Rapid Response System

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University of Virginia dataset

- Dataset from University of Virginia (UV) [1]
- Represents the 63 years data of **8,105** acute care patients admitted to a tertiary care academic medical center
- Measurement features:
  - Vital signs measurements (7): temperature, HR, blood pressures, RR, oxygen saturation (SpO2), oxygen flow rate, Glasgow Coma Scale.
  - LABS (24): Albumin, calcium, chloride, glucose, etc.
  - ECG monitoring (15)
- Labels:
  - Non-event patients (all timepoint labeled as 0): never had to be transferred to ICU
  - Event patients (contain both 0 and 1 timepoint): performed the early signs **24 hours** prior to the ICU transfer

UV dataset

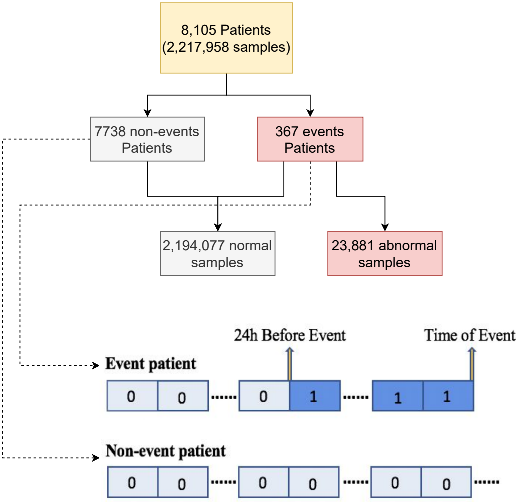

Figure: UV dataset

Table: UV data characteristics ($n = 8,105$) (CI: confidence interval).

Characteristic	Value
Patients characteristic ($n = 8,105$)	
Age (years), mean (95% CI)	63.74 (63.42 - 64.07)
Race (white/black/other), n(%)	6559(80.9%)/ 1374(16.9%)/ 172(2.2%)
Vital signs (number of features)	7 features
Laboratory test (number of features)	24 features
ECG monitoring (number of features)	15 features
Clinical status (even/ non-event), n(%)	367 (4.5%)/7738 (95.4%)

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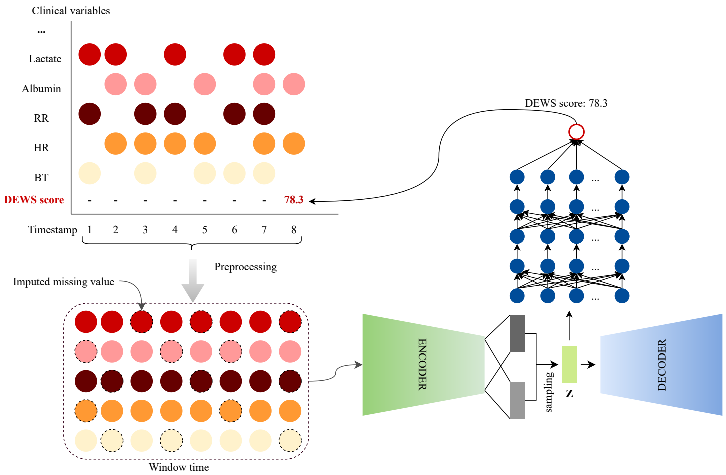

Figure: The overall framework of proposed Temporal Variational Autoencoder base Deep Early Warning System (TVAEDEWS). DEWS score = abnormal probability.

Temporal window sliding mechanism

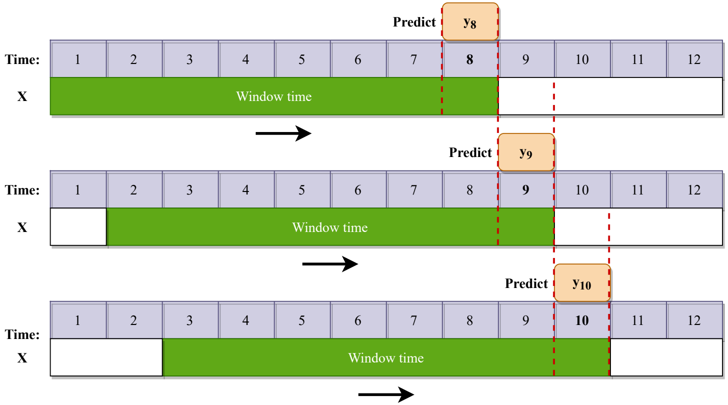

Figure: Process of sliding window mechanism working on proposed system. x denoted for input patient's measurement features, y presented output patient's event probability. Window time size $W = 8$; sliding step $k = 1$.

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Experiment setting

- For the UV dataset, select $1,000$ among $7,738$ normal patients and select all 367 abnormal patients for experiment.
- Compare with FCNs (same architecture of clinical prediction decoder), Kwon's RNN [2], BiLSTM Attention [3]
- 5-fold cross validation. Report mean AUROC, AUPRC, late alarm rate (LAR(%))

Experimental Results

Table: Experiment results two datasets. Window size $W = 8$, sliding step side $k = 1$. LAR: late alarm rate; CI: confidence interval; ↑: higher is better; ↓: lower is better.

Dataset	Model	AUROC ↑ (95% CI)	AUPRC ↑ (95% CI)	LAR ↓ (%) (95% CI)
CNUH	FCN	0.898 (0.885 - 0.911)	0.83 (0.808 - 0.851)	20.18 (20.16 - 20.21)
	RNN [2]	0.897 (0.875 - 0.919)	0.865 (0.839 - 0.891)	20.41 (20.36 - 20.45)
	BiLSTM + Att [3]	0.798 (0.771 - 0.825)	0.773 (0.743 - 0.804)	40.06 (40.0 - 40.12)
	VAE (Proposed)	**0.959 (0.947 - 0.972)**	**0.894 (0.843 - 0.945)**	**7.91 (7.88 - 7.93)**
UV	FCN	0.973 (0.968 - 0.978)	0.899 (0.893 - 0.904)	4.89 (4.88 - 4.90)
	RNN [2]	0.897 (0.875 - 0.919)	0.865 (0.839 - 0.891)	20.41 (20.36 - 20.45)
	BiLSTM + Att [3]	0.823 (0.593 - 1)	0.744 (0.552 - 0.935)	34.7 (34.24 - 35.17)
	VAE (Proposed)	**0.983 (0.976 - 0.99)**	**0.909 (0.906 - 0.913)**	**2.96 (2.95 - 2.98)**

Abnormal probability (DEWS score)

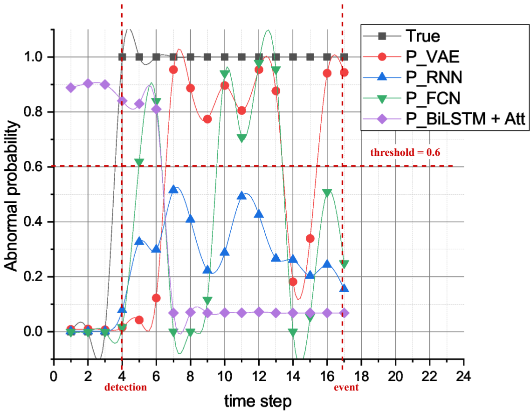

Figure: Abnormal probability results samples on CNUH dataset (sample 1).

Abnormal probability (DEWS score)

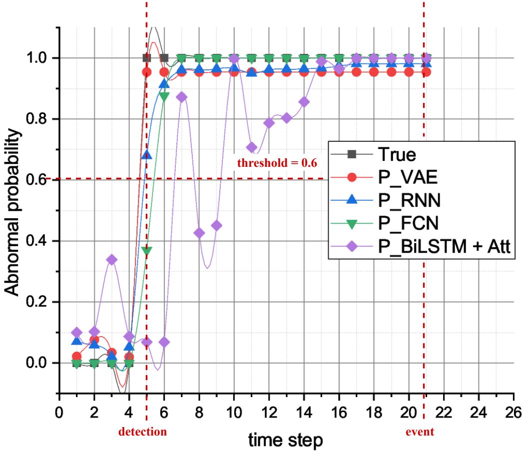

Figure: Abnormal probability results samples on CNUH dataset (sample 2).

Abnormal probability (DEWS score)

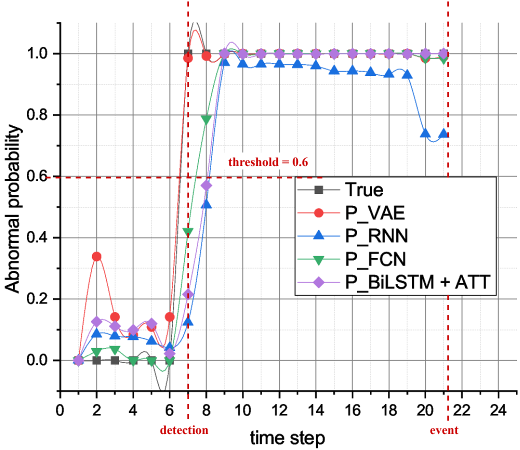

Figure: Abnormal probability results samples on UV dataset (sample 1).

Abnormal probability (DEWS score)

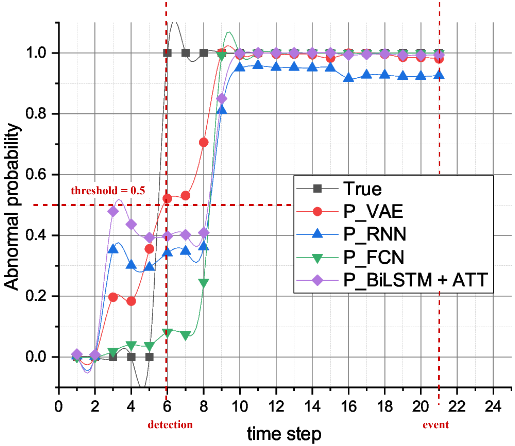

Figure: Abnormal probability results samples on UV dataset (sample 2).

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Plan

- Experiment with on the other size of window time size to select the best window time for system.

References

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J. M. Kwon, Y. Lee, Y. Lee, S. Lee, and J. Park, "An algorithm based on deep learning for predicting in-hospital cardiac arrest," *Journal of the American Heart Association*, vol. 7, no. 13, pp. 1–11, 2018.

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Thank you!