Reference	Title of the work	Authors	Year
36	A New Effective Machine Learning Framework for Sepsis Diagnosis	Wang, X. et al.	2018
37	Learning representations for the early detection of sepsis with deep neural networks	Kam and Kim	2017
38	An Improved Multi-Output Gaussian Process RNN with Real-Time Validation for Early Sepsis Detection	Futoma et al.	2017
39	Predict Sepsis Level in Intensive Medicine – Data Mining Approach	Gonçalves et al.	2013
40	Early detection of sepsis in the emergency department using Dynamic Bayesian Networks	Nachimuthu et al.	2012
41	Prediction of Sepsis in the Intensive Care Unit With Minimal Electronic Health Record Data: A Machine Learning Approach.	Desautels et al.	2016
42	Multicentre validation of a sepsis prediction algorithm using only vital sign data in the emergency department, general ward and ICU	Mao et al.	2018
43	Development and Evaluation of a Machine Learning Model for the Early Identification of Patients at Risk for Sepsis	Delahanty et al.	2019
44	Machine-Learning-Based Laboratory Developed Test for the Diagnosis of Sepsis in High-Risk Patients	Calvert et al.	2019
45	Evaluation of a machine learning algorithm for up to 48-hour-advance prediction of sepsis using six vital signs	Barton et al.	2019
46	Development and Validation of an Automated Sepsis Risk Assessment System	Back et al.	2016
47	Development and External Validation of an Automated Computer-Aided Risk Score for Predicting Sepsis in Emergency Medical Admissions Using the Patient's First	Faisal et al.	2018
48	Creating an automated trigger for sepsis clinical decision support at emergency department triage using machine learning	Horng et al.	2017
49	Non-invasive classification of severe sepsis and systemic inflammatory response syndrome using a nonlinear support vector machine: a preliminar study	Tang et al.	2010

50	Natural language processing of electronic medical records can identify sepsis following orthopedic surgery	Arvind et al.	2018
51	Leveraging implicit expert knowledge for non-circular machine learning in sepsis prediction	Schamoni. et. al.	2019
52	Predicting sepsis with a recurrent neural network using the MIMIC III database	Scherpf et al.	2019
53	An attention based deep learning model of clinical events in the intensive care unit	Kaji et al.	2019
54	LiSep LSTM: A Machine Learning Algorithm for Early Detection of Septic Shock	Fagerström et al	2019
55	Predictive models of sepsis in adult ICU patients	Wang, R.Z. et al.	2018
56	A machine Learning Algorithm to Predict Severe Sepsis and Septic Shock: Development, Implementation, and Impact on Clinical Practice	Giannini et al.	2019
57	A minimal set of physiomakerkets in continious high frequency data streams predict adult sepsis onset earlier	van Wyk et al.	2018
58	An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU	Nemati et al.	2018
59	Using peptidomics and machine learning techniques to predict mortality of patients with septic shock	Byrne, H.	2018
60	Mortality prediction of septic patients in the Emergency Department based on Machine Learning	Perng et al.	2019
61	From vital signs to clinical outcomes for patients with sepsis: a machine learning basis for a clinical decision support system	Gultepe et al.	2014
62	Semantically Enhanced Dynamic Bayesian Network for Detecting Sepsis Mortality Risk in ICU Patients with Infection	Wang, T. et al.	2018
63	Prediction of in-hospital Mortality in Em, Department patient with sepsis: A Local Big Data–Driven, Machine Learning Approach	Taylor et al.	2016
64	Heart rate variability based machine learning models for risk prediction of suspected sepsis patients in the emergency department	Chiew et al.	2019

65	Severe sepsis mortality prediction with logistic regression over latent factors	Ribas et al.	2012
66	From data to optimal decision making: a data-driven, probabilistic machine learning approach to decision support for patients with sepsis	Tsoukalas et al.	2015
67	A machine learning-based model for 1-year mortality prediction in patients admitted to an Intensive Care Unit with a diagnosis of sepsis	García-Gallo et al.	2018
70	Early Diagnosis and Prediction of Sepsis Shock by Combining Static and Dynamic Information Using Convolutional-LSTM	Lin et al.	2018
71	Data-driven discovery of a novel sepsis pre-shock state predicts impeding septic shock in the ICU	Liu et al.	2019

Place of publication	ML Task(s)	Primary purpose
IEEE ACCESS	Sepsis Detection	Diagnosis accuracy and identify the most important biomarkers
Computers in Biology and Medicine An international	Sepsis Prediction Sepsis Detection	Develop detection models for the early stage of sepsis using deep learning methodologies
Journal of Machine Learning Research (JMLR)	Sepsis Prediction Sepsis Detection	Predict sepsis before it occurs with laboratory results, vital signs and medications
Advances in Information Systems and Technologies	Sepsis Detection	Support doctor's decision-making on predicting the Sepsis level
Journal of the American Medical Informatics Association (JAMIA)	Sepsis Detection	Detect the presence of sepsis soon after the patient visits the emergency department
Journal of Medical Internet Research (JMIR)	Sepsis Prediction Sepsis Detection	Study and validate a sepsis prediction method, using a minimal set of variables
BMJ OPEN	Sepsis Severity Prediction Sepsis Detection	Detection and prediction, using only six vital signs
Annals of Emergency Medicine	Sepsis Detection	Developed and evaluated a new screening tool for sepsis, the Risk of Sepsis (RoS) score
Diagnostics	Sepsis Detection	Detection of sepsis in high-risk patients (aged 45 or older and with a length-of-stay of four days or longer) using a minimal set of variables
Computers in Biology and Medicine	Sepsis Prediction Sepsis Detection	Increase timelty sepsis detection and prediction using electronic health records and compares the performance with the existing methods
Research in nursing and health	Sepsis Detection	Develops and verifies an Automated Sepsis Risk, applying data mining techniques to electronic health records
Critical Care Medicine	Sepsis Detection	Predict the risk of sepsis using the vital signs and blood test results
PLOS ONE	Sepsis Detection	Identifies patient with suspect of sepsis in the emergency department with free text data, vital signs and demographic data
IOP Publishing	Sepsis Detection	Classifies sepsis, severe sepsis and systemic inflammatory response syndrome

The Spine Journal	Sepsis Detection	Develop a machine learning algorithm that can identify post surgical sepsis based on unstructured patient notes
Artificial Intelligence in Medicine	Sepsis Prediction	Develop a machine learning sepsis prediction model and validate it by using an independent ground truth of sepsis status
Computers in Biology and Medicine	Sepsis Prediction	Predict sepsis using recurrent neural networks and performance comparision with InSight
PLOS ONE	Sepsis Prediction	Predict sepsis, myocardial infarction or vancomycin antibiotic administration
Scientific Reports	Sepsis Prediction	Predict septic shock in the 48 hours preceding its onset
IEEE International Conference on Healthcare Informatics	Sepsis Prediction	Develops models for predicting sepsis, and compare their performance
Critical Care Medicine	Sepsis Prediction	Develop and implement a maching learning algorithm ("EWS 2.0") to predict severe and septic shock
International Journal of Medical Informatics	Sepsis Prediction	Detect at-risk sepsis patients at an early stage
Critical Care Medicine	Sepsis Prediction	Develops and validates sepsis expert algorithm for early prediction of sepsis
FIB Universitat de Barcelona	Mortality Prediction	Analyses peptidomics data and prediction of risk of death of patients in septic shock
Journal of Clinical Medicine	Mortality Prediction	Predict mortality (within 72 h and 28 days)of suspected infected patients in Emergency Department
Journal of the American Medical Informatics Association (JAMIA)	Mortality Prediction	Develops a system to identify patients at high risk for hyperlactatemia and laboratory studies
ArXiv	Mortality Prediction	Identifies patient at risk of life-threatening sepsis
Academic Emergency Medicine Official Journal of the Society for Academic Emergency Medicine (SAEM)	Mortality Prediction	Predictive analytics in emergency care with clinical decision rules
Scientific Reports	Mortality Prediction	Identification of high-risk patients in ED department by means of machine learning, including HRV parameters as predictors

Expert systems with applications	Mortality prediction	Model based to obtain such new sets of descriptors, or prognostic factors
Journal of Medical Internet Research (JMIR)	Mortality Prediction	Develops and assess method that deduce the current state of patients with sepsis
Medicina Intensiva	Mortality Prediction	Develops a model for predicting 1-year mortality in critical patients diagnosed with sepsis
IEEE International Conference on Healthcare Informatics	Sepsis Severity Prediction	Obtains local characteristics of EHRs to predict is septic shock
Scientific Reports	Septic Shock Prediction	Prediction of septic shock in ICU patients

Key findings	Data set and target country
Decision making tool for the diagnosis of sepsis	77 patients China
Verifies capacity and improves the performance of advanced neural networks	5,789 patients MIMIC-II
Learning model that detects sepsis early and also optimal treatment strategies	51,697 patients USA
Predicts sepsis level in real-time using Data Mining	1,749 patients Portugal
Model to perform the detect specific diseases such as sepsis	3,100 patients USA
Tool for predicting sepsis onset	22,853 ICU stays MIMIC-III
Predicts and identifies septic shock 4 hours prior to onset	90,535 patients UCSF USA Transfer learning: 21,604 patients MIMIC-III
The RoS score demonstrated significantly better discrimination than the benchmarks (SOFA, qSOFA, SIRS, MEWS, NEWS) across all time thresholds (1, 3, 6, 12, 24 hours after an	2,759,529 emergency departments patients USA
Outperforms the standard clinical scores (SIRS, MEWS and qSOFA) using data from a 3-hour window and only 6 variables	122,672 records of high-risk patients (aged 45 or older and length-of-stay of four days or longer) Data from 2 Medical centers in USA,
Algorithm predicts sepsis up to 48h in advance, trained and tested on different patient populations	17,467,987 (UCSF) 53,542 (MIMIC-III) trained and tested on separate datasets
Increases the effectiveness of sepsis care by helping nurses to tailor the care and monitoring of sepsis risk	2020 patients Korea
Validate the risk of sepsis models using data from different hospitals	26,247 development patients United Kingdom 30,996 validation patients United
Vital signs and demographic information, utilizing free text drastically improves the discriminatory ability of identifying infection	230,936 visits USA
Suggests the combinatory use of cardiovascular spectrum analysis for classifies sepsis	26 patients Autralia

Model used for real-time surveillance and for automated identification of patient complications with sepsis	947 patients (15,004 notes) MIMIC-III
Achieves state-of-the-art AUC scores	620 patients in surgical ICU Germany
Predicts sepsis 3h prior to sepsis onset and compare the performance for 6 and 12h prediction time for both approaches	31,238-31,575 patients (MIMIC-III)
Predicts sepsis one day prior to onset	56,841 ICU admissions (36,176 patients) MIMIC-III
LSTM network detects septic shock earlier than a Cox proportional hazards model.	50373 ICU admisssions(MIMIC-III)
Performs the correct identification of sepsis ICU patients before onset is emphasized	19,358 patients MIMIC-III
The tool triggered 5-6 hours prior to the onset of severe sepsis or septic shock	54,464 non-ICU patients USA
Models to predict sepsis 5h before the onset	
Predicts the onset of sepsis in an ICU patient 4-12 hours prior to clinical recognition with data available in the ICU in real-time	27,527 development patients USA 42,411 validation patients MIMIC-III
Classification of patient outcome, from patient peptidome taken 48 hours after shock diagnosis	29 patients ShockOmics
Mortality prediction with variables obtained during ED stay	88,789 patients admitted to Emergency Department (Chang Gung Memorial Hospital). Taiwan
Lactate levels and mortality risk can be provided for the mortality prediction	741 patients USA
Derives a mortality risk and compares the predictive accuracy with the score systems	19,623 patients (24,506 ICU stays) MIMIC-II
Traditional analytic techniques for predicting in-hospital mortality of ED patients with sepsis	4,676 patients (5,278 visits) USA
Outperforms the standard clinical scores (qSOFA, NEWS and MEWS) using 6 vital signs plus 22 HRV parameters	214 patients Singapore

Derives a prognostic score from a set of physiopathologic and therapeutic variables	156 patients Spain
Provides a framework for sepsis treatment, favorable actions, predict mortality and length of stay with high accuracy	745 patients USA
The clinical information of the first 24hr after admission, develop a 1-year mortality prediction model	5,650 admissions of patients USA
The early detection of sepsis can be predicted <5 hours in the future	3,738 visits (145,421 total events) USA
A novel pre-shock state is defined. Models developed calculate a risk score every time that new data is available for a patient. This risk score determines if a patient is in pre-	15,930 patients with suspected infection from MIMIC-III ~140,000 patients from eICU database used for validation

Cases	Contribution of the project
42 sepsis	Clinical decision support tool for the diagnosis of sepsis
360 sepsis	Early detection of sepsis after 3 h with 5 h of data collection
21,4% sepsis	Clinical baselines, and improves on a previous related model for detecting sepsis
334 severe sepsis 1,415 septic shock	Predicts sepsis level for alerts in ICU
20% sepsis	Detects sepsis with variables that are mostly collected at the bedside and WBC
2,577 sepsis	Predicts sepsis with health record data. Comparison between inSight vs qSofa, MEWS, SIRS, SOFA.
UCSF USA 1,1179 sepsis 349 severe sepsis 614 septic shock	Detection and prediction of three sepsis-related gold standards, using only six vital signs
54,661 sepsis	This new screening tool indentify patients at risk for sepsis better than the benchmark
22,817 sepsis	A small set of 6 variables is enough to detect sepsis in high-risk patients
91,445 patients (UCSF) 21,507 patients (MIMIC-III)	Predicts sepsis up to 48 h in advance and identifies sepsis onset more accurately than commonly used tools
404 sepsis	Seven predictors included in the Auto-SepRAS after initial analysis were admission via the ED
Development 4,861 sepsis 1,387 severe sepsis	Estimate risk of sepsis for emergency medical admissions
32,103 infections	Uses routinely collected free text data at triage to predict infection
18 sepsis	Spectral indices of autonomic neural activity, to ascertain its diagnostic usefulness in the sepsis continuum

3,547 notes from patients positive for sepsis	Identify post-surgical sepsis based on unstructured patient notes
200 sepsis	Proposes a questionnaire for clinical practitioners as an alternative of standard severity scores for sepsis status labeling, in order to avoid bias induced by using the same information for
Diagnosis during patient stay: sepsis(995.91), severe sepsis(995.92), and/or septic shock(785.52)	Compares the model developed with InSight. Demostrates the predicition performance and show the correct detection of sepsis onset for a retrospective analysis
ICU admissions with lenght of stay 2 days or longer (n = 56,841)	Demonstrates the input variables are important to predict and could provide a degree of interpretability for clinicians
11224 sepsis cases	Predictions are more realiable closer to the onset of septic shock
4,915 sepsis	Predictive models to improve in ICU the earlier detection of patients at risk of becoming septic
347 predict to develop severe sepsis or septic shock	Decrease in time to ICU transfer but no significant change in mendian length of stay in the ICU or all-cause mortality
904 patients 377 patients had developed sepsis and had data at least 3h prior to the onset of sepsis	Predict the onset of sepsis in patients who are admitted to ICU using continuos minute-by-minute data captured at the beside
USA 2,375 sepsis MIMIC-III	Sepsis expert algorithm for early prediction of sepsis
6 deaths	Identify 8 relevant peptides that may provide some clinical insight into the pathophysiology of septic shock
42,220 patients that had blood culture collected and had received intravenous antibiotics	Deep learning predicts mortality better than other machine learning methods
151 sepsis (52 deaths) 261 deaths in the dataset	New scheme for the prediction of lactate levels and mortality risk from patient vital signs and WBC
2,829 deaths	Reduces time and costs necessary to implement a physician's knowledge/reasoning logic into operational systems
260 deaths	Demonstrates several notable advantages for clinical predictive analytics
40 30-day in-hospital deaths	A machine learning model incorporating HRV can improve ED mortality prediction compared to standard predictors

34% mortality	Extracted indicators are then applied to the prediction of mortality caused by sepsis
170 sepsis	Patient information used to predict mortality and length of stay intervals
43,3% 1-year mortality rate	Generates of a customized model for accurate mortality prediction
1,869 positives 1,869 negatives	Develops framework for evaluation: visit level early diagnosis and event level early prediction
3,475 septic shock (MIMIC-III) No information available for eICU	A way to identify a patient in a novel pre-shock state is proposed.

Techniques used	Performance metrics
Kernel Extreme Learning Machine	Accuracy Sensitivity, specificity Matthews Correlation Coefficient
Deep Feedforward Network Long Short-Term Memory	Area Under ROC Sensitivity, Specificity
Multi-output Gaussian Processes Recurrent Neural Network (Long Short-Term Memory)	Area Under ROC Area Under PR
Support Vector Machine Decision Trees Naive Bayes	Accuracy Sensitivity, Specificity
Dynamic Bayesian Network	Area Under ROC Sensitivity, Specificity Precision (Positive Predictive Value) Negative Predictive Value
InSight	Area Under ROC Area Under PR
Gradient Tree Boosting (InSight)	Area Under ROC Sensitivity, Specificity
Gradient-Boosted Decision Trees	Alert rate Area Under ROC Sensitivity, Specificity Precision (Positive Predictive Value)
Gradient-Boosted Decision Trees	Area Under ROC Sensitivity, Specitificty Positive Predictive Value Negative Predictive Value
Gradient-Boosted Decision Trees	Area Under ROC LR+, LR- Sensitivity, Specificity Diagnostic Odds Ratio
Logistic Regression	Area Under ROC Sensitivity, Specificity Precision (Positive Predictive Value) Negative Predictive Value
Logistic Regression	Area Under ROC Sensitivity, Specificity
Support Vector Machine	Area Under ROC Sensitivity, Specificity Precision (Positive Predictive Value) Negative Predictive Value
Support Vector Machine	Accuracy Sensitivity, Specificity Precision (Positive Predictive Value) Negative Predictive Value

Support Vector Machine	Area Under ROC Accuracy Sensitivity, Specificity
Linear Regression Neural Network	Area Under ROC
Recurrent Neural Networks	Area Under ROC Sensitivity, Specificity
Long Short-Term Memory Recurrent Neural Networks	Area Under ROC PPV Sensitivity
Long Short-Term Memory	AUC
Logistic Model Trees Logistic Regression Support Vector Machine	Area Under ROC Sensitivity, Specificity Precision (Positive Predictive Value) Negative Predictive Value
Random Forest	Sensitivity, Specificity Precision (Positive Predictive Value) Likelihood ratios
Random Forest	Area Under ROC F1 score Sensitivity, Specificity Accuracy, PPV
Weilbull-Cox Hazards model	Area Under ROC Accuracy Sensitivity, Specificity
Logistic Regression Support Vector Machine Multilayer Preceptron	Area Under ROC Accuracy Sensitivity, Specificity Precision (Positive Predictive Value)
k-Nearest Neighbors Random Forest SoftMax SVM	AUC Accuracy
Naïve Bayes Support Vector Machine	Area Under ROC Accuracy Sensitivity, Specificity F-score
Dynamic Bayesian Network	Area Under ROC Sensitivity, Specificity
Random Forest Logistic Regression Classification and Regression Trees	Area Under ROC
k-Nearest Neighbors Random Forest Adaptive Boosting Gradient-Boosted Decision Trees	Area Under PR Sensitivity Precision (Positive Predictive Value) F1

Logistic Regression	Area Under ROC Sensitivity, Specificity
Support Vector Machine	Area Under ROC Accuracy
Least Absolute Shrinkage and Selection Operator Stochastic Gradient Boosting	Area Under ROC
Long Short-Term Memory	Area Under ROC Sensitivity Precision (Positive Predictive Value)
Generalized Linear Model XGBoost Recurrent Neural Network	Area Under ROC Sensitivity, Specitificty Precision (Positive Preditive Value)

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