An interpretable deep learning model for time-series electronic health records: Case study of delirium prediction in critical care

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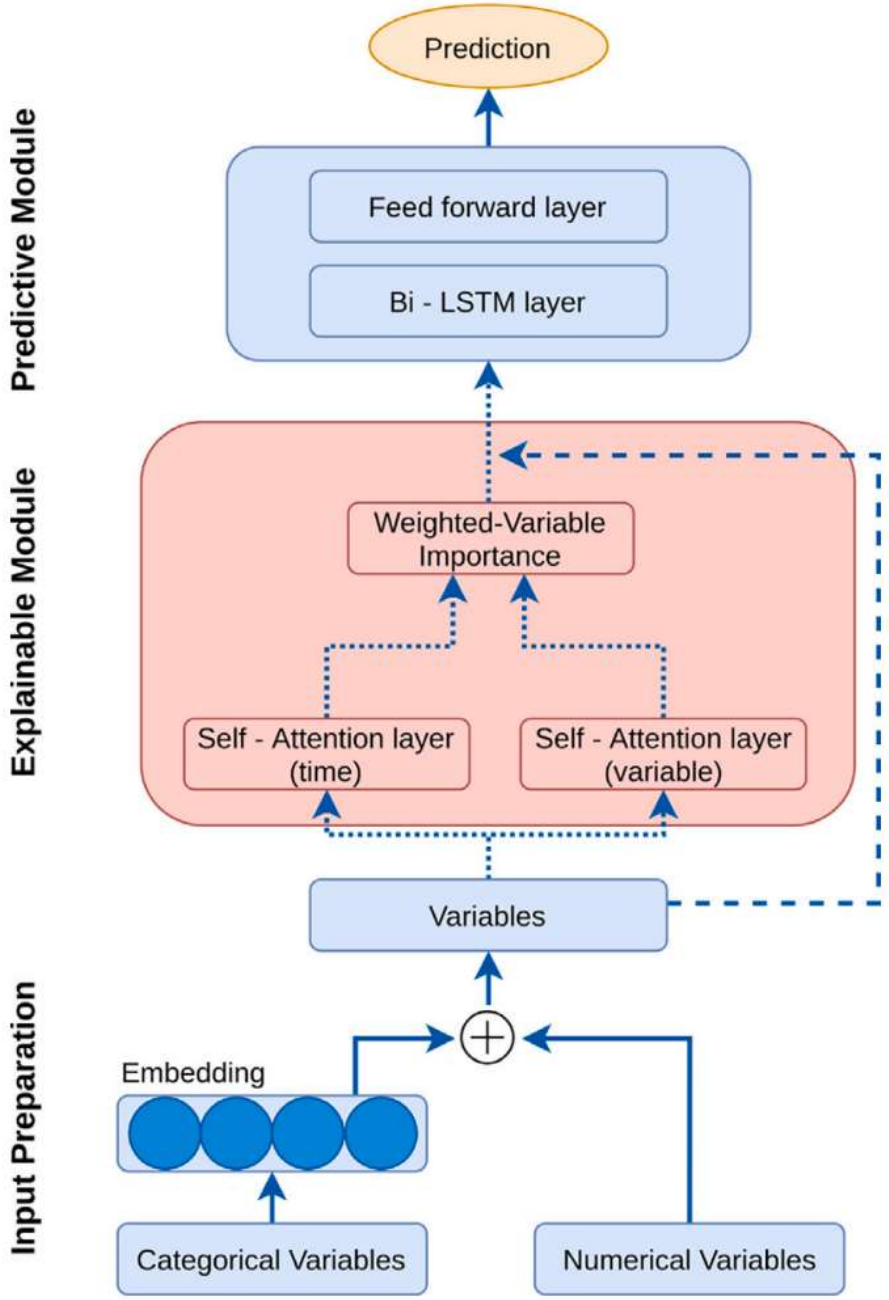
Introduction

- Conventional machine learning models have been used in the **intensive care unit (ICU)**, which are interpretable but cannot capture non-linear relationship in data.
- It is because the data in ICU is recorded in a **time-series** and conventional ML models do not have an intrinsic ability to deal with time-series inputs.

Proposed Method

- Each patient can be viewed as a sequence of medical records (vital signs, laboratory measurements, and demographics) ordered by time, and each record contains a set of clinical variables including **numerical and categorical variables**.
- Categorical variables are represented using **entity embedding**.



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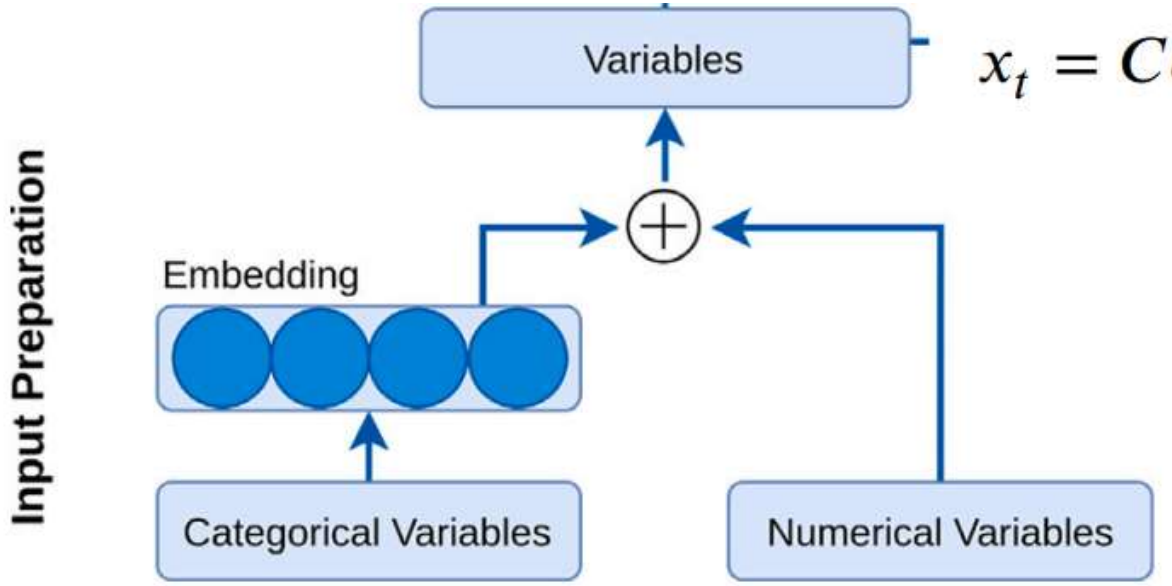
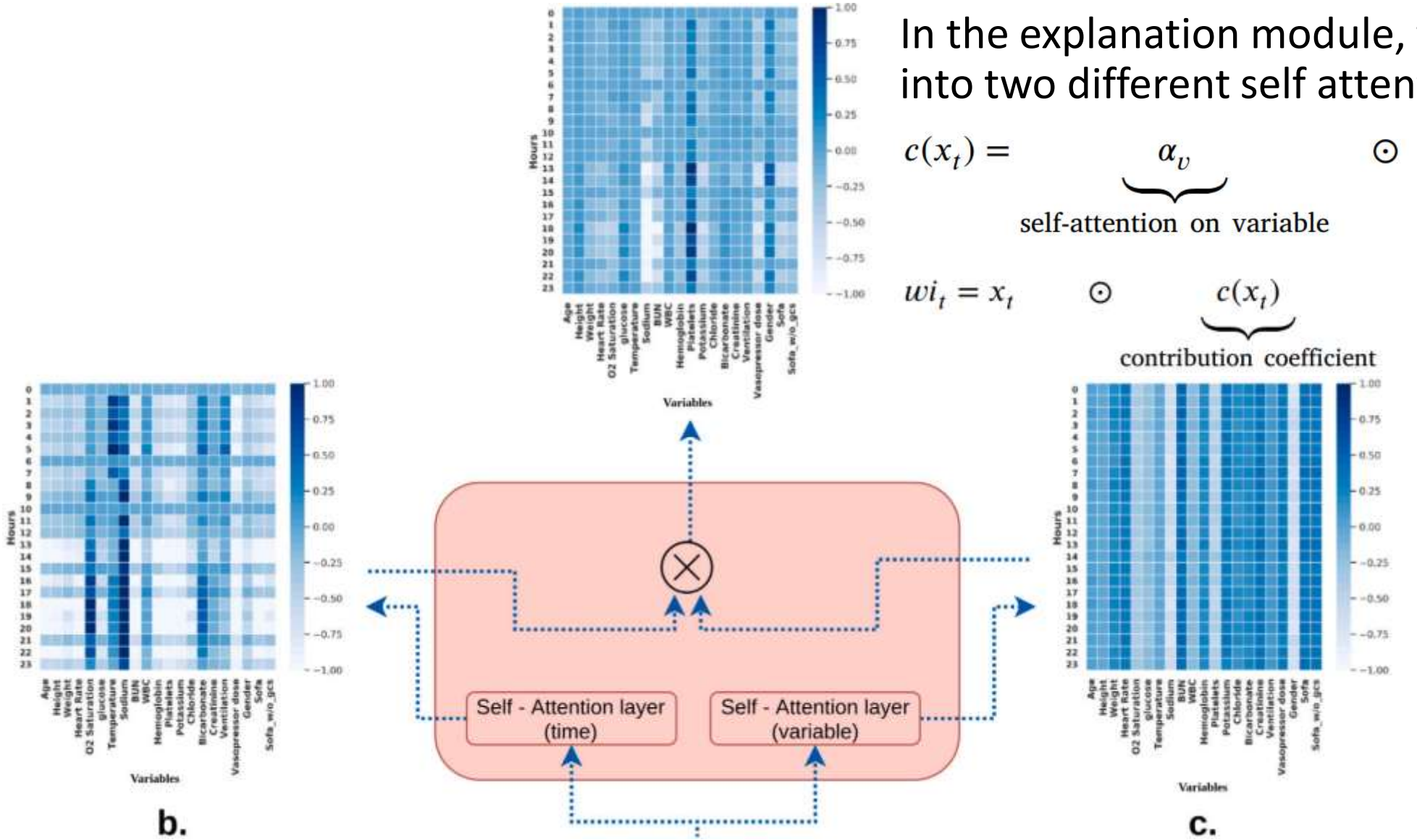
Proposed Method



$$x_t = Concat[Numerical_t, U(Categorical_t)]$$

- $Numerical_t$ stands for the numerical variable, $Categorical_t$ stands for the categorical variable at time t, and U is the embedding matrix.

Proposed Method



In the explanation module, the input x_t is fed into two different self attention layers

$$c(x_t) = \underbrace{\alpha_v}_{\text{self-attention on variable}} \odot \underbrace{\alpha_t}_{\text{self-attention on time}}$$

$$wi_t = x_t \odot \underbrace{c(x_t)}_{\text{contribution coefficient}}$$

Experiment Results

Predictive performance on MIMIC-III dataset.

Model	Observation window 12 h – Prediction window 48 h			
	AUROC% (95% CI)	AUPRC% (95% CI)	Precision% (95% CI)	Recall% (95% CI)
BiLSTM	71.37 (67.99–74.72)	29.81 (27.33–31.88)	28.45 (25.74–31.17)	65.98 (59.82–72.13)
DSA	68.66 (64.99–72.33)	28.58 (23.64–33.20)	26.70 (22.56–30.85)	59.85 (51.93–67.77)
Kaji model	67.56 (64.91–70.22)	27.90 (25.68–30.46)	24.31 (22.01–26.60)	58.07 (52.48–63.66)
Model	Observation window 24 h – Prediction window 12 h			
	AUROC% (95% CI)	AUPRC% (95% CI)	Precision% (95% CI)	Recall% (95% CI)
BiLSTM	81.24 (76.44–86.11)	44.45 (40.35–48.81)	35.03 (30.73–39.33)	71.16 (64.54–77.77)
DSA	80.50 (77.23–83.85)	44.90 (41.28–49.40)	35.58 (33.71–37.44)	68.98 (62.69–75.27)
Kaji model	78.33 (76.11–80.62)	41.69 (38.55–45.15)	32.39 (28.52–36.25)	65.63 (57.78–73.48)

Table 4
Predictive performance on eICU-CRD dataset. Highlighted in bold are results with statistically significant differences.

Model	Observation window 12 h – Prediction window 48 h			
	AUROC% (95% CI)	AUPRC% (95% CI)	Precision% (95% CI)	Recall% (95% CI)
BiLSTM	84.20 (82.52–85.86)	33.24 (29.41–36.54)	**28.37 (27.15–29.58)**	74.44 (70.91–77.98)
DSA	82.51 (80.33–84.67)	31.21 (28.01–33.70)	24.92 (24.22–25.61)	75.99 (72.20–79.78)
Kaji model	81.64 (80.05–83.27)	30.19 (27.41–32.27)	24.60 (23.23–25.97)	75.00 (70.56–79.44)
Model	Observation window 24 h – Prediction window 12 h			
	AUROC% (95% CI)	AUPRC% (95% CI)	Precision% (95% CI)	Recall% (95% CI)
BiLSTM	88.02 (86.31–89.75)	42.69 (38.71–46.1)	**38.19 (36.78–39.6)**	80.39 (76.62–84.16)
DSA	87.10 (85.15–89.03)	42.20 (38.78–45.69)	34.17 (32.88–35.46)	82.89 (78.54–87.25)
Kaji model	85.85 (84.16–87.57)	38.03 (34.64–41.02)	35.82 (34.48–37.15)	76.63 (72.84–80.42)

Conclusion

- This study demonstrated that DSA, can learn importance of variables for predicting delirium where the individual variables underlying these predictions can be explored using attention mechanisms.