

Murmur Classification with U-net State Prediction

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ABSTRACT

Background and Objective: Heart sounds are recorded which is known as phonocardiography (PCG). However, characteristic of PCG and influence of noise, the detection and classification of PCG are challenging. Generally, murmur is detected in systolic or in diastole state. Our team predicted four states of PCG and classified heart sound into three class that are absent, present, and unknown.

Methods: PCG signal were denoised by butterworth filter and spike removal method and then segmented into 4096 samples. S1, systolic, S2, diastole state was predicted by U-net model. The results of U-net prediction were used as feature along with the denoised PCG signal for classification. Considering the murmur locations, from the result of U-net model S1 and S2 state were replaced with zeros. Transformed denoised PCG signals were classified by ResNet multi-classification method.

Results: U-net accuracy of predicting four state of heart signal was 0.97. The mean squared error (MSE) score was 0.02. Moreover, standard deviation of systolic and diastole were 39ms and 61ms respectively. Our team MainLab's challenge training time according to the leaderboard was 1 hours 47 minutes, and Murmur weighted accuracy was 0.602 and outcomes was 9715 respectively.

Conclusion: Novelty of our proposed method is that murmur is detected on systolic and diastole state and, our method predicts additional information. Additional information in this case would be four states of heart sound S1, systolic, S2, and diastole. And classify murmur from PCG signal combined with predicted state of PCG.

1. INTRODUCTION

Phonocardiography is heart sound recorded by using digital stethoscope. The acquisition method of PCG is non-invasive and can provide early diagnoses of heart conditions. However, heart sound signal is weak and vulnerable to external noise. Despite the disadvantage of PCGs, digital stethoscope is low-cost measurement which are needed in developing countries.

According to the order of occurrence in cardiac cycle the heart sound is divided into four states: S1, systole, S2, and diastole. Generally, murmur is detected in systolic and diastole state. Therefore, segmenting state of heart sound is an essential step in analysis of PCG.

Heart Murmur Detection from Phonocardiogram Recordings: The George B. Moody PhysioNet Challenge 2022 presented large new data of heart sound measurement, each labelled absent, present, and unknown for murmur classification. [1]

Our team MainLab tackled the problem of classification of murmur by segmenting PCG signal by four states. U-net model segmented the PCG signals into four states and ResNet model was implemented for classification. [2]

2. METHODS

Our objective was to segment PCG signals into four states: S1, systolic, S2, and diastole and gain new feature of PCG signal for enhanced learning. Model overview is depicted in Figure 1. U-net model for labelling four state of signal and

multi-classification method was implemented. S1 and S2 state obtained by U-net model were replaced as zeros as shown in Figure 2. Transformed data are then trained. Modified ResNet model was used as classification model depicted in Figure 3.

2.1. Datasets and Preprocessing

The dataset contains 3163 recordings from 942 patients and sampling rate of each recording are 4000Hz. Each record was segmented to 4096 sampling points which is approximately 1 second. Shown in Table 1, when segmenting PCG signal unannotated state segments of the signals were excluded resulting total of 3214 segmented present data, 741 segmented unknown data, and 13298 segmented absent data. Train and test set data ratio were 5:1.

After segmentation, dataset was preprocessed. Denoised methods implemented in our study were 25~400Hz 4th butterworth bandpass filter and spike removal method. [2] For spike removal maximum absolute amplitude (MAA) is calculated in each window size of 500 sampling points. MAA that exceeds three times the mean value of MAA the corresponding point were detected as spike for removal which was replaced to zero.

Each patient records have up to four different measurement location that are pulmonary valve (PV), tricuspid valve (TV), aortic valve (AV), and mitral valve (MV). Phc records corresponding to any other auscultation location were excluded. Moreover, patient with missing measurement location were replaced as zero value.

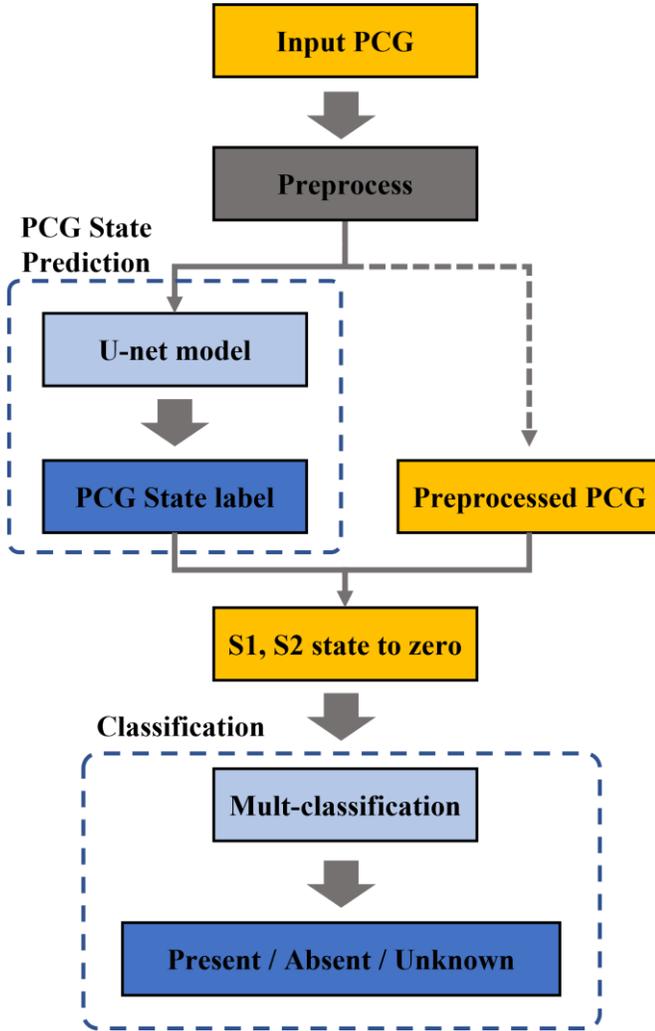


Figure 1. Model overview of proposed method.

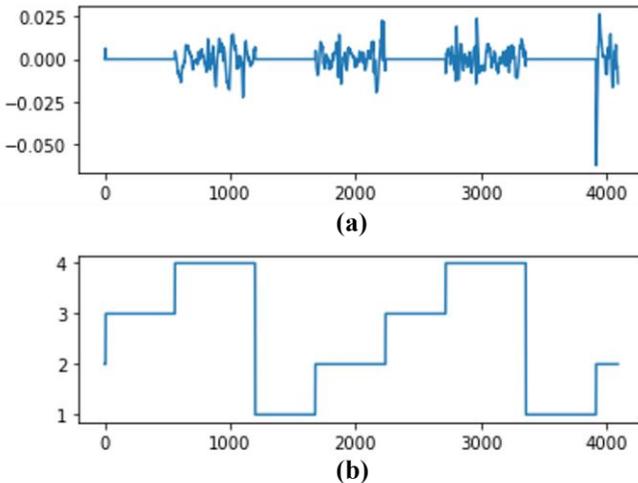


Figure 2. Result of S1 and S2 state values replaced with zeros are shown in (a). The state label is depicted in (b) where S1 is 1, systolic is 2, S2 is 3, and diastole is 4.

Table 1. Dataset number of recordings and segments.

	Present	Unknown	Absent	Total
Patient	179	68	695	942
Segment	3214	741	13298	17253

2.2. Model description

The U-net model is depicted in Figure 3. To avoid the bottleneck skipped connection, all channels were concatenated at corresponding layers [3]. The encoder part consisted of four residual blocks with convolution layers. Same residual block was used as in the classification model depicted in Figure 4. Batch normalization and ReLU were used except for the first layer. The decoder consisted of four up convolutions. The last layer of the decoder part, ReLU was used as an activation function. The learning rate was 0.005 and batch size was 32; the kernel size and stride length were 4 and 2, respectively.

ResNet model is shown in Figure 4. Convolution layer, max pooling layer following with two residual blocks were used as one block. Total of five blocks were stacked. The first layer and initial two block have 16 convolution filters. Number of filters increases by a factor of two by each block. Kernel size decreases by two starting from nine. Learning rate and dropout were 0.001 and 0.2 respectively. The model was trained for in total 150 epochs.

2.3. Model evaluation

Mean squared error score and standard deviation were calculated to evaluate U-net model. The mean squared error measures the average of squared difference between the predicted state label (X) and reference label (Y) as shown in (1)

$$MSE = \frac{1}{N} \sum_{i=1}^N (X_i - Y_i)^2 \quad (1)$$

Moreover, the standard deviation of duration difference of predicted state of systolic and diastole were calculated to evaluate performance of U-net model. Lower MSE score and standard deviation the better performance of the model. Classification model was validated by challenge metrics in which our team scored 0.602 accuracy provided by the Challenge submission system.

3. RESULTS

Figure 5 shows the difference between predicted state label and reference state label. The performance of state segmentation effects our classification results. Therefore, the standard deviation was calculated as mentioned in section 2.3 model evaluation. Standard deviation for systolic and diastole were 39ms and 61ms respectively. Moreover, the MSE value were 0.002.

Confusion matrix of 3451 test set segment classification results is shown in Figure 6. The precision and f1-score are shown in Table2.

Overall models were validated by challenge metrics in which our team scored 2712 provided by the Challenge submission system.

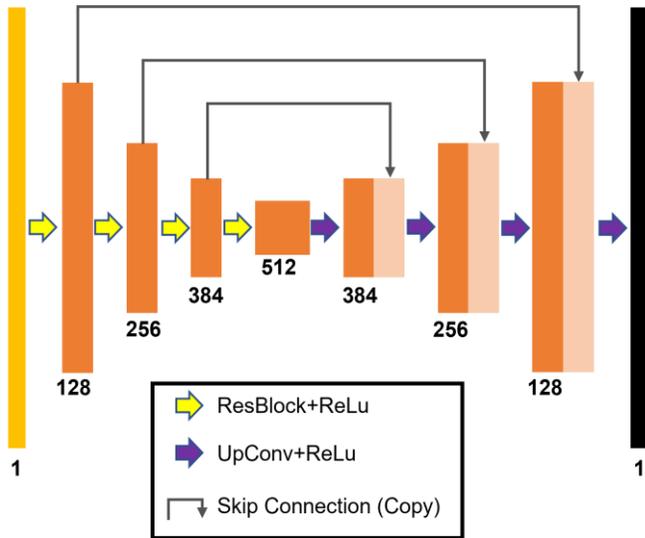


Figure 3. U-net architecture model.

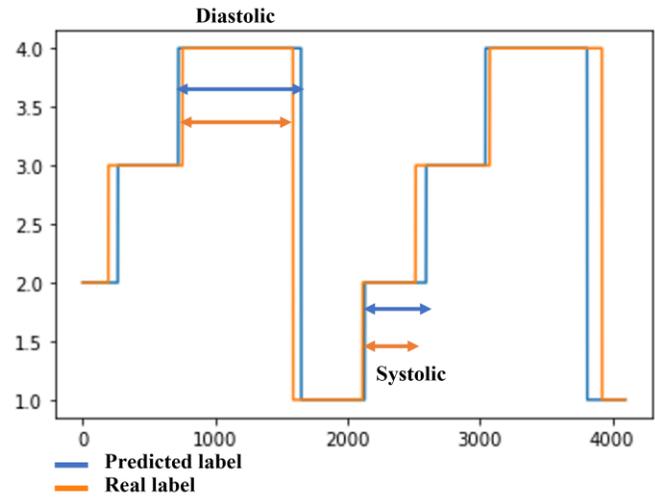


Figure 5. Result of predicted state. Blue line represents the predicted state, and the orange line represents the reference state segment of heart sound. Duration of systolic and diastole length between predicted and reference are not same.

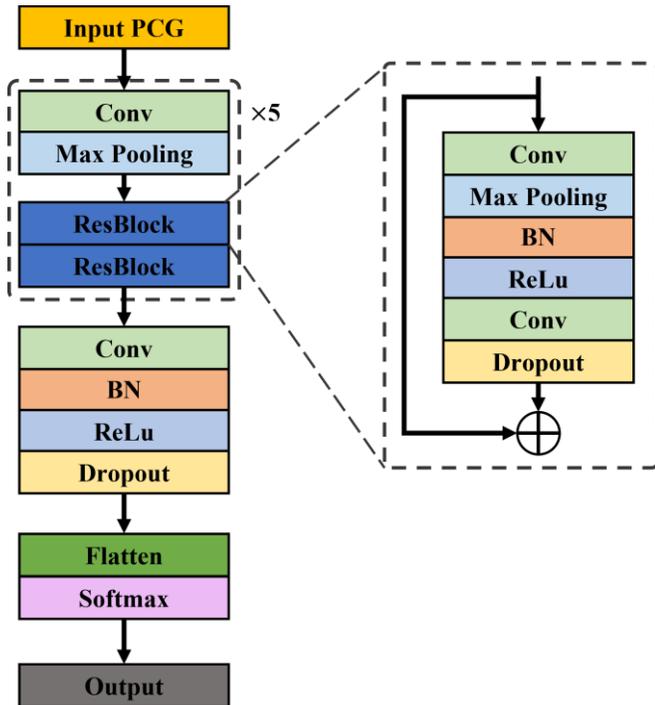


Figure 4. Classification model architecture.

Present	319	9	285
Unknown	4	6	124
Absent	139	48	2517
	Present	Unknown	Absent

Figure 6. Confusion matrix of test set.

Table 2. Precision and F1-score of Test set.

	Precision	F1-score
Present	0.69	0.59
Unknown	0.10	0.06
Absent	0.86	0.89

4. DISCUSSION

We have proposed murmur classification by using systole and diastole region obtained by U-net segmentation model. Our approach was to classify unknown, absent, and present. Low MSE score and standard deviation shown great performance of segmentation of four state of heart sound. However, classification results low.

U-net segmentation results were promising, however classifying absent, present, and unknown were not. The main limitation was mainly due to lack of unknown data and its unclearness. Our model outcome relies mostly on U-net segmentation. Despite the low standard deviation and low MSE score there are still difference between predicted state and reference state. And replacing S1, and S2 state in PCG according to the result of U-net model may have excluded the murmur.

Obtaining additional information from PCG signal to detect murmur is novelty of our proposed method. In this case additional information would be S1, systolic, S2 and, diastole

state which are the main component of heart sound. In the future work, we intend to improve our model by segmenting input data by same cycle. Each segment's start point would be S1 and end point as diastole. Also, instead of replacing S1 and S2 state data as zero, different weight values for each state will be given.

REFERENCES AND FOOTNOTES

A. References

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