

# XGBoost

- Clinical decision support using pseudo-notes from multiple streams of EHR data
- Development and validation of a machine learning-based risk prediction model for stroke-associated pneumonia in older adult hemorrhagic stroke
- Machine learning algorithms for prediction of cerebrospinal fluid leakage after posterior surgery for thoracic ossification of the ligamentum flavum
- Prediction of the 180 day functional outcomes in aneurysmal subarachnoid hemorrhage using an optimized XGBoost model
- Machine learning-based prediction of diabetic peripheral neuropathy: model development and clinical validation
- Machine learning-based prediction of 6-month functional recovery in hypertensive cerebral hemorrhage: insights from XGBoost and SHAP analysis
- Automated feature learning and survival prognostication in grade 4 glioma using supervised machine learning models
- Prediction of outcomes following intravenous thrombolysis in patients with acute ischemic stroke using serum UCH-L1, S100beta, and NSE: a multicenter prospective cohort study employing machine learning methods

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XGBoost, which stands for eXtreme Gradient Boosting, is a popular and powerful [machine learning algorithm](#) used for both [classification](#) and [regression tasks](#). It is known for its high [performance](#) and [efficiency](#) and is widely utilized in various [data science](#) and [machine learning applications](#).

## Key characteristics and features

**Gradient Boosting:** XGBoost is an ensemble learning technique based on the gradient boosting framework. It builds multiple decision trees sequentially, with each tree correcting the errors of the previous ones. This helps improve the model's accuracy over time.

**Boosting Algorithm:** XGBoost uses a boosting algorithm, which combines the predictions of multiple weak learners (typically decision trees) to create a strong predictive model.

**Regularization:** XGBoost incorporates L1 (Lasso) and L2 (Ridge) regularization techniques to prevent overfitting, making it more robust to noisy data.

**Parallel Processing:** XGBoost is designed for parallel processing and can take advantage of multi-core CPUs, making it significantly faster than traditional gradient boosting implementations.

**Tree Pruning:** It employs a technique called “pruning” to reduce the depth of trees, which helps prevent overfitting and improves computational efficiency.

**Handling Missing Values:** XGBoost can handle missing values in the dataset by making informed decisions about how to treat them during the training process.

**Cross-Validation:** Cross-validation is often used with XGBoost to assess model performance and avoid

overfitting. It helps determine the optimal number of boosting rounds or trees.

**Feature Importance:** XGBoost provides a feature importance score, which indicates the contribution of each feature in making predictions. This is valuable for feature selection and understanding the model.

**Wide Applicability:** XGBoost is versatile and can be used for various tasks, including classification, regression, ranking, and anomaly detection.

**Community and Support:** XGBoost has a strong user community and support, with active development and ongoing improvements. It's widely used in data science competitions and real-world applications.

**Parameter Tuning:** XGBoost offers a range of hyperparameters that can be tuned to optimize model performance, such as learning rate, maximum depth of trees, and the number of trees.

XGBoost is particularly well-suited for structured data, but it has also been applied to text data and image analysis tasks with appropriate feature engineering. It has gained popularity in the machine learning community for its robustness, speed, and competitive performance in predictive modeling tasks. Many machine learning libraries and frameworks offer XGBoost implementations, making it accessible to a wide range of data scientists and practitioners.

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The [health record data](#) of [patients](#) hospitalized at an advanced [emergency](#) and [critical care medical center](#) in [Kumamoto, Japan](#), were collected electronically. A decision tree ensemble model using extreme gradient boosting (XGBoost) and a sparse linear regression model using least absolute shrinkage and selection operator (LASSO) regression. To evaluate the predictive performance of the model, we used the area under the receiver operating characteristic curve (AUROC) and the Matthews correlation coefficient (MCC) to measure discrimination and the slope and intercept of the regression between predicted and observed probabilities to measure calibration. The Brier score was evaluated as an overall performance metric. We included 11,863 consecutive patients who underwent surgery with general anesthesia between December 2017 and February 2022. The patients were divided into a derivation cohort before the COVID-19 pandemic and a validation cohort during the COVID-19 pandemic. Postoperative delirium was diagnosed according to the confusion assessment method.

A total of 6497 patients (68.5, SD 14.4 years, women n=2627, 40.4%) were included in the derivation cohort, and 5366 patients (67.8, SD 14.6 years, women n=2105, 39.2%) were included in the validation cohort. Regarding discrimination, the XGBoost model (AUROC 0.87-0.90 and MCC 0.34-0.44) did not significantly outperform the LASSO model (AUROC 0.86-0.89 and MCC 0.34-0.41). The logistic regression model (AUROC 0.84-0.88, MCC 0.33-0.40, slope 1.01-1.19, intercept -0.16 to 0.06, and Brier score 0.06-0.07), with 8 predictors (age, intensive care unit, neurosurgery, emergency admission, anesthesia time, BMI, blood loss during surgery, and use of an ambulance) achieved good predictive performance.

The XGBoost model did not significantly outperform the LASSO model in predicting [postoperative delirium](#). Furthermore, a parsimonious logistic model with a few important predictors achieved comparable performance to machine learning models in predicting postoperative delirium <sup>1)</sup>.

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The study presents a well-executed analysis of predictive models for postoperative delirium. The

comparison of machine learning models to a simpler logistic model is particularly informative. However, a more in-depth discussion of the study's limitations and a discussion of how these models might be integrated into clinical practice would have strengthened the paper.

1)

Matsumoto K, Nohara Y, Sakaguchi M, Takayama Y, Fukushige S, Soejima H, Nakashima N, Kamouchi M. Temporal Generalizability of Machine Learning Models for Predicting Postoperative Delirium Using Electronic Health Record Data: Model Development and Validation Study. JMIR Perioper Med. 2023 Oct 26;6:e50895. doi: 10.2196/50895. PMID: 37883164.

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