

A Systematic Review of Predictive Analytics Solutions for Septic Patients

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Background

- Early detection and efficient management of sepsis are important for improving healthcare quality, effectiveness, and costs.
- Septic patients tend to remain in the hospital for a significantly longer period of time, increasing costs and resources.
- Improving prediction and detection can potentially help lower the burden of cost associated with treating sepsis as well as preserve organ function while reducing mortality by decreasing the response time of clinicians, allowing them to administer antibiotics and care at an earlier stage. ^(1,2)

Objective

To understand predictive analytics solutions for sepsis patients, either in early detection of onset or mortality by systematically identifying various studies and to see if there are any optimal solutions for sepsis detection or mortality associated with sepsis being explored.

Methods

("sepsis" OR "septicemia" OR "septic" OR "septic shock" OR "severe sepsis") AND ("prediction" OR "predict" OR "analytics") AND ("machine learning" OR "big data" OR "AI" OR "NLP" OR "neural network" OR "algorithm")

Inclusion Criteria:

- Published in a peer-reviewed journal or conference
- Published within the last 10 years
- Used at least one machine learning or model technique
- Identified the features and dataset used

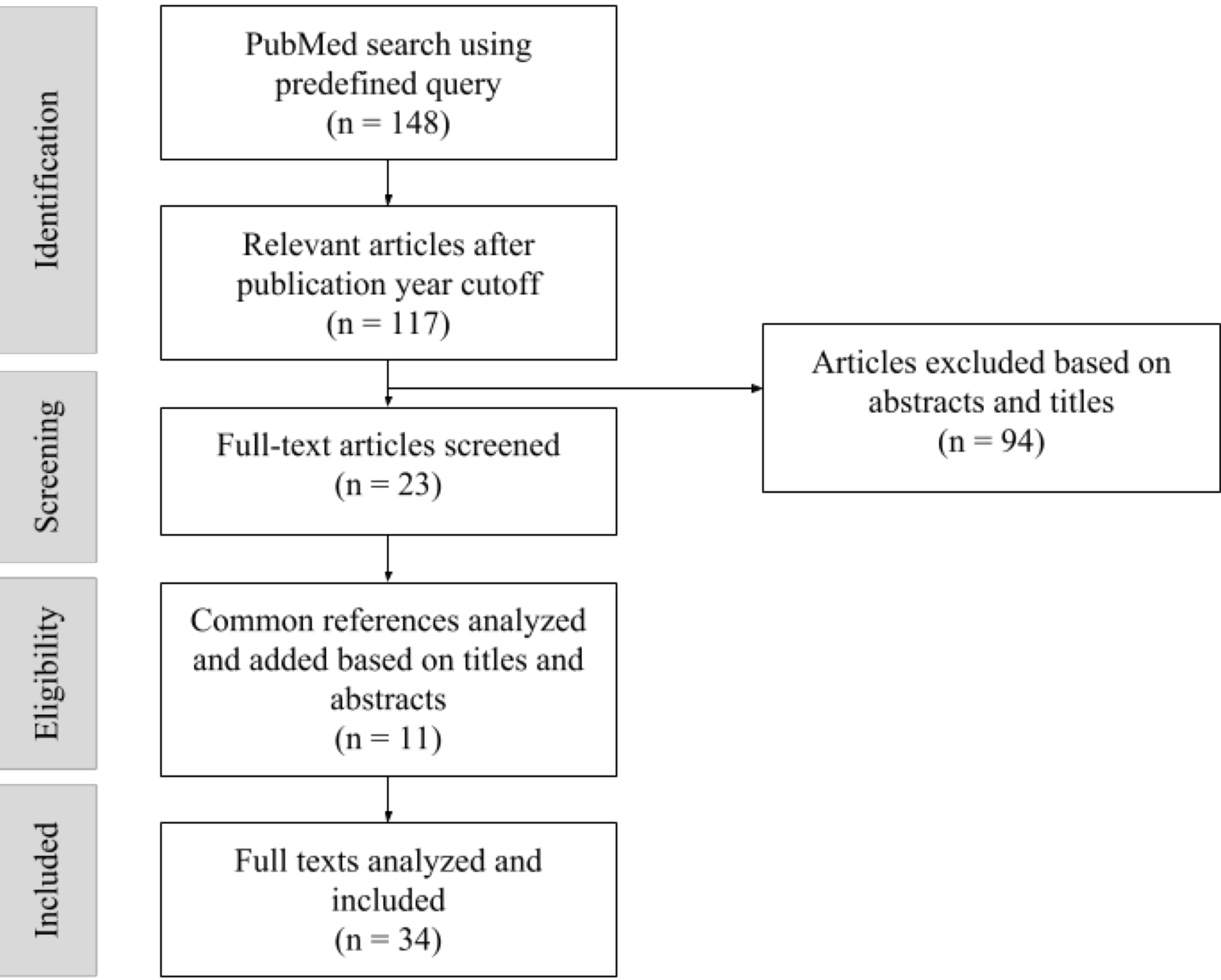


Figure 1: PRISMA Diagram

Conclusion

- Found variation in the domain of predictive analytics tools for septic patients (feature and population size to choice of algorithm).
- Overall evident that implementing predictive analytics tools are beneficial in the early detection of sepsis or death related to sepsis.
- Since most of these studies were retrospective, the translational value in the real-world setting should be further investigated as other variables such as changes in workflow may also have an impact on outcome.
- Additionally, many solely used one dataset, which is not generalizable across institutions, or even within departments.
- It will be interesting to see if a predictive analytics tool can be built on top of institutions that have implemented a common data model.

References and Acknowledgments

Mentioned studies cited below; for all analyzed studies scan QR code on right. This was supported by the National Library of Medicine Training Grant T15LM007442.

1. <https://www.cdc.gov/sepsis/data/reports/index.html>

2. <https://www.sepsis.org/sepsis-alliance-news/new-u-s-government-report-reveals-annual-cost-of-hospital-treatment-of-sepsis-has-grown-by-3-4-billion/>

3. Sutherland A, Thomas M, Brandon RA, Brandon RB, Lipman J, Tang B, McLean A, Pascoe R, Price G, Nguyen T, Stone G. Development and validation of a novel molecular biomarker diagnostic test for the early detection of sepsis. *Critical care*. 2011 Jun;15(3):R149.

4. Mao Q, Jay M, Hoffman JL, Calvert J, Barton C, Shimabukuro D, Shieh L, Chettipally U, Fletcher G, Kerem Y, Zhou Y. Multicentre validation of a sepsis prediction algorithm using only vital sign data in the emergency department, general ward and ICU. *BMJ open*. 2018 Jan 1;8(1):e017833.

5. Shimabukuro DW, Barton CW, Feldman MD, Mataraso SJ, Das R. Effect of a machine learning-based severe sepsis prediction algorithm on patient survival and hospital length of stay: a randomised clinical trial. *BMJ open respiratory research*. 2017 Nov 1;4(1):e000234.

6. Langley RJ, Tsalik EL, Van Velkinburgh JC, Glickman SW, Rice BJ, Wang C, Chen B, Carin L, Suarez A, Mohnhey RP, Freeman DH. An integrated clinico-metabolomic model improves prediction of death in sepsis. *Science translational medicine*. 2013 Jul 24;5(195):195ra95-195ra95.

7. McCoy A, Das R. Reducing patient mortality, length of stay and readmissions through machine learning-based sepsis prediction in the emergency department, intensive care unit and hospital floor units. *BMJ Open Qual*. 2017 Oct 1;6(2):e000158.

8. Calvert J, Desautels T, Chettipally U, Barton C, Hoffman J, Jay M, Mao Q, Mohamadlou H, Das R. High-performance detection and early prediction of septic shock for alcohol-use disorder patients. *Annals of medicine and surgery*. 2016 Jun 1;8:50-5.

9. Lukaszewski RA, Yates AM, Jackson MC, Swingle K, Scherer JM, Simpson AJ, Sadler P, McQuillan P, Titball RW, Brooks TJ, Pearce MJ. Presymptomatic prediction of sepsis in intensive care unit patients. *Clinical and Vaccine Immunology*. 2008 Jul 1;15(7):1089-94.

10. Stanculescu I, Williams CK, Freer Y. Autoregressive hidden Markov models for the early detection of neonatal sepsis. *IEEE journal of biomedical and health informatics*. 2014 Sep;18(5):1560-70.

11. Sawyer AM, Deal EN, Labelle AJ, Witt C, Thiel SW, Heard K, Reichley RM, Micek ST, Kollef MH. Implementation of a real-time computerized sepsis alert in nonintensive care unit patients. *Critical care medicine*. 2011 Mar 1;39(3):469-73.

12. Nemati S, Holder A, Razmi F, Stanley MD, Clifford GD, Buchman TG. An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU. *Critical care medicine*. 2018 Apr 1;46(4):547-53.

13. Horng S, Sontag DA, Halpern Y, Jernite Y, Shapiro NI, Nathanson LA. Creating an automated trigger for sepsis clinical decision support at emergency department triage using machine learning. *PloS one*. 2017 Apr 6;12(4):e0174708.



andrewteng.github.io/cic19

Results

We identified variations in using predictive analytics for septic patients and grouped them into four themes.

Variance in machine learning or modelling techniques

Variance in feature selection

Non-retrospective methods can offer different insight

Mixed samples can offer more generalizable results

Author	Algorithm or Model	Population Size	Feature Set Size	Main Findings
Sutherland et al.	LASSO	85 patients (4 centers)	42 biomarkers	AUC: 0.86-0.92
Sawyer et al.	Recursive partitioning regression tree	270 patients (6 wards)	9 vitals/labs	71% vs. 56%, intervention vs. non
Shimakukuro et al.	<i>InSight</i>	75 control, 67 cases	7 vitals/labs	AUC: 0.86–0.93
Nemati et al.	Weibull-Cox proportional hazards model	85,069 patients	65 vitals/labs	AUC: 0.82-0.85
Stanculescu et al.	Autoregressive Hidden Markov Model	24 neonates	6 vitals/labs 6 clinical events	AUC: 0.74
Horng et al.	Support Vector Machine	230,936 patients	12 vitals/text fields	AUC: 0.85–0.87

- Some used industry created tools to validate the performance of the tool compared to more traditional methods. (Mao et al., Shimabukuro et al., McCoy et al., and Calvert et al.)
- Biomarkers to compare gene expression change, detect sepsis before microbiology results. (Southerland et al.)
- Blood and/or protein profiles to help curate individualized detection of sepsis. (Langley et al.)
- Leukocytes and cytokines as features to classify those who are more likely to develop sepsis from a genetic predisposition. (Lukaszewski et al.)
- Biological data from neonates for their real-time sepsis prediction tool; was *not statistically significant from their previous work using hidden Markov models using vital signs*. (Stanculescu et al.)
- Unstructured data, including text from clinician notes, were also found to provide more insight and improved the accuracy of select models. (Horng et al.)
- Sutherland et al.: prospectively predicted sepsis onset by using the ACCP/SCCM consensus statement and if the patient had suspected infection based on microbiological diagnosis.
- Lukaszewski et al. prospectively monitored molecular changes to identify presymptomatic individuals with an admission diagnosis of “likely septic”. They built five neural network classifiers to ascertain whether the neural networks derived predictive accuracies that were statistically significant; able to predict sepsis before SIRS criteria.
- Sawyer et al. pilot tested a real-time automated sepsis alert that would increase the rate of interventions within 12 hours of detection. They found that their alert system resulted in an increase in early intervention for those who were at risk.