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Letter

Severity Classification of Obstructive Sleep Apnea Using Electrocardiogram Signals

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In this paper, we propose a method of classifying the severity of obstructive sleep apnea (OSA) using electrocardiogram (ECG) signals and deep learning. In our previous research, we presented an ECG-based signal segmentation-free model for OSA severity classification. Its key feature is using the unsegmented overnight ECG signal as input and directly predicting the four categories of OSA severity as output. The overall performance of our previous work has been demonstrated to significantly exceed those of most existing studies. On the basis of a preliminary study, a method of improving the accuracy of OSA severity classification is proposed in this paper. Modifications to the model architecture for OSA severity classification were made, and a squeeze-and-excitation network (SENet) was integrated into this work. Finally, our experimental results indicated that the accuracy of the four-category classification of OSA severity in this paper is 57.91%, which is slightly higher than 57.55% achieved in our previous research.

1. Introduction

Obstructive sleep apnea (OSA) is a widespread sleep disorder that considerably impacts sleep quality. If untreated, it can lead to numerous health issues, including cardiovascular diseases, diabetes, and dementia.[(1)] The current gold standard for diagnosing OSA is overnight polysomnography (PSG). By analyzing PSG recordings, the apnea-hypopnea index (AHI), which represents the average number of apnea and hypopnea events per hour, is determined. This index is used to classify OSA severity into four categories: normal ($AHI < 5$), mild ($5 \leq AHI < 15$), moderate ($15 \leq AHI < 30$), and severe ($AHI \geq 30$).[(2)] However, PSG is an expensive and time-intensive test, requiring patients to wait for extended periods before undergoing the test in a hospital. Accordingly, extensive efforts have been made to assess OSA severity using a single signal, especially the electrocardiogram (ECG) signal alone.[(3–7)]

In our recent study on OSA severity classification,[(6)] unsegmented ECG signals were used to directly classify the four-level OSA severity, which is the first in the literature. This work has the following advantages: First, the model in Ref. 6 used unsegmented ECG signals as input, in

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contrast to all existing methods that rely on signal segmentation. This means that the considerable effort and time spent on signal segmentation and labeling tasks can be fully eliminated. Second, the model was tested using the largest amount of data to ensure a high generalization ability, thus giving the model an improved reliability for clinical use. Third, the approach proposed in Ref. 6 has an accuracy of 57.55% for four-level OSA severity classification, which outperforms most existing methods.

In this paper, we propose an improved architecture of an OSA detection model to further enhance the performance of our original work. There is no doubt that the unsegmented ECG signals are also used as input in this work to keep all the aforementioned advantages. Moreover, an improved accuracy of OSA severity classification in the presented model will be experimentally demonstrated at the end of this paper.

2. Methodology and Model

Figure 1 is the framework of the improved OSA severity classification model proposed in this paper. Similarly to Ref. 6, the input to the model is a 1D ECG signal with a length of 6 h and a sampling frequency of 100 Hz, resulting in an input shape of 2160000 × 1. Thus, only 1D convolutional layers are applied to the model. The block abbreviated as 'Conv1D, (32, 11, 6)' in Fig. 1 indicates that the number of filters, kernel size, and the number of strides are set to 32, 11, and 6, respectively. The dimension of each feature map appears at the lower right corner of the corresponding block in Fig. 1.

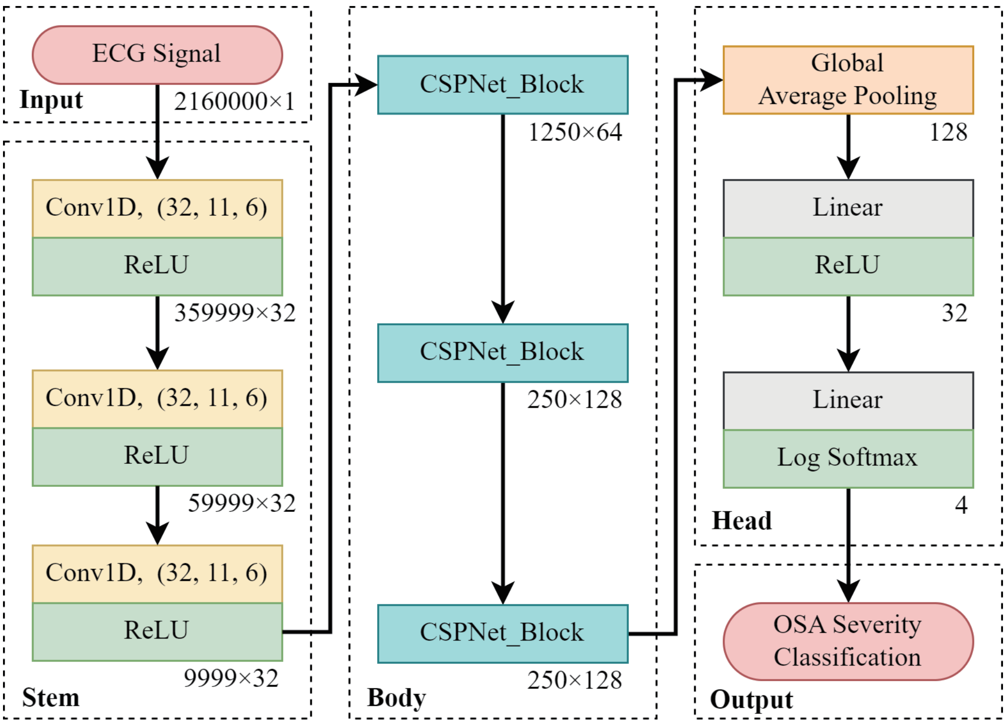

Fig. 1. (Color online) Framework of the presented four-level OSA severity classification model.

Next, the detailed framework of a cross stage partial network [(CSPNet)_Block] in Fig. 1 is presented in Fig. 2, where $C_n = C_i/2$ in the first three convolutional layers, W_o is a known quantity, and the C_o, K, and S of the last convolutional layer are listed in Table 1. As stated in Ref. 8, a CSPNet can be used to strengthen the learning ability of a convolutional neural network (CNN), remove computational bottlenecks, and reduce memory costs. Therefore, two cascaded residual network (ResNet)[9] blocks, i.e., ResNet_Blocks, were employed in the right branch of Fig. 2. The framework of a ResNet_Block is shown in Fig. 3 where three convolutional layers are used, and the parameters of the first two are listed in Table 1. Moreover, the squeeze-and-excitation network (SENet)_Block framework in Fig. 3 is illustrated in Fig. 4 where a SENet was employed.[10]

Compared with Ref. 6, two modifications in the model architecture were made in this paper. The first modification is the stem module in Fig. 1. The second is the SENet module that has been added within the ResNet_Block in Fig. 3. The rest of the model architecture remains the same as in Ref. 6.

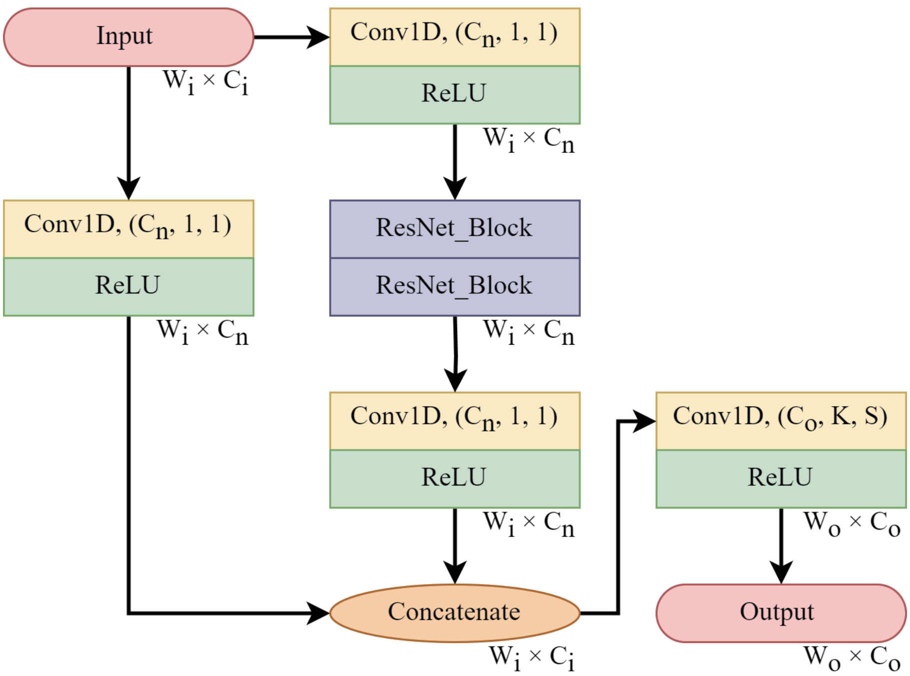

Fig. 2. (Color online) Framework of CSPNet_Block.

Table 1
Parameter setting in each CSPNet_Block and ResNet_Block.

Module		Parameters in each block		
		(C_o, K, S)	(C_1, K_1)	(C_2, K_2)
CSPNet_Block	ResNet_Block	(64, 15, 8)	(32, 3)	(32, 3)
CSPNet_Block	ResNet_Block	(128, 9, 5)	(64, 3)	(64, 3)
CSPNet_Block	ResNet_Block	(128, 1, 1)	(32, 1)	(32, 3)

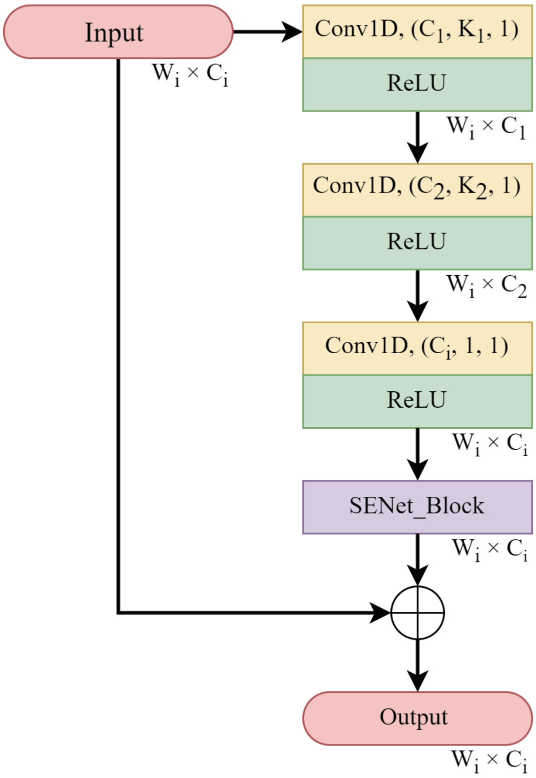

Fig. 3. (Color online) Framework of ResNet_Block.

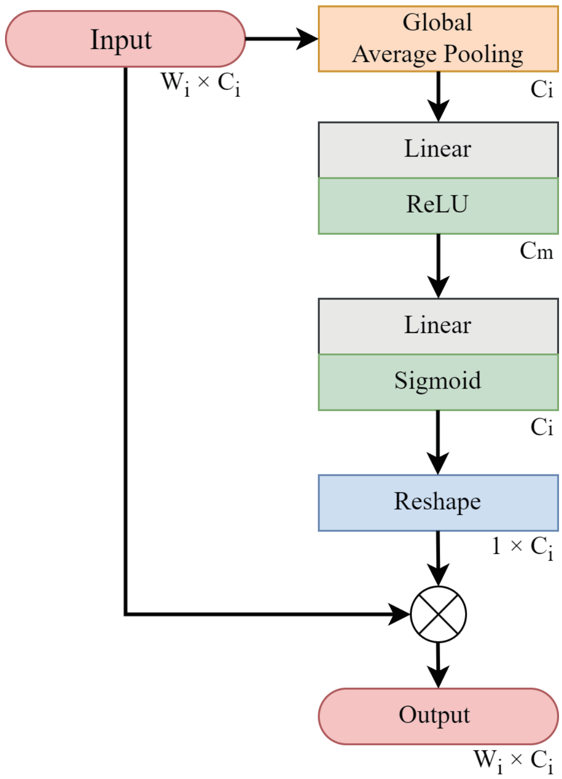

Fig. 4. (Color online) Framework of SENet.

This work was built by Python and PyTorch programming with a GeForce RTX 3090 graphics card. A categorical cross-entropy loss function and an Adam optimizer were used to train the presented model with a batch size of 64 and 300 epochs.

3. Experimental Results

To conduct a fair comparison, in this work, we trained and tested the model using the same datasets as those in Ref. 6, which are listed in Table 2. These data comprise three publicly available datasets, namely, the Sleep Heart Health Study (SHHS), MrOS, and MESA datasets, all of which were obtained from the National Sleep Research Resource (NSRR).[11] A total of 11381 and 5300 recordings were employed as the training and test sets, respectively.

Figure 5 gives a 4 × 4 confusion matrix for performance analysis on the test set. Additionally, the performance metrics including sensitivity, precision, F1-score, and overall accuracy are presented in Table 3. The sensitivities of 67.59, 57.36, 46.20, and 55.81% were obtained in the categories of normal, mild, moderate, and severe, while the F1-scores in normal, mild, moderate, and severe were 65.67, 53.93, 48.72, and 65.88%, respectively. The model has an overall accuracy of 57.91% for four-level OSA severity classification.

Two recently published counterparts, Refs. 6 and 7, were included as comparison subjects because their models were tested using a large amount of test data for a high generalization

Table 2
Training and test datasets used in this work.

Dataset	OSA severity category				Amount
	Normal	Mild	Moderate	Severe	
Training set	1654	3921	3296	2510	11381
Test set	1623	1848	1132	697	5300

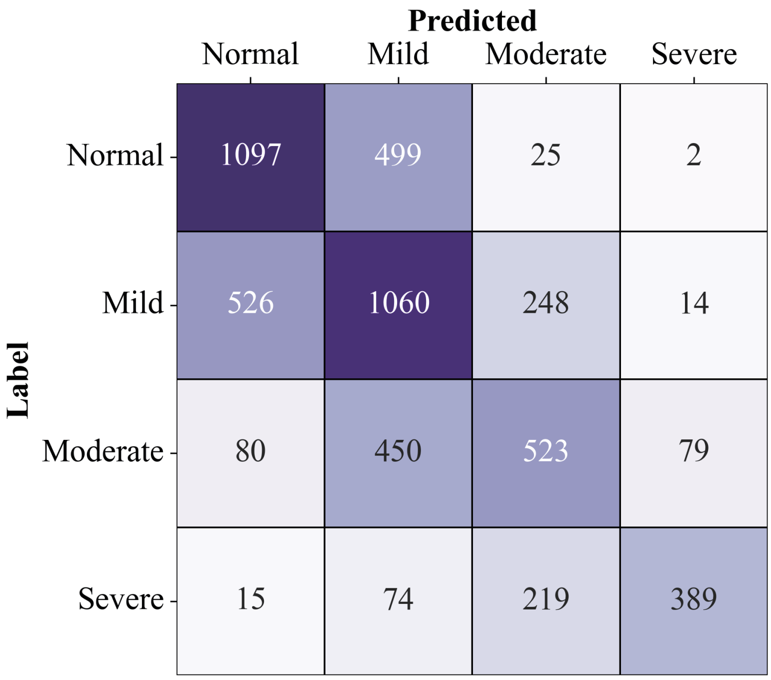

Fig. 5. (Color online) Confusion matrix for performance analysis.

Table 3
Performance metrics of the presented model.

Category	Sensitivity (%)	Precision (%)	F1-score (%)
Normal	67.59	63.85	65.67
Mild	57.36	50.89	53.93
Moderate	46.20	51.53	48.72
Severe	55.81	80.37	65.88
Accuracy (%)		57.91	

ability, unlike those tested using as few as 70 pieces of data from the Apnea-ECG dataset.(12) The overall accuracy reported in Ref. 6 was 57.55%, whereas it was 43.37% in Ref. 7. It is evident that we significantly outperformed Ref. 7 in terms of overall accuracy, that is, 57.91% vs 43.37%. Note that the sensitivity of the normal category in this work has been considerably increased by above 14% in comparison with our original work.

4. Conclusions

A method of improving the accuracy of OSA severity classification was presented in this paper. Modifications to the model architecture for OSA severity classification were made in this work, including adding an SENet module. Because the same approach of model input for OSA severity classification in our original work was adopted in this work, there is no doubt that all the aforementioned advantages of our original work are kept in this study. Our experimental results indicated that this work achieved an accuracy of 57.91% for four-level OSA severity classification, which is slightly higher than that of our previous research. Additionally, the method proposed here significantly outperforms the method described in Ref. 7.

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