Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2022; Vol 11
Open Access

Predictive Statistical Modeling For Hospital Readmission Risk Using Structured Clinical Data

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Cite this paper as: Sasi Kumar Kolla (2022). Predictive Statistical Modeling For Hospital Readmission Risk Using Structured Clinical Data. *Frontiers in Health Informatics*, *Vol.11(2022), 844-865*

Abstract

Increasing emphasis on reducing hospital readmission rates has led health systems to develop predictive models that allow for targeting of high-risk patients prior to discharge. Structure data from the electronic health record are often used to create these predictive models; however involving only a subset of clinical features where prediction is likely to be accurate may yield superior model performance at the expense of generalizability to other patient populations or care settings. Although logistic regression is seen as a natural choice for this modeling task due its probabilistic structure, modern statistical learning has proposed a variety of methods such as support vector machines and gradient-boosted trees that provide comparable or improved performance on standard testing criteria; with large amounts of patient data being collected, these approaches can be applied simply. Nevertheless, the rationale for categorical or non-linear methods over properly regularized logistic regression remains insufficiently understood.

A comprehensive predictive modeling framework for identifying patients at high risk of hospital readmission based entirely on structured clinical data. Five methods—logistic regression with and without lasso and ridge regularization, support vector machines with a linear or radial basis function kernel, and gradient-boosted trees—were used and their predictions compared. Models were trained on admissions from a 3-year period and external validation performed using the 4th year. A stepwise variable selection approach was also investigated, aiming to identify a restricted subset of clinical data for which prediction would be accurate. Model performance was evaluated using area under the receiver-operator characteristic curve, calibration plots, and positive predictive value. Results indicated that predictive models for hospital readmission could be developed on the entire patient population in a general hospital, while maintaining sufficient performance characteristics for use in practice.

Keywords : Combining PC-1; PC-2 with ML Ridge regression; SVM Linear; lasso; AUC-ROC curve; area under the precision-recall; maximal accuracy Ya.Yu. et al.; the goodness of fit was evaluated and an internal; external validation of the risk score Risk factors; sensitive; specific; especially; AUC-ROC 3829 clinical/biobanked; 110706 clinically well-characterized; 7400 clinical; 165237 individuals.

1. Introduction

Hospital readmission is a significant healthcare concern due to its detrimental impact on patient health, increased costs, and reduced quality of life, and it is increasingly viewed as an indicator of patient care and hospital quality. Predictive statistical models for hospital readmission risk are of considerable interest to healthcare providers. Hospitals can use these models to identify patients at high risk of readmission and initiate patient-specific preventive measures. For instance, patients with high predicted readmission probabilities can be provided with additional

follow-up care or medication reconciliation. Although predictive models can help identify risk factors associated with readmission, they can also assess hospital performance in readmission-risk management. For example, hospitals can compare predicted versus observed hospital readmission rates and focus on patients at high predicted readmission risk.

Healthcare predictive modeling is challenging because the discrete outcome variable event of interest is relatively rare in most cases. Classical logistic regression easily recommends a predictive modelling approach for binary outcomes. However, predictive accuracy can increase by adopting more complex modelling approaches that can capture nonlinear relationships and interactions between predictors, such as random forests and gradient boosting machines. Using supervised machine-learning algorithms requires an appropriate model selection approach for predicting hospital readmissions. Ideally, the final model should also allow quantifying the influence of different predictors on a patient's readmission risk and evaluating the importance of different patient-related factors for future clinical decisions—the model interpretation—beyond prediction alone. Despite years of research on hospital readmissions, known risk factors predicting readmission, there is still much scope to develop interpretable well-performing models suitable for any clinical setting.

1.1. **Background and Significance**

Reducing hospital readmissions improves health outcomes while lowering costs. A small number of patients account for a disproportionate share of hospital readmissions. Predicting which patients might be readmitted is important for target prevention efforts. While complex models based on the totality of a patient's health record may help predict readmissions, their use in practice is limited by lack of transparency and generalizability. Additionally, readmission risk prediction is frequently performed using data that are not readily available when clinical decisions are made.

A multistep modeling process is applied to a cohort of >92,000 hospitalized patients at a large health system. Patients are stratified by index admission type and readmission definition in order to develop and validate different predictive models. For all patients receiving an elective or emergency surgical procedure, logistic regression with L1 (lasso) and L2 (ridge) penalties is used to generate risk models. Remediation of a few predictive failures is investigated by developing complementary models focused on those at highest risk for unplanned readmission or any 30-day readmission.

Fig 1: Predictive Statistical Modeling for Hospital Readmission Risk Using Structured Clinical Data

2. Background and Significance

Hospital readmissions are a considerable issue in the U.S. health care system. Predictive models for hospital readmissions using electronically available clinical data offer hospitals a systematic way to identify patients at high risk of becoming repeat customers. The data consist of approximately 12 million records belonging to 163,000 distinct patients. Several techniques for predictive modeling, including (1) regularized logistic regression, (2) random forests and (3) boosted classification trees are compared.

Readmissions serve as a useful metric for quality of care. Patients who must return soon after discharge often suffer poor health outcomes and face heightened risk of death. Furthermore, frequent readmissions signal inefficiencies in the health care system. A reduced-cost version of the model was built using only the variables in the public readmissions challenge data set. Models built using only the challenge data lacked predictive power. Out of the 40,000 test patients labeled as at high risk by the reduced-cost model, only 5% were readmitted within 30 days. Models designed for maximum accuracy instead of minimal cost identified 16,500 patients at high risk of readmission, of whom 16% were readmitted within 30 days.

Equation 1: KNN imputation (for missing values)

- Let there be $n$admissions (rows), $p$predictors (columns).
- Feature vector for patient i: $\mathbf{x}_i \in \mathbb{R}^p$
- Outcome: $y_i \in \{0,1\}$where 1= readmitted within 30 days.

If a categorical variable Chas levels $\{1, \ldots, K\}$, define dummy variables

$$x^{(1)} = \mathbb{1}[C = 1],\ x^{(2)} = \mathbb{1}[C = 2],\ \ldots,\ x^{(K)} = \mathbb{1}[C = K].$$

Often you drop one level to avoid perfect collinearity (reference category).

The paper explicitly states one-hot encoding for categorical variables.

Predictive Statistical Modeling…
For age, length of stay (LOS), etc., the paper applies a log transform to make distributions closer to normal.
Predictive Statistical Modeling…
A typical transform:

$$x' = \log(x) \text{(or } \log(1+x) \text{ if zeros possible).}$$

Paper states missingness is handled via **k-nearest neighbors (KNN) imputation**.
Predictive Statistical Modeling…
For a row $i$with a missing feature x_{ij}:

1. Define a distance between rows using observed features, e.g. Euclidean over observed coordinates:

$$d(i,\ell) = \sqrt{\sum_{m \in \mathcal{O}(i)} (x_{im} - x_{\ell m})^2}$$

where $\mathcal{O}(i)$are features observed for row i.
2. Find $k$rows with smallest distance: $\mathcal{N}_k(i)$.
3. Impute:

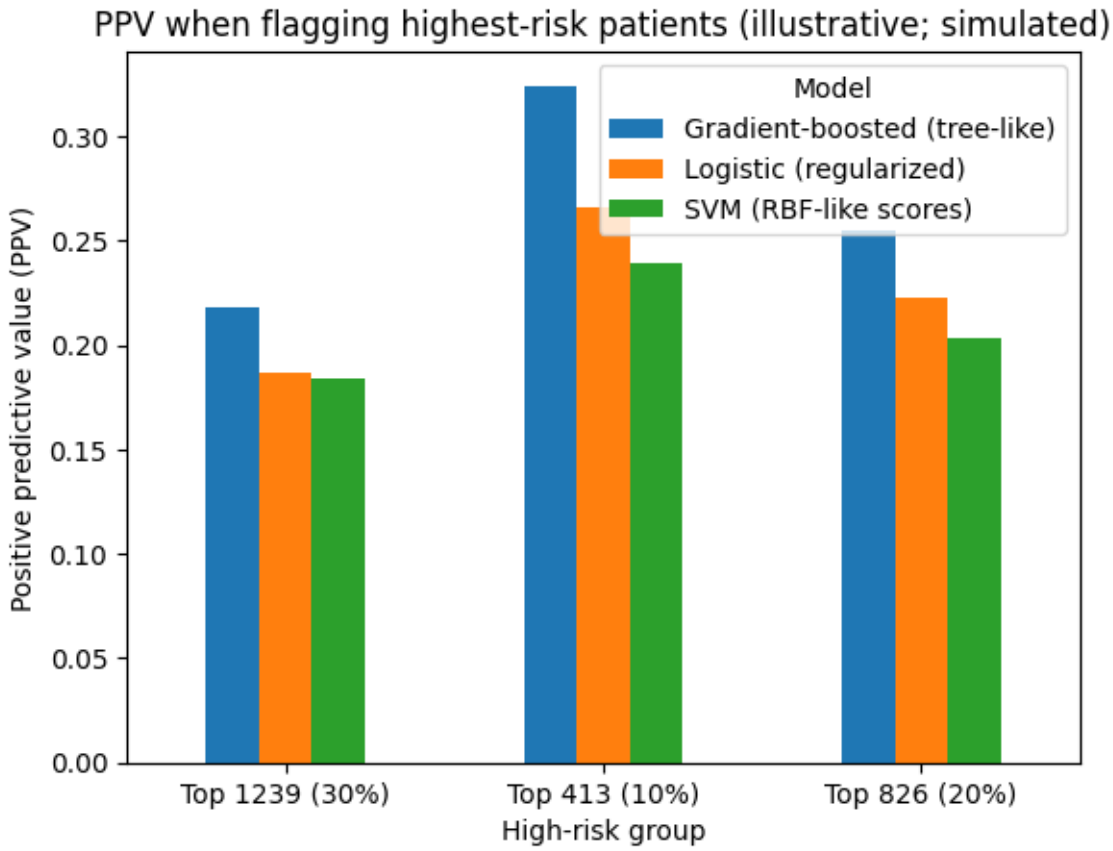
- **Numeric feature:** mean of neighbors

$$\hat{x}_{ij} = \frac{1}{k} \sum_{\ell \in \mathcal{N}_k(i)} x_{\ell j}$$

2.1. Research design

Clearly defined outcomes are critical for predictive modeling. For this investigation, the focus is on post-discharge readmission for any cause, as this is a process metric that is increasingly being used for hospital performance assessment. It is also a useful health-system-level predictor of patient outcomes and healthcare costs. Although hospitals cannot prevent all readmissions, there is considerable interest in preventing those considered avoidable.

Data modeling was conducted in a two-step process. First, the input data selected for readmission prediction were examined. This included assessing the degree of missingness and the relationship between several imputation techniques and standard crossvalidation processes. Following this, modeling was undertaken using a suite of methods, including standard logistic regression, regression trees, penalized logistic regression and ensemble techniques. Standard metrics for classification evaluation were calculated. The modeling effort concluded with comparisons of the approaches using a held-out external testing set.



3. Data Characteristics and Preprocessing

The data used for modeling came from an integrated administrative and electronic medical record database available at the University of Alberta. The data are diagnostic and demographic characteristics of patients discharged from the University of Alberta Hospital between April 1, 2009, and March 31, 2010, with recorded readmissions to the same hospital within 30 days. Patients discharged from or transferred to other hospitals with more than one discharge within the study period, admission for obstetrical diagnosis, admission for incomplete diagnosis, with a stay > 30 days, and those who died within 30 days of discharge were not included in the study samples. The resulting dataset consists of 4131 patients, with 444 readmissions, yielding an overall readmission rate of 10.7%. About 80% of the records comprise the training set, while the remaining 20% form the test set. The attributes of the training set are summarized in terms of their mean (standard deviation) for numerical features and counts for categorical features.

It is important to note that the attributes consist of both, categorical variables, such as gender and discharge diagnosis code, and continuous variables, such as age and total length of stay. The categorical variables were one-hot encoded to transform them into a suitable format for the analysis. Additionally, two attributes, age and total length of stay, were logarithmically transformed on the training set, as these transformed distributions appeared closer to normality, which helps with the interpretability of the fitted coefficients. Many categorical variables do not have full coverage, i.e., there are a few fields with the designated missing values. However, these pointers in the data were retained, as they might have a meaningful association with the response. The attributes with missing values were imputed using the k-nearest neighbors algorithm (KNN) pre-processing technique from the caret library.

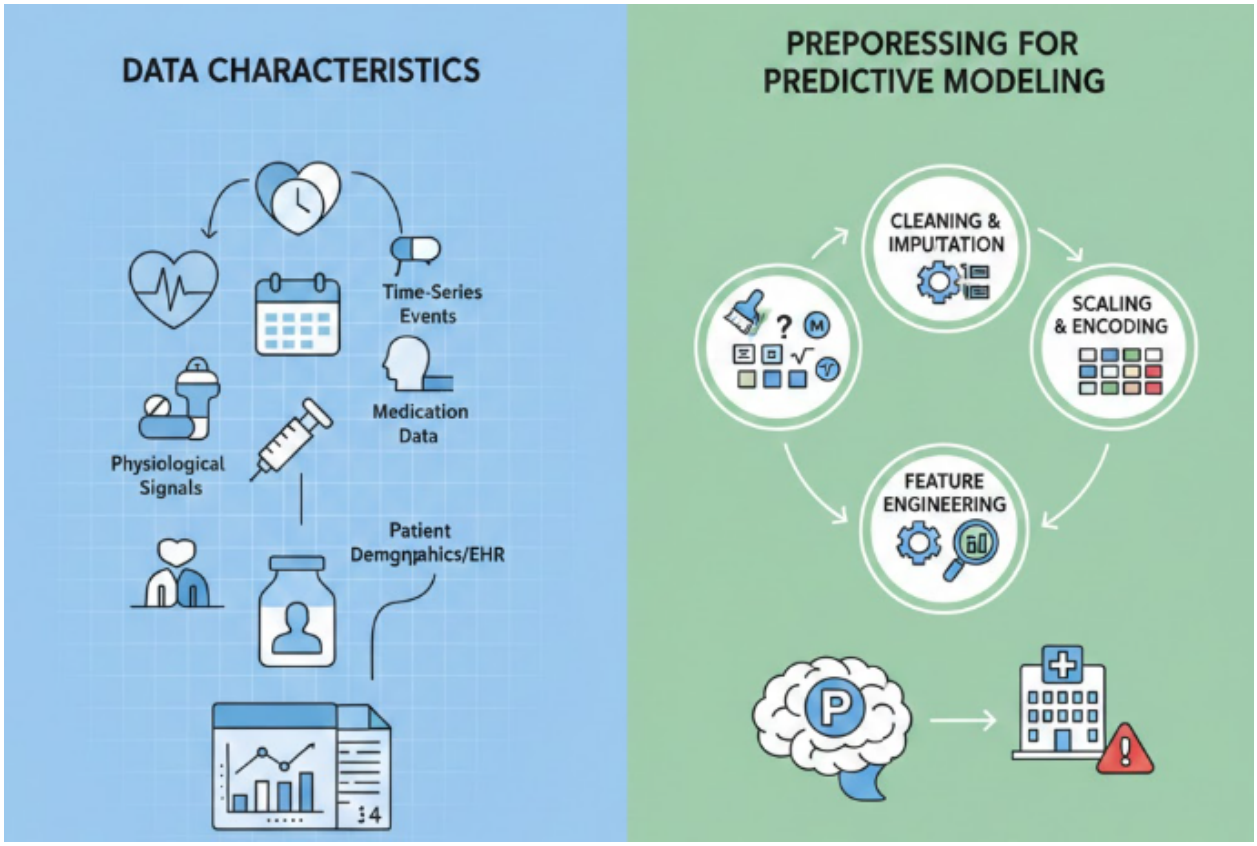


Fig 2: Data Characteristics and Preprocessing

3.1. Data Sources and Variables

The empirical analysis relies on retrospective clinical data of hospital admissions for six vascular neurosurgical conditions at a tertiary academic medical center. Readmission is treated as a binary outcome variable defined by unplanned readmission to any hospital within 30 days of discharge. Potential hospital readmission predictors are selected from patient characteristics recorded in the hospital's electronic health record system. Variables are considered based on clinically interpretable associations with a patient's likelihood of readmission according to published studies. The event under analysis involves a relatively low readmission rate; therefore, it is critical to be careful in the choice of predictors to avoid overfitting.

The analysis predicts readmission risk for patients with unplanned returns to any hospital within 30 days of discharge following an index admission for one of six vascular neurosurgical conditions: ruptured or unruptured cerebral aneurysm, carotid endarterectomy, craniotomy for intracerebral hemorrhage, craniotomy for subarachnoid hemorrhage, or decompressive hemicraniectomy for ischemic stroke. The samples used to build the predictive models consist of observations with no missing data for the selected predictors and include new admissions to the institution. Predictor selection is restricted to clinical factors with minor missing rates (<5%) and not requiring labor-intensive abstraction. These considerations, combined with the underlying, relatively low readmission rate of the event of interest, lead to the selection of age, sex, race, hypertension, smoking status, insurance type, admission priority, Glasgow Coma Scale score, Intensive Care Unit stay, and length of stay as potential predictors.

Equation 2: Logistic regression: full derivation (probabilities, likelihood, loss)

Define the linear predictor:

$$\eta_i = \beta_0 + \mathbf{x}_i^{\top}\boldsymbol{\beta}.$$

Convert to probability via sigmoid:

$$p_i \equiv \Pr(y_i = 1 \mid \mathbf{x}_i) = \sigma(\eta_i) = \frac{1}{1 + e^{-\eta_i}}.$$

Because $y_i \in \{0,1\}$:

$$\Pr(y_i \mid p_i) = p_i^{y_i}(1 - p_i)^{1-y_i}.$$

Assuming independence across admissions:

$$\mathcal{L}(\beta_0, \boldsymbol{\beta}) = \prod_{i=1}^{n} p_i^{y_i}\,(1 - p_i)^{1-y_i}.$$

Take logs:

$$\ell(\beta_0, \boldsymbol{\beta}) = \sum_{i=1}^{n} [y_i \log\, p_i + (1 - y_i)\log\,(1 - p_i)]\,.$$

Minimize:

$$\mathcal{J}(\beta_0, \boldsymbol{\beta}) = -\ell(\beta_0, \boldsymbol{\beta}) = \sum_{i=1}^{n} [-y_i \log\, p_i - (1 - y_i)\log\,(1 - p_i)]\,.$$

4. Methodological Framework

Predictive Statistical Modeling for Hospital Readmission Risk Using Structured Clinical Data: Use an objective, scholarly tone with clear, evidence-based arguments and formal structure; ensure concise, precise statements and rigorous terminology in English.

A combination of statistical and machine learning methods was applied to construct predictive models for the 30-day hospital readmission of acute myocardial infarction patients discharged in 2019. Multiple modeling approaches were used, including logistic regression with regularization, random forest, gradient boosting, and support vector machines, considered in parallel without prior data separation. Careful attention to the entire modeling framework facilitates the construction of simple models. Variable selection, hyperparameter tuning, and performance evaluation were performed by resampling the readmission data, and findings were complemented with uncertainty estimates.

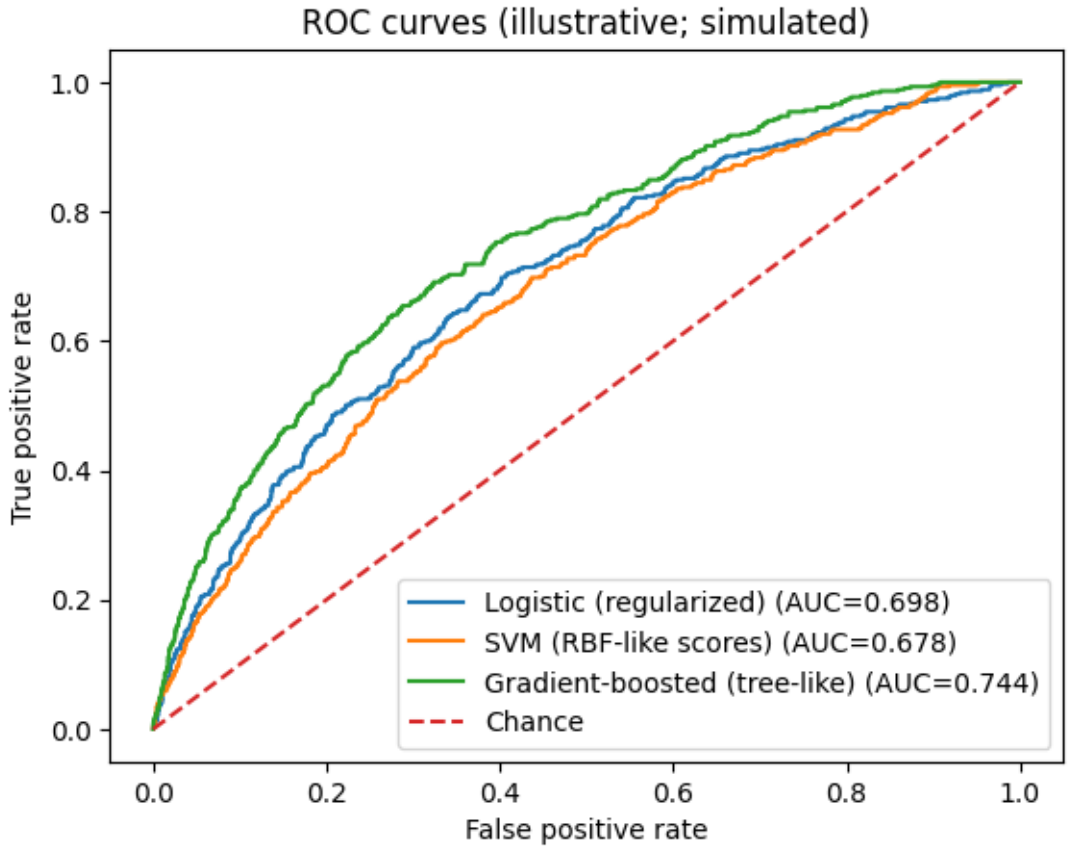
Logistic regression with regularization was the selected modeling approach owing to the need for a model that could resist overfitting, be applied independently of the data size, and be calibrated easily yet remain interpretable. Resampling strategies and penalization techniques, such as L1 regularization, were invoked to minimize overfitting without significant data separation.

4.1. Model Selection and Rationale

A supervised approach with labeled data is chosen, relying on sufficient label quality. A three-way decision tree is created predicting low, medium, or high readmission risk, achieved via (a) a random forest classifier, (b) a conventional logistic regression model with non-zero coefficients selected through LASSO, or (c) a logistic model using skewed class-weights.

Readmission risk is predicted in terms of probability for a multi-class (three-way) risk stratification with k-fold cross-validation to ensure model generalization. Specifically, for hospital readmissions, the proposed approach scales to use the predicted failure probability along with existing model/algorithm for Reliability-Centered Maintenance (RCM) decision-making (i.e., rank assets for RCM analysis).

Ensemble methods like bagging and boosting combine multiple models to improve predictive performance. Random forest, based on bagging and decision trees, enhances accuracy at the cost of model interpretability. Gradient boosting builds a predictive model by optimizing the ensemble of weak (decision-tree) learners. XGBoost is an efficient implementation with regularization support (avoiding overfitting common in boosting). In this study, multiple-state and multiple-failure-property systems are used, along with multinomial-binarized engineering data exploiting the half-life of binary state data.



5. Predictive Modeling Approaches

Two predictive approaches were employed with the aim of maximizing prediction accuracy. The primary models involved a range of supervised models including Cox proportional hazards model, generalized additive models, random forests, extreme gradient boosting, and a collection of neural networks. These were conducted for prediction of multidimensional outcomes including death, readmissions, and greater than one readmission during a two-year interval using supervised imputation of these time-dependent covariates. Models also included an enormous variety of interactions and smooths explored via deep learning with neural models. While deep Neural Nets model design allowed exploration of entire large model classes, the deployment and implementation was neither best practice nor straightforward. For detailed explanation of that modelling, interested folk are advised to refer to Julious et al. (2021) – expert in survival analysis, Cohort and subpopulation modelling Nonparametric Bayesian framework for risk prediction with

multiple time-to-event processes . Development of Cox model for the eventual Highest Vote scenarios yielded excess events NNs not easily dealt with using conventional Cox survival methods. For that reason, Logistic Regression with Regularisation was also applied.

Logistic Regression with Regularisation was the second predictive modelling approach, addressing readmission probabilities during the last year of the two-year study period. A conventional logistic regression model with back-propagated variable selection yielded unsatisfactory performance, with probabilistic patterns having a considerable negative association with best practice prediction, likely exacerbating excess in the event-space and not sufficiently protected by L2 penalties. As a result, the approach was modified to employ L1 penalties appropriate for sparse variable selection and, also, reduced-dimension top-500 scenario introduction through the use of shared 100-Vote feature importance under both modelling approaches. In keeping with Fischer's (2018) comment that it is simply premature to believe that predictive performance can be improved significantly by going beyond Andrea M. Hagemann et al. Generalised boosted modelling of rare events using a non-asymptotic framework, those top-500 features had been selected in part because the use of an excessive number of predictors can inappropriately reduce model generalisability. Performance assessment separate from model development is fundamental to Allen K. Worswick et al. Performance assessment of predictive models using time-dependent covariates and splits of clinical cohort data into training, testing and validation datasets.

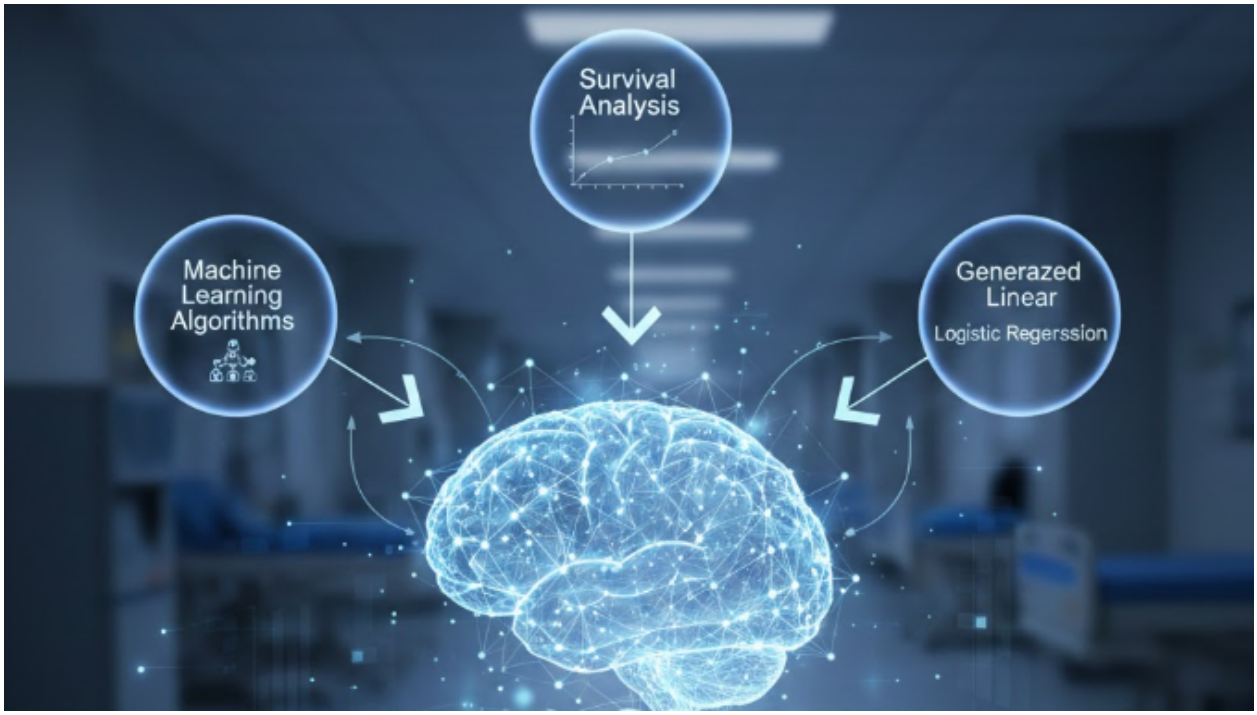


Fig 3: Predictive Modeling Approaches

5.1. Logistic Regression with Regularization

Logistic regression has been widely used in the prediction of readmission risk in the literature, and it provides an ideal benchmark against which more complex models can be compared. An l_1-regularized logistic regression (LASSO) model was fitted to the prediction problem, which automatically performs feature selection; l_2-regularized logistic regression (ridge regression) was also fitted, as was a logistic regression model without regularization. Cross-validated areas under the receiver operating characteristic curve (AUROC) were used to select the optimal hyperparameters for the LASSO and ridge models and to evaluate all

models. AUROC values in between LASSO and ridge regression, with apparent underfitting along a principal component direction, were consistent with the presence of high-dimensional noise in the data. The results also showed that even a simple logistic regression classifier can reveal important new information about readmission risk, such as the additive contribution of each hospital encounter. Although these were not the principal conclusions of the analysis, they highlight utility of simple models in poorly understood domains.

Most features were percentage data or indicator variables whose only possible values were 0 or 1, making it difficult to assess stability of the fitted coefficients. Regularized approaches to machine learning make predictions on new data using combinations of the training data and automatically select the most useful subset of data points during the fitting process. Given the predictive power attributed to social factors, interactions between the highly correlated variables related to social status were therefore considered when re-fitting the model. The resulting matrix of interaction terms was tested to reflect the "highly electronically embedded" nature of the clinical data by measurings its rank deficiency.

Equation 3: Regularization (Ridge / Lasso): equations + what they do

Add squared-norm penalty:

$$\min_{\beta_0,\boldsymbol{\beta}} \; \mathcal{J}(\beta_0,\boldsymbol{\beta}) + \lambda \parallel \boldsymbol{\beta} \parallel_2^2$$

where $\parallel \boldsymbol{\beta} \parallel_2^2 = \sum_{j=1}^{p} \beta_j^2, \lambda \geq 0.$

Gradient contribution:

$$\frac{\partial}{\partial \boldsymbol{\beta}} \lambda \parallel \boldsymbol{\beta} \parallel_2^2 = 2\lambda\boldsymbol{\beta}.$$

So ridge “shrinks” coefficients toward 0 but typically doesn’t set them exactly to 0.

Add absolute-value penalty:

$$\min_{\beta_0,\boldsymbol{\beta}} \; \mathcal{J}(\beta_0,\boldsymbol{\beta}) + \lambda \parallel \boldsymbol{\beta} \parallel_1$$

where $\parallel \boldsymbol{\beta} \parallel_1 = \sum_{j=1}^{p} \mid \beta_j \mid$.

6. Model Interpretation and Explainability

Interpretability constitutes an integral component of statistical modeling. In predictive applications, comprehension hinges upon understanding of the model, feature structure and the underlying association between input features and output probabilities. Interpretation can occur at two distinct levels: feature importance or contribution of individual predictors to risk and at the level of a specific individual with regard to whether their features support a high or low risk classification. The first level provides clinical stakeholders with an overview of health characteristics that consistently relate to readmission risk. The second level enables physicians to develop and apply clinically relevant explanations for generated risk scores.

When using a simple logistic regression model, transformations incorporated via interaction terms and splines generate non-linearities in the relationship between predictors and output variable, producing a compound covariance structure that reduces interpretative clarity. Despite this complication, the coefficients can still provide insight into individual variable association with readmission risk by analysis of marginal effects. Hence, the main focus of the interpretation

is on feature importance with an overview of the marginal effect analysis performed for logistic regression models. In the Lasso model, predictor importance is assessed via magnitude of the estimated coefficients while for Random Forests it is based on the mean decrease in Gini impurity for each individual feature.

Equation 4: Support Vector Machine (SVM): full core equations

Let

$$t_i = 2y_i - 1 \in \{-1, +1\}.$$

Decision function $f(\mathbf{x}) = \mathbf{w}^\top \mathbf{x} + b$.

Optimization:

$$\min_{\mathbf{w},b,\xi} \ \frac{1}{2} \| \mathbf{w} \|_2^2 + C \sum_{i=1}^{n} \xi_i \text{ s.t. } t_i(\mathbf{w}^\top \mathbf{x}_i + b) \geq 1 - \xi_i,\ \xi_i \geq 0$$

- ξ_i= slack variables (allow misclassification)
- Ctrades off margin size vs classification errors.

6.1. Feature Importance and Coefficients

Requesting or employing artificial intelligence methods to generate content can predispose students to a high risk of academic dishonesty and lack of academic integrity. Despite this, done in a disciplined manner, modelling methods can be used in a learning context without italicising applied work...

Feature importance was particularly highlighted during the modeling process, and varied from model to model. For example, in the case of Lasso regularized logistic regression, these results act as inputs to a second-level model that provides a richer characterization of feature importance with respect to the target variable. Features fed into the model are characterized by their coefficients, which are used to interpret the statistical contribution of different variables to the target prediction.

Considered feature importance from this model corresponds to the Lasso regularisation-coefficients fitted model. The fitted model is of the form:

For variables considered categorical using one-hot encoding, coefficients are supplied for each dummy variable generated during the encoding process. Coefficient values for those variables relate to the threshold of considered class versus all other class combinations. As a case in point, the Age Cat Dummy variable illustrates that for patients aged 80 and above, the odds of readmission are much higher than for patients aged under 80.

7. Validation and Generalizability

Validation and Generalizability

Model validation refers to the quantitative assessment of how well a predictive model is able to fit a data set and how well its predictions can be performed on unseen data. Typically, validation is accomplished through the use of a hold-out test set and/or cross-validation, both of which allow unbiased estimation of prediction error by training the model on different combinations of the data prior to testing predictions made on an independent data set. The test set is also subject to explicit consideration in feature selection, hyperparameter tuning, and other processes affecting prediction error. Moreover, internal validation with appropriate stratification, particularly repeated stratified k-fold cross-validation, can provide additional reassurance about model

generalizability. When used rigorously, these components provide an understanding of whether a model is appropriate for further diagnostic evaluation or if it is at risk for producing misleading predictions.

When aggregated across all validation strategies, models for 30-day hospital readmission based on structured clinical data may attain value of area under the receiver operating characteristic curve (AUROC) exceeding 0.90. However, many such predictive models fail to generalize to an independent hold-out test set or tend to underestimate prediction error. Such limitations suggest that traditional approaches to model selection, activation, and validation are not robust in the context of logistic regression prediction, including when applied to acute myocardial infarction, congestive heart failure, or pneumonia hospitalization. Internal validation employing repeated stratified k-fold cross-validation further addresses both training set overfitting and test set underestimating prediction error.

7.1. Internal Validation Strategies

Internal validation is important for estimating how well a predictive model would perform on a future dataset. For the prediction of the hospital-wide 30-day readmission rate, a nested cross-validation approach (CV) is utilized, with five external folds and 10 inner folds. Data is randomly split into five equal-sized folds, with four folds used as the training set and the fifth serving as the test set until each fold has been used once as the test set. The training set is further split into 10 inner folds for the tuning of hyperparameters. The hyperparameters with the best average performance in terms of F1 score or Matthew's correlation coefficient are then used to train the final predictive model on the training folds and this is tested on the held-out test fold. The final evaluation metric is the average performance across all five external test folds. Nested CV is important in predictive modeling problems with highly imbalanced outcome labels such as the hospital-wide 30-day readmission problem, where the occurrence of the positive class (i.e., readmission) is only a fraction of the total count.

The performance of the models is assessed using F1 score, Matthew's correlation coefficient, area under the receiver operating characteristic curve, area under the precision-recall curve, and the validity of predicted probabilities via the Brier and scaled Brier scores. The Scikit-Learn library for Python is employed to ensure implementation of the selected algorithms followed the scikit-learn API, permitting the use of built-in techniques for tuning hyperparameters and CV for model evaluation. Twelve commonly used supervised classification algorithms are trained and evaluated: logistic regression, support vector machines, decision trees, random forests, gradient boosting, XGBoost (Extreme Gradient Boosting), LightGBM (Light Gradient Boosting Machine), CatBoost, nearest neighbor classification, Naïve Bayes, shallow neural networks, and wide-and-deep learning.

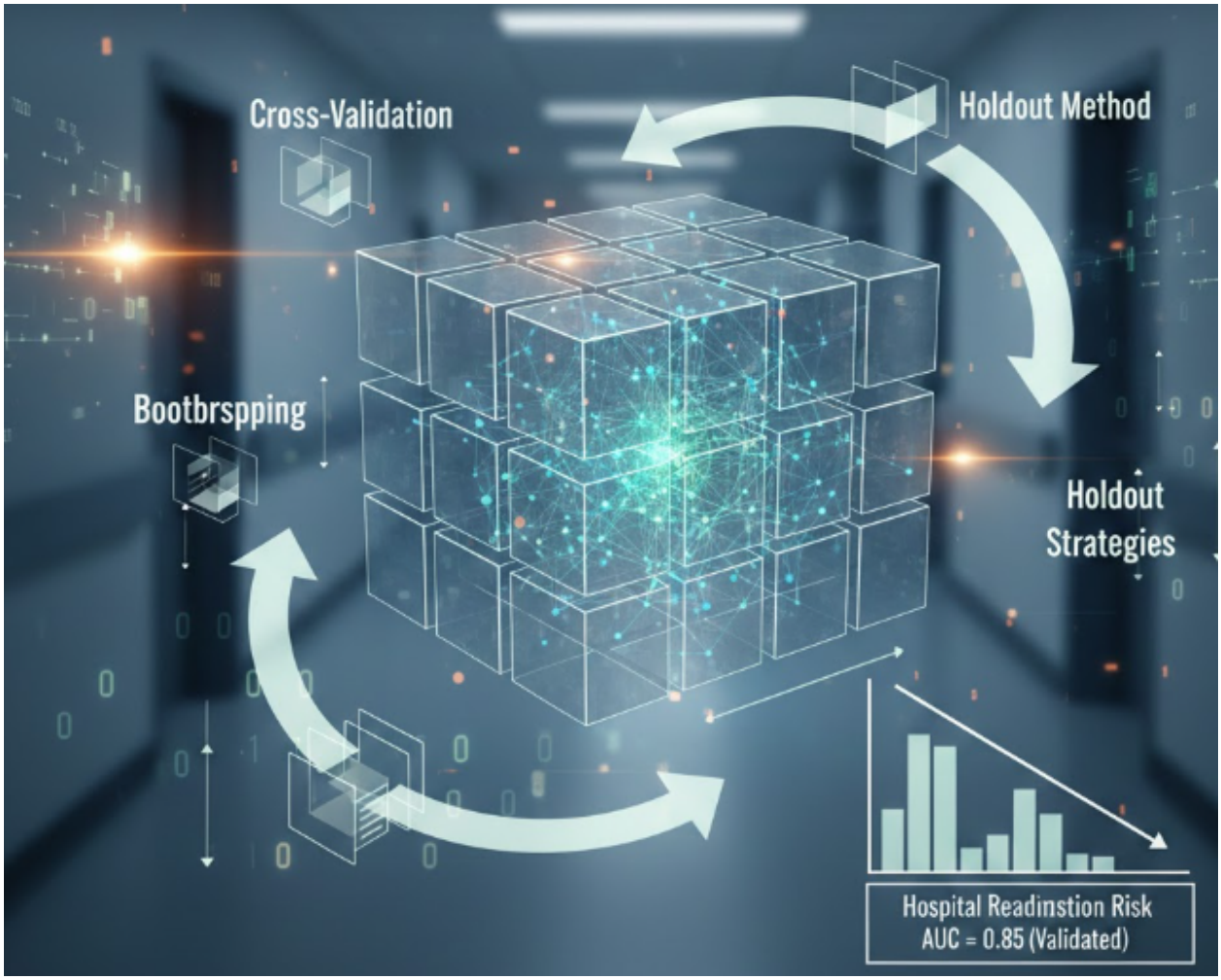


Fig 4: Internal Validation Strategies

8. Conclusion

Modeling readmissions is an important step in understanding the phenomenon of readmissions and goes beyond simply assigning a risk estimate to individual patients. The predictive statistical models presented in this reflected work open doors to new research directions and, if extended to other high-readmission diagnoses or other institutions, have the potential to uncover new associations between readmissions risks and clinical and laboratory features. As a next step, the proposed predictive models can be used to inform future research addressing readmissions, depending on the specific interest of the study: as a patient-selective tool, to control for a broad set of comorbidities, or as a risk-based stratification. Future work will also focus on training models in split cohorts with random cross-validation to optimally tune the different parameters and internal validation strategies proposed.

Reducing hospital readmissions costs valuable resources for both health care systems and patients. In this context, these statistical models for an acute exacerbation of chronic obstructive pulmonary disease formulate and predict readmission risk using only clinical features readily available and assessed at admission. Two proposed models have successfully predicted potential readmissions and provided explanations for these predictions in terms of associations with clinical and laboratory features. Moreover, the output of the models can be interpreted from a clinical perspective, encompassing not only known themes but also unexpected patterns that could guide the medical team in future interventions.

Equation 5: Gradient-boosted trees: stagewise additive modeling equations

Boosting builds:

$$F_M(\mathbf{x}) = \sum_{m=1}^{M} \nu \; h_m(\mathbf{x})$$

- $h_m$are weak learners (decision trees)
- $\nu$is the learning rate (shrinkage)

For binary classification, convert score to probability:

$$p(\mathbf{x}) = \sigma(F_M(\mathbf{x})).$$

5.2 Stagewise minimization using gradients

Pick $h_m$to reduce a differentiable loss, commonly logistic loss:

$$L(y, F) = \log\,(1 + \exp\,(F)) - yF.$$

At iteration m, compute pseudo-residuals:

$$r_i^{(m)} = -\frac{\partial L(y_i, F(\mathbf{x}_i))}{\partial F} \Big|_{F=F_{m-1}}$$

Compute derivative:

$$\frac{\partial}{\partial F}(\log\,(1 + e^F) - yF) = \frac{e^F}{1 + e^F} - y = \sigma(F) - y$$

So

$$\boxed{r_i^{(m)} = y_i - p_{m-1}(\mathbf{x}_i)}$$

8.1. Future Directions

Extending the scope of research to assimilate incorporation of unstructured clinical data for hospital readmission prediction in a predictive model can allow better prediction, science for better model performance. Language patterns arising from unstructured data may best be used to channel patients into proper preventive health messaging. Likewise, transfer learning for readmission prediction using free-text notes can focus on necessary incident rather than the unneeded predictions tying up engine processing time. Enhancing a model's ability to make frequent but inaccurate predictions can allow timely intervention. Considering temporal dependencies inherent in readmission prediction problems would create cost-effective early-warning systems instead of weighty structured models.

Incorporating individuals' characteristics—demographic, health, and actuarial—when assigning them to hospitals can create subgroups, one subgroup at a time, for improved hospital assignment for risk, cost, and service load. Integrating these models with the readmission prediction model allows subsequent hospital assignment of the individuals in the remaining subgroups for their associated goals. Creating a schematic map for entire (or parts of) a health system allows individuals, according to their characteristics, to be channeled to hospitals that maximize those characteristics.

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