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

PubMed

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("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")
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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

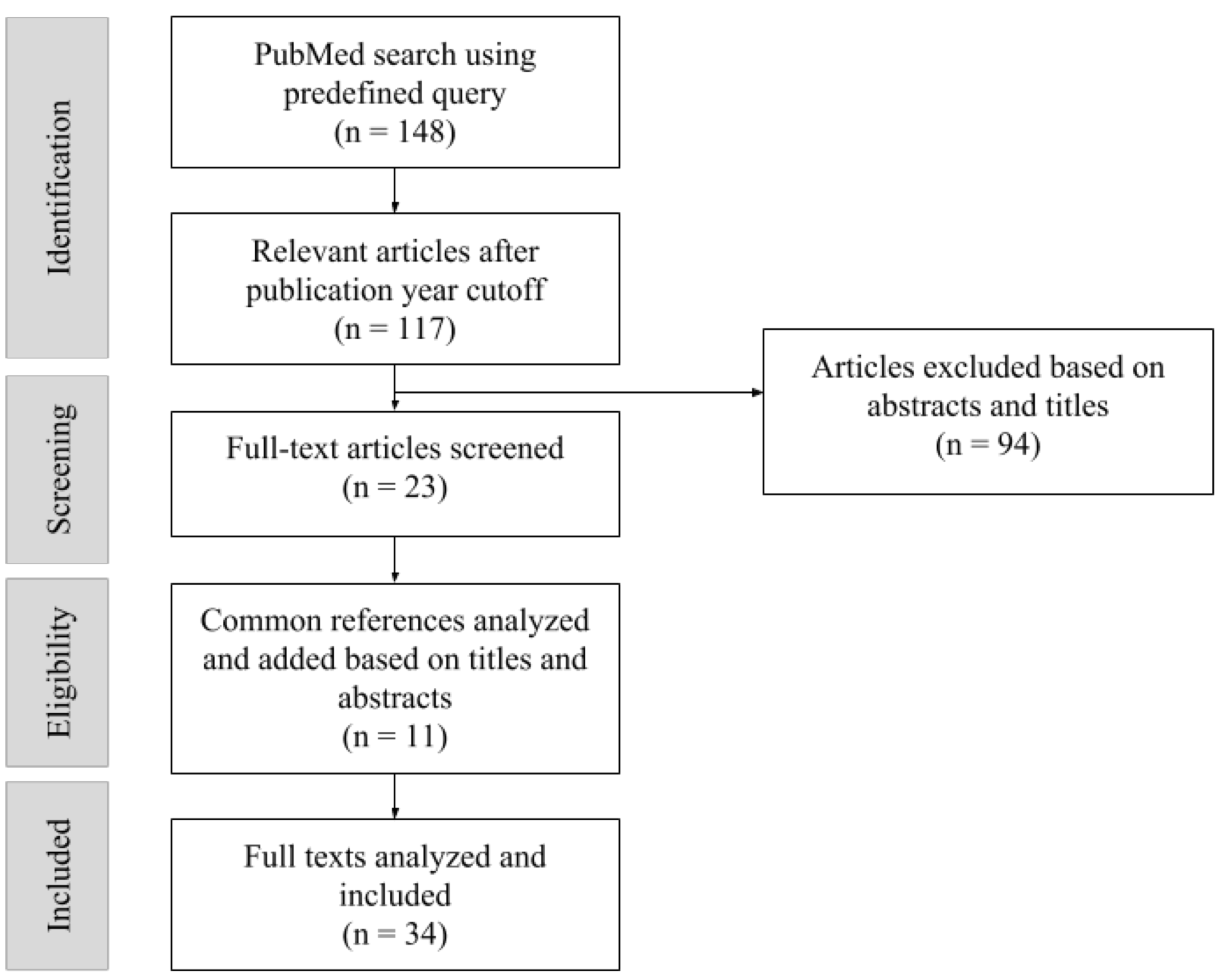

Figure 1: PRISMA Diagram

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.	*InSight*	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.

- 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.

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.

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andrewteng.github.io/cic19