BAIS6070 Data Science Final Project

Assessing Postoperative Complication Predictions in General Surgery

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INTRODUCTION

General surgery is a broad field that encompasses a wide range of surgical procedures, from minor outpatient procedures to complex surgeries requiring hospitalization. While surgical procedures are generally safe and effective, there is always a risk of postoperative complications. These complications can range from minor issues, such as wound infections or nausea, to more serious problems, such as blood clots or organ failure. In one 2022 study, postoperative complications were observed in over 30% of general surgery patients and were significantly associated with various comorbidities [1]. Postoperative complications occurred in 41 of 62 (66.13%) hypertensive patients, 42 of 51 (82.35%) diabetic patients, 12 of 20 (60%) patients with chronic kidney disease, three of five (60%) patients with chronic pulmonary disease, and five of nine (55.5%) patients with bronchial asthma [1]. Interestingly, out of 10 patients who developed intraoperative complications, nine had postoperative complications (90%) [1]. We aim to address the prevalence of postoperative complications by constructing different models that can predict if a patient will develop a postoperative complication. By identifying a vulnerable patient population, we hope to minimize postoperative complications that are not properly identified.

DATA COLLECTION AND PREPROCESSING

Dataset Description

For this project, we analyzed data obtained from Kaggle, which was originally collected by Sessler et al. in their study titled “Operation Timing and 30-Day Mortality After Elective General Surgery” [2]. Our dataset consists of a single CSV file that includes the records of 14,635 patients who underwent elective general surgery. Specifically, the dataset has information on the patient’s age, gender, race, body mass index (BMI), comorbidities, several surgical indices, and the surgical timing predictors. The outcome variable of interest in this dataset was the occurrence of in-hospital complications. Outcome variable was indicated by binary flags in the dataset. Table 1A provides a detailed description of the 25 features included in the dataset.

We also consulted external sources in order to gain a deeper understanding of the variables involved. Specifically, the variable *ahrq_ccs*, the Clinical Classification Software developed by the Agency for Healthcare Research and Quality (AHRQ), was used to match codes to corresponding surgical procedures [3]. Additionally, both risk stratification indices, *mortality_rsi* and *complication_rsi*, were utilized. These indices are open source, nationally validated, risk stratification methodologies that allow for outcomes such as duration of hospitalization and mortality to be compared equally across institutions. The RSI's for 30-day mortality and in-hospital complication "provide a reliable way for hospitals to accurately and independently predict length-of-stay and mortality for surgical patients using only administrative data" [4]. Furthermore, the variables *cssMort30Rate* and *cssComplicationRate* represent the rates of complications and mortality, categorized by each AHRQ-CCS procedure category.

Data Cleaning and Preprocessing

To analyze our data, we employed the Feature Statistics Widget available in Orange. Notably, our dataset did not contain any missing values and we identified no significant outliers that could negatively impact our models. To ensure consistency, we converted categorical data to the "categorical" format in Orange and standardized our features by centering them to a mean of 0 and scaling them to a variance of 1. Furthermore, in cases where we were dealing with discrete variables, we chose the most frequent value as the base case (Figure 1).

To train and evaluate our models, we split our dataset into training and validation sets, with 80% of the data used for training and validation, and the remaining 20% used for testing. To ensure the robustness of our models, we utilized 10-fold cross-validation for all of our models.

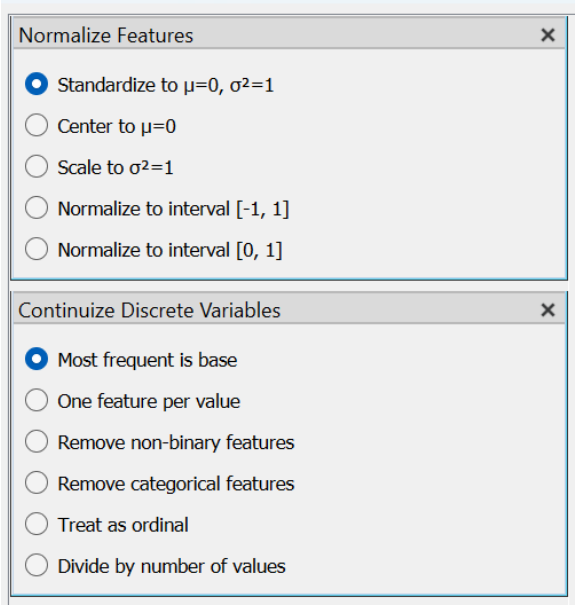


Figure 1: Data Preprocessing widget in Orange.

FEATURE ENGINEERING

To perform feature engineering, we examined the correlations between each variable in our dataset. Our analysis revealed that the variables *complication_rsi* and *mortality_rsi,* as well as *ccsComplicationRate* and *ccsMort30Rate*, exhibited the highest correlation (Figure 2). This observation is logical since mortality is often associated with high-risk complications, and vice versa.

In addition to using the Correlations Widget, we also utilized box plots to help with feature selections. Through our analysis, we noted that the grouping of complication predictions in both complication and mortality indices tended to demonstrate greater differences than other variables (Figure 3). On the other hand, we also identified several features that might not be as important for our prediction models. As shown in Figure 4, Hour, Day of Week, Month, Moon Phase, and Charlson Comorbidity Index features generally do not impact the probability of patients experiencing complications.

In our modeling approach, we utilized regularization and pre-pruning rules to automatically select the most relevant features for prediction, with the exception of the KNN model. For the KNN model, features with a substantial negative impact on the AUC were removed, as well as features with similar outcomes in complication rate by subgroup. Five variables were removed from this model: Hour, Day of Week, Month, Moon Phase, and Charlson Comorbidity Index.

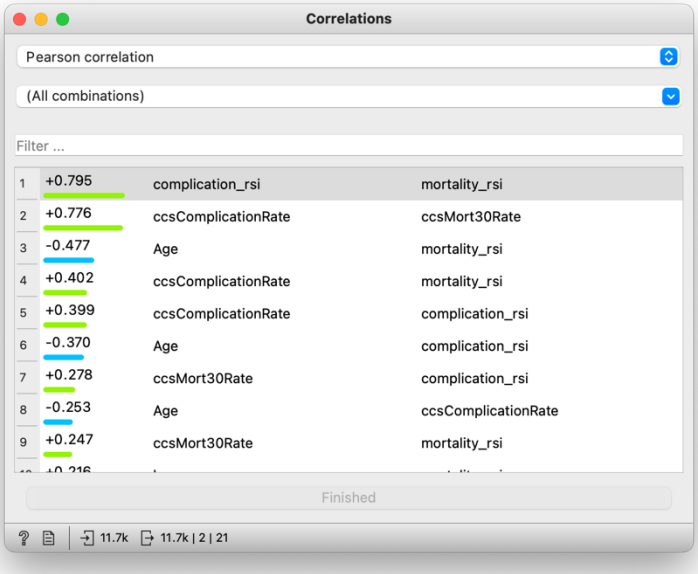


Figure 2: Correlations of variables.

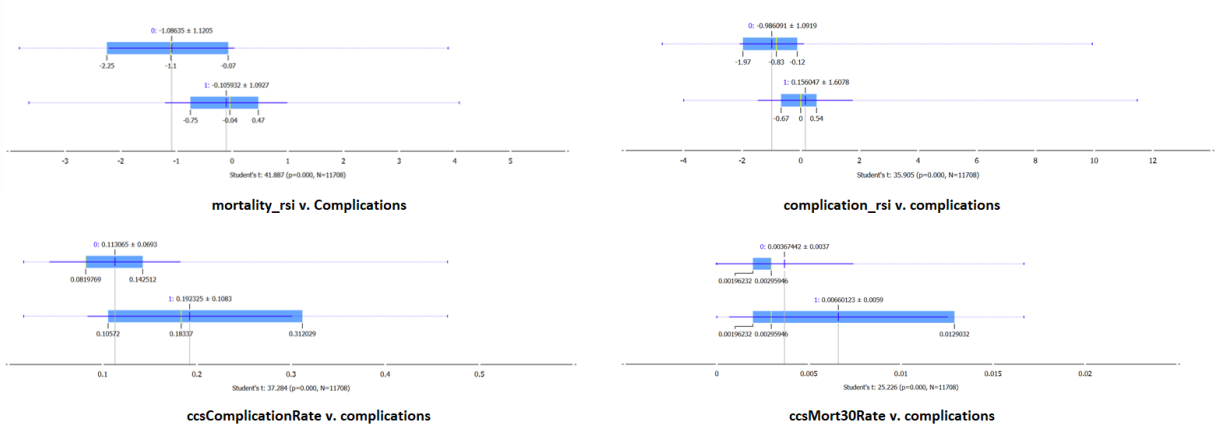


Figure 3: Box plot of complications v. complication/mortality indices.

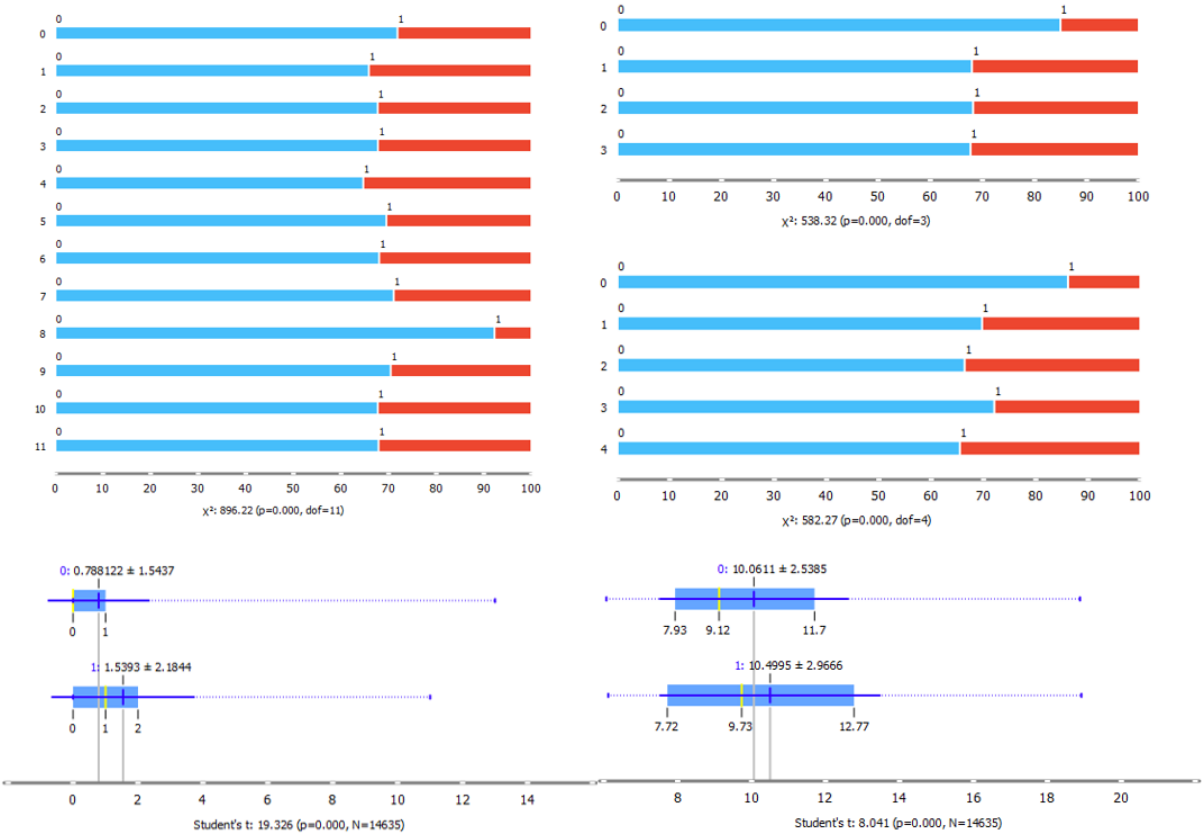


Figure 4: Box Plot Comparison of Complications and Other Features from Top-Down: Left - Month and Charlson Comorbidity Index, Right - Moon Phase, Day of Week, and Hour.

METHODS

Our final model is the random forest model due to its high AUC and specificity as shown in Table 1. The following methods section details the models we investigated and how we determined to move forward with the random forest. The six models investigated are k-nearest neighbors, logistic regression with lasso regularization, neural networks, classification tree, gradient boosted ensemble, and random forest. Detailed further in the PROFIT/COST ANALYSIS section, ROC curves for models used ratios of 1:6 for false positive to false negative cost. This ensured that sensitivity was targeted to minimize the rate of false negatives.

Table 1: Model summaries.

No.	Model	AUC	Sensitivity	Specificity
1	Random Forest	0.923	0.90	0.74
2	Gradient Boosted Ensemble	0.932	0.85	0.84
3	Classification Tree	0.909	0.87	0.74
4	Neural Network	0.824	0.86	0.62
5	Logistic Regression	0.820	0.90	0.55
6	KNN	0.839	0.90	0.60

K Nearest Neighbors

We developed the K Nearest Neighbors model using the feature selection process described in the Feature Engineering section. The best model produced an AUC of .839, as shown in Figure 5. The confusion matrix for the model is shown in Figure 6. This model is not very accurate, predicting 57.9% of the group with complications as not having complications, inaccurately labeling the patient. However, it has a very low false negative rate, as 93.6% of the population without complications is labelled as such. The ROC curve, shown in Figure 7, shows that the tangential model produces a sensitivity of approximately 0.90 and specificity of 0.60. This restates the failure of the model to accurately predict individual complications, as the model will have a large false positive population.

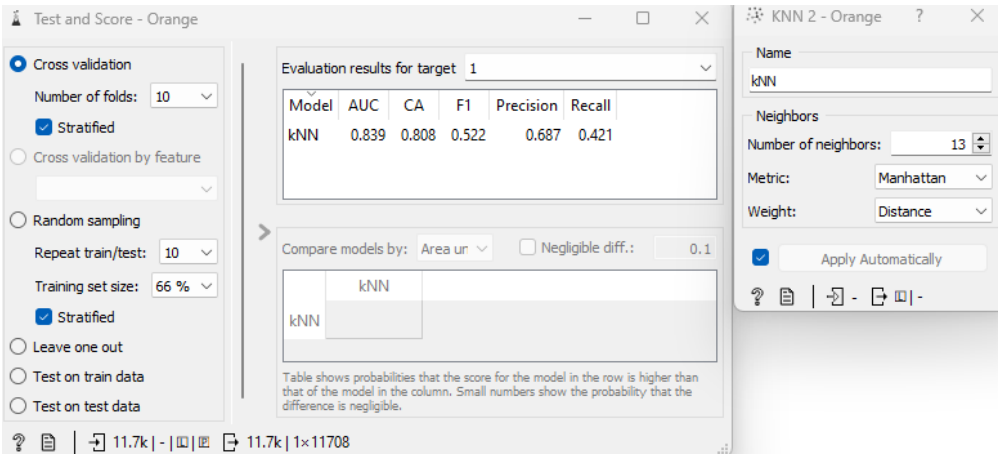


Figure 5: Scores and settings of K Nearest Neighbors models.

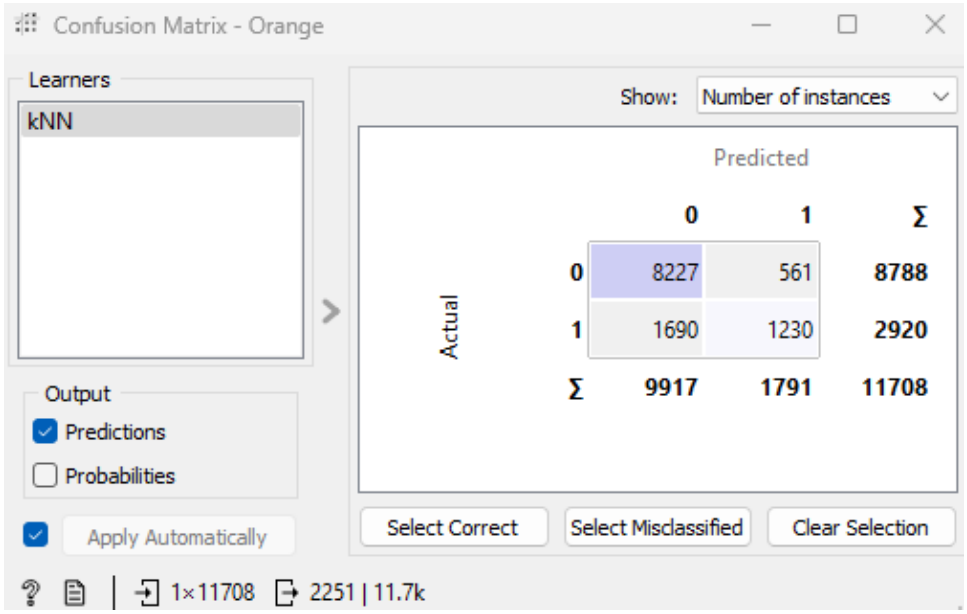


Figure 6: Confusion Matrix for KNN model.

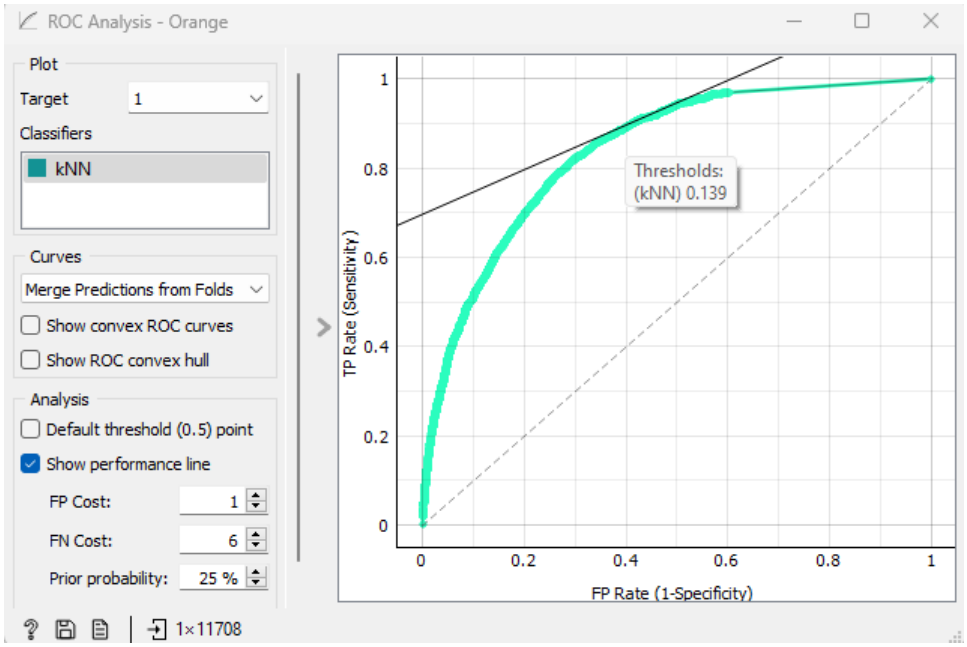


Figure 7: ROC Curve Analysis on Training data.

Logistic Regression

We developed two logistic regression models with Ridge and Lasso regularization, utilizing alpha values of 0.140 and 0.160, respectively. Both models returned the same AUC value of 0.820. However, an evaluation of additional measures from the confusion matrix indicates that the Lasso regularization model performs marginally better compared to the Ridge model. Figure 8 shows that with a false positive cost to false negative cost ratio of 1 to 6, the Lasso model has a sensitivity score of approximately 0.9 and a low specificity score of 0.55. This is achieved with a probability threshold of 0.358 (Figure 9). The ROC curve suggests that the model is relatively good at identifying patients who are at high risk of experiencing surgery complications, but it may also flag a considerable number of patients who are not actually at risk. In other words, the model may be too sensitive and may generate too many false positives, which could result in unnecessary testing or interventions.

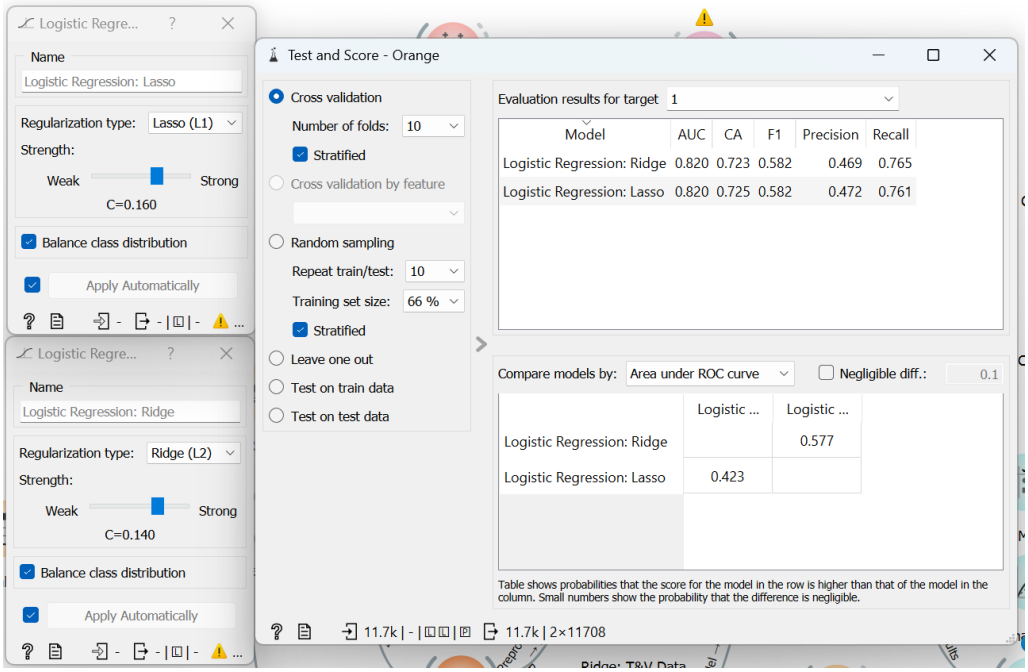


Figure 8: Scores and settings of Logistic Regression models.

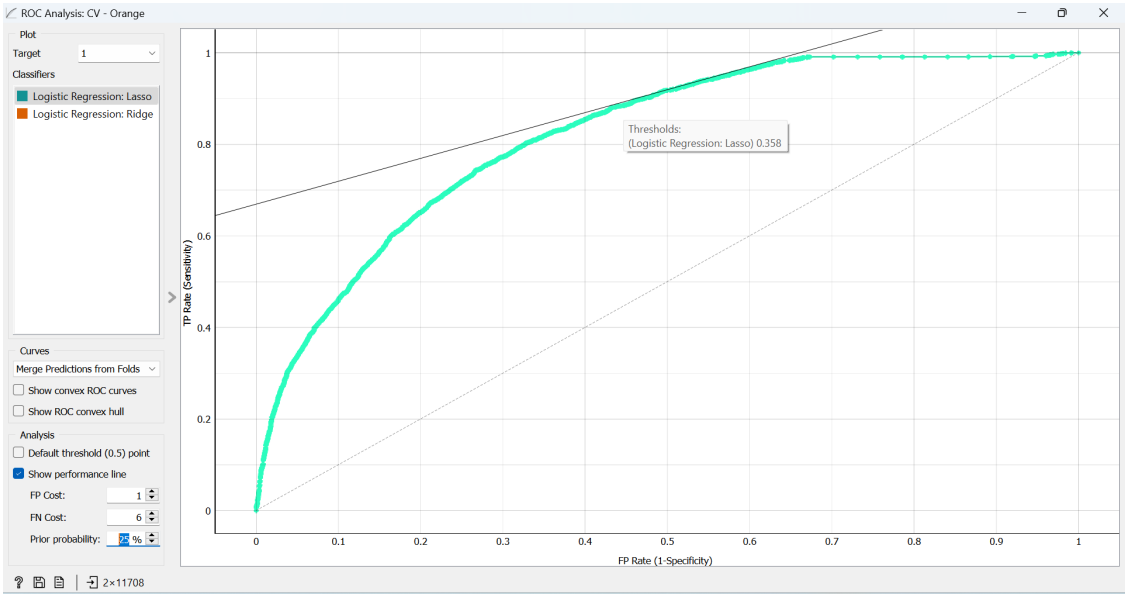


Figure 9: ROC Curve Analysis on Training data.

Neural Network

For our neural network model, we found that all numerical and categorical values against complication have p-values smaller than 0.05, hence we did not remove any variables. Moreover, the model is intelligent enough to add regularization. We constructed three hidden layers with 10 neurons in each layer, activation function is ReLu, solver is Adam and Regularization for penalizing

weight is alpha = 4 (Figure 10). The AUC of Neural Network is 0.824 (Figure 11). The ROC curve in Figure 12 shows the varying sensitivity and specificity values for all values of confusion matrix. At the tangential threshold, sensitivity is approximately 0.86 and specificity is 0.62.

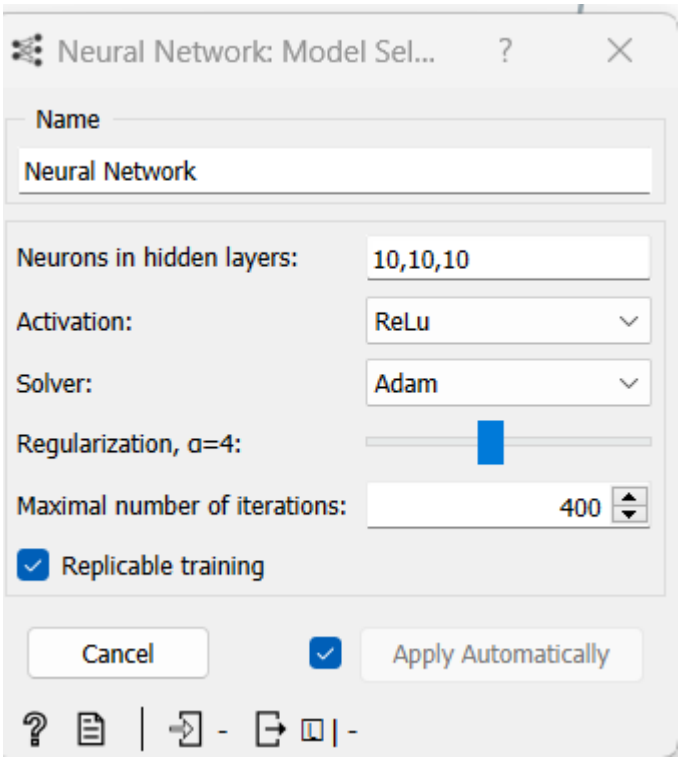


Figure 10: Neural Network parameter.

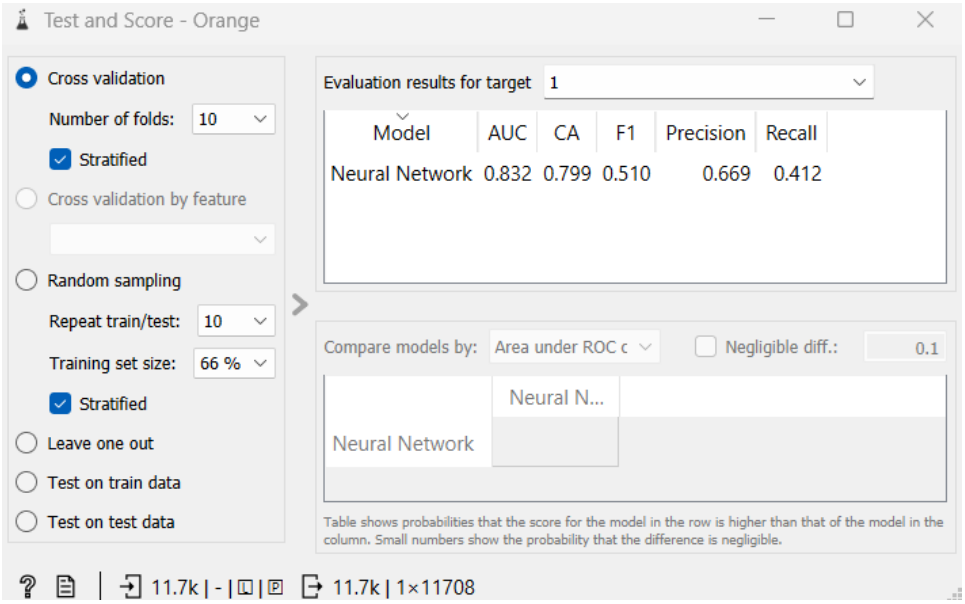


Figure 11: Neural Network test and score widget.

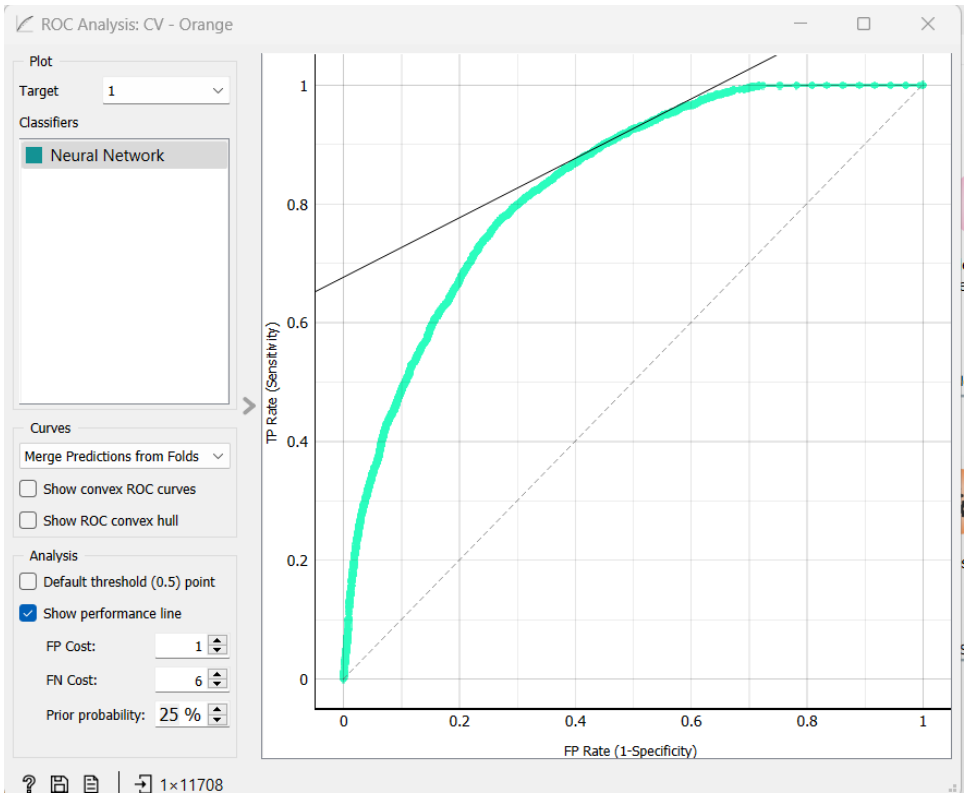


Figure 12: Neural Network ROC curve.

Classification Tree

We developed a classification tree model with pre-pruning parameters listed in Figures 13 and the test and score widget in Figure 14. Upon evaluation from the testing and validation are an AUC of 0.909, and at a probability threshold of 0.150, a sensitivity of approximately 0.87 and specificity of 0.74 (Figure 15). Overall, this is a good model, but the random forest and gradient boosting models performed better.

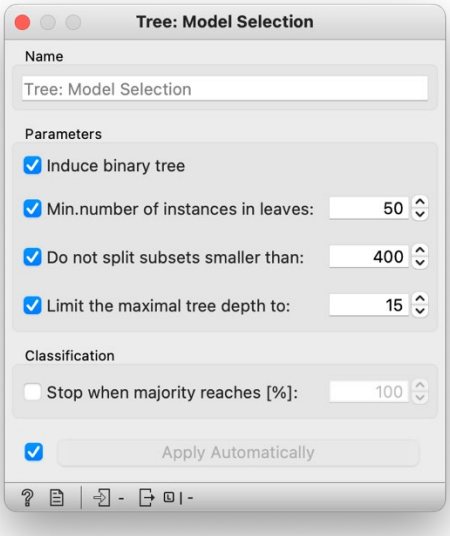


Figure 13: Classification tree parameters.

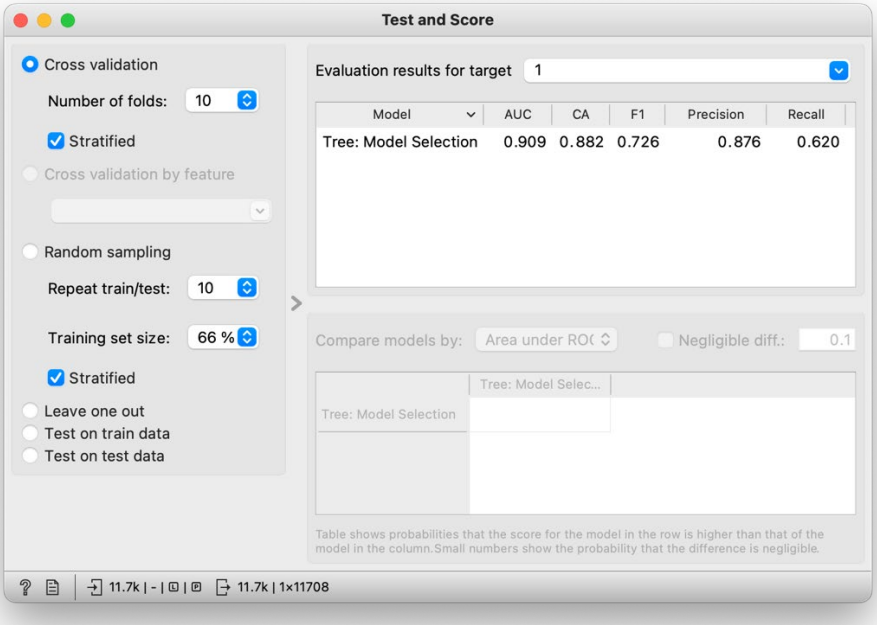


Figure 14: Classification tree test and score widget.

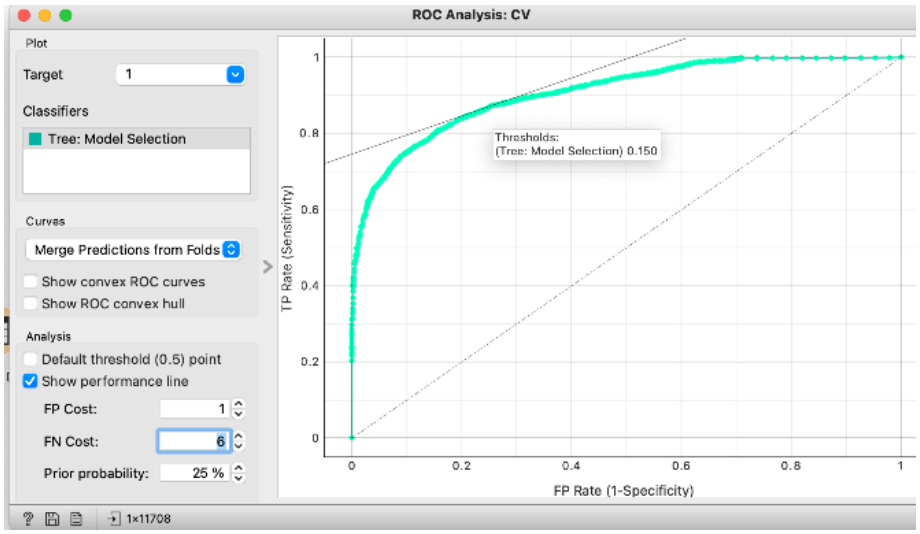


Figure 15: Classification tree ROC curve of training and validation data.

Gradient Boosting

The gradient boosting ensemble was made with pre-pruning parameters of 500 trees, 0.01 learning rate, lambda of 2, and a limit depth of 6 trees using extreme gradient boosting (Figure 16). The gradient boosting provides the highest AUC at 0.932 (Figure 17), 0.9% higher than the random forest model of 0.923. At the probability threshold of 0.188, sensitivity is approximately 0.85 and specificity of 0.84 (Figure 18).

The main reason gradient boosting was not selected as the final model was upon investigation of log loss values (Figure 19). There are extensive log loss values 3.5 and above that create a pattern in ages 75 to over 90, as well as ages below 30. Although these were not mispredictions of *complication* = 1, this pattern in high log loss values means the model is not making reliable predictions for *complication* = 1. Since that is the target class, we did not move forward with this model.

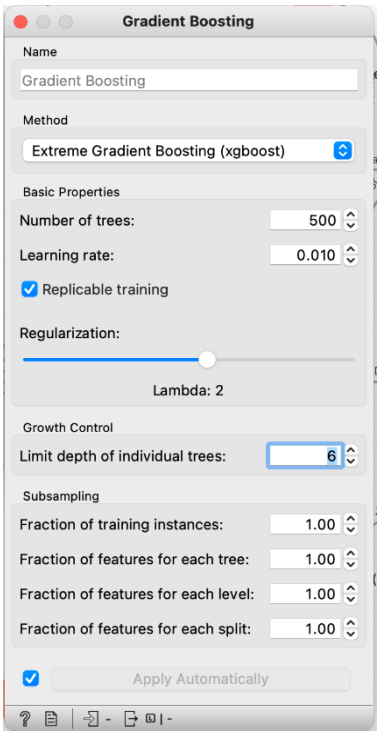


Figure 16: Gradient boosting ensemble pre-pruning parameters.

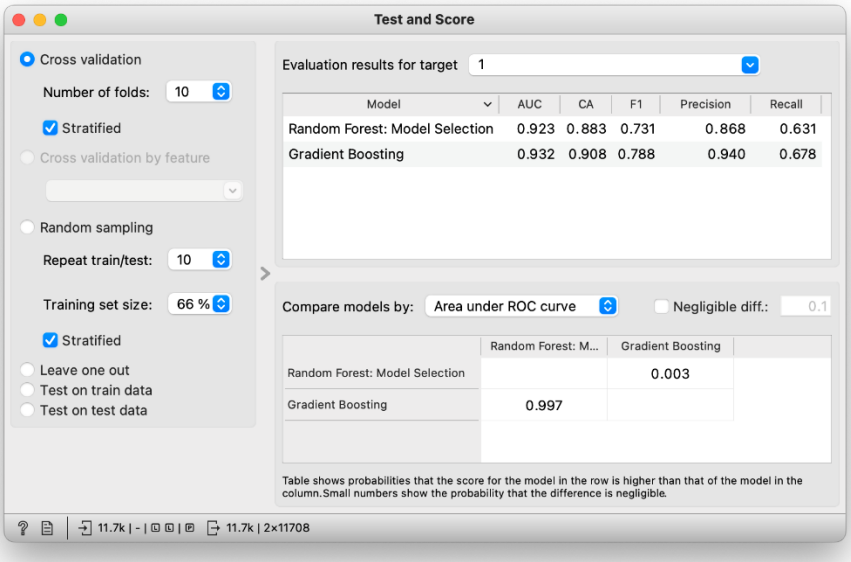


Figure 17: Gradient boosting and Random Forest test and score widget.

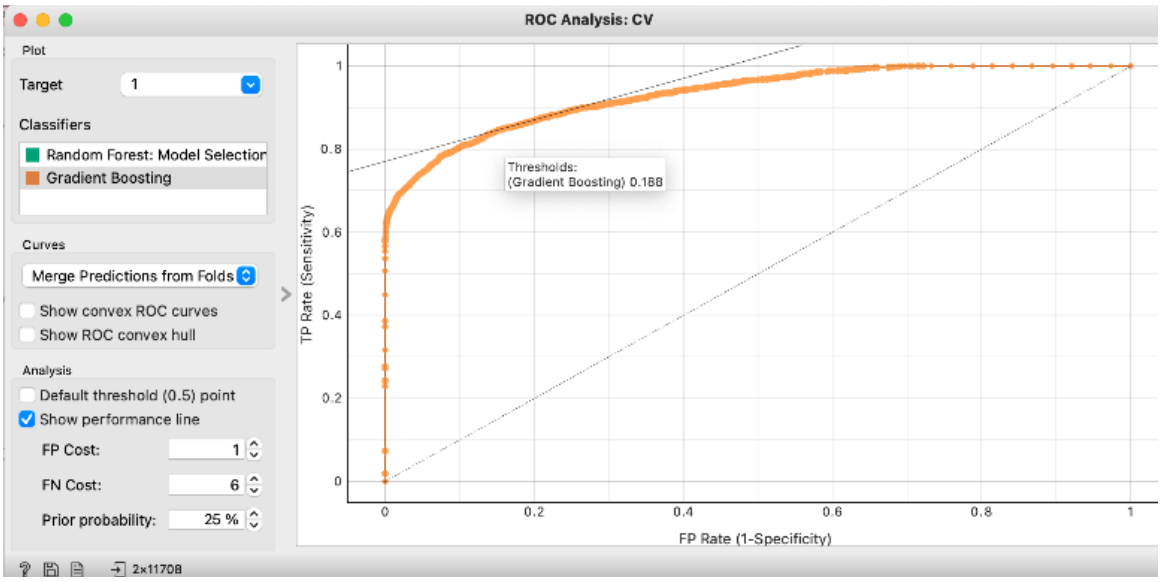


Figure 18: Gradient boosting ensemble.

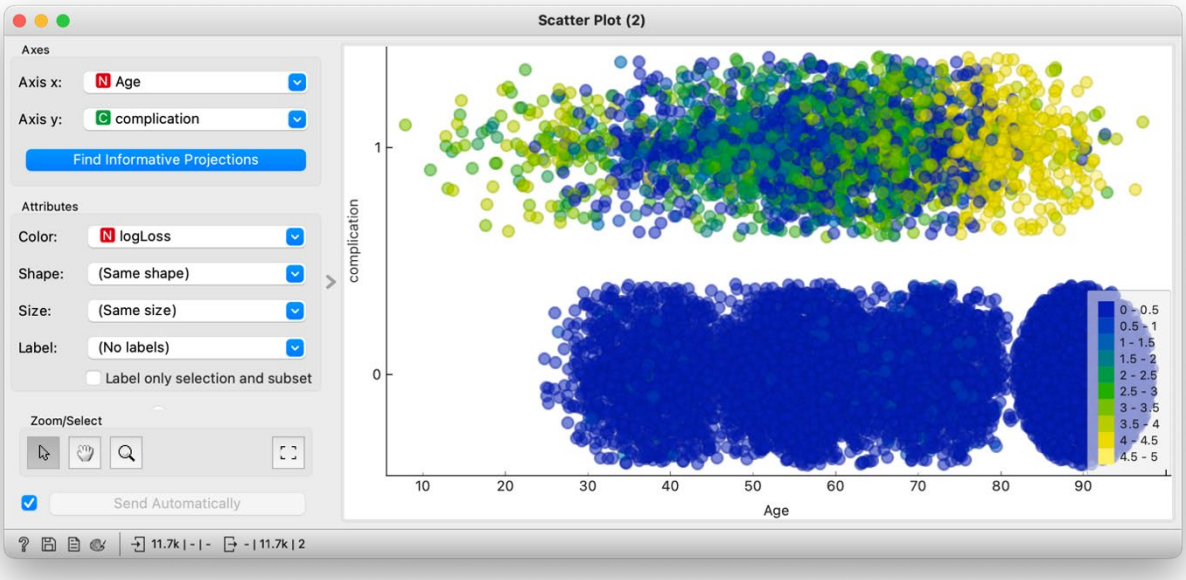


Figure 19: Gradient boosting ensemble log loss scatter plot of Age vs. Complication.

Random Forest

Our final model is the random forest model. This model provides a combination of high AUC, high sensitivity, moderately high sensitivity, and importantly, low log loss values. The parameters for the model are seen in Figure 20, with 600 trees and 15 attributes considered at each split. These parameters provided an AUC of 0.923 in the test and score widget (Figure 17). Seen in Figure 21, a threshold of 1:5 FP to FN cost ratio at a probability threshold of 0.2 provided sensitivity of

approximately 0.90 and specificity of 0.74. This provided the highest attained sensitivity while still also maintaining moderately high specificity.

Finally, we investigate log loss values to determine the reliability of the model's predictions. Pictured in Figure 22, there are very few log loss values 3.5 and greater. Additionally, there is no less pattern in log loss values when compared to the predictions in the gradient boosted ensemble model. The higher log loss values can still be seen in the 75 and older population, however, these are much smaller errors. In that way, the random forest predictions are more reliable for predicting a complication.

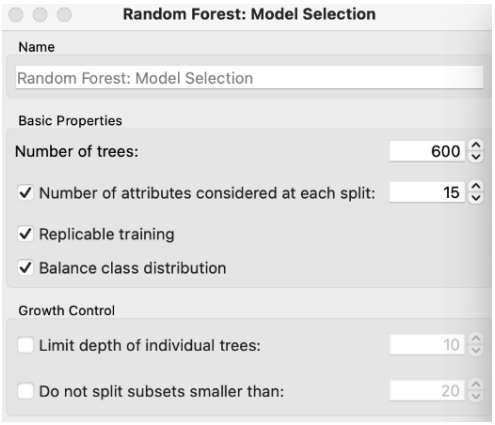


Figure 20: Random Forest pre-pruning parameters.

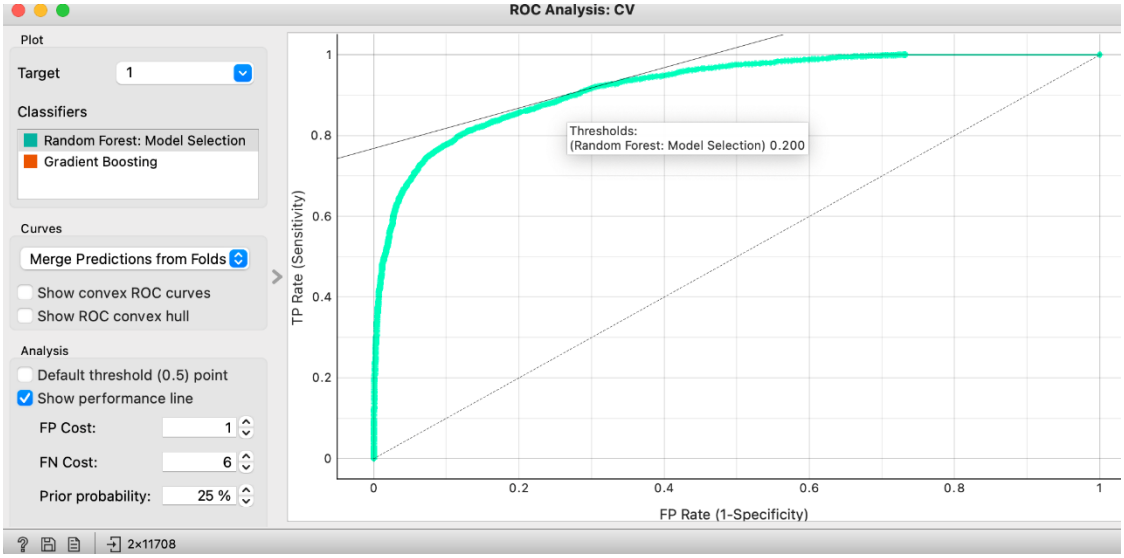


Figure 21: Random Forest ROC curve.

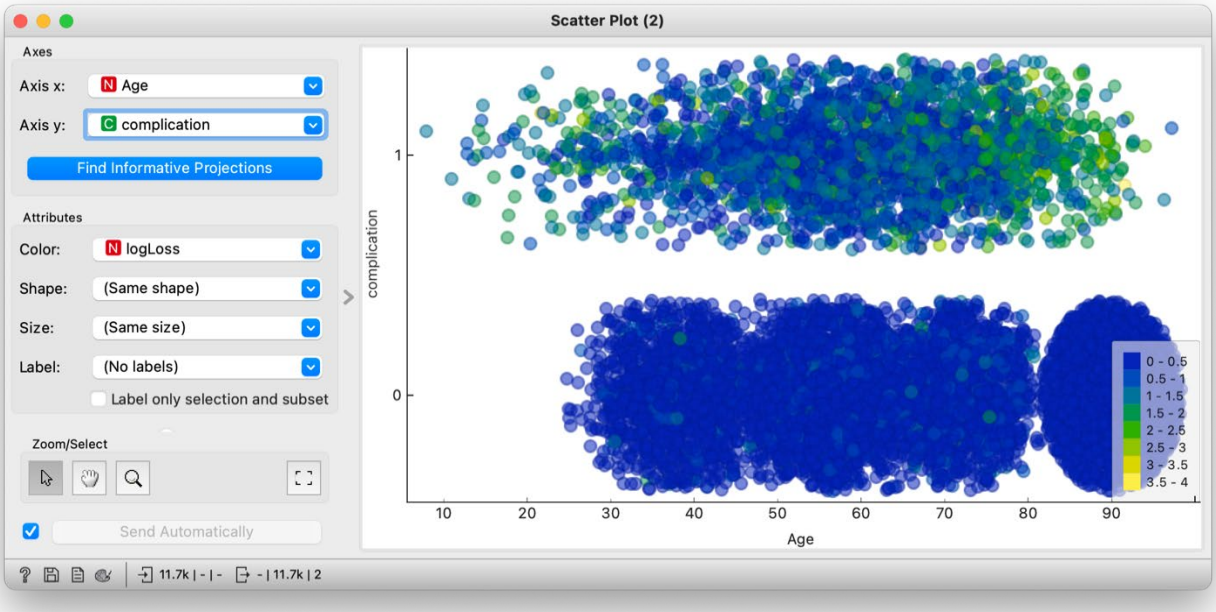


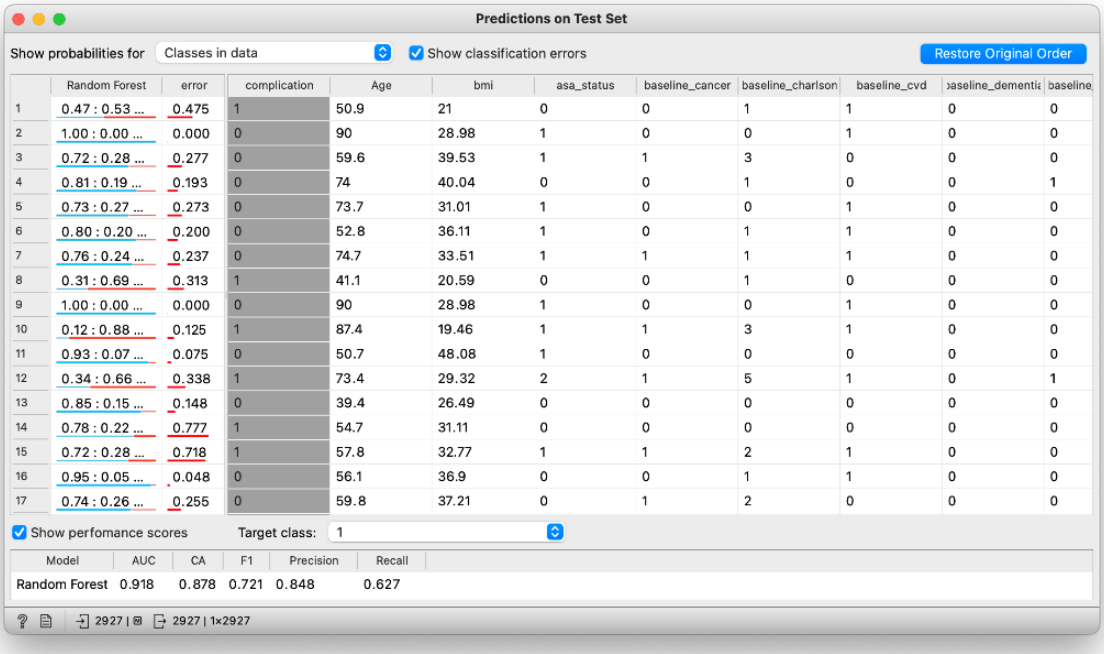
Figure 22: Random Forest log loss scatter plot of Age vs. Complication.

Although gradient boosting provided a slightly higher AUC (0.9% higher), both models had AUC values above 0.9, and since the random forest model had a 2% higher sensitivity and no pattern in log loss errors, we selected random forest as the final model for testing. The test outcomes on the remaining 20% of the data are pictured in Figures 23-26. The test AUC is 0.918, so our random forest model is highly accurate in its predictions (Figure 23).

The rank widget displays the information gain from each variable, which offers insight into the forest (Figure 24). a*hrq_ccs* provided the most information at 0.140, followed by *ccsComplicationRate, mortality_rsi,* and *complication_rsi.* These variables would not change based on a patient's demographics, suggesting that overall, a complication is largely dependent on the type of surgery performed. The top three variables related to demographics are *baseline_osteoart, bmi,* and *baseline_charlson.* For the osteoarthritis variable, having this could mean a person is in general less healthy, possibly older, and overall, more prone to complications. This seems to also be the case for bmi and the charlson comorbidity index, where a higher number represents increased comorbid conditions predicting 10-year mortality. All in all, a less healthy individual seems more prone to developing a complication. Interestingly, *month* was the 7th highest rank; this variable could be investigated further to see if there is any correlation between the month of a surgery and complications.

The ROC curve in Figure 25 displays that at a probability threshold of 22.2%, sensitivity is approximately 0.89 (89% of the patients with complications are correctly identified) and specificity is 0.78 (78% of the patients without complications are correctly identified). This threshold maximizes our sensitivity while still maintaining moderately high specificity.

The lift curve in Figure 26 shows the lifts of increasing p-rates of the test set. Lift=3.933 when P-rate = 4%, meaning there are 0.04 * 2927 observations = 118 observations with the largest predicted probabilities of *complication* = 1 being considered. The annotated point has a threshold of 82.8%, meaning that these 126 observations correspond to the observations with a predicted probability of a complication occurring being greater than or equal to 82.8%. The lift at 3.933 means that there are ~4x more observations with *complication* = 1 than would be found in 118 randomly-selected observations.



	Random Forest	error	complication	Age	bmi	asa_status	baseline_cancer	baseline_charlson	baseline_cvd	baseline_dementia	baseline
1	0.47 : 0.53 ...	0.475	1	50.9	21	0	0	1	1	0	0
2	1.00 : 0.00 ...	0.000	0	90	28.98	1	0	0	1	0	0
3	0.72 : 0.28 ...	0.277	0	59.6	39.53	1	1	3	0	0	0
4	0.81 : 0.19 ...	0.193	0	74	40.04	0	0	1	0	0	1
5	0.73 : 0.27 ...	0.273	0	73.7	31.01	1	0	0	1	0	0
6	0.80 : 0.20 ...	0.200	0	52.8	36.11	1	0	1	1	0	0
7	0.76 : 0.24 ...	0.237	0	74.7	33.51	1	1	1	1	0	0
8	0.31 : 0.69 ...	0.313	1	41.1	20.59	0	0	1	0	0	0
9	1.00 : 0.00 ...	0.000	0	90	28.98	1	0	0	1	0	0
10	0.12 : 0.88 ...	0.125	1	87.4	19.46	1	1	3	1	0	0
11	0.93 : 0.07 ...	0.075	0	50.7	48.08	1	0	0	0	0	0
12	0.34 : 0.66 ...	0.338	1	73.4	29.32	2	1	5	1	0	1
13	0.85 : 0.15 ...	0.148	0	39.4	26.49	0	0	0	0	0	0
14	0.78 : 0.22 ...	0.777	1	54.7	31.11	0	0	0	0	0	0
15	0.72 : 0.28 ...	0.718	1	57.8	32.77	1	1	2	1	0	0
16	0.95 : 0.05 ...	0.048	0	56.1	36.9	0	0	1	1	0	0
17	0.74 : 0.26 ...	0.255	0	59.8	37.21	0	1	2	0	0	0

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.918	0.878	0.721	0.848	0.627

Figure 23: Random Forest predictions on test set.

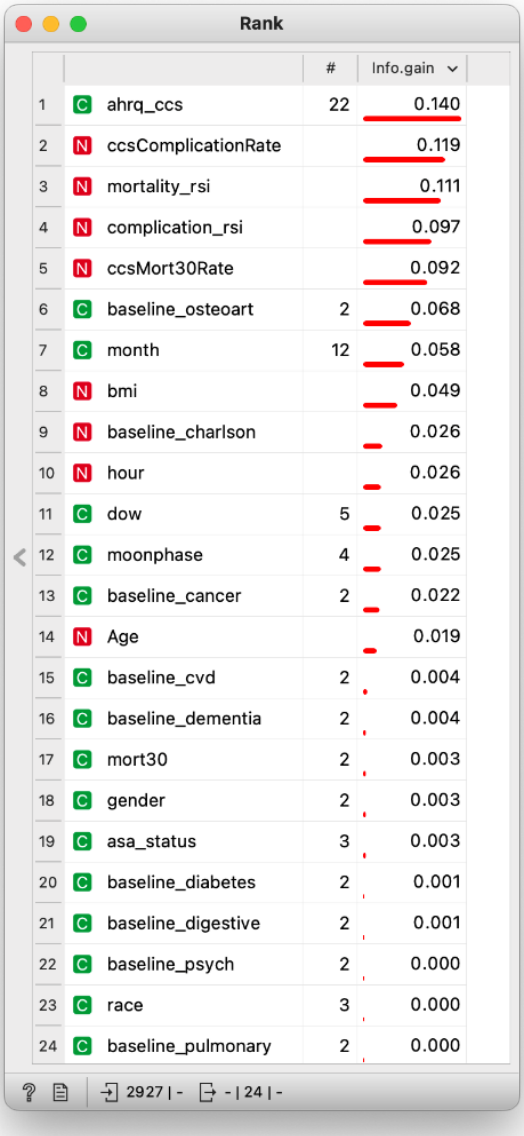


Figure 24: Random Forest rank widget.

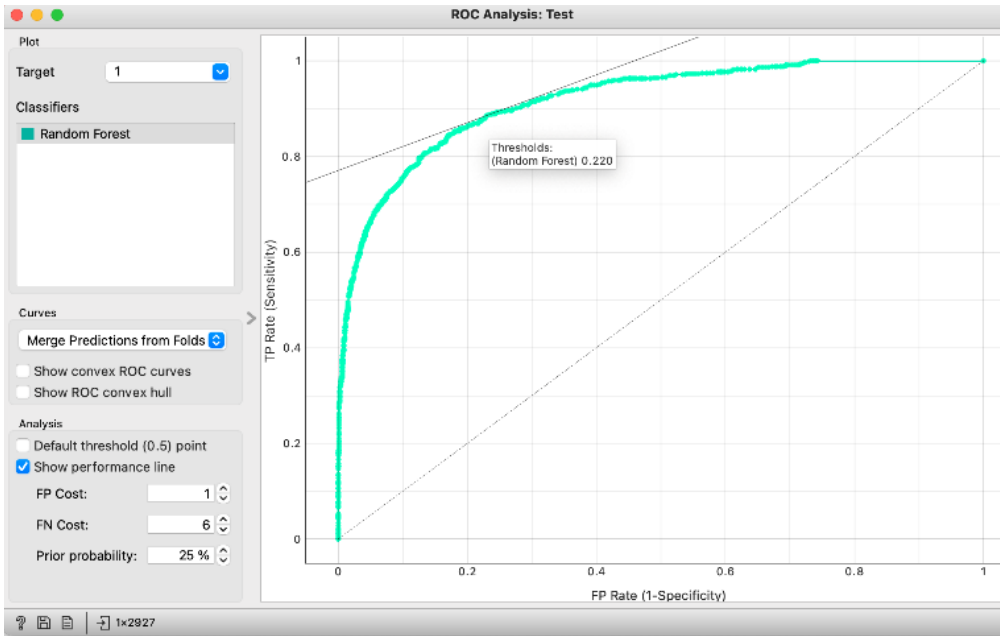


Figure 25: Random Forest ROC curve on test set.

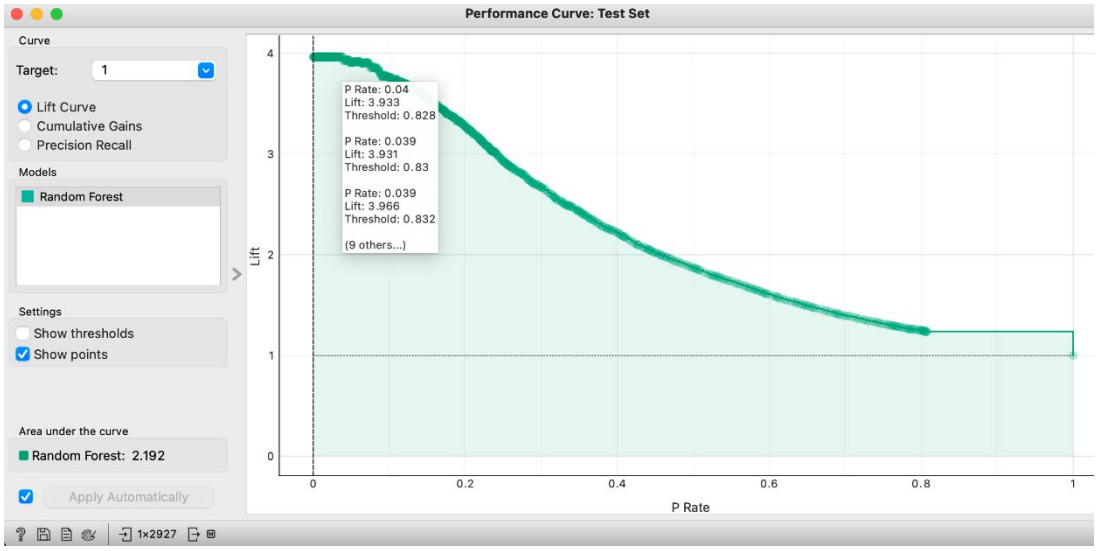


Figure 26: Random Forest lift curve on test set.

PROFIT/COST ANALYSIS

The tangential probability threshold obtained in Figure 25 above uses a 1:6 false positive to false negative cost ratio; this produced the 22.2% probability threshold on the test set, meaning that if the *P(complication = 1)* >= 0.222, the patient will be classified as developing a postoperative complication. This ratio is obtained from Table 2 below (-$16k:-$92k), with specific assumptions and calculations further explained in Table 2A.

This 22% probability threshold offers valuable insight as this represents the most vulnerable patient population. Hospitals should be acutely aware of increased risk of postoperative complications with this patient group for future predictions. As mentioned previously, with a*hrq_ccs* providing the most information gain in the model, a postoperative complication is largely dependent on the type of surgery performed, so hospitals should continue to monitor patients who have undergone inherently riskier surgeries closely.

Specific actions that could be taken for this vulnerable population include more extensive care post-operation, including increased monitoring following surgery, follow-up appointments, and medication management. Additionally, an emphasis of patient education, with patients and caregivers receiving information about their condition, treatment options, and postoperative care, can help patients understand what to expect after surgery, how to manage their symptoms, and when to seek medical attention if needed. Overall, an increase in awareness of the vulnerable population for surgeons, nurses, and other healthcare providers can ensure these patients are given more extensive care and are properly educated on postoperative conditions.

Table 2: Profits and costs for the average hospital for a general surgery.

Measure	**Meaning**	**Hospital Profit/Cost**	**Source**
True Positive	Postoperative complication is caught and treated	$13,000	[5]
True Negative	No postoperative complication	$19,000	[6]
False Positive	Patient unnecessarily treated for a complication	($16,000)	[5],[7]
False Negative	Patient discharged with undiagnosed complication	($92,000)	[8]

CONCLUSION

The best model is the Random Forest model, with an AUC of 92%, sensitivity of 89%, and specificity of 78%. Applying our model to a real-life cost scenario identifies a vulnerable patient population, where in our test set, these patients were identified at a probability threshold of 22%. This optimal model prioritizes minimizing false negatives due to the disproportional loss sustained compared to the other outcomes, at the cost of increasing the number of false positives in order to catch as many complications as possible. However, the model still maintains a relatively high specificity to prevent large numbers of patients receiving unnecessary care. This balance between false negatives and false positives is important because there are potential costs saved from proactively treating patients labeled as at-risk as the cost to hospitals for resources spent to treat patients who would not have experienced complications is much less than the potential cost for a malpractice suit occurring from a false negative. Overall, we have aimed to effectively identify patients who are at-risk of postoperative complications in order to help hospitals maintain efficient and safe practices.

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APPENDIX

Table 1A: Dataset description of variables.

No.	Feature	Data Type	Description	Units	Key
1	*ahrq_ccs*	Categorical	United States Agency for Healthcare Research and Quality's Clinical Classifications Software (AHRQ- CCS) Procedure Category		
2	*age*	Number	Age	years	
3	*gender*	Categorical	Gender		0 = male; 1 = female
4	*race*	Categorical	Race		0 = Caucasian 1 = African American 2 = Other
5	*asa_status*	Categorical	American Society of Anesthesiologist Physical Status		0 = I – II 1 = III 2 = IV - VI
6	*bmi*	Number	Body Mass Index	kg/m^2	
7	*baseline_cancer*	Categorical	Cancer		0 = No; 1 = Yes
8	*baseline_cvd*	Categorical	Cardiovascular/Cerebrovascular Disease		0 = No; 1 = Yes
9	*baseline_dementia*	Categorical	Dementia		0 = No; 1 = Yes
10	*baseline_diabetes*	Categorical	Diabetes		0 = No; 1 = Yes
11	*baseline_digestive*	Categorical	Digestive Disease		0 = No; 1 = Yes
12	*baseline_osteoart*	Categorical	Osteoarthritis		0 = No; 1 = Yes
13	*baseline_psych*	Categorical	Psychiatric Disorder		0 = No; 1 = Yes
14	*baseline_pulmonary*	Categorical	Pulmonary Disease		0 = No; 1 = Yes
15	*baseline_charlson*	Number	Charlson Comorbidity Index		
16	*mortality_rsi*	Number	Risk Stratification Index (30-Day Mortality)		
17	*complication_rsi*	Number	Risk Stratification Index (In-Hospital Complications)		
18	*ccsMort30Rate*	Number	Overall Incidence of 30-day Mortality for Each AHRQ-CCS Procedure Category		
19	*ccsComplicationRate*	Number	Overall incidence of In-Hospital Complications for Each AHRQ- CCS Procedure Category		
20	*hour*	Number	Operation Hour		
21	*dow*	Categorical	Day of Week		0 = Monday

					1 = Tuesday 2 = Wednesday 3 = Thursday 4 = Friday
22	*month*	Categorical	Month of Year		0 = January 1 = February 2 = March 3 = April 4 = May 5 = June 6 = July 7 = August 8 = September 9 = October 10 = November 11 = December
23	*moonphase*	Categorical	Phase of Moon		0 = new moon 1 = first quarter 2 = full moon 3 = last quarter
24	*mort30*	Categorical	30-Day Mortality		0 = No; 1 = Yes
25	*complication*	Categorical	In-Hospital Complication		0 = No; 1 = Yes

Profit/Cost Analysis explanations:

There is a 5.75 fold increase in hospital costs when comparing false positives to false negatives. For simplicity, ROC curves for our potential and final models used ratios of 1:6 for this cost. This ensured that sensitivity was targeted to minimize the rate of false negatives. A cost-to-charge ratio (CCR) of 32% was used to calculate hospital profits for general surgery. 32% was cited to be the average nationwide hospital CCR in 2020 [9]. This ratio is determined by the cost to the hospital to perform the surgery to the amount charged to the patient. A CCR closer to 1 indicates a smaller gap between a hospital's charges and total expenses, while a ratio closer to 0 suggests a higher markup of costs to a patient [9].

Table 2A: Calculations and assumptions for hospital profits and costs.

Measure	**Calculations**
True Negative	https://pubmed.ncbi.nlm.nih.gov/21562405/ cited mean costs per case at $27,946 for 1,200 patients undergoing surgery from 2005 to 2008. 32% is an $8,934 cost to the hospital, so *$27,946 - $8,934 = $19,003*. Rounded down to $19,000 in profit per surgery for hospitals.
True Positive	According to AHRQ, complications represent a subset of adverse events, and for each adverse drug event, on average, hospitals incur an additional $5,746 in costs caring for a patient above and beyond the

	costs associated with an inpatient stay without complications (https://www.ahrq.gov/hai/pfp/haccost2017-results.html). *$19,003 - $5,746 = $13,257*. Rounded down to $13,000 in hospital profit with correctly treated complication.
False Positive	We assumed a patient treated for no complication would be kept overnight for an extra night. One extra night costs a hospital around $4,000, according to the CCR of patient costs for an overnight stay (https://mycreditsummit.com/average-cost-of-a-hospital-stay/). Additionally, there is increased risk to a patient of contracting hospital acquired infections, which could add an additional cost to the hospital of $31,000 (https://www.ahrq.gov/hai/pfp/haccost2017-results.html). So *$19,000 - (31,000 + 4,000) = -$16,000.* Although a false positive is less costly to the hospital than a false negative, the hospital is still losing up to $16,000 in possible costs if a patient were to obtain a hospital acquired infection.
False Negative	We assumed a patient sued for malpractice in the case of false negatives. With a median indemnity of around $111,000 (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3204310/), the hospital cost is *$19,000 - $111,000 = -$92,000.* 5.75 times more costly than a false positive.