Forecasting Postoperative Mortality after General Surgery Based on MIMIC III Data
Heinz 95-845: Machine Learning for Health Care

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Abstract

This study aims to use machine learning models to predict postoperative mortality for patients in intensive care units (ICU) after general surgery. Multiple machine learning algorithms are trained and tested with the data collected in Multiparameter Intelligent Monitoring in Intensive Care III (MIMIC III) database. Through these models, items considered to be significant in post-surgery care are examined and their contribution to post-surgery death are disccussed in this study. In this study, the performance of each algorithm is also compared with each other, to suggest on the most useful and reliable model that could be used in future postoperative mortality prediction.

1. Introduction

In medical field, the traditional method to analyzing the effect of an intervention is to conduct a randomized clinical trial and analyze the outcomes. Though high levels of recommendation could derive from them, with many limitations such as the size of population involved in the trial and ethical concerns, randomized clinical trials may not be able to be launched or completed, or the conclusions could be not broadly applicable. Besides, the complicated recruiting stage, the compliance issue of participants, and the long period of the trial and follow-ups make the randomized clinical trial unefficient and costly.

Recent advances in machine learning and the transfer from paper health records to eletronic health records have provided huge opportunities to health care research. With large volume of patient data and the high-speed data processing, we are now able to research on the topics that are used to be impposible for randomized clinical trial.

MIMIC III database is a large and freely available database that consists of deidentified health-related data on over 40,000 patients collected from ICU of the Beth Israel Deaconess Medical Center between 2001 and 2012 cit (2016). Some amount of progress on mortality prediction has been made by studying MIMIC III data. One research uses the abundance of ICU data to analyze the relationship between using selective serotonin reuptake inhibitors and the increase of mortality (Ghassemi M and LA, 2014), but it only does statistical tests on the outcome instead of building machine learning models. And another reaserch makes mortality predictions among patients with sepsis and hypotension by using dynamic data during hypotensive episode(Mayaud L and D, 2013). Although it only uses logistic regression to build the model, it has the movelty that using multiple perform measures to compare this model with traditional medical protocols. And another study builds a targeted real-time early warning score for septic shock by using lab data (Katharine E. Henry and Saria, 2015), which outperforms other widely-used protocols.

In this work, we use the MIMIC III data to predict the post-surgery mortality for ICU patients who just had genral surgery. Unlike to other studies using MIMIC data, this work makes the prediction not related to a specific condition. The purpose of it is to have a more general forecast that can be applied to all ICU patients with general surgery, and to provide a guide for nurses to provide better post-surgery care through the examination of indicators of mortality.

In Section 2, we provide background on the postoperative mortality. In section 3, we have a basic elaboration of the models used in this study. Then in section 4, experimental setup is provided to allow for replication of the study. Section 5 gives the results of the model. And more discussions on this study and related work are in section 6.

2. Background

With more and more emphases on heath care quality and patient safety, lowering the post-operative risk is extremely significant. Although the national death rate from complications of medical and surgical care is decreasing over years cit (2012), post-surgery death is still a big issue especially for the acute or unplanned surgery. Therefore, good postoperative care is important. To have a guidance on indicators of postoperative risk of death means not only better patient safety outcomes but also a relief from alert fatigue for nurses.

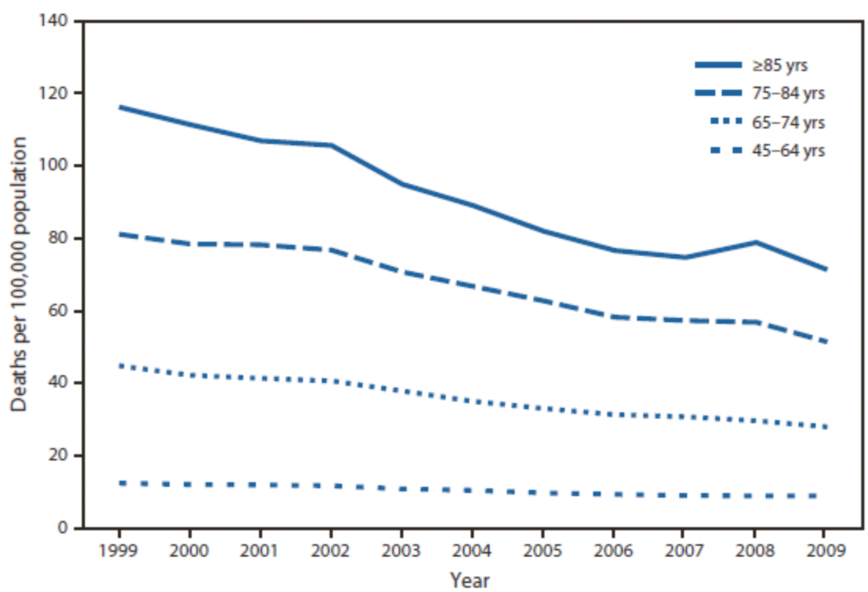

Figure 1: Death Rate From Complications of Medical and Surgical Care Among Adults Aged 45 Years, by Age Group United States, 1999 2009

3. Logistic Regression, Naive Bayes, Tree Augmented Naive Bayes, Decision Tree, and Random Forest Models

In this study, multiple machine learning models are used in R programming with packages: Logistic Regression, Naive Bayes, Tree Augmented Naive Bayes, Decision Tree, and Random Forest.

After training and testing all models, they are evaluated based on the accuracy of classification the outcome, receiver operating characteristic curve (ROC curve), and precision-recall curve (PR curve).

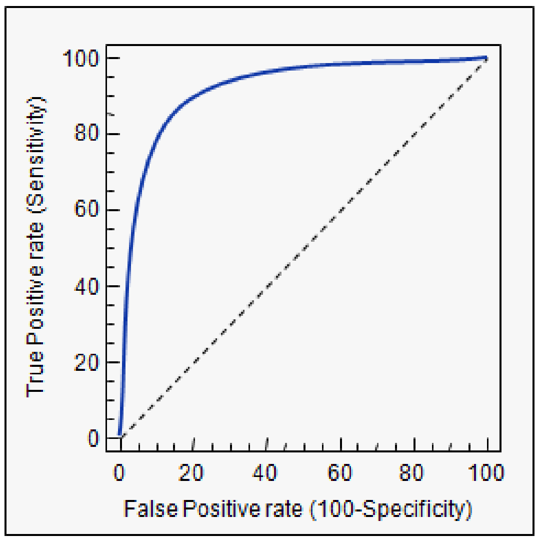

Figure 2: ROC Curve; source: https://www.medcalc.org/manual/roc-curves.php

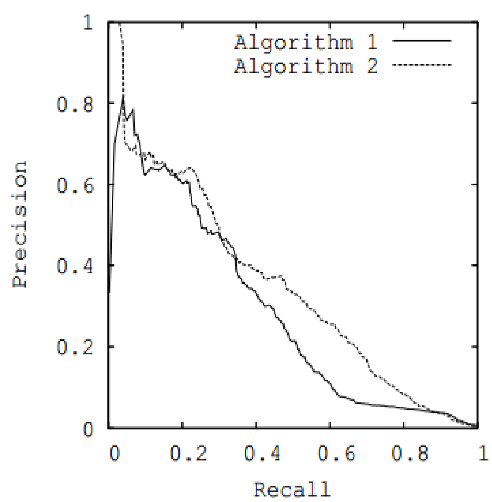

Figure 3: PR Curve; source: https://www.quora.com/What-is-Precision-Recall-PR-curve

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

Code is available at `https://github.com/xml93/MLforHC_FinalProject`.

4. Experimental Setup

4.1 Cohort Selection

The MIMIC III database contains over 40,000 patients' records and related health information. Since this study focuses on the patients who have general surgery and stay in ICU at the time of recording, only patients who have "ICU" as the cost center and "SURG" (which represents general surgery, other specific categories of surgery are marked respectively) as the current service. After selection, only 3580 patients are left.

Gender	Outcome (%)	RR	O2 Saturation(%)	Temp(F)	Systolic BP	HR
Female	Survival: 954 (61.5%)	18.72	89.07	98.33	115.81	87.81
1551	Death: 597 (38.5%)	19.56	90.93	97.86	116.80	87.95
Male	Survival: 1164 (57.4%)	18.31	88.92	98.50	116.80	87.95
2029	Death: 865 (42.6%)	19.59	91.69	98.11	107.46	88.06

4.2 Data Extraction

All datasets are downloaded from MIMIC III database and are in different spreadsheets of topics. Basic sql queries are used to link them. Since each patient has multiple admission records and each is related to general surgery, in order to predict the mortality after surgery, only the most recent admission is kept. And all other patient information is only kept for this most recent admission record. Each patient's admission has an ICD-9 Diagnosis code indicating the diagnosis. They are transformed into 19 groups using the first 3 digitd of ICD-9 code based on the ICD-9 diagnositic groups, making such data more informative.

4.3 Feature Choices

Features used in the model are mainly based on protocols used in the postoperative care. We want to know which medication and what physiology of patient are useful indicators of post-surgery death. Therefore, top 10 medications with highest prescription frequency are selected. They are Lactated Ringers ("LR1000"), Insulin ("INSULIN"), Furosemide ("FURO40I"), Magnesium Sulfate ("MAG2PM"), Sodium Chloride 0.9% Flush ("NACLFLUSH"), Metoprolol ("METO5I"), Depakote 500 mg ("NS500"), 250 cc of 5 % dextrose

Diagnoses

001 - 139	Infectious and Parasitic Diseases
140 - 239	Neoplasms
240 - 279	Endocrine, Nutritional, Metabolic, Immunity
280 - 289	Blood and Blood-Forming Organs
290 - 319	Mental Disorders
320 - 389	Nervous System and Sense Organs
390 - 459	Circulatory System
460 - 519	Respiratory System
520 - 579	Digestive System
580 - 629	Genitourinary System
630 - 677	Pregnancy, Childbirth, and the Puerperium
680 - 709	Skin and Subcutaneous Tissue
710 - 739	Musculoskeletal System and Connective Tissue
740 - 759	Congenital Anomalies
760 - 779	Conditions Originating in the Perinatal Period
780 - 789	Symptoms
790 - 796	Nonspecific Abnormal Findings
797 - 799	Ill-defined and Unknown Causes of Morbidity and Mortality
800 - 999	Injury and Poisoning

Figure 4: ICD-9 Diagnosis Group

solution (”D5W250”), Depakote 250 mg (”NS250”), and Depakote 1000 mg (”NS1000”). And the medications are trandsormed into a set of vectors with binary value indicating whether each patient has had such drug. And the patient’s physiologies that matter in postoperative care are: respiratory rate (”RR”), oxygen saturation (”SPO2”), temperature (”T”), systolic blood pressure (”BP”), pulse rate, and level of consciousness, according to the National Early Warning Score (NEWS Score) cit (2015). Due to the few record size of pulse rate and the difficulty to categorize consciousness level from the raw data, the last two physiologies are not included in this study. The other 4 physiologies have abundant data in the chartevent table, which means they are recoreded several times within each admission. The mean value of each physiology is calculated as the feature value.

After checking the missing pattern of each colomn, colomns with over 50% missing values and patients with over 5 missing items are dropped. And the remaining missing values are all the averaged physiologies in the previous feature selection step instead of direct records in raw data, so they are missing at random. R package ”amelia” is used to impute the missing value for the remaining dataset, with 5 folds. However, after imputation, there are still 61 patients with less than 2 missing values unable to be imputed, so they are dropped.

4.4 Evaluation Criteria and Method Comparison

Since the existing models used to predict the mortality each focuses on a specific disease or condition and the models built in this study are more general and relatively novel in providing general guidance for postoperative care, models in this study are not compared to existing models. Instead, the models themselves are compared against each other to evaluate the performance, by using accuracy, ROC curve, and PR curve.

5. Results

The variable importance for each algorithm is showed repectively in each subsection, except for Naive Bayes and Tree Augmented Naive Bayes (no method to show the variable importance), to find the useful indicators of postoperative mortality. And the performance of each algorithm is evaluated and compared to decide on the best model.

5.1 Results on Logistic Regression

After 2 rounds of training the Logistic Regression model, the final model has the features and importance as plotted below.

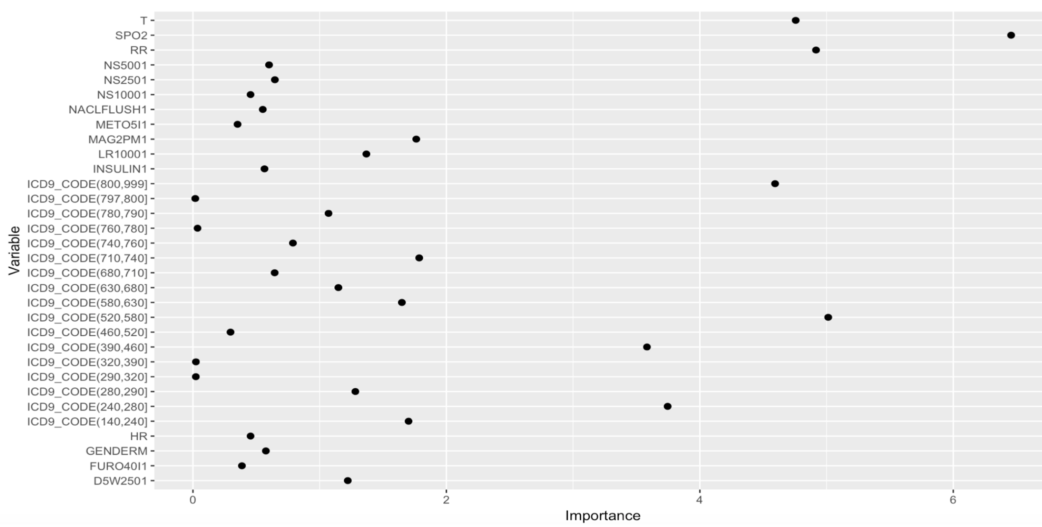

Figure 5: The variable importance in predicting mortality of Logistic Regression

From the plot we can know that the importance of all variables in this model is not very high, which means that they are not very useful in predicting the outcome. How these variables contribute to the postoperative mortality are listed below.

Coef	Estimate	p-value
Intercept	19.608118	0.000711
Endocrine, Nutritional, Metabolic, Immunity	-1.664949	0.000167
Circulatory System	-0.996860	0.000165
Digestive System	-1.023103	0.00000026
RR	0.084609	0.0000004
SPO2	0.079917	0
T	-0.285080	0.000002

Based on this model, features of the patient's respiratory rate, oxygen saturation, temperature, and whether the patient's diagnosis is related to Endocrine, Nutritional, Metabolic, Immunity / Circulatory System / Digestive System are of significance in predicting post-surgery death.

5.2 Results on Desicion Tree

The Decision Tree after pruning is shown below.

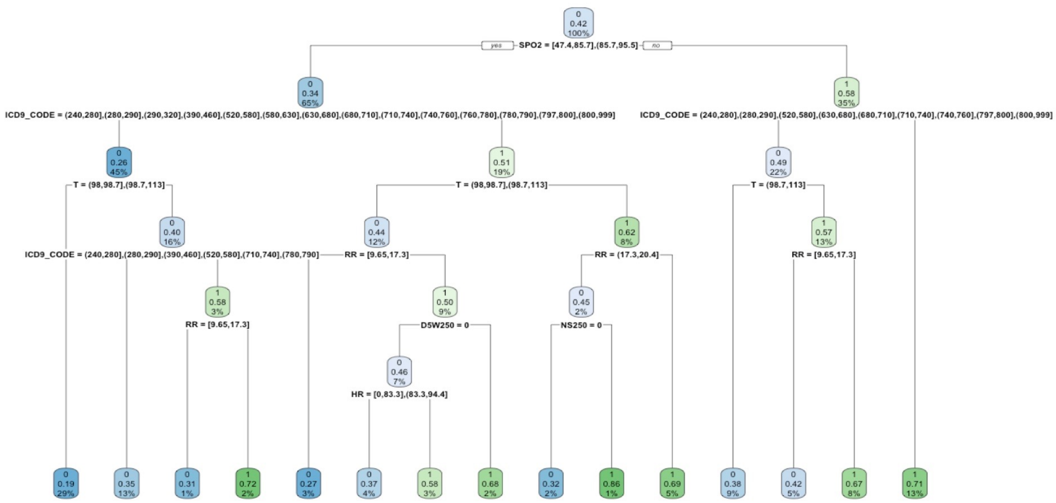

Figure 6: Decision Tree

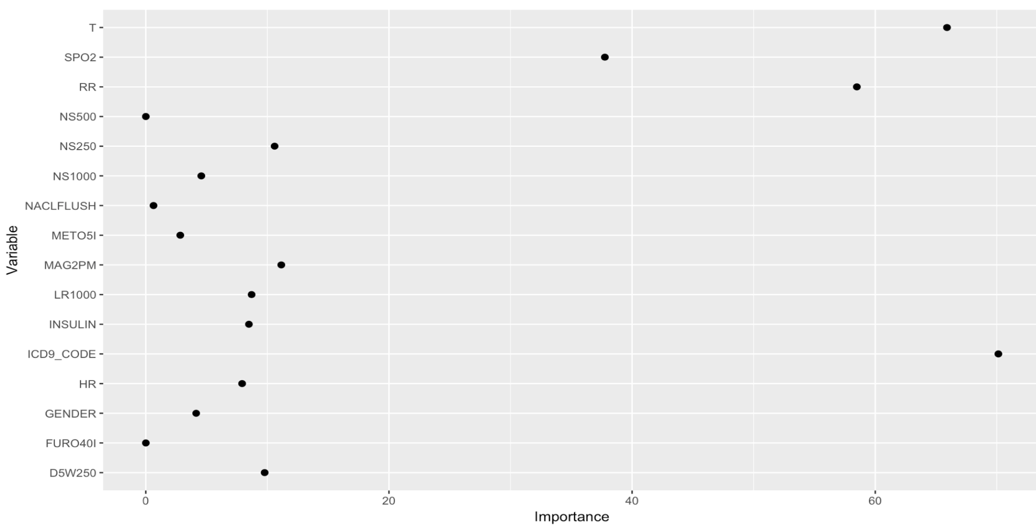

Figure 7: The variable importance in predicting mortality of Decision Tree

Here we can find that ICD-9 code (diagnosis group) and the patient's respiratory rate and oxygen saturation have a really high contribution to the patient's mortality. Also, some medications such as Magnesium Sulfate and Depakote are also strong indicators.

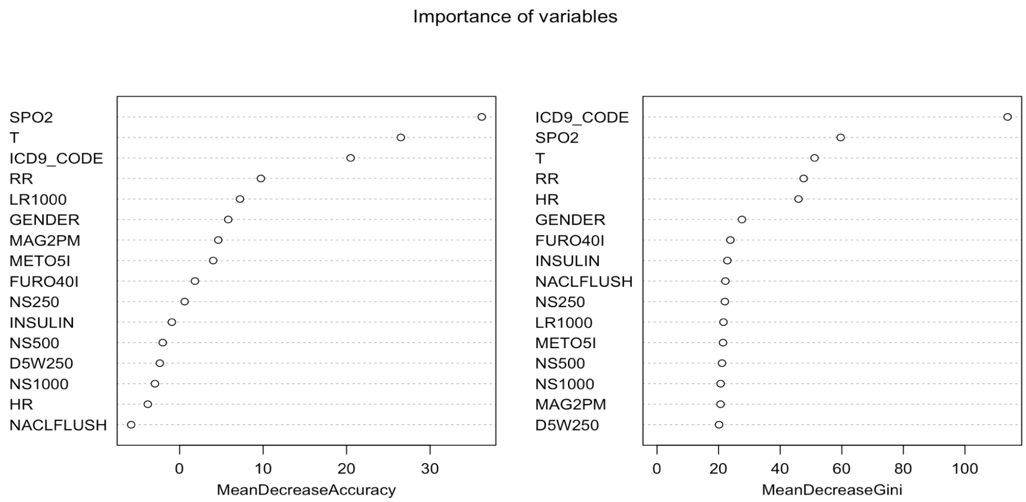

Figure 8: The variable importance in predicting mortality of Random Forest

5.3 Results on Random Forest

Here Random Forest uses 1000 as the number of trees and have votes on all trees to decide the contribution of each variable to the outcome. We can find that diagnosis, patient's temperature, oxygen saturation, and respiratory rate are still the top 4 variables that contribute the most to postoperative mortality, both on accuracy and Gini. Other features are not so significant or have inconsistent contribution regarding the model accuracy and Gini.

5.4 Model Evaluation and Comparison

Method	Accuracy	95% Confidence Interval
Logistic Regression	0.6473	0.6215 0.6732
Naive Bayes	0.6588	0.6331 0.6845
Tree Augmented Naive Bayes	0.6321	0.6059 0.6582
Decision Tree	0.6580	0.6323 0.6837
Random Forest	0.6351	0.6090 0.6612

Based on accuracy, Naive Bayes and Decision Tree outperform other models since they have a higher accuracy and also confidence interval. However, when looking at the ROC and PR curves, Logistic Reggression has the curve dominates other algorithms. Logistic Regression also has a relatively high accuracy. Combining the three measures, Logistic Regression is an effective model to predict post-surgery death and the features selected in this model are useful indicators.

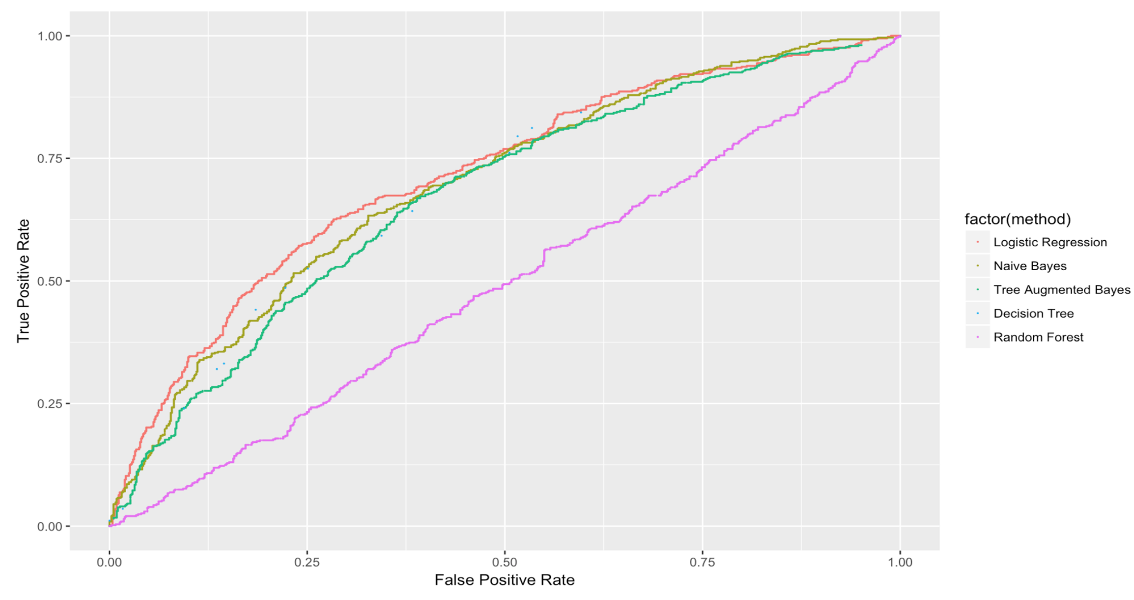

Figure 9: ROC Curve

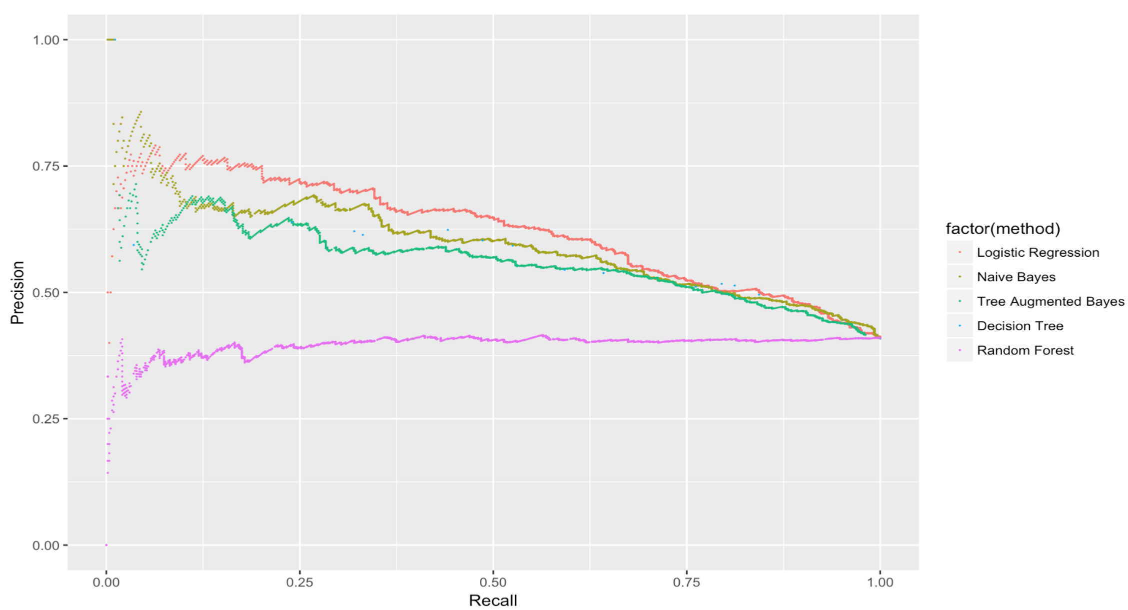

Figure 10: PR Curve

6. Discussion and Related Work

Compared to other models built on MIMIC data, this model is more shallow but more widely applicable. With no focus on specific conditions, it can serve as a reference for nurses to check the patient's physiologies and medications in postoperative care. Though not robust as other models are, this model provides an insight on what kind of patient information should be pay special attention to and what kind of data-driven models could be used to forecast the patient outcome after surgery.

However, this study has many notable limitations that deserve concern. First is the feature selection issue. For patient information, age is not included in the data, since it is shifted for confidential purposes. To simplify the study, age is excluded from analysis. And the features selected for this model are completely dependent on medical knowledge, that is, the features are all considered of significance in general madical protocols. In this way, this model is more a proof of existing medical professional sugestions than a new method completely relying on machine learning. Second, the model is too general and could be not as reliable as other specific models. No matter the surgery itself or the death related to surgery, they are highly relevent to the diagnosis. Although several diagnosis groups are proved to be an important contributor to death, it appears that comparing mortality across diseases makes little sense. Third, the raw data itself is not perfect for analysis. MIMIC III database is super huge and has data collected from different source systems, such as CareVue and MetaVision. Different systems sometimes use different coding methods for the same item which are not interoperable. Dealing with such data is a complicated issue, and to simplify the study, some of such items are not included. And there are also some apparent errors on raw data when combining them into MIMIC database, such as the over 90 patient's temperature in Celcius degrees. Besides, MIMIC data is collected from one single hospital. The model's applicability to other patients with different demographic backgrounds needs further research.

7. Conclusion

In conclusion, this model provides a non-condition-specific method to forecast the post-operative mortality for ICU patients who have general surgery. With this model and the indicators suggested in the model, postoperative care can be better managed and patients are more likely to have better outcomes with lower risk of death.

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