

스마트 서비스 응용



Multi-classification of Respiratory Diseases through Dimension Combinations

Disease diagnosis using respiration data

Introduction

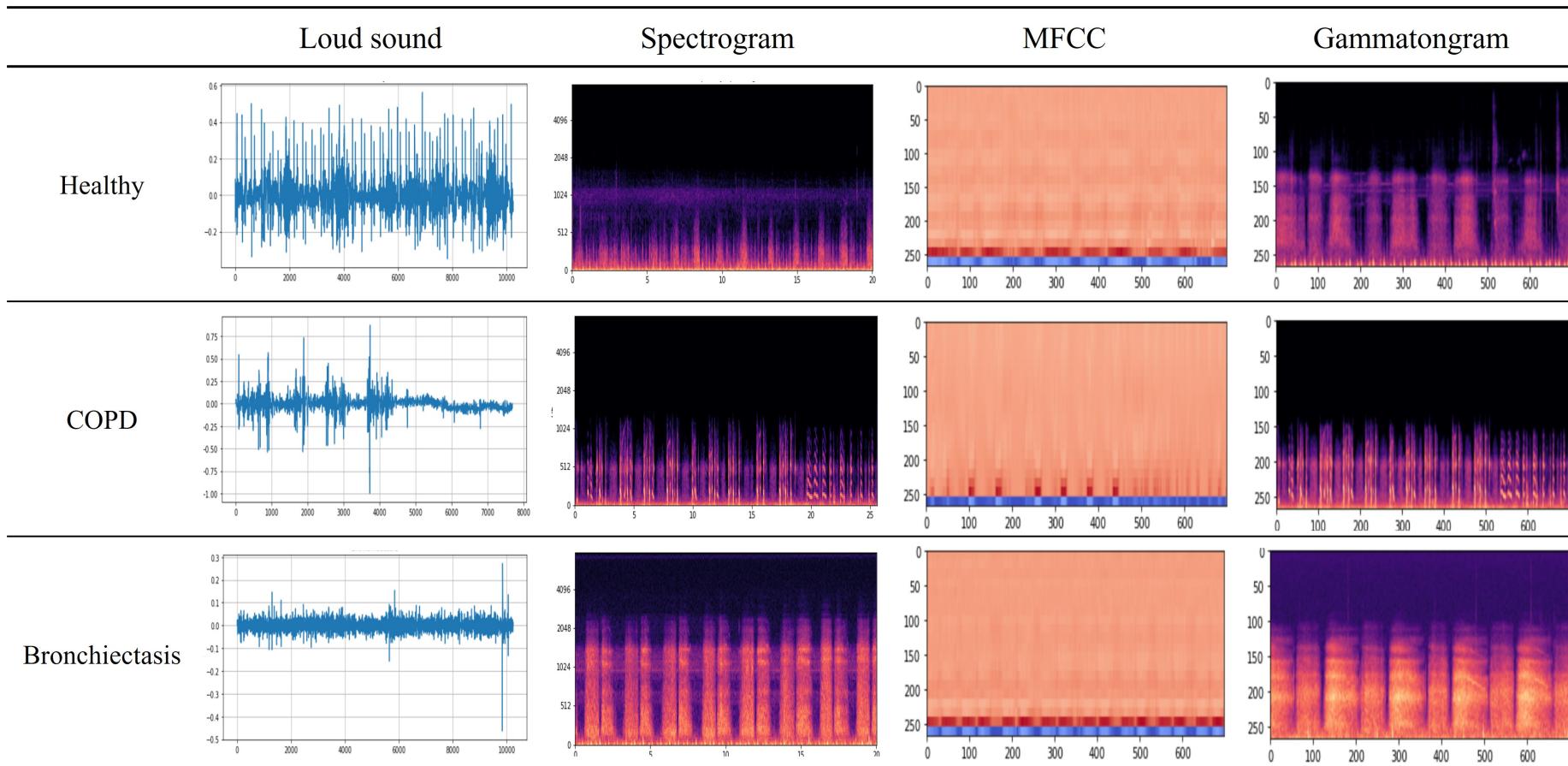
- Research on classification of respiratory data for multiple classification of lung diseases is actively underway.
 - In previous studies, methods such as spectrogram and gammatogram, which are 2D image conversion methods, are used.
 - However, the performance for respiratory disease multi-class classification is still poor.
- ⇒ Conduct multi-classification study of respiratory diseases through combination of 1-dimensional and 2-dimensional features
- ⇒ Advantage of fast learning speed of 1D model + Advantage of high accuracy verification of 2D model
- ⇒ Improved model learning speed and accuracy compared to using only the existing 2D converted image

Method

- Disease diagnosis using respiration data (ICBHI 2017 Challenge Dataset)
 - ① Pathological data classification task (Normal/Abnormal)
 - 1) Learning by converting to one-dimensional value
 - 2) Learning by converting to 2-dimensional images (spectrogram, gammatogram, MFCC)
 - 3) Learning using a combination of 1D and 2D features
 - ② Disease multi-classification task
 - 1) Learning by converting to one-dimensional value
 - 2) Learning by converting to 2-dimensional images (spectrogram, gammatogram, MFCC)
 - 3) Learning using a combination of 1D and 2D features

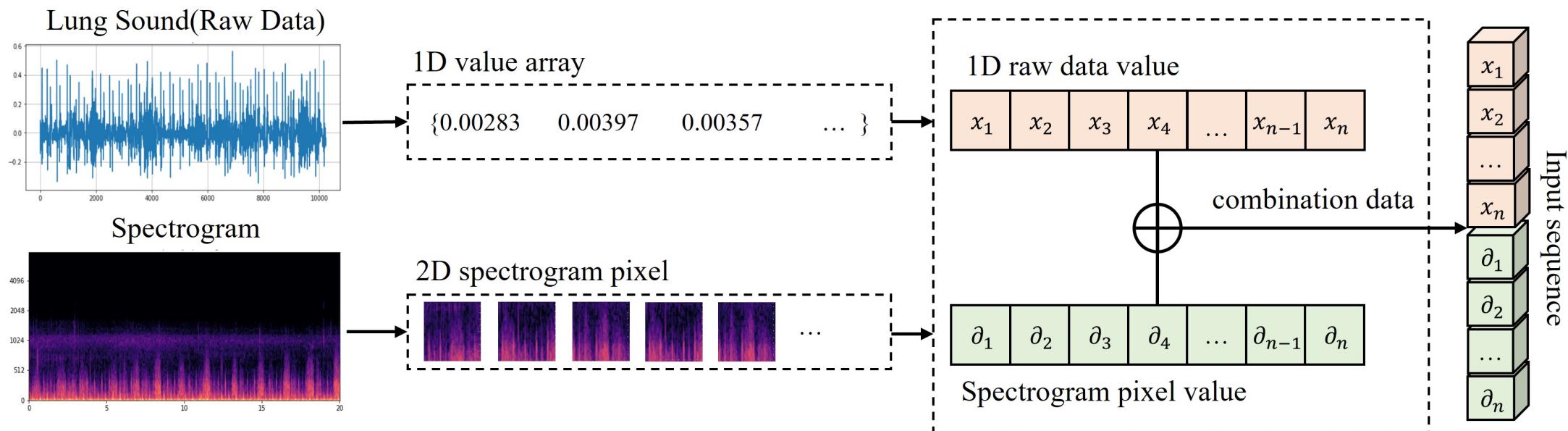
Method

1) Learning by single data



Method

2) Learning using a combination of 1D and 2D features

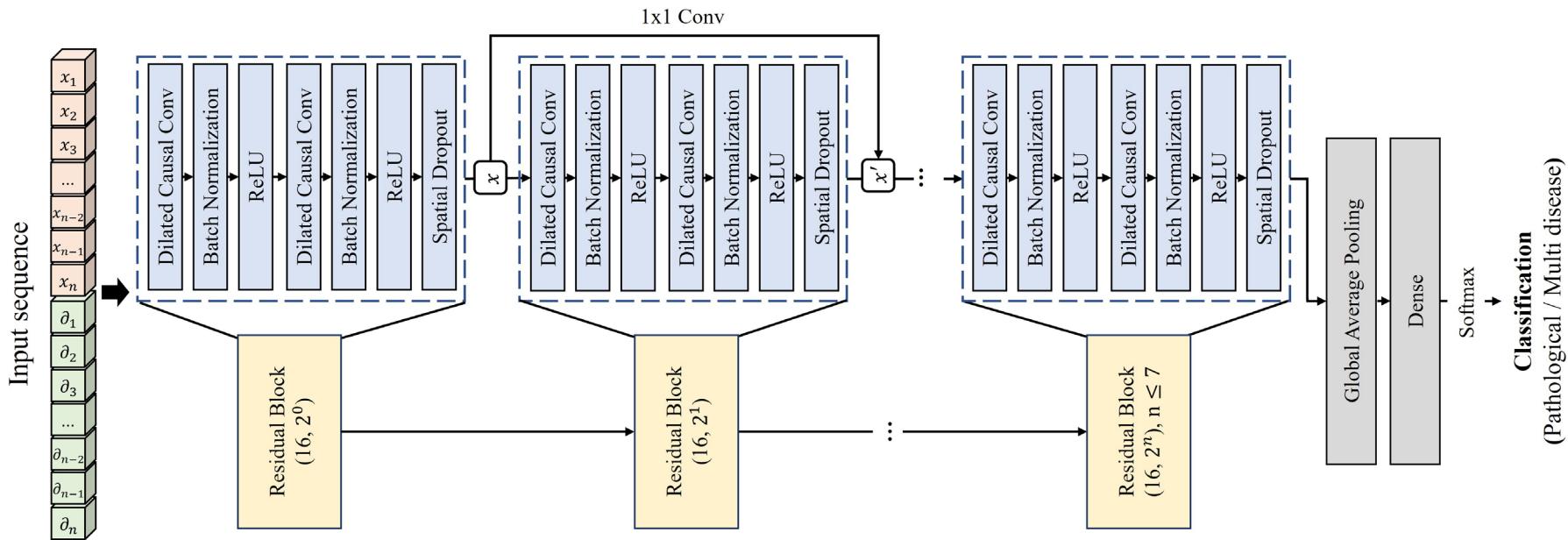


Method

- Time series models

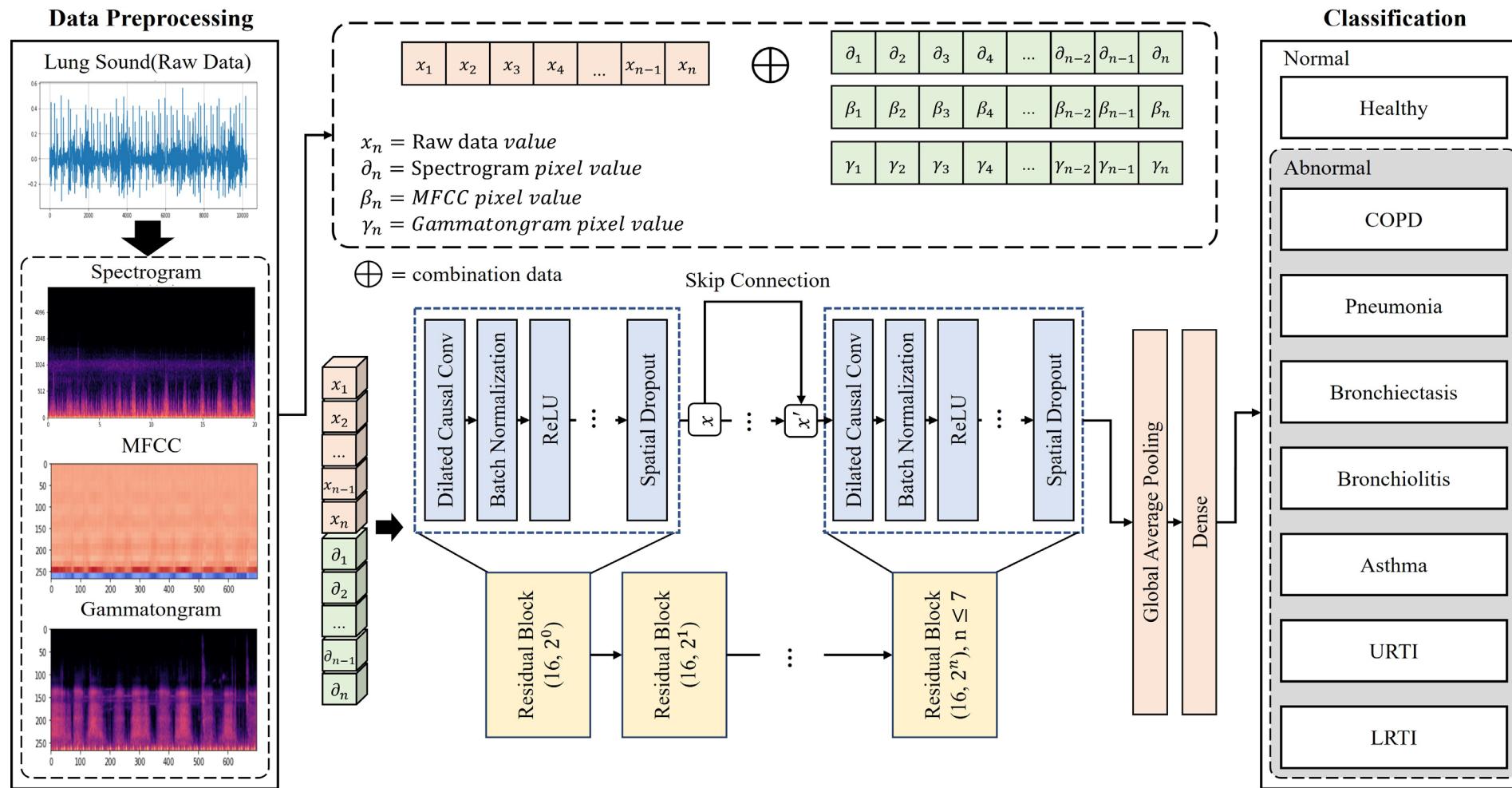
1. TCN(Temporal Convolutional Network)

- It is a cnn-based model proposed in 2018 and used for processing time-series data such as natural language and music.
- Characteristics of parallel processing and flexible receptive field size
- It shows longer effective memory and higher performance than rnn-based LSTM/GRU.



Method

- Process



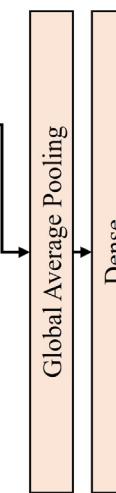
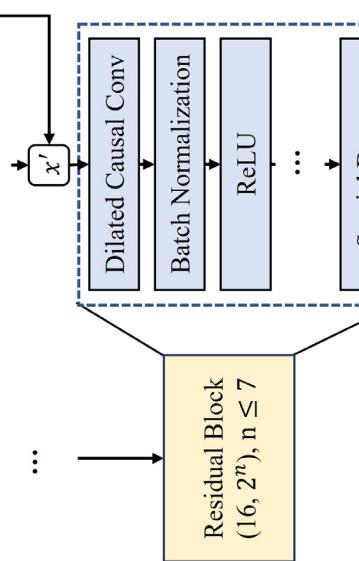
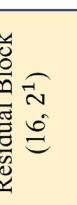
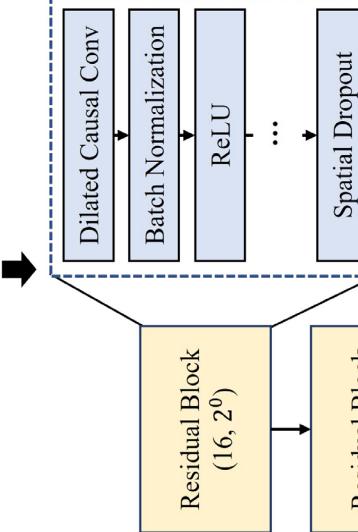
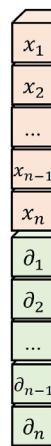
x_n = Raw data value
 ∂_n = Spectrogram pixel value
 β_n = MFCC pixel value
 γ_n = Gammatongram pixel value



∂_1	∂_2	∂_3	∂_4	...	∂_{n-2}	∂_{n-1}	∂_n
β_1	β_2	β_3	β_4	...	β_{n-2}	β_{n-1}	β_n
γ_1	γ_2	γ_3	γ_4	...	γ_{n-2}	γ_{n-1}	γ_n

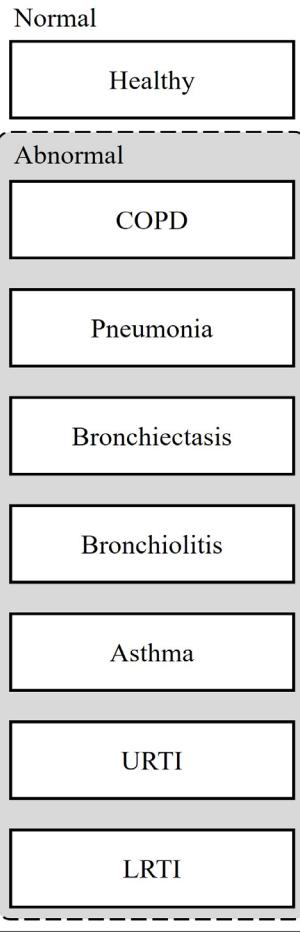
\oplus = combination data

Skip Connection



Dense

Classification



Experiment Result

- Comparison of experiment results

1) Disease classification

① Accuracy

1D Model+1D Data(Vector)			2D Model+2D Data(Spectrogram)		
2D Model+2D Data(Gammatongram)			2D Model+2D Data(MFCC)		
TCN	ICBHI	Signal	88.04%	VGG	92.93%
Wavenet		Resnet	87.03%	ICBHI	90.76%
Bi-LSTM		Transformer	75.00%	Spectrogram	89.13%

TCN	ICBHI	Signal + MFCC	88.58%
Wavenet			88.04%
Bi-LSTM			88.50%
1D Model+(1D Data+MFCC)			
TCN	ICBHI	Signal + Spectrogram	92.934%
Wavenet			90.22%
Bi-LSTM			87.50%
1D Model+(1D Data+Spectrogram)			
TCN	ICBHI	Signal + Gammatongram	91.30%
Wavenet			90.76%
Bi-LSTM			87.50%
1D Model+(1D Data+Gammatongram)			

② Training time(100 epoch)

Model	VGG	Resnet	Transformer	TCN	Wavenet	BiLSTM
Training Speed	350.31s	260.03s	280.17s	89.35s	199.64s	99.07s

Experiment Result

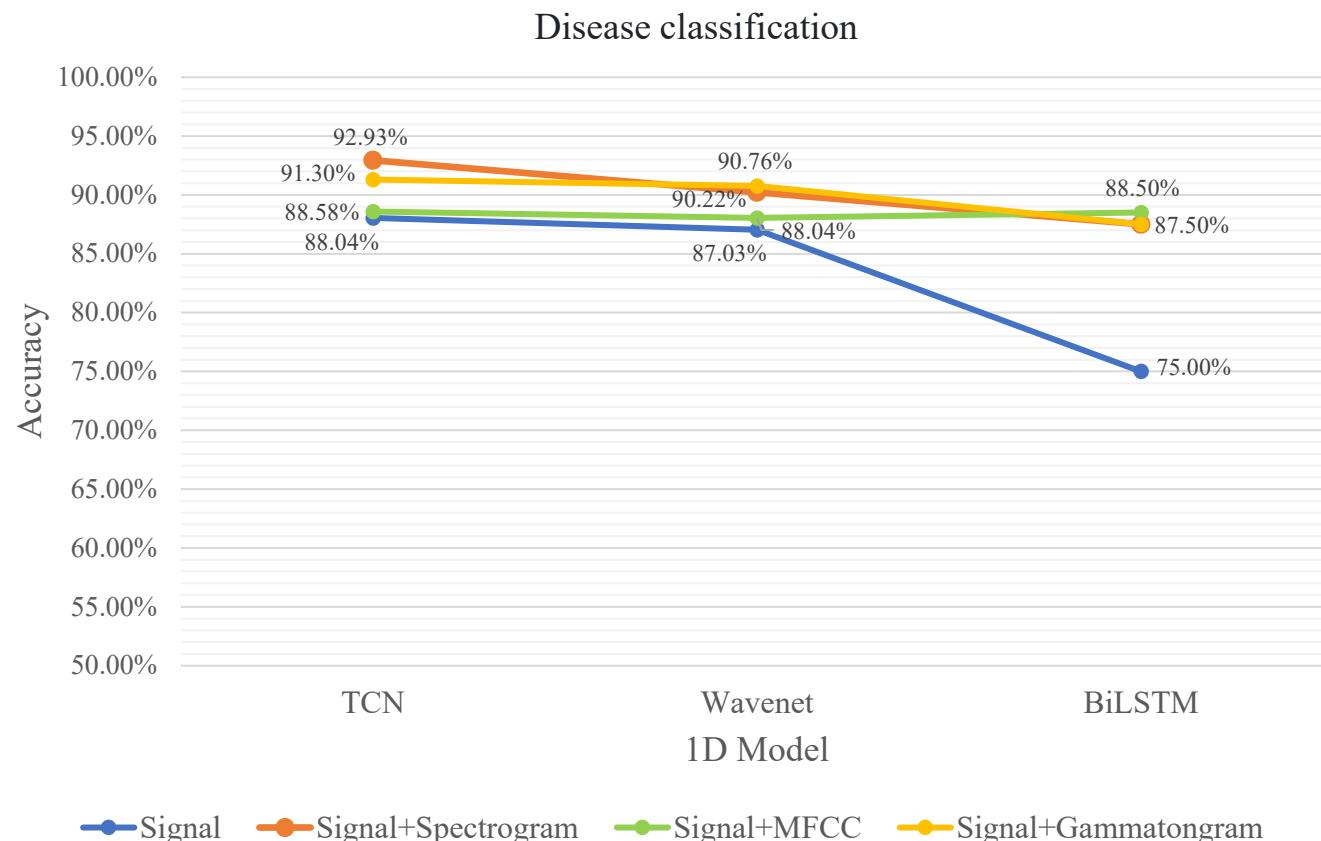
- Comparison of experiment results

Task	Data	Model	Data Type	Auccuracy
Disease classification	ICBHI	TCN	Signal	88.04%
		Wavenet		87.03%
		Bi-LSTM		75.00%
		VGG	Spectrogram	92.93%
		Resnet		90.76%
		Transformer		89.13%
		VGG	Gammatongram	91.30%
		Resnet		89.13%
		Transformer		87.50%
		VGG	MFCC	91.85%
		Resnet		90.21%
		Transformer		87.52%
Disease classification	ICBHI	TCN	Signal+Spectrogram	92.934%
		Wavenet		90.22%
		Bi-LSTM		87.50%
		TCN	Signal+Gammatongram	91.30%
		Wavenet		90.76%
		Bi-LSTM		87.50%
		TCN	Signal+MFCC	88.58%
		Wavenet		88.04%
		Bi-LSTM		88.50%

Experiment Result

- Comparison of experiment results

2) Accuracy (1D Model)



Conclusion

- Improvement of respiratory disease multi-classification accuracy by considering both 1D data features and 2D data features
- Speeding up learning using 1D models
- Accuracy improvement using 2D data features
- 4.63% accuracy improvement over existing studies in multi-disease data classification
- Federated learning can be applied for personal information protection