# Predicting the next-day median ED-LoS using LSTM

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## Introduction

Length of stay (LoS)

- an important operational efficiency indicator in Emergency Departments (ED)
- Reducing unit-level LoS can potentially reduce healthcare costs and improve patients' outcomes and satisfaction

The proposed next-day median ED-LoS prediction algorithm

- provides an early warning to ED managers to take proactive actions to reduce future ED-LoS
- Lightweight, deployment-friendly, real-time, end-to-end, only operational inputs based (no clinical features required), ED-LoS unitlevel prediction

#### Limitations from previous work

In a recent review <sup>1</sup>, three major gaps are identified from relevant works: *i*) patient-level LoS predictions

- $\rightarrow$  require a massive amount of data elements,
  - $\rightarrow$  some important predictors are not easily accessible.

For example: individual patient physiological data (blood test results); *ii*) two-step approaches:

- → predict LoS based on supply and demand predictions
- $\rightarrow$  not end-to-end;
- iii) static models:
  - $\rightarrow$  commonly used
  - $\rightarrow$  lack the ability to dynamically update in real-time.



Figure 1. Diagram of the proposed method

a real-time, end-to-end, lightweight, deployment-friendly, ED-LoS unit-level prediction model):

Target values: daily unit-level median ED-LoS

### Inputs (all operational features):

1) the number of daily ED arrival cases

2) the number of daily placed imaging orders including ultrasound, CT, MRI and X-rays modalities.

3) previous day median ED-LoS,

We predict the next-day median ED-LoS by training a long short-term memory (LSTM) network<sup>2</sup>.

#### References

 <sup>1</sup> El-Bouri R, Taylor T, Youssef A, Zhu T, Clifton D, "Machine learning in patient flow: a review ", Progress in Biomedical Engineering. 2021; 3(2).
<sup>2</sup> Hochreiter S; Schmidhuber J (1997). "Long short-term memory". Neural Computation. 9 (8): 1735–1780. doi:10.1162/neco.1997.9.8.1735. PMID 9377276. S2CID 1915014.

#### Results

Validation Dataset: one-year historical data from one collaborator hospital with 300-500 ED daily cases.

**Training split:** the first half-year/6 months as training and the second half as a prediction period.

**Network specifications**: One LSTM layer with parameter unit/inner dimension 50 and a fully connected layer. The loss function is mean absolute percentage error, and an Adam optimizer is used. The model is trained on a single CPU machine for 50 epochs.

**Result:** Figure 2 shows the input features and the results of the prediction. The predicted ED-LoS is smoother and has a strong correlation with the ground truth. The model successfully predicts both the trend and the peak of median ED-LoS in early December. ED managers can utilize predicted ED-LoS peaks to take proactive actions. The limitation of the output of the model is the prediction of the exact value.

Figure 2. Top: Input features to the model. Imaging order numbers missed on some days in May and December.

Bottom: Predicting half-year next-day median ED-LoS.

Root mean squared error (RMSE) between normalized predictions and tagets=10% (90% similar for normalized values in RMSE sense with normalized values are plotted below.



## Conclusion

- A dynamic, real-time, lightweight, deployment-friendly, end-to-end next-day median ED-LoS prediction algorithm using time-series LSTM is proposed.
- The model behaves well with low normalized prediction error, predicting both trends and predicting high median ED-LoS (peak)s.
- Based on increasing trends and peak predictions from the model, it provides early warning information to ED managers to take proactive actions for reducing future ED-LoS.

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