Predicting Sepsis Onset Using Recurrent Neural Networks and the MIMIC-III Database

(A Replication Project)

BANA650

Group AJA

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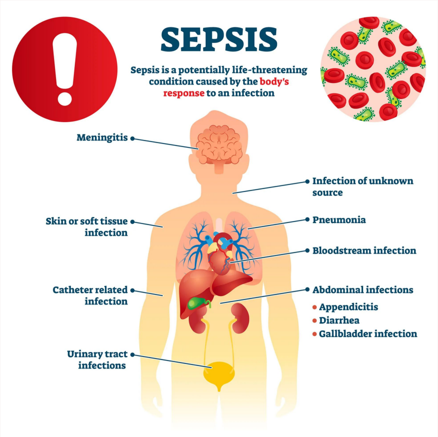
Healthcare Problem & Objective

Problem:

Accurately predicting sepsis onset in ICU patients is a critical healthcare challenge due to its complex, heterogeneous, and subtle clinical presentation.



Objective:

1. Assess the performance of the RNN in predicting sepsis onset at **3, 6, and 12 hours** before diagnosis.
2. Analyze the impact of varying **look-back windows (5, 10, 15, and 20 hours)** on model accuracy to determine how much historical data optimizes prediction performance.
3. Compare the RNN's performance to the InSight algorithm using evaluation metrics such as AUROC, sensitivity, and specificity.

Data Collection & Extraction

Calvert's Gold Standard

Criteria 1	Sepsis diagnosis during patient stay
Criteria 2	Pt manifests SIRS for at least 5 hrs

MIMIC-III Admissions

Criteria 1	ICU Admissions, ages 18+
Criteria 2	At least 1 measurement for SIRS
Criteria 3	Exclude sepsis diagnoses with undetectable beginning of sepsis
Criteria 4	Exclude sepsis diagnoses before prediction windows

Minimum 2 SIRS Parameters:

- Temperature <36℃ or >38℃
- Heart Rate > 90 BPM
- Respiratory rate > 20/min, or PaCO2 <32mmHg
- White Blood Cell Count <4k/μL or >12k/μL

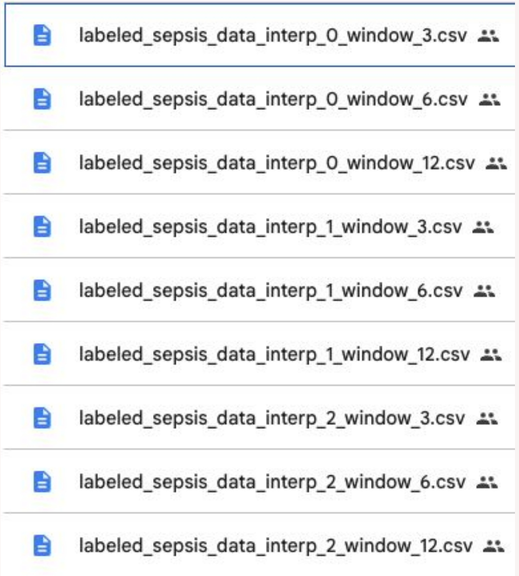
Additional Parameters for Prediction:

- Systolic blood pressure
- Diastolic blood pressure
- pH value
- Blood Oxygen Saturation

Data Preprocessing

Interpolations and Prediction Windows

- 6 different interpolations of the initial extraction (0/1/2/3/4/5)
- Apply 3 different prediction windows (3h/6h/12h)
- Result: 18 different versions



Example of data files for 18 different extractions

Data Preprocessing

Normalization

- Scaled all parameters into a range between 0 and 1 using Min-Max

Look-back Windows

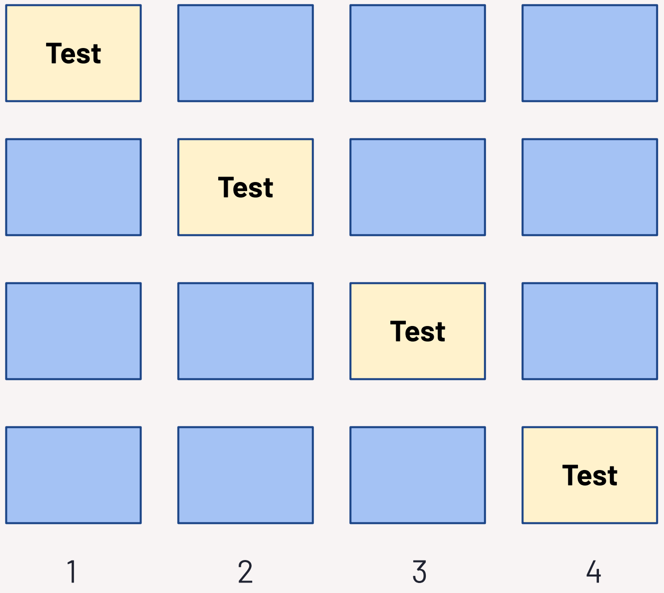
- Windows of 5, 10, 15 and 20 hours for impact on prediction accuracy

hadm_id	charttime	Blood Oxygen Saturation (SO2)	CO2 Partial Pressure (PaCO2	Diastolic Blood Pressur	Heart Rate	Respiratory Rate	Systolic Blood Pressur	Temperature	White Blood Cell Count	pH Value	sepsis_label
101019	2/24/19 8:00	0.92		0.32	0.41	0.36	0.55	0.45			0
101019	2/24/19 8:30	1.00		0.17	0.42	0.36	0.48	0.45			0
101019	2/24/19 9:00	1.00		0.19	0.38	0.30	0.34	0.45			0
101019	2/24/19 9:30	1.00		0.35	0.37	0.21	0.56	0.45			0
101019	2/24/19 9:40	0.92		0.68	0.38	0.23	0.44	0.45			0
101019	2/24/19 9:45	1.00		0.68	0.37	0.26	0.20	0.45			0
101019	2/24/19 9:50	1.00		0.14	0.37	0.53	0.29	0.45			1
101019	2/24/19 9:55	1.00		0.08	0.35	0.47	0.30	0.45			1

Example of data file with normalized parameters

Additional Model Preparation

Stratified K-Fold Cross Validation



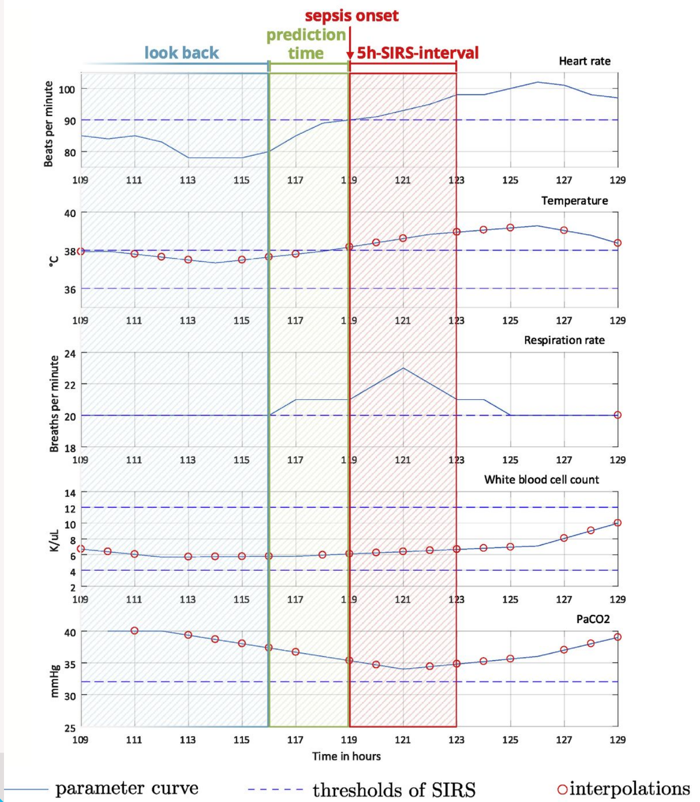
Stratified K-Fold Cross Validation (4 Folds)

- Ensures the proportion of each class label is preserved in every fold
- Training data split into training and validation as such:
- 9/16 training; 3/16 validation; 1/4 test

Synthetic Minority Oversampling Technique (SMOTE)

- Creates more balanced data based on existing data to boost underrepresented classes (i.e., sepsis onset vs no sepsis onset)
- Only applied to training data

Example of Patient Parameter Trends

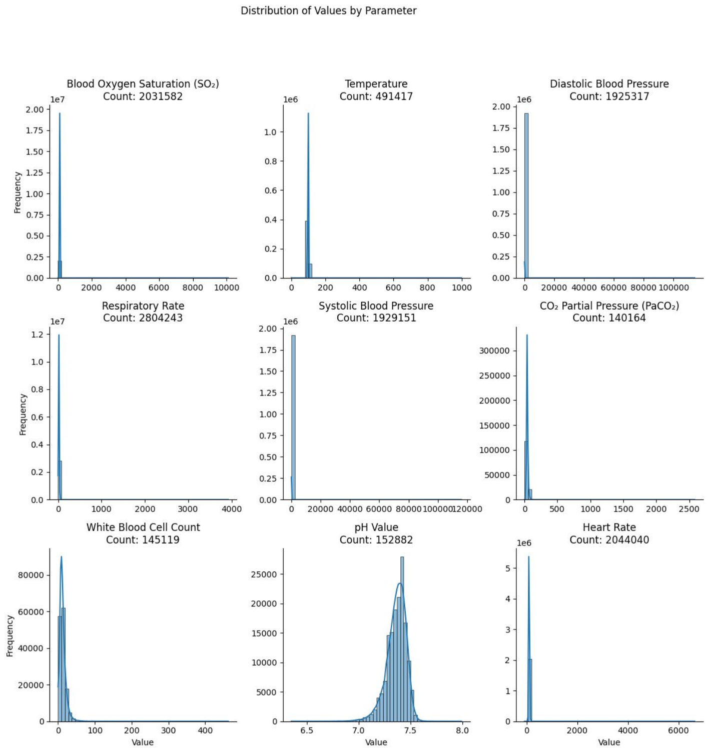


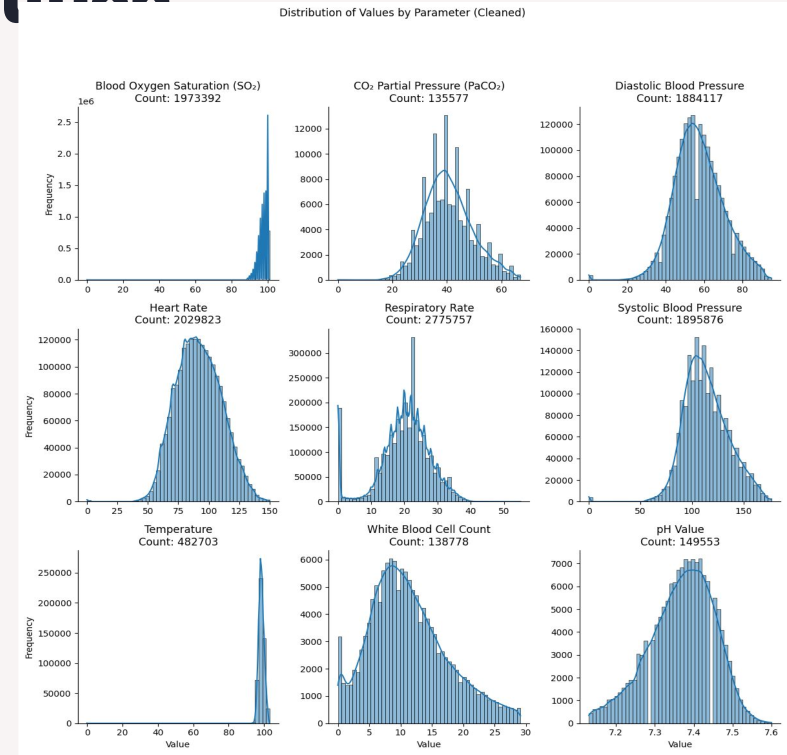
Patient Parameters Against 3h Prediction Time and and Look Back Windows

- Lookback is the sequence used to predict sepsis onset
- Prediction time represents duration between sepsis onset and the last value of lookback
- 5h-SIRS-Interval displays that each parameter sustains SIRS levels for at least 5 hours from sepsis onset

Matthieu Scherpf, Felix Gräßer, Hagen Malberg, Sebastian Zaunseder,
Predicting sepsis with a recurrent neural network using the MIMIC III database,
Computers in Biology and Medicine, Volume 113, 2019, 103395,ISSN 0010-4825,
https://doi.org/10.1016/j.compbiomed.2019.103395.

Preprocessing Effects on Parameter Distribution





Model Methodology

RNN Model predict sepsis on onset using time-series ICU data

Input features

- hourly vitals, lab values, SIRS parameters

Look back windows - (5/10/15/20) hours preceding prediction

Preprocessing

- missing values addressed with linear interpolation

Features normalized

- min-max scaling

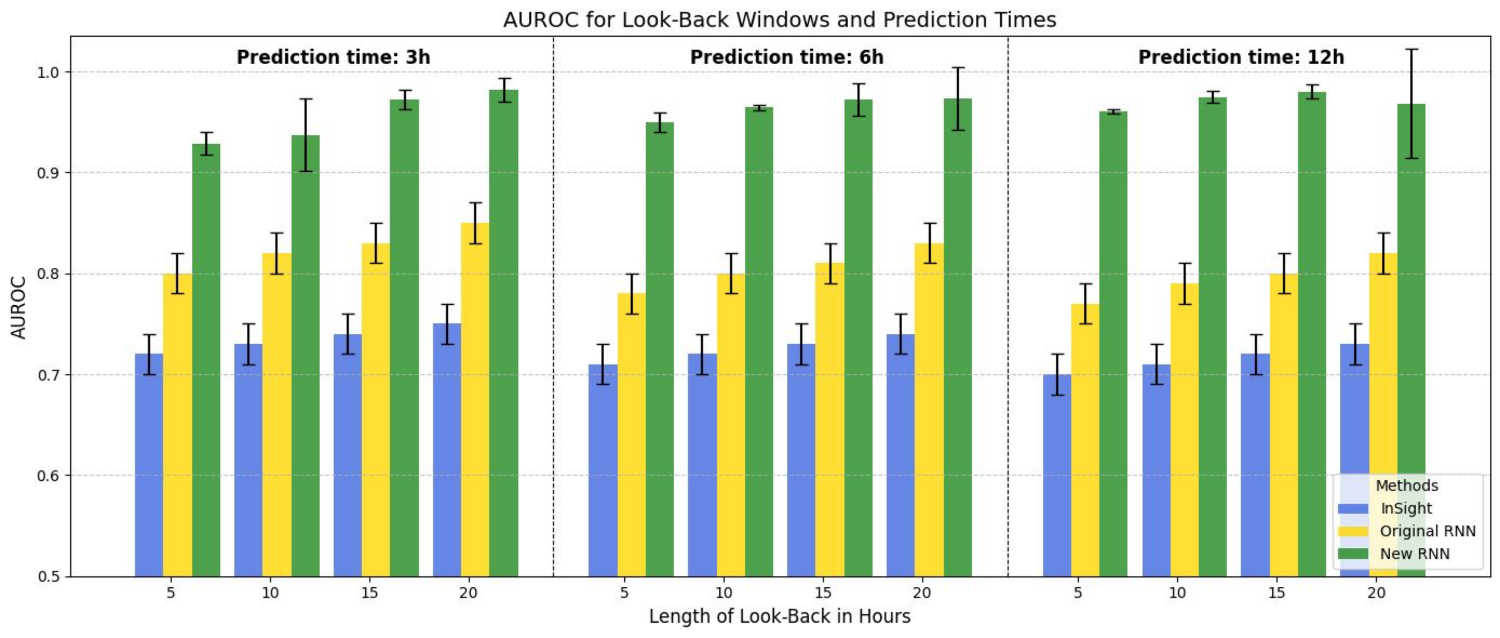
SMOTE

- applied to handle class imbalance and improve sensitivity

Training process

- RNN model trained with 4 fold cross validation
- Optimized using binary cross entropy loss

Model Comparison & Results



AUROC for 5/10/15/20h look-back windows and 3/6/12h prediction time and 0 accepted interpolations

Conclusion & Learnings

Based on our model performance, we reconfirmed that RNNs are capable of effectively predict sepsis onset

Implications to Consider:
- This RNN is designed specifically for ICU Admissions
- Accuracy detection is affected by missing data imputation via interpolation
- May not perform well in cases that are diagnosed with sepsis but do not exhibit the right criteria for sepsis onset

Recommendation:
- Test performance against non-ICU admissions
- Fine tune RNN for specific environment use-cases

Overall Learnings:
- Complex preprocessing requires meticulous attention to detail
- Value of project deliverable timelines

Thank You!