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Interpretable one-dimensional AlexNet for detecting ineffective efforts during expiration in mechanical ventilation

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Background and Objective

Ineffective efforts during expiration (IEE) is one of the most common manifestation of patient-ventilator asynchrony (PVA) in mechanically ventilated patients. Because the poor interaction between the patient and the ventilator is associated with inferior clinical outcomes, every effort should be made to identify and correct their occurrence. Deep learning has shown promising ability in PVA detection; however, lack of interpretability hampers its application in clinic.

Methods

We proposed an interpretable one-dimensional convolutional neural network (1DCNN) to detect IEE in pressure control ventilation (PCV) mode. Class activation map (CAM) was incorporated with a 1DCNN model to visualize which sections of the waveform was focused on when the model made a classification. Fig. 1 illustrates the proposed 1DCNN architecture and the class activation mappings work flow.

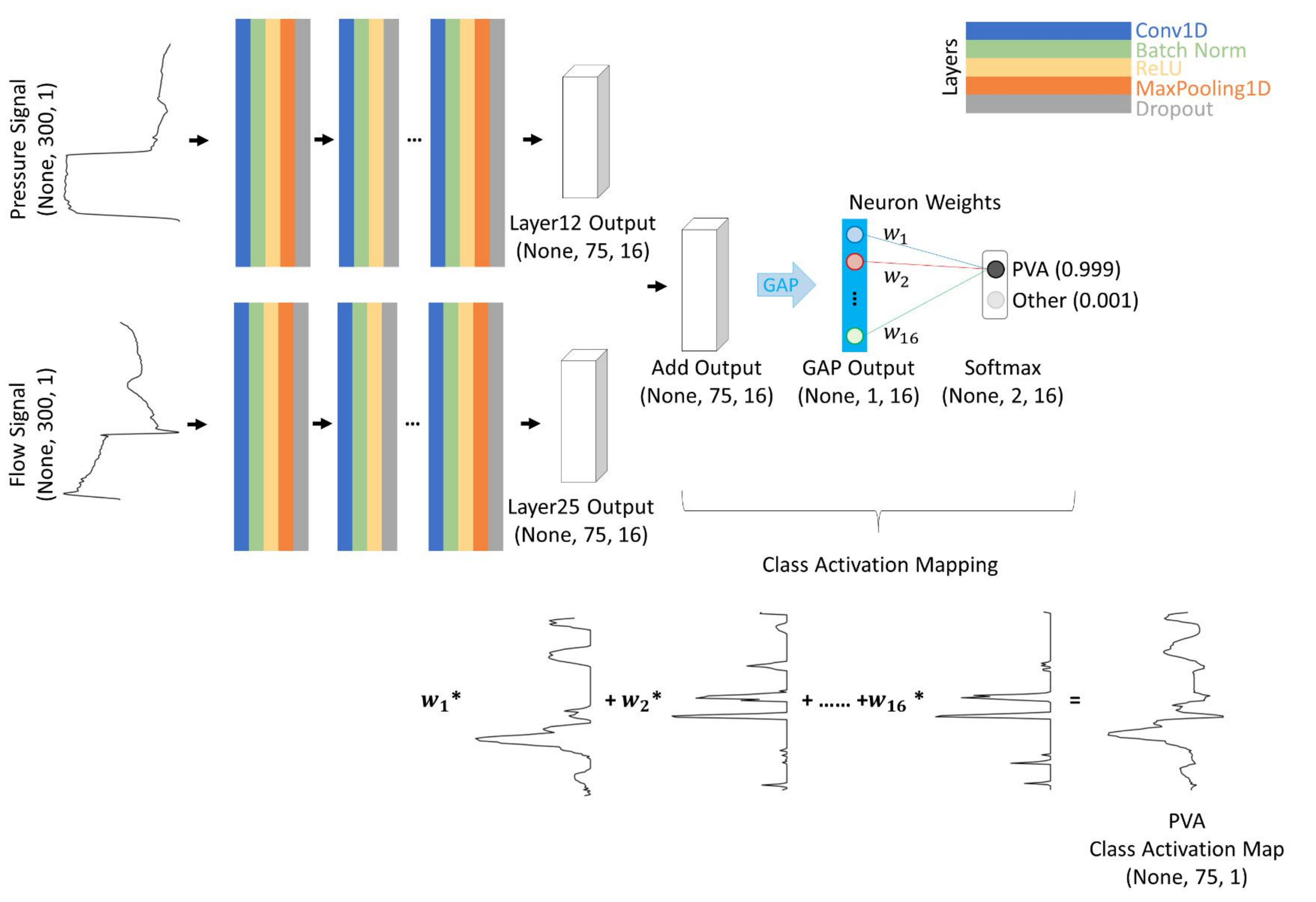

Fig. 3. Architecture of the proposed 1DCNN network with the procedure for generating CAM.

Results

The proposed interpretable 1DCNN exhibits comparable performance with the state-of-the-art deep learning model, with the F1 score of 0.973 for IEE detection. The performance of the networks is evaluated using 5-fold cross validation and result was given in Table 1. The sections of the waveform highlighted by the CAM are consistent with the understanding of this type of PVA by experts. The interpretation of the classification is illustrated in Fig. 2.

Table 1. The overall performance of the networks.

	Acc	Sen	Spe	F1
1DCNN	0.973± 0.003	0.984± 0.007	0.963± 0.007	0.973± 0.004
2-layer LSTM	0.971± 0.003	0.984± 0.006	0.959± 0.003	0.970± 0.003

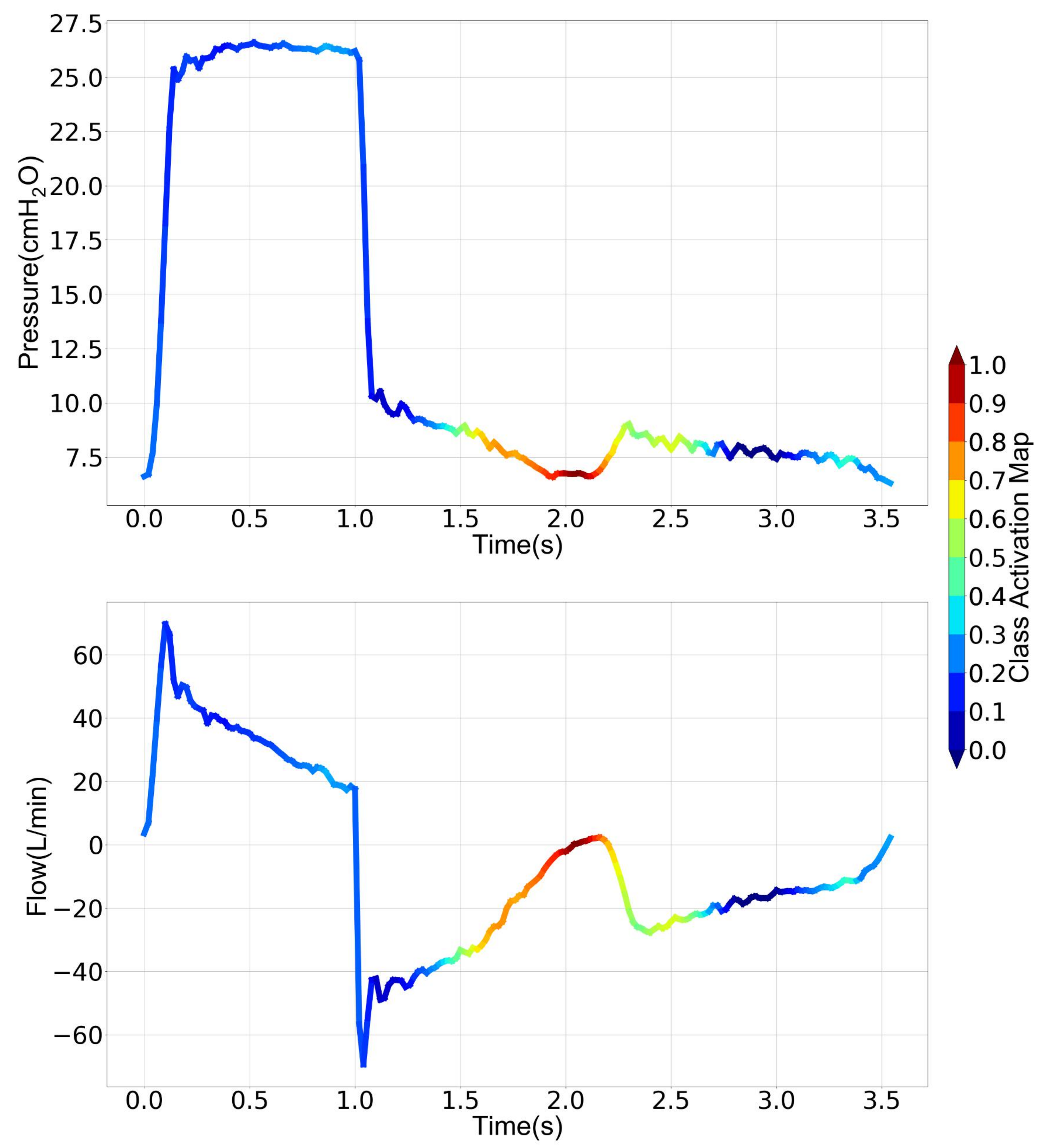

Fig. 2. The interpretation of the classification of IEE.

Conclusions

The findings suggest that the proposed 1DCNN can help detect PVA, and enhance the interpretability of the classification process that help clinicians to better understand the deep learning technology.

References

[1] E.-M. Antonogiannaki, D. Georgopoulos, E. Akoumianaki, Patient-Ventilator Dyssynchrony, Korean J Crit Care Med, 32 (2017) 307-322.
[2] M. de Wit, K. B Miller, D. A Green, H. E Ostman, C. Gennings, S. K Epstein, Ineffective triggering predicts increased duration of mechanical ventilation, 2009.
[3] L. Zhang, K. Mao, K. Duan, S. Fang, Y. Lu, Q. Gong, F. Lu, Y. Jiang, L. Jiang, W. Fang, X. Zhou, J. Wang, L. Fang, H. Ge, Q. Pan, Detection of patient-ventilator asynchrony from mechanical ventilation waveforms using a two-layer long short-term memory neural network, Computers in biology and medicine, 120 (2020) 103721.
[4] D. Li, J. Zhang, Q. Zhang, X. Wei, Classification of ECG signals based on 1D convolution neural network, 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom), 2017, pp. 1-6.
[5] B. Zhou, A. Khosla, À. Lapedriza, A. Oliva, A. Torralba, Learning Deep Features for Discriminative Localization, 2016.