dimension of feature embedding,respectively. Then, we can multiply the obtained spectrum by the learnable filter K to achieve the effect of modulating the spectrum.

$$\tilde{X} = K \odot X, \tag{2}$$

$$\tilde{F} \leftarrow FFT^{-1}(\tilde{X}) \in R^{n\times d}, \tag{3}$$

where $\odot$ is the element-wise multiplication. Note that X is a complex tensor and represents the spectrum of F. Then, we can multiply the obtained spectrum by the learnable filter K to achieve the effect of modulating the spectrum. The learnable filter K can be optimized by the Adam optimizer to adaptively represent any filter in the frequency domain. At the same time, after the proof in [12], it can be known that the multiplication in the frequency domain is equivalent to the circular convolution in the time domain, and has a larger receptive field in the whole sequence, so it can better capture the periodic characteristics of the heart sound signal. Finally, we transform the modulation spectrum X back to the time domain by an Inverse Fast Fourier Transform (IFFT) and update the sequence representation. After this series of operations, the noise in the recorded data can be effectively reduced, resulting in a clearer feature representation.

2.3.3. Encoder

Since our current task is a classification task, not a time series prediction task, we only need to use the encoder module in the Transformer model. Each encoder layer consists of a multi-head self-attention mechanism sub-layer, followed by a fully connected feed-forward network. As described in [13], we use skip connections and layer normalization in each sublayer. The long-term dependencies of the heart sound signal are captured by the transformer encoder module, which enables the network to learn more effective features from the input signal.

2.4. Voting Decision Strategy

According to the scoring rules of the 2022 PhysioNet/CinC challenge, we know that the model's final prediction results are for patients. However, in the data preprocessing stage, this paper divides each heart sound recording of the patient into several segments. Therefore, how to aggregate the diagnostic results of the segmented fragments into the final diagnosis of the patient is crucial. Our aggregation strategy is based on the majority voting rule. First we aggregate the segment-level to record-level (summarize predictions from multiple segments of a heart sound recording into predictions for this heart sound recording). Then, the prediction results of one record or multiple records of the patient are aggregated into the prediction results of the patient.During the aggregation period, we may experience some tie-breakers. In response to these situations, we set priorities according to the official calculation cost flow chart. Priority for three categories: Present>Unkown>Absent.

2.5. Training Setup

Our learnable filter-based transformer model was trained for 60 epochs with a batch size of 64 on a machine with 64 GB RAM, 8-core CPU and one NVIDIA GeForce RTX 2080 Ti GPU.The model parameters were optimized with the Adam op-timizer [10]. The learning rate during training is set to 0.001 and rescheduled to 0.0001 at the 30th epoch and 0.00001 at the 50th epoch.

2.6. Results

We train and evaluate the model using 10-fold cross-validation, where 10-fold is used for model training and the rest is used for model testing. Repeat ten times to generate ten trained models. Then select the best model from the 10 models and upload it for testing on the official test set. Table 1 and Table 2 show the final results and ranking obtained on the murmur detection task and the clinical outcome identification task, respectively

Training	Validation	Test	Ranking
0.582 ± 0.013	0.394	0.402	39/40

Table 1. Weighted accuracy metric scores (official Challenge score) for our final selected entry (team Bear_FH) for the murmur detection task, including the ranking of our team on the hidden test set.

Training	Validation	Test	Ranking
7493 ± 132	11331	15982	35/39

Table 2. Cost metric scores (official Challenge score) for our final selected entry (team Bear_FH) for the clinical outcome identification task, including the ranking of our team on the hidden test set.

3. Conclusions

In this paper, we propose a learnable filter-based transformer architecture. The model utilizes learnable filters to adaptively reduce noise information in the frequency domain and can better capture periodic features. At the same time, the long-term dependence of the heart sound signal is captured by the transformer encoder module. However, during the experiment, it was found that our method has potential over-fitting risks and does not take full advantage of the unique advantages of the transformer. We will find more detailed solutions in future work.

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