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|  | Paper | Method | Approach |
| 1 | Machine Learning and Prediction of All-Cause Mortality in COPD | random survival forests (RSF) | RSF for feature selection then Cox regression |
| 2 | Can machine learning improve mortality prediction following cardiac surgery? | neural network, random forest, naive Bayes and **retrained LR** | Predictive model |
| 3 | Machine learning for real-time prediction of complications in critical care: a retrospective study | recurrent deep neural network (RNN) | Predictive model |
| 4 | Emergency department triage prediction of clinical outcomes using machine learning models | Lasso regression, random forest, gradient boosted decision tree, and deep neural network | Predictive model |
| 5 | Machine learning models in breast cancer survival prediction | Naive Bayes (NB), Trees Random Forest (TRF), 1-Nearest Neighbor (1NN), AdaBoost (AD), (SVM), RBF Network (RBFN), and Multilayer Perceptron (MLP) | Predictive model |
| 6 | Cardiovascular Event Prediction by Machine Learning: The Multi-Ethnic Study of Atherosclerosis | random survival forests (RSF) | Feature selection and prediction |
| 7 | A machine learning approach for mortality prediction only using non-invasive parameters | LightGBM, **XGBoost**, rand forest (RF) and logistic regression | Feature selection by Bayes error rate and prediction |
| 8 | Machine learning based early warning system enables accurate mortality risk prediction for COVID-19 | Logistic Regression, Support Vector Machine, Gradient Boosted Decision Tree, and Neural Network | Predictive model |
| 9 | Early prediction of mortality risk among patients with severe COVID-19, using machine learning | logistic regression, partial least squares (PLS) regression, elastic net (EN) model, random forest and bagged flexible discriminant analysis (FDA) | Feature selection and prediction |
| 10 | Prediction model development of late-onset preeclampsia using machine learning-based methods | Logistic regression, decision tree model, naïve Bayes classification, support vector machine, random forest algorithm, and **stochastic gradient boosting** | Predictive model |
| 11 | An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU | Artificial Intelligence Sepsis Expert | Weilbull-Cox proportional hazards model for the feature selection and AISE for the prediction |
| 12 | Improving risk prediction in heart failure using machine learning | boosted decision tree algorithm | Predictive model |
| 13 | Prediction of Childbirth Mortality Using Machine Learning | Random forest | Predictive model |
| 14 | Machine Learning Prediction Models for In-Hospital Mortality after Transcatheter Aortic Valve Replacement | adaptive boosting, naive Bayes, K-nearest neighbours, and random forest | Predictive model |
| 15 | Prediction of In-hospital Mortality in Emergency Department Patients With Sepsis: A Local Big Data-Driven, Machine Learning Approach | random forest | Predictive model |
| 16 | Machine learning prediction for mortality of patients diagnosed with COVID-19: a nationwide Korean cohort study | **LASSO, SVM**, SVM with radial basis function kernel, random forest (RF), and k-nearest neighbors | Cox proportional hazards regression for feature selection, other ml for prediction |
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**Case Prediction**

**Rate prediction**

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|  | Paper | Method | Approach |
| 1 | Predicting the hotspots of age adjusted mortality rates of lower respiratory infection across the continental United States Integration of GIS spatial statistics and machine | logistic regression (LR), random forest (RF), gradient boosting decision trees (GBDT), k-nearest neighbors (KNN), and support vector machine (SVM) | Moran’s I and Getis-Ord General G were employed to investigate the extent to which the nearby counties had similar LRI rates. ML algorithms were employed to predict the presence/absence of hotspots (P≤0.05) for elevated age-adjusted LRI mortality rates in a geographic information system framework. |
| 2 | Mapping risk of ischemic heart disease using machine learning a Brazilian state | K-Nearest Neighbors, Bayesian Naive Neural Network, Partial Least Squares with Wide Kernel, Principal Component Regression, Random Forest, Bagged Cart, XGboost, SVM with Kernel Linear | Prediction is the secondary goal of HHCI outcome. Through the predicted mortality rate compared to the observed mortality rate, it is possible to define for each municipality an index of health attention |
| 3 | What weather variables are important in predicting heat-related mortality\_ a new application of statistical learning methods | Random Forest | applied random forests to determine the most important weather variables predicting excess daily all-cause mortality for four cities |
| 4 | Association between weather data and COVID-19 pandemic predicting mortality rate: Machine learning approaches | Linear models (Linear Regression, Lasso, Ridge, Elastic Net, Least Angle, Lasso Least Angle Regression, Orthogonal Matching Pursuit, Bayesian Ridge, Automatic Relevance Determination, Passive Aggressive Regressor, Random Sample Consensus, TheilSen Regressor, Huber Regressor). Moreover, ensemble learning-based modes such as Random Forest, Extra Trees Regressor, AdaBoost Regressor, Gradient Boosting Regressor. Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM) , and CatBoost Regressor, Kernel Ridge, SVM, KNN, Multi-level Perceptron. | Predictive model |
| 5 | Spatial distribution of esophageal cancer mortality in China: a machine learning approach | Genetic programming (GP), a hierarchical Bayesian model and sandwich estimation |  |
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**Modelling**

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|  | Paper | Method | Approach |
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**Association**

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|  | Paper | Method | Results |
| 1 | Association of Long-term Exposure to Community Noise and Traffic-related Air Pollution With Coronary Heart Disease Mortality | The Cox proportional hazards regression model was used to deter-mine the associations between noise or air pollution and CHD mortality | 4% (95% confidence interval: 1,8) increases in CHD mortality |
| 2 | Long term effects of traffic noise on mortality in the city of Barcelona, 2004-–2007 | For each of the specific causes of mortality, we specified generalized linear mixed models with binomial response (case or control) and a logistic link | After adjusting for confounders, we found that traffic noise was associated with myocardial infarction mortality, with Type II diabetes mellitus in men and with mortality from hypertension in women |
| 3 | Road traffic noise is associated with increased cardiovascular morbidity and mortality and all-cause mortality in London | Poisson regression models | Positive but non-significant associations were seen with mortality for cardiovascular and ischaemic heart disease, and stroke. Results were similar for the elderly. |