


# AI in EHR - AI capstone

Intro slide deck:  AI in EHR - AI capstone.pdf

Video: [https://youtube.com/playlist?list=PLYsINdwWlnhwZreq7P\\_XLfV7Y3eh1Jo-3](https://youtube.com/playlist?list=PLYsINdwWlnhwZreq7P_XLfV7Y3eh1Jo-3)

Data:  AI in EHR Dataset (Please login with your NYCU Google account)

## Project Description:

1. Prediction tasks (choose one):
  - a. **Task 1:** Patients who are admitted to the ICU may have sepsis, and **we would like to predict the sepsis onset in ICU at least 4 hours earlier** with the vital signs, lab results, diagnosis in prior inpatient visits, and demographic information collected at least 4 hr before the onset of sepsis.
  - b. **Task 2:** Patients who are admitted to the ICU have a high mortality rate, and **we would like to predict the in-hospital mortality** with the vital signs, lab results, diagnosis in prior inpatient visits, and demographic information collected at the early stage (first 6 hours) of ICU admission.
2. Study cohort
  - a. patients had at least one ICU stay
  - b. first ICU stay, if the patients had multiple ICU stays in the dataset
  - c. patients should have
    - i. at least 4 hours of records before onset (task 1)
    - ii. at least 6 hours of records before discharge (task 2).

### TODO 1:

- Select the study cohort from the dataset we provide.
- Draw a flow chart for the cohort selection. If you are not sure about the “flow chart”, here are the [examples](#).

3. Features
  - a. Age & Gender
    - i. in *Patient* table
  - b. BMI
    - i. in *chartevents* table
    - ii. calculation needed
  - c. Laboratory results from the ICU
    - i. in *labevents* tables
    - ii. “Suggested” important laboratory items are listed below
  - d. Vital signs from the ICU
    - i. in *chartevents* tables
    - ii. “Suggested” important vital signs are listed below
  - e. Diagnosis from the **previous** hospitalization (if available)

- i. in *diagnosis* tables
- f. Task targets
  - i. Task 1: Sepsis onset or not: The definition is a bit complicated, so we have the labels for you!
  - ii. Task 2: In-hospital mortality or not

#### **TODO 2:**

- Extract features listed above.
  - Perform descriptive analysis across all features.
4. Data preprocess
- a. multiple measurements (temporal information)
  - b. missing values
  - c. outliers
  - d. ...others

#### **TODO 3:**

- Explain your strategies for data preprocessing.
5. Build a machine learning model to predict sepsis onset (task 1) or in-hospital mortality (task 2), with whatever algorithms.
- a. How to deal with multiple measurements?
  - b. How to incorporate temporal information?

#### **TODO 4:**

- Describe the strategies of model development and evaluation
  - Draw the proposed model architecture and describe it in detail
  - Provide the evaluation results and state the conclusion (**The model's performance will not be perfect with only a limited number of patients**)
6. Share the codes, the results and descriptions from all the **TODOs**, and your conclusion based on the results.

## References

### **About the data**

1. MIMIC official site: <https://mimic.mit.edu/>
2. MIMIC tutorial: <https://mimic.mit.edu/docs/iv/tutorials/video/>
3. MIMIC IV paper: <https://www.nature.com/articles/s41597-022-01899-x>

### **About the task 1 (sepsis onset)**

1. Moor, M., Bennett, N., Plečko, D., Horn, M., Rieck, B., Meinshausen, N., Bühlmann, P., & Borgwardt, K. (2023). Predicting sepsis using deep learning across international sites: a

retrospective development and validation study. *EClinicalMedicine*, 62, 102124.

<https://doi.org/10.1016/j.eclinm.2023.102124>

2. Shashikumar, S. P., Wardi, G., Malhotra, A., & Nemati, S. (2021). Artificial intelligence sepsis prediction algorithm learns to say “I don’t know.” *NPJ Digital Medicine*, 4(1), 134. <https://doi.org/10.1038/s41746-021-00504-6>
3. Reyna, M. A., Josef, C. S., Jeter, R., Shashikumar, S. P., Westover, M. B., Nemati, S., Clifford, G. D., & Sharma, A. (2020). Early Prediction of Sepsis From Clinical Data: The PhysioNet/Computing in Cardiology Challenge 2019. *Critical Care Medicine*, 48(2), 210–217. <https://doi.org/10.1097/CCM.0000000000004145>

#### **About the task 2 (in-hospital mortality)**

1. Gao, J., Lu, Y., Ashrafi, N., Domingo, I., Alaei, K., & Pishgar, M. (2024). Prediction of sepsis mortality in ICU patients using machine learning methods. *BMC Medical Informatics and Decision Making*, 24(1), 228. <https://doi.org/10.1186/s12911-024-02630-z>
2. Iwase, S., Nakada, T.-A., Shimada, T., Oami, T., Shimazui, T., Takahashi, N., Yamabe, J., Yamao, Y., & Kawakami, E. (2022). Prediction algorithm for ICU mortality and length of stay using machine learning. *Scientific Reports*, 12(1), 12912. <https://doi.org/10.1038/s41598-022-17091-5>
3. Hou, N., Li, M., He, L., Xie, B., Wang, L., Zhang, R., Yu, Y., Sun, X., Pan, Z., & Wang, K. (2020). Predicting 30-days mortality for MIMIC-III patients with sepsis-3: a machine learning approach using XGboost. *Journal of Translational Medicine*, 18(1), 462. <https://doi.org/10.1186/s12967-020-02620-5>

#### **About the data preprocess and modeling (EHR, in general)**

1. Singh A, Nadkarni G, Gottesman O, Ellis SB, Bottinger EP, Guttig JV. Incorporating temporal EHR data in predictive models for risk stratification of renal function deterioration. *J Biomed Inform*. 2015 Feb;53:220–8. <http://dx.doi.org/10.1016/j.jbi.2014.11.005>
2. Meng Y, Speier W, Ong MK, Arnold CW. Bidirectional representation learning from transformers using multimodal electronic health record data to predict depression. *IEEE J Biomed Health Inform*. 2021 Aug;25(8):3121–9. Available from: <http://dx.doi.org/10.1109/JBHI.2021.3063721>
3. Solís-García, J., Vega-Márquez, B., Nepomuceno, J. A., Riquelme-Santos, J. C., & Nepomuceno-Chamorro, I. A. (2023). Comparing artificial intelligence strategies for early sepsis detection in the ICU: an experimental study. *Applied Intelligence*, 53(24), 30691–30705. <https://doi.org/10.1007/s10489-023-05124-z>
4. Chen, Z., Tan, S., Chajewska, U., Rudin, C., & Caruna, R. (22 Jun–24 Jun 2023). Missing Values and Imputation in Healthcare Data: Can Interpretable Machine Learning Help? In B. J. Mortazavi, T. Sarker, A. Beam, & J. C. Ho (Eds.), *Proceedings of the Conference on Health, Inference, and Learning* (Vol. 209, pp. 86–99). PMLR. <https://proceedings.mlr.press/v209/chen23a.html>

5. Shashikumar, S. P., Josef, C. S., Sharma, A., & Nemati, S. (2021). DeepAISE - An interpretable and recurrent neural survival model for early prediction of sepsis. *Artificial Intelligence in Medicine*, 113, 102036. <https://doi.org/10.1016/j.artmed.2021.102036>
6. Shukla, S. N., & Marlin, B. (2020, October 2). Multi-Time Attention Networks for Irregularly Sampled Time Series. *International Conference on Learning Representations*. [https://openreview.net/pdf?id=4c0J6lwQ4\\_](https://openreview.net/pdf?id=4c0J6lwQ4_)
7. Yang, Z., Mitra, A., Liu, W., Berlowitz, D., & Yu, H. (2023). TransformEHR: transformer-based encoder-decoder generative model to enhance prediction of disease outcomes using electronic health records. *Nature Communications*, 14(1), 7857. <https://doi.org/10.1038/s41467-023-43715-z>

## Hints of relatively important features

(just for your reference, you can use features not on this list, of course):

### Laboratory results from the ICU

Features	table	itemid
BUN	labevents	51006
Alkaline Phosphatase	labevents	50863
Bilirubin	labevents	50885
Creatinine	labevents	50912
Glucose	labevents	50931
Platelets	labevents	51265
Hemoglobin	labevents	51222

### Vital signs from the ICU

Features	table	itemid
Heart Rate	chartevents	220045
Respiratory Rate	chartevents	220210
Mean Arterial Pressure	chartevents	220052
Temperature	chartevents	223762
Systolic Blood Pressure (SBP)	chartevents	220179

## Pre-process done by TAs:

1. re-code the subject ID
2. re-code the admission ID, including admission ID (hadm\_id) and ICU stay ID (stay\_id)
3. edit the original "date"

Filter 30% of the original population data from all the tables you need in the Hospital and ICU modules to complete the following homework.

The same data can be applied to both tasks.

### 1. Sepsis prediction task

	Original Population		Selected for AI Capstone		Percentage (B) / (A)
	N (A)	Percent	N (B)	Percent	
Sepsis cases	25,323	38%	7,500	39%	30%
Non-Sepsis cases	40,916	62%	11,495	61%	28%
Total	66,239	-	18,995	-	29%

### 2. Mortality prediction task

	Original Population		Selected for AI Capstone		Percentage (B) / (A)
	N (A)	Percent	N (B)	Percent	
Non-survivors	6,966	11%	3,648	19%	52%
Survivors	59,273	89%	15,347	81%	26%
Total	66,239	-	18,995	-	29%