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Using Attention-based Residual Neural Network for Homecare-oriented Electrocardiogram Diagnosis System

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Cardiovascular diseases pose a significant global health challenge, and electrocardiography (ECG) plays a crucial role in their detection and classification. Consequently, developing a homecare-oriented ECG diagnosis system is highly beneficial for patients to their daily lives. We present a lightweight ECG diagnosis system, utilizing state-of-the-art sensors and advanced sensing technologies to enhance the quality of healthcare. By incorporating an attention-based residual neural network (ResNet) and the Conformer model, our system improves the accuracy and efficiency of ECG signal processing, making it suitable for real-time monitoring applications in healthcare environments. To enhance the spatial and channel information of the embedded features, we investigate the use of attention-based ResNet. Additionally, we employ the Conformer neural network, which incorporates a residual mechanism, to extract both local features and global contextual information. Experimental results demonstrate that our proposed approach outperforms existing models such as wide and deep transformer neural network (denoted as PRNA), weighted ResNet, and squeeze-and-excitation ResNet. Compared with ResNet Transformer, our method is more compact in size while achieving similar performance levels. These findings indicate that our system offers a resource-efficient and high-performance solution for ECG diagnosis, making it a promising candidate for real-world healthcare applications.

1. Introduction

Cardiovascular diseases (CVDs), including arrhythmia and cardiomyopathy, constitute a significant global health challenge as they remain the leading causes of death and disability. Electrocardiography (ECG) plays a vital role in the detection and classification of these cardiac

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conditions by recording the electrical activities of the heart.[1] Despite its advantages, the interpretation of ECG data typically requires the expertise of medical professionals, necessitating patients to visit hospitals for evaluation. Therefore, developing a homecare-oriented ECG diagnosis system would be very useful for patients in daily life. Moreover, the AI algorithms used need to be sufficiently lightweight to enable the development of an ECG diagnosis system.

CVDs, including coronary artery disease, arrhythmia, valvular heart disease, coronary artery heart disease, cerebrovascular disease, rheumatic heart disease, and other related diseases, significantly impact health, often leading to complications that threaten vital organs.[2] They claim about 17.9 million lives annually worldwide, with heart disease being the second leading cause of death in Taiwan, where there were around 23000 fatalities in 2022.[3,4] These statistics underscore the urgent need for effective CVD detection systems to improve patient outcomes and alleviate healthcare burdens. Current detection methods include cardiac catheterization, echocardiography, and ECGs. While catheterization is invasive and echocardiography requires at least 15 min, ECG is non-invasive and quick, taking only about 5 min.[5] However, ECG interpretation typically requires the expertise of medical professionals. Therefore, an intelligent decision system should be used to implement a homecare-oriented ECG diagnosis system for preventing CVDs.

Recently, deep learning techniques, such as convolutional neural networks (CNNs), recurrent neural networks, and long short-term memory (LSTM) models, have significantly influenced cardiac arrhythmia detection. For instance, Yildirim *et al.* introduced an end-to-end model using 1-D CNN to identify 17 different cardiac arrhythmia disorders without relying on handcrafted feature extraction.[6] Wang *et al.* developed a deep multiscale fusion CNN architecture capable of detecting nine classes of arrhythmias, validated on two public datasets.[7] Similarly, Hannun *et al.* achieved high diagnostic accuracy in classifying 12 rhythm classes from a substantial dataset of 91232 single-lead ECGs, rivaling cardiologists' performance.[8] Moreover, Hou *et al.* employed an LSTM-based autoencoder combined with support vector machines for classifying five arrhythmias.[9] While these studies yielded promising results, they often faced limitations due to the quantity and diversity of ECG samples in public datasets, leading to the insufficient exploration of multilabel and multiclass arrhythmia symptoms critical for clinical applications.[10] Consequently, the previous studies focused on multilabel arrhythmia detection for a restricted set of arrhythmia classes. However, a simplified model that classifies arrhythmias into significantly fewer categories offers limited utility in clinical applications.

In this study, a homecare-oriented ECG diagnosis system is proposed to assist patients in monitoring CVDs. To effectively represent ECG signals, a neural encoder utilizing a CNN and an inter-lead attention mechanism is developed. To accurately enhance the spatial and channel information of the embedded features, an attention-based residual neural network (AttResNet) is investigated. Additionally, to extract local features and global contextual information, the Conformer neural network with a residual mechanism is adopted.

The development of ECG diagnosis systems has greatly benefited from advancements in sensor technologies, which enable the continuous, noninvasive monitoring of cardiovascular health. In this study, we leverage high-performance ECG sensors and related materials, combining them with cutting-edge neural network models to create a system capable of accurate arrhythmia detection. This approach aligns with ongoing efforts to incorporate wearable sensing devices into personalized healthcare solutions.

The rest of this paper is organized as follows. The proposed homecare-oriented ECG diagnostic system, including the inter-channel attention mechanism, AttResNet, and Conformer, is described in Sect. 2. In Sect. 3, a series of experiments to evaluate the performance of our approach are described. Conclusions and recommendations for future research are given in Sect. 4.

2. Methods

In this study, a homecare-oriented ECG diagnostic system (shown in Fig. 1) is proposed to help patients in daily living. First, each lead of the input ECG signals is encoded using CNNs, and the lead information is fused using inter-lead attention. Second, the output embedding features are processed for information extraction using AttResNet. Third, the Conformer neural network is applied to extract local features and global contextual information. Finally, the output block is applied to obtain the final decision using fully connected neural networks. The process is described below.

2.1 Inter-lead attention block

The inter-lead attention block (shown in Fig. 2) includes the convolutional layer (CL), batch normalization (BN), mish activation function (MF), and inter-lead attention mechanism. The CL convolves the input and encodes it into an embedding feature. The BN is used to recenter and rescale the embedding feature to obtain a stable feature. The input x of the BN can be defined as

$$\mathrm{BN}(x) = \gamma \frac{x-\mu}{\sqrt{\sigma^2+\varepsilon}} + \beta, \tag{1}$$

where *m*, *s*, and *e* are the per-dimension mean, the standard deviation, and an arbitrarily small constant, respectively. *b* and *g* are the transformation parameters subsequently learned in the optimization process.

MF is an activation function, Mish(), which is a smooth approximation of the rectifier and is defined as

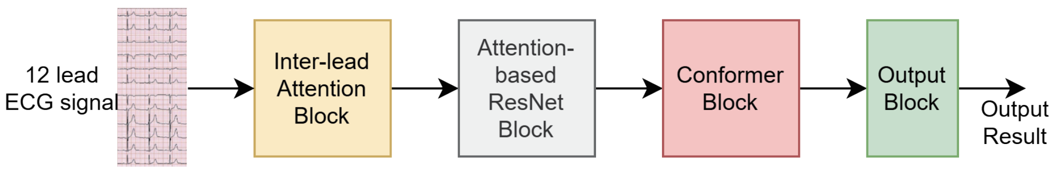

Fig. 1. (Color online) Flowchart of the proposed homecare-oriented diagnostic system. The proposed neural network comprises four distinct blocks: an inter-lead attention block, an attention-based ResNet block, a Conformer block, and an output block.

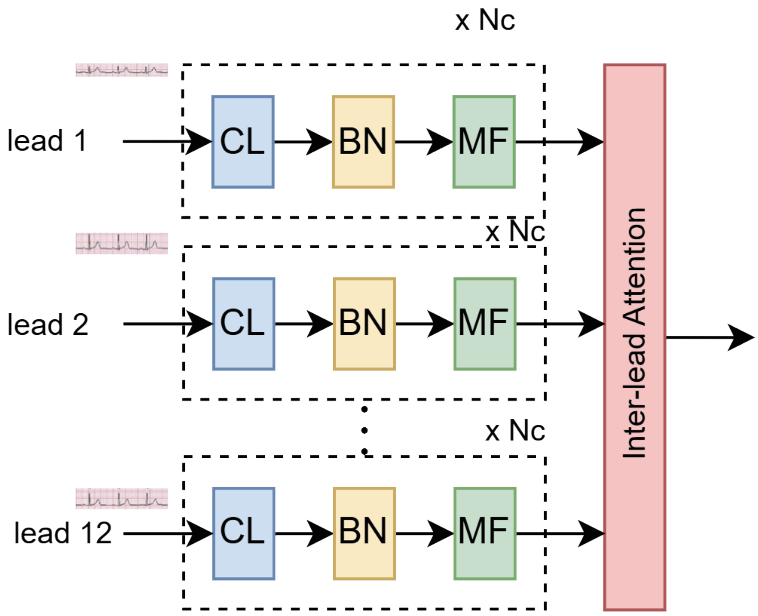

Fig. 2. (Color online) Architecture of the inter-lead attention block, which primarily enhances the model's ability to capture relationships between different leads.

$$\text{Mish}(x) = x\tanh\left(\log\left(1+e^{x}\right)\right), \tag{2}$$

where tanh() is the hyperbolic tangent. The inter-lead attention is implemented using scaled dot-product attention, which is used to weigh the significance of different parts of the embedding feature.[10]

2.2 Attention-based ResNet block

The architecture of AttResNet (shown in Fig. 3) is a variant of ResNet and is used with the attention mechanism. Therefore, it can achieve a richer gradient combination and concentrates on the most relevant features. The CL is applied to encode the features and then the parametric rectified linear unit (PreLU) is selected as the activation function following the CL. Moreover, the channel attention model (CA) and spatial attention model (SA) are used to improve the channel information and spatial information, respectively.[11] Finally, the improved embedding features are fused and added to the input embedding features. The operations × and + are the element-wise product and element-wise addition, respectively.

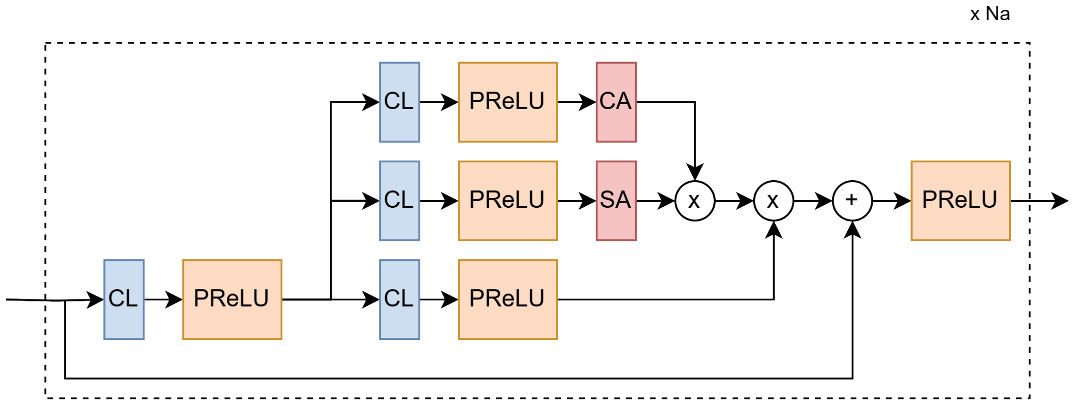

Fig. 3. (Color online) Architecture of the proposed AttResNet block, which can achieve a richer gradient combination and concentrates on the most relevant features.

2.3 Conformer block

Figure 4 shows the architecture of the Conformer block, which includes a fully connected layer (FCL), multihead self-attention mechanism (MHSAM), and CL.[12] In the Conformer block, a sandwich structure, inspired by Macaron-Net, is adopted.[13] The original feed-forward layer in the traditional Transformer is replaced by two half-step feed-forward layers. One is positioned before the MHSAM and the other after. As in Macaron-Net, half-step residual weights are used in the FCL. The second FCL is followed by a post-layernorm layer (LN).

3. Experimental Results

To verify the proposed approach, an independent external public dataset provided by the China Physiological Signal Challenge (CPSC 2018) was selected.[14] This dataset contains 6877 12-channel ECG records from 11 hospitals. The sampling rate was normalized as 500 Hz, and the number of classes for cardiology diseases was 27. In addition, the K-fold cross-validation technique was adopted to evaluate the proposed approaches, and k was 10 in this study. Nc, Na, and Nr were 2, 3, and 3, respectively. The Adam algorithm with $b = 0.9$, $b_2 = 0.98$, and $e = 10^{-9}$ was selected as the optimizer for training neural networks. The number of iterations and the batch size were 30 and 128, respectively.

In this study, we adopted a challenge scoring metric (CM) specifically designed for PhysioNet/Computing in Cardiology Challenge 2020 to assess our proposed approach.[15] The rationale for selecting CM lies in its ability to mirror clinical realities, where certain misdiagnoses can have more severe consequences than others, necessitating a nuanced scoring system. Moreover, it is considered that misclassifying certain classes carries less risk than confusing others, thereby providing a more comprehensive evaluation of model performance.

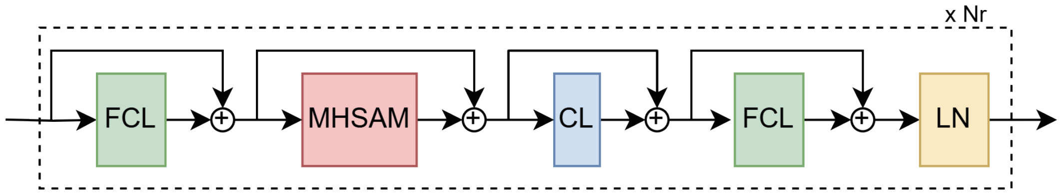

Fig. 4. (Color online) Architecture of the Conformer block, which can effectively capture both local features and global contextual information.

Table 1
Experimental results of the proposed approach and baseline systems.

Fold	Proposed approach	Baseline (R, RC)	Baseline (A, C)	Baseline (A, T)
0	0.587	0.569	0.610	0.636
1	0.652	0.608	0.567	0.582
2	0.650	0.638	0.542	0.598
3	0.612	0.570	0.643	0.622
4	0.600	0.559	0.612	0.604
5	0.597	0.510	0.591	0.587
6	0.572	0.550	0.599	0.614
7	0.632	0.553	0.641	0.563
8	0.642	0.554	0.555	0.578
9	0.517	0.594	0.504	0.541
Avg C.M	0.606	0.571	0.586	0.593

3.1 Experimental results of AttResNet

To evaluate the effectiveness of the attention mechanism, the conventional ResNet with two CLs and PReLU is selected for comparison with the proposed AttResNet. Moreover, the conventional Conformer and Transformer are selected for comparison with the proposed Transformer block. AttResNet and conventional ResNet, which are adopted to implement the attention-based ResNet block, are denoted as A and R, respectively. Moreover, the proposed Conformer, conventional Conformer, and conventional Transformer, which are used to implement the Conformer block, are denoted as RC, C, and T, respectively. The experimental results are shown in Table 1; the proposed approach outperforms the others.

Compared with the baseline (R, RC), the proposed AttResNet is very useful for identifying the CVDs. Moreover, the proposed Conformer network with residual mechanisms is useful and simplified compared with the conventional Conformer or transformer architecture. Thus, the proposed architecture is suitable for the homecare-oriented ECG diagnosis system.

3.2 Results of comparison with other approaches

In this study, we selected ResNet Transformer,(16) PRNA,(5) Weighted ResNet,(17) and SE-ResNet(18) as baseline models for comparison with our proposed approach. The experimental results for these approaches are 0.608, 0.533, 0.520, and 0.514 for the ResNet Transformer, PRNA, Weighted ResNet, and SE-ResNet, respectively. Our proposed approach demonstrates superior performance compared with PRNA, Weighted ResNet, and SE-ResNet. Notably, while its performance is very similar to that of the ResNet Transformer, our model is smaller in size, offering a more efficient alternative.

4. Conclusions

CVDs remain a pressing global health issue, making effective detection and classification imperative. In this study, we successfully developed a lightweight ECG diagnosis system specifically designed to enhance the quality of healthcare. By utilizing the AttResNet model, we were able to enrich the spatial and channel information of embedded features, thereby improving diagnostic accuracy. Furthermore, the incorporation of the residual-based Conformer neural network facilitated the extraction of both local features and global contextual information, contributing to the robustness of our approach. The experimental evaluations have demonstrated that our proposed system outperforms established models, including PRNA, Weighted ResNet, and SE-ResNet, while maintaining a compact architecture comparable to that of the ResNet Transformer. This makes our system not only efficient in resources but also effective in performance, positioning it as a suitable candidate for healthcare-oriented ECG diagnosis systems. Furthermore, we demonstrated the potential of integrating advanced ECG sensors with AI-driven diagnostic models, providing an effective and resource-efficient solution for cardiovascular disease detection. In future research, we aim to expand the system's diagnostic capabilities by incorporating additional arrhythmia classes and patient feedback mechanisms. Additionally, exploring federated learning for privacy-preserving ECG analysis could enhance its clinical applicability.

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