Classification Presentation Slides

A Model to Help Prospective Patients Estimate the Likelihood of Mortality Following an Elective Surgery

George Pappy - 10 November 2021

Introduction

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- Knee and Hip Replacements
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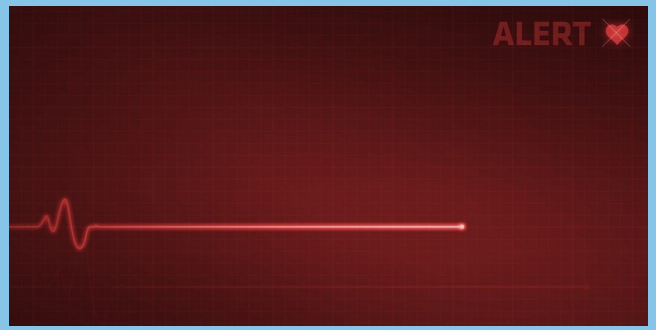
- Hernia Repairs
- Many Others of Varying Severity

Introduction (con’t.)

A small percentage (≈ 0.414 %) of these surgeries result in patient morality within 30 days



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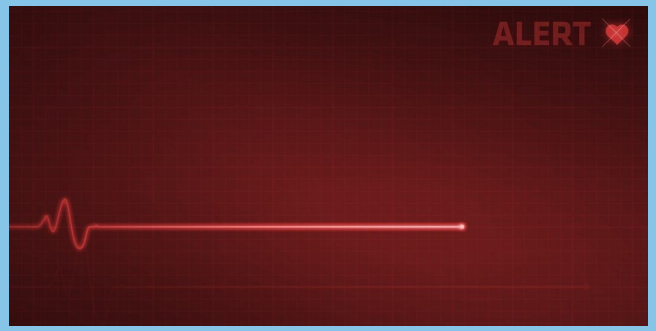

Patients have a right to know their own risk of post-surgical mortality

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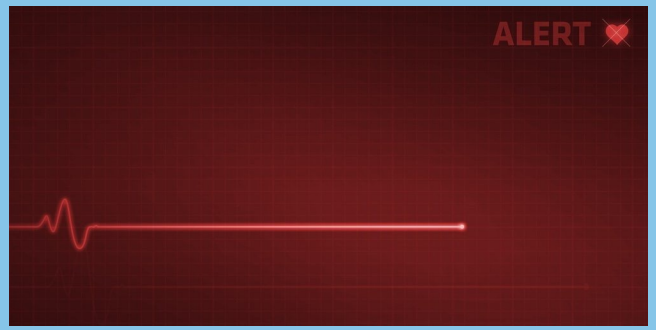

Patients have a right to know their own risk of post-surgical mortality

⇒ **May influence their decision to proceed with a surgery that’s not strictly necessary**

Introduction (con't.)

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  - Risk (example): {*Low*, *Moderate*, *High*}

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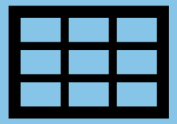

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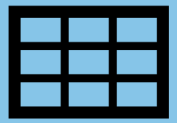
  - 23 predictors (patient characteristics, diagnoses, surgical procedure, etc.)



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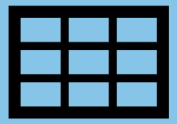

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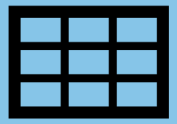
  - 28,287 rows (each is one surgical encounter) 
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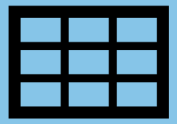
  - 28,287 rows (each is one surgical encounter) 
  - 23 predictors (patient characteristics, diagnoses, surgical procedure, etc.)
  - Target variable: Mortality within 30 days of surgery (1 = yes, 0 = no)
    - Highly imbalanced 
    - 99.586% negatives (0's) TO 0.414% positives (1's)

Methodology (con't.)

Methods & Tools

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- **Matplotlib/Seaborn**: visualizing data exploration, modeling and final results
- **Python 3.8**: to run all of the above

Results

Six individual models and three ensemble models built:

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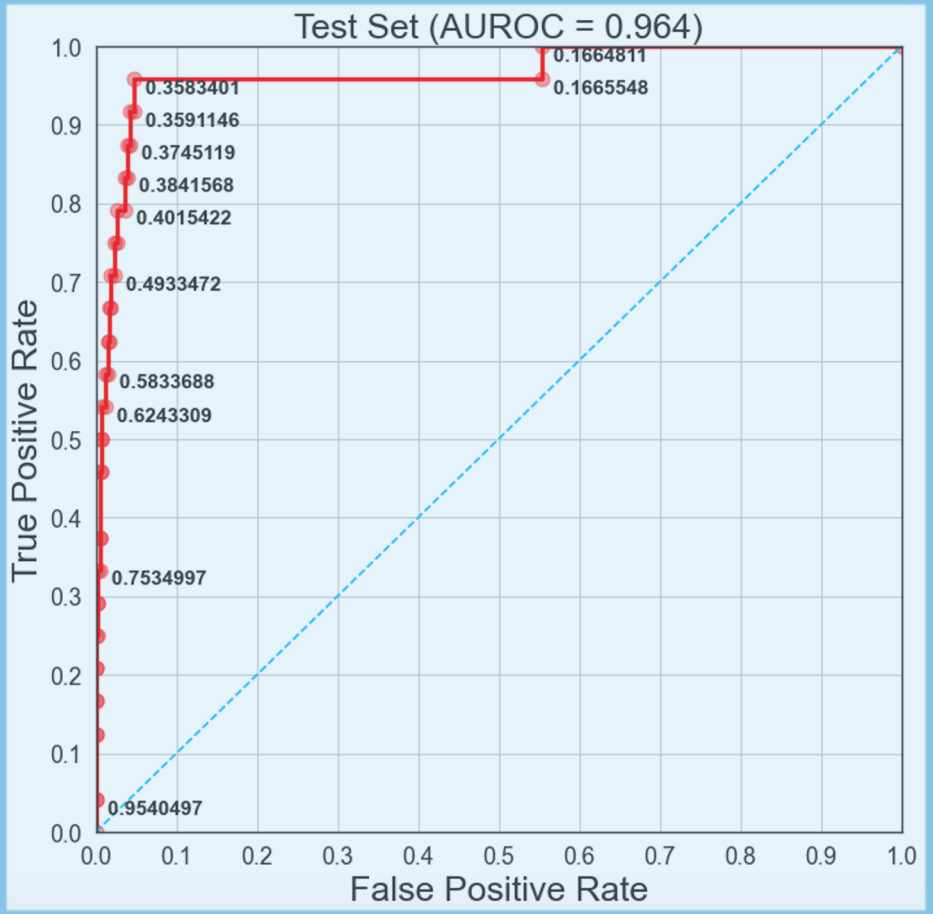
Minimize False Negatives (FN) so the model **misses as few Elevated Risk patients as possible**

- As FN decreases, TPR increases
- But as FN decreases, False Positive Rate increases…

Results (con't.)

Best Model: Voting Classifier (soft)
(Logistic Regression + XGBoost, AUC-optimized)



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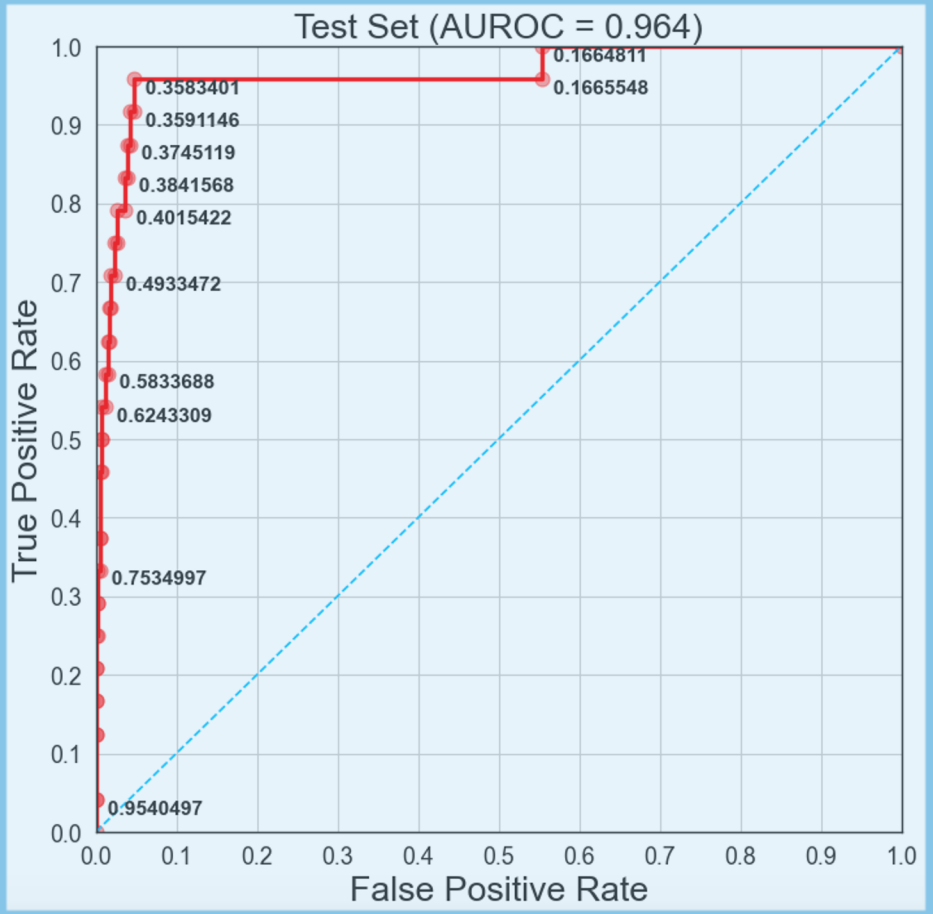

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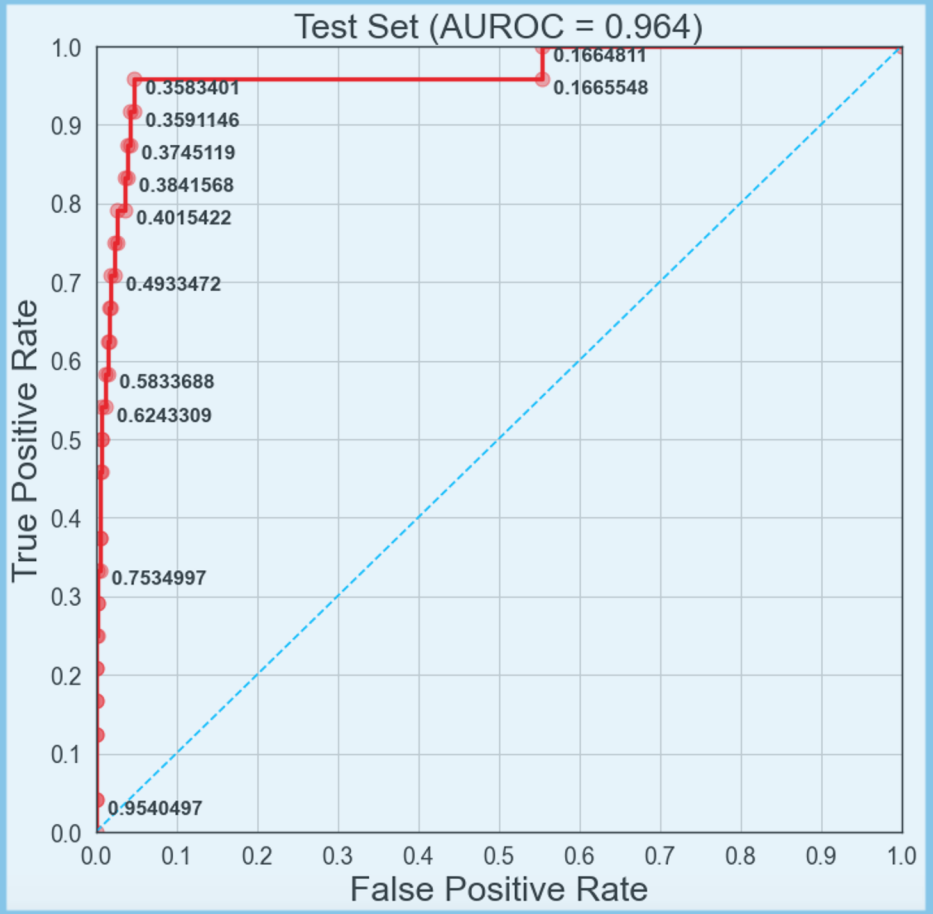

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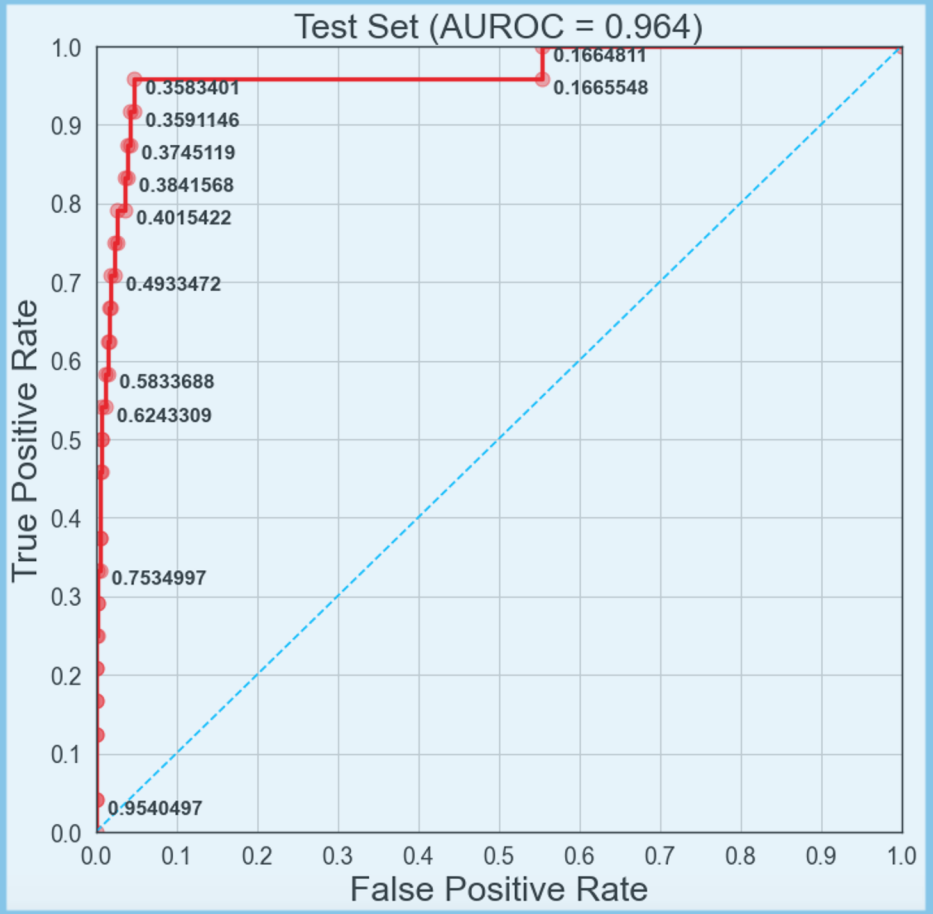

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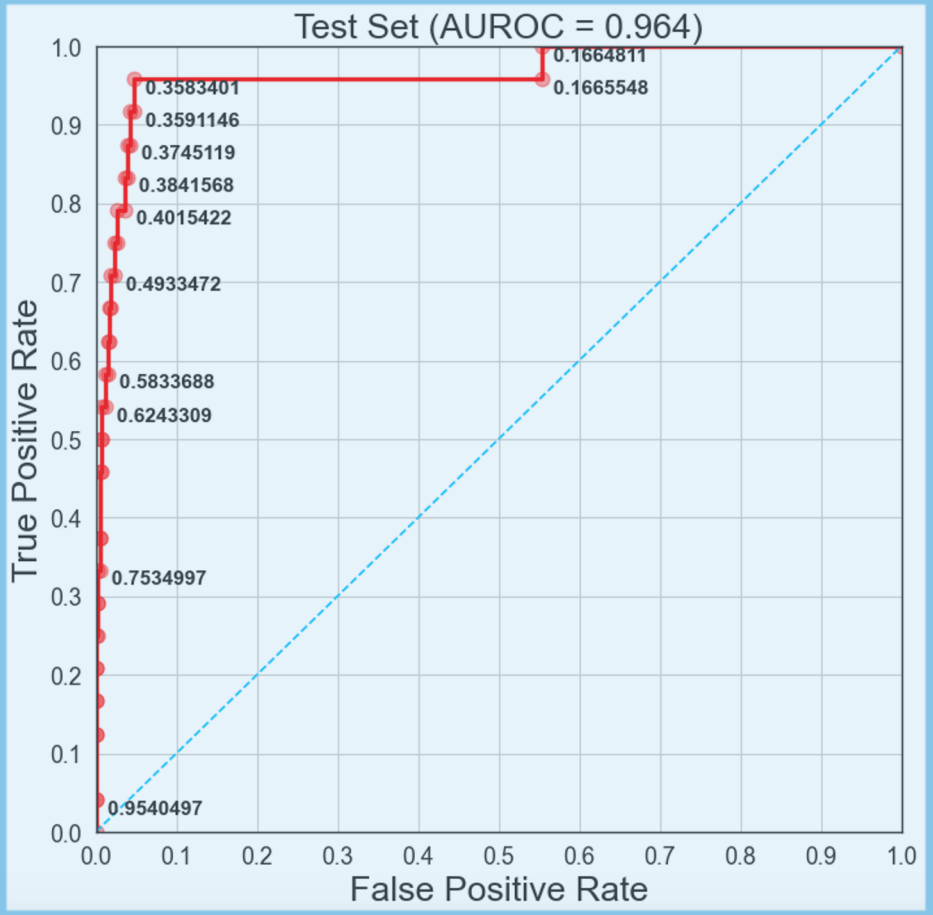

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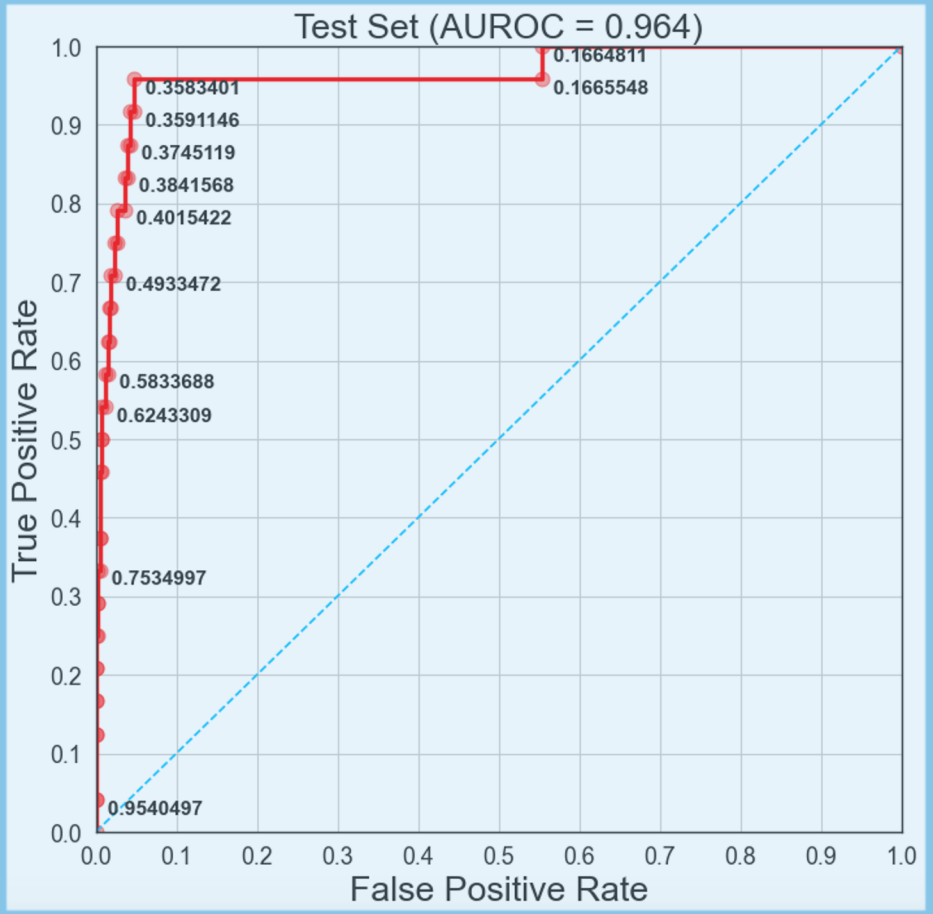

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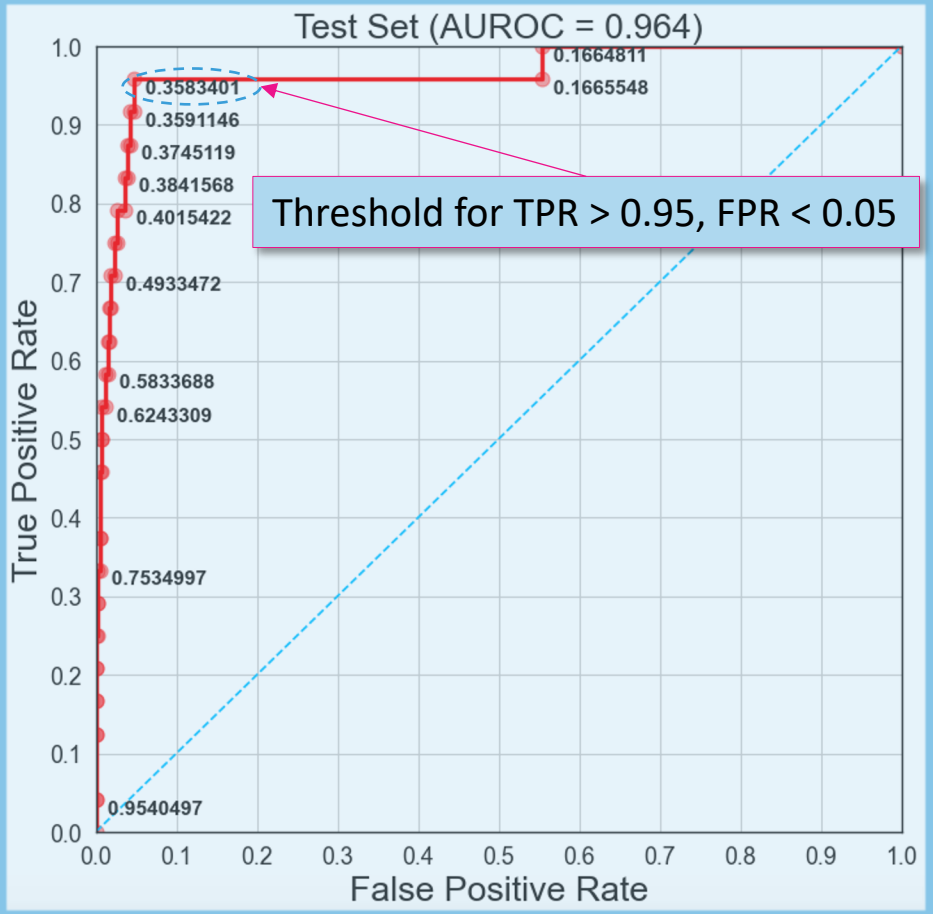

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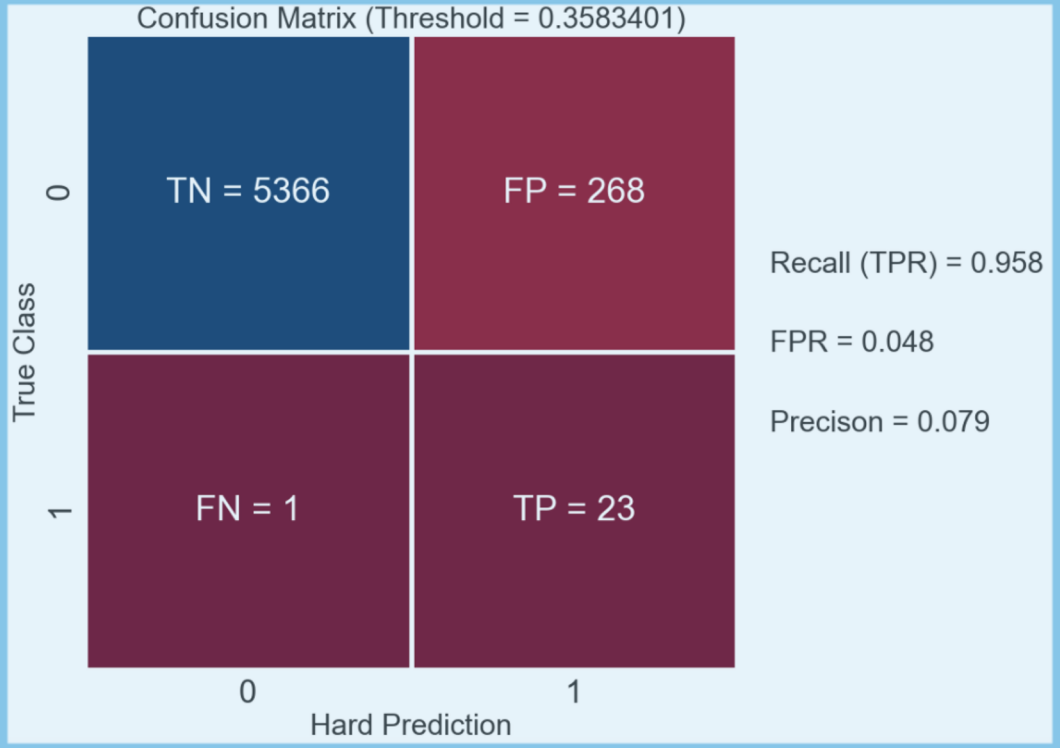

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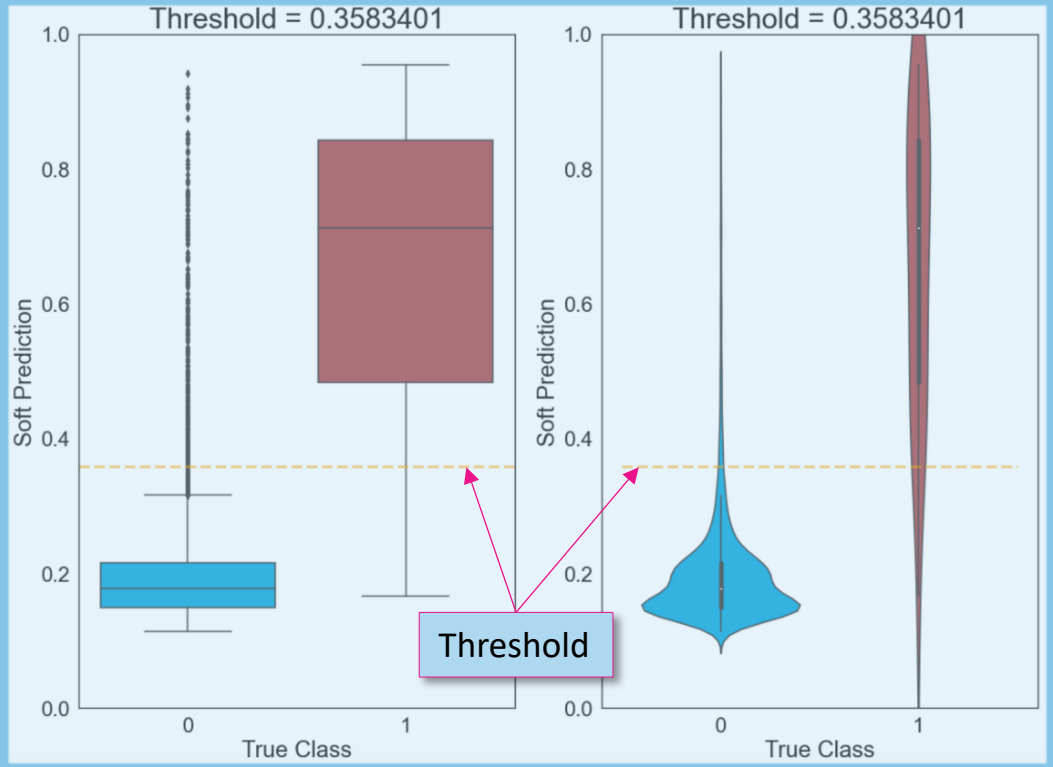


Conclusions

Recommendations

- Deploy this model (Voting Classifier w/ Logistic Regression & XGBoost)
- Develop an explicit ranking scheme for the model's soft predictions with "Elevated Risk" patients

  → Example: {*Low, Moderate, High*}

Conclusions (con't.)

Future Work

- Track the deployed model's performance over time:

  → Does it maintain TPR > 0.95 and FPR ≈ 0.05 (i.e., current performance)?

- Retrain the model periodically as more data accrues (new surgeries)
- Build Deep Learning models for potentially better performance

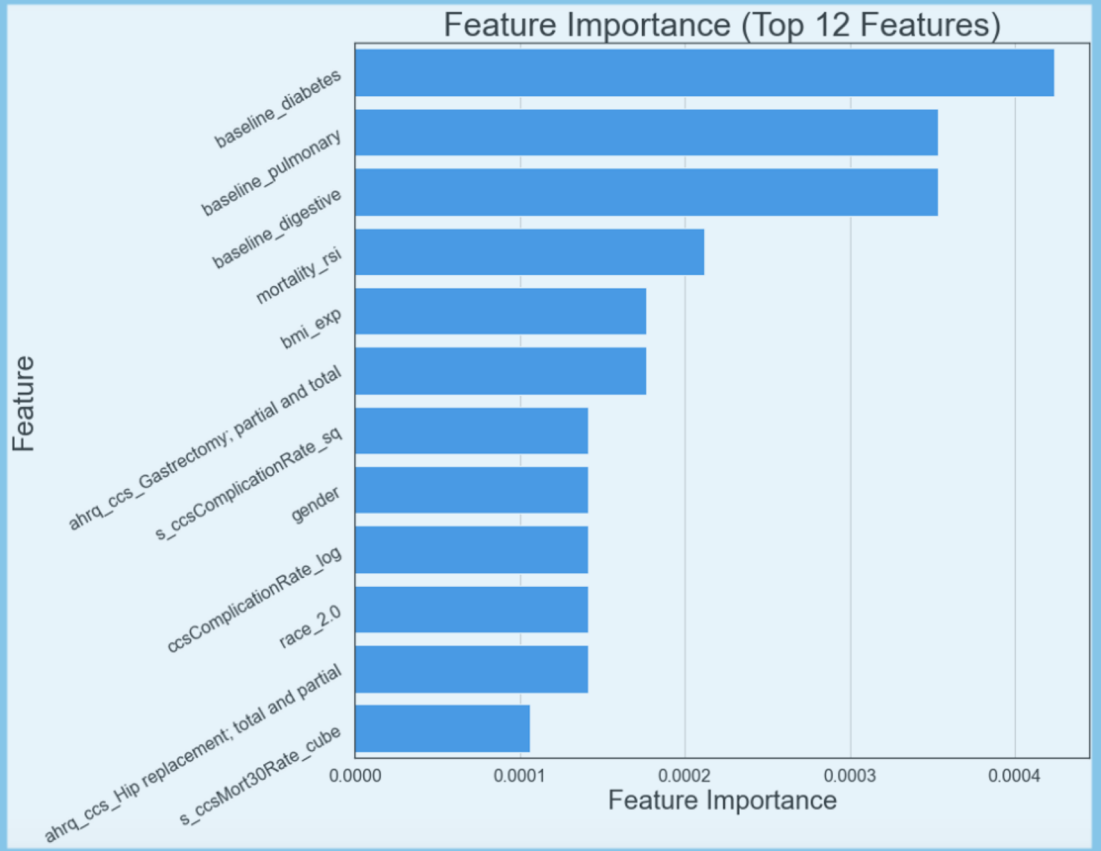
Appendix

Feature Importance

Best Model: Voting Classifier

(Logistic Regression + XGBoost, AUC-optimized)

- Interestingly, this model finds the most importance in much different features than the underlying models do (see the next few slides)
- Diabetes, pulmonary diagnoses and digestive disorders appear to play a significant role in mortality outcomes as judged by this model
- Body mass index and mortality_rsi (risk stratification index) also play non-trivial roles)
- Gastrectomy and Hip Replacement procedures appear to play outsized roles relative to other procedures
- Reliable interpretability may be an inherent weakness of this model

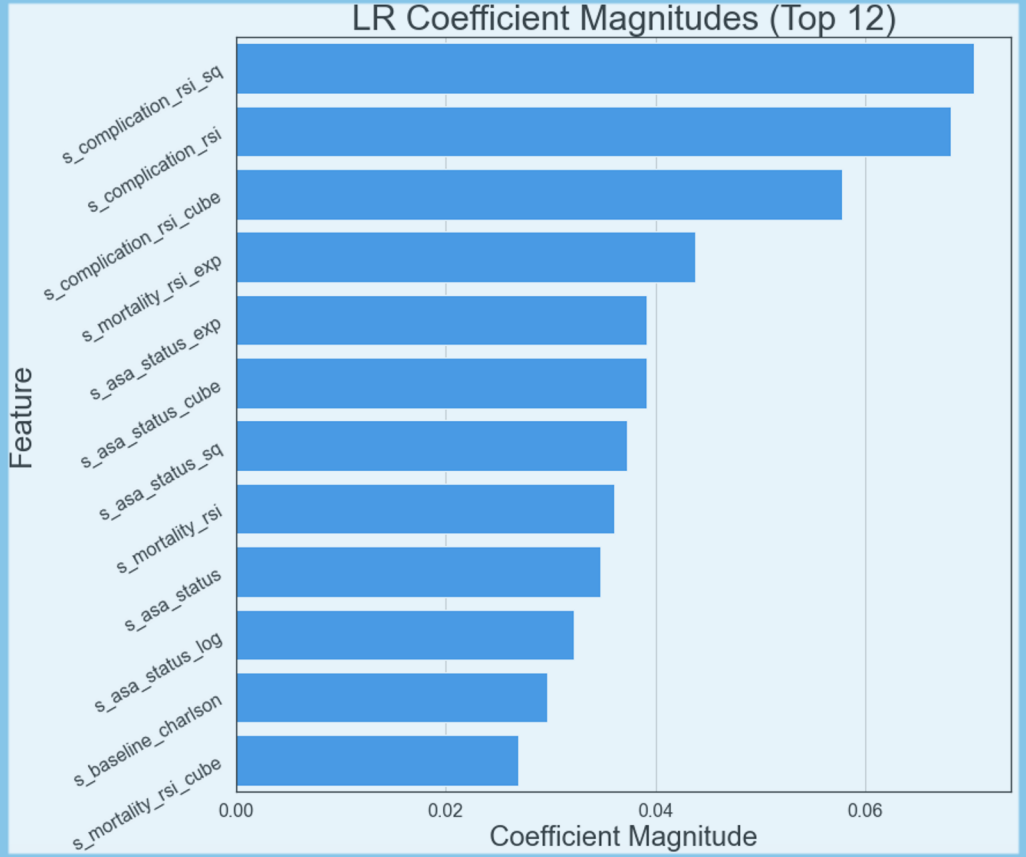


Feature Importance (con't.)

Best Model: Voting Classifier

(Logistic Regression + XGBoost, AUC-optimized)

- The underlying Logistic Regression model appears largely dependent upon features different than the most important ones found in the overall voting classifier
- This model depends most upon on multiple engineered features based on the same original variable (complication_rsi, mortality_rsi, asa_status)
- The one area of overlap between this model and the overall ensemble seems to be mortality_rsi (not surprising)

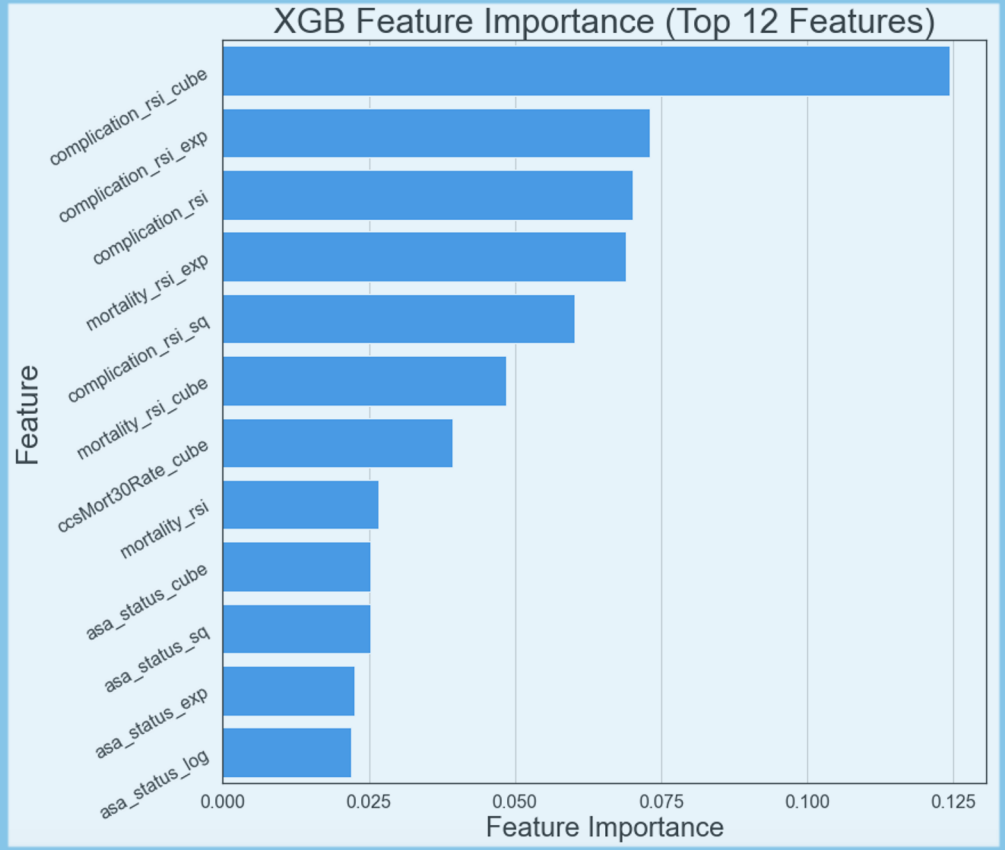


Feature Importance (con't.)

Best Model: Voting Classifier

(Logistic Regression + XGBoost, AUC-optimized)

- The underlying XGBoost model also appears largely dependent upon features different than the most important ones found in the overall voting classifier
- However, this model seems to agree with the underlying Logistic Regression in large part about the most significant features (complication_rsi, mortality_rsi, asa_status)
- The one area of overlap between this model and the overall ensemble seems to be mortality_rsi (just as with the Logistic Regression model)

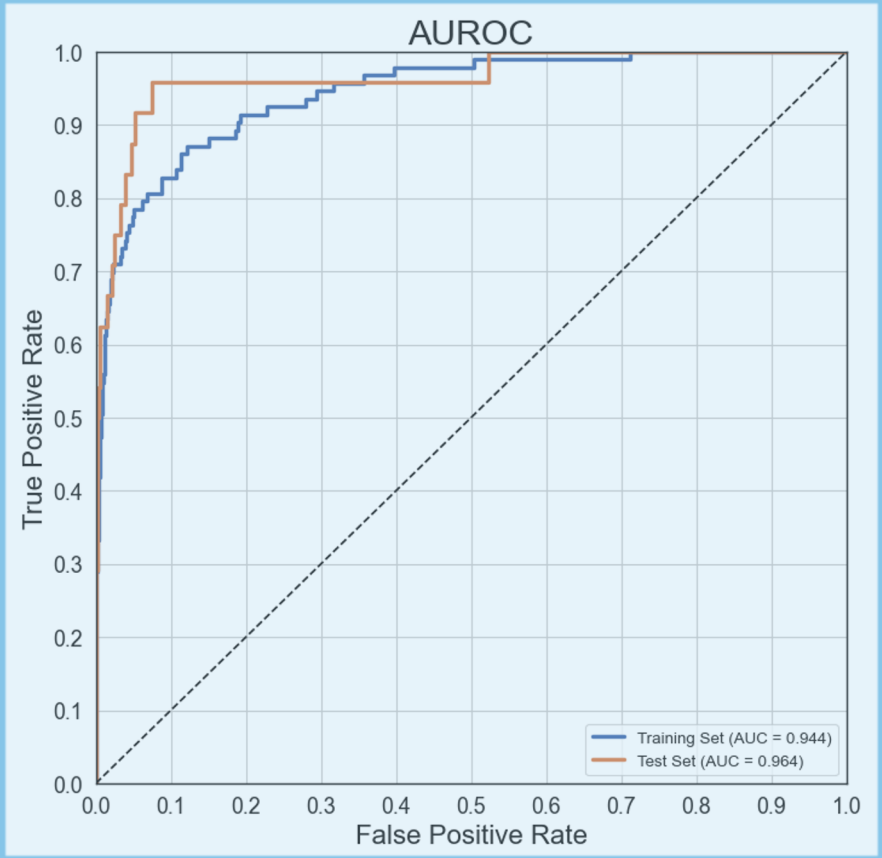


First Individual Model Developed

Logistic Regression

(Regularization parameters optimized to AUC)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.074 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)

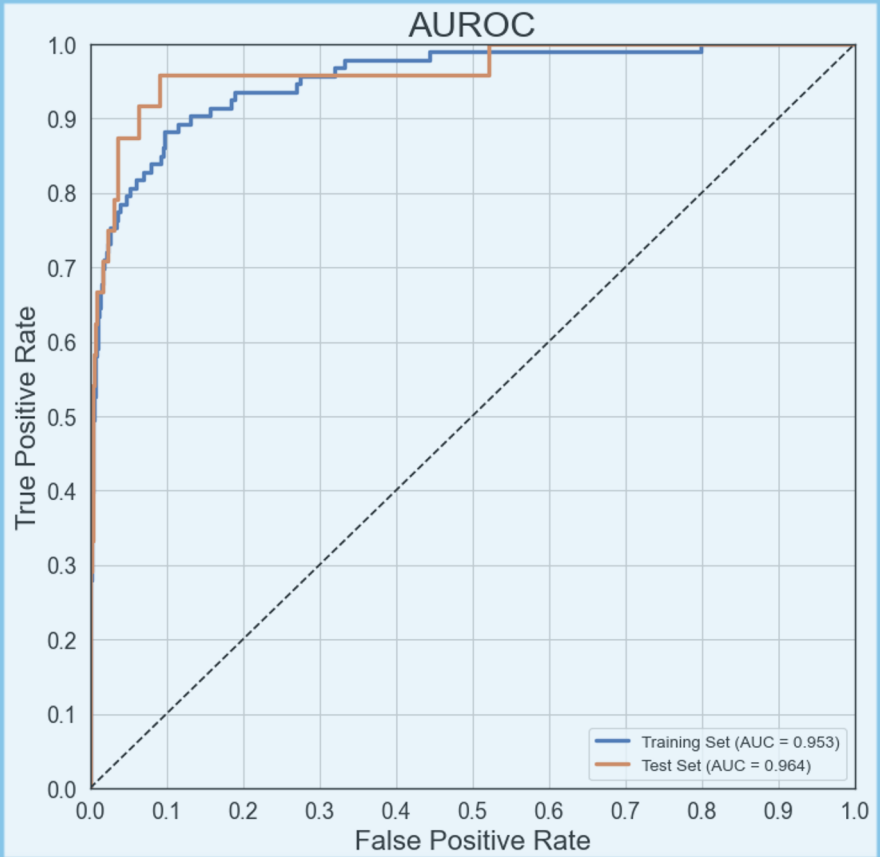


Second Individual Model Developed

Logistic Regression

(Regularization parameters optimized to log-loss)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.091 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)

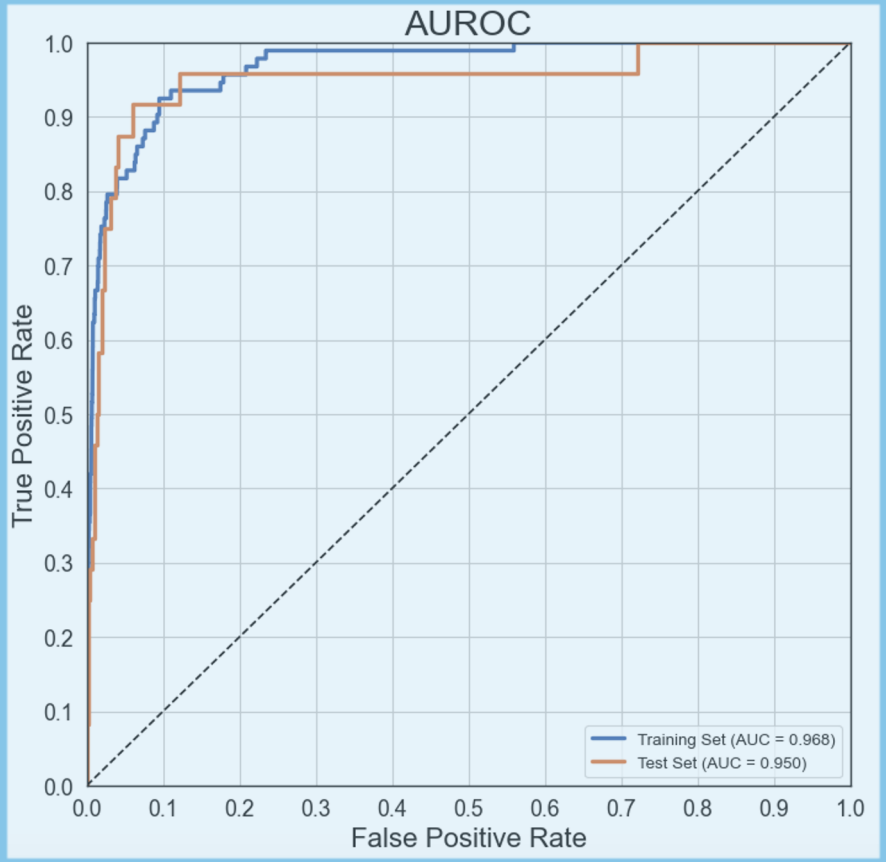


Third Individual Model Developed

Random Forest

(Regularization parameters optimized to AUC)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.122 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)

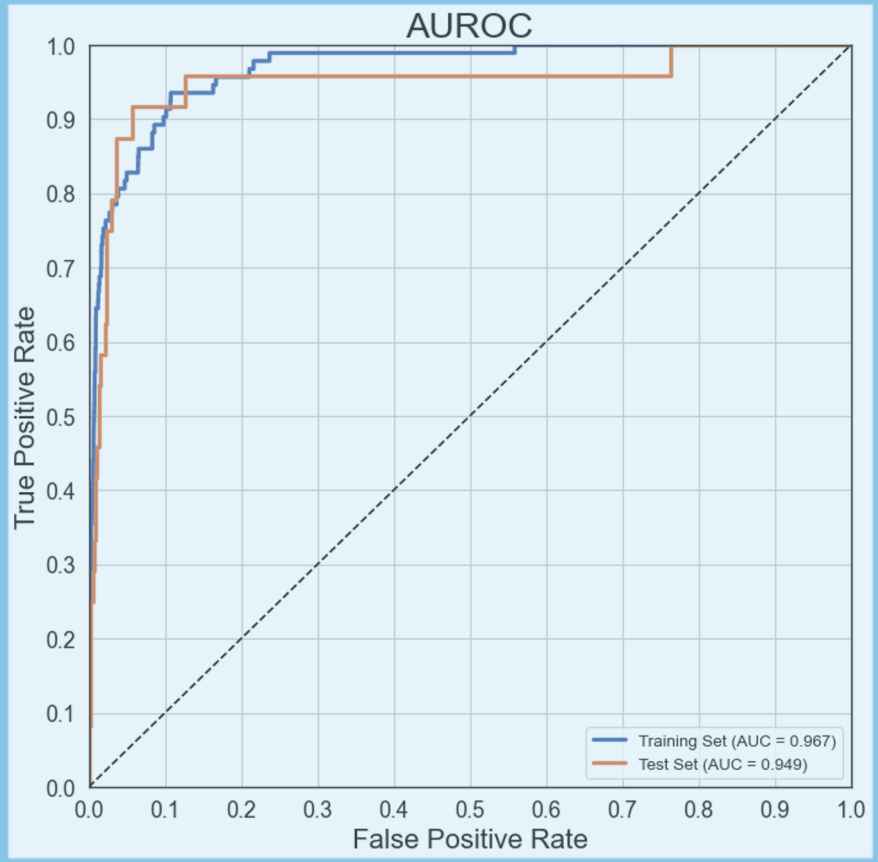


Fourth Individual Model Developed

Random Forest

(Regularization parameters optimized to log-loss)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.126 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)



Fifth Individual Model Developed

XGBoost

(Regularization parameters optimized to log-loss)

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- FPR = 0.074 for TPR = 0.958
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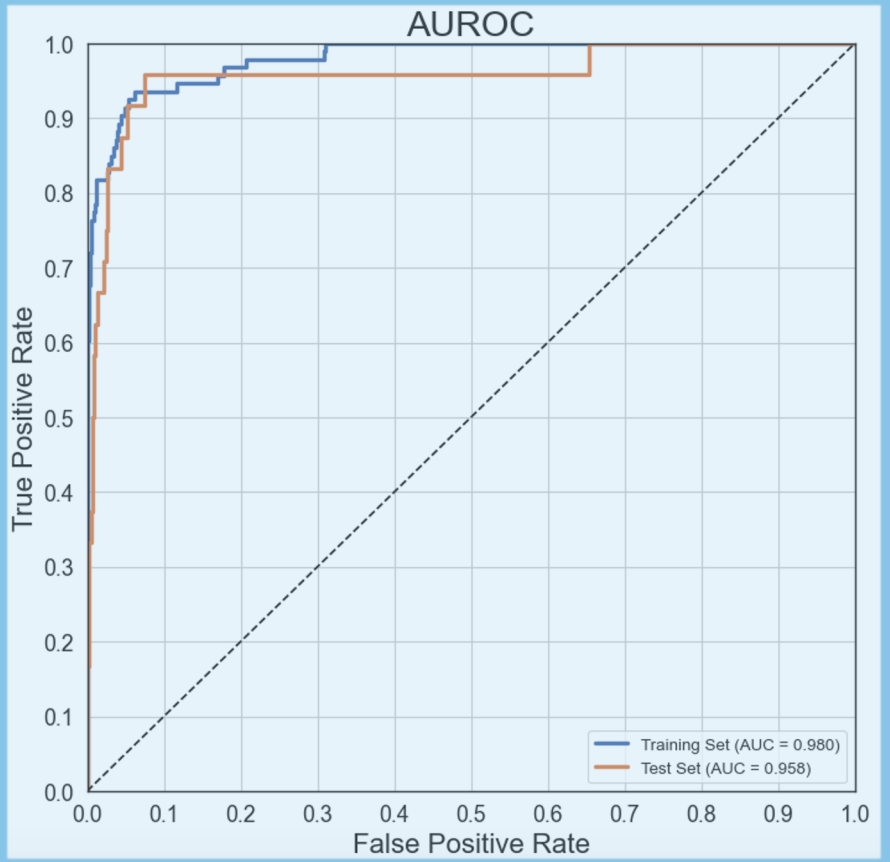
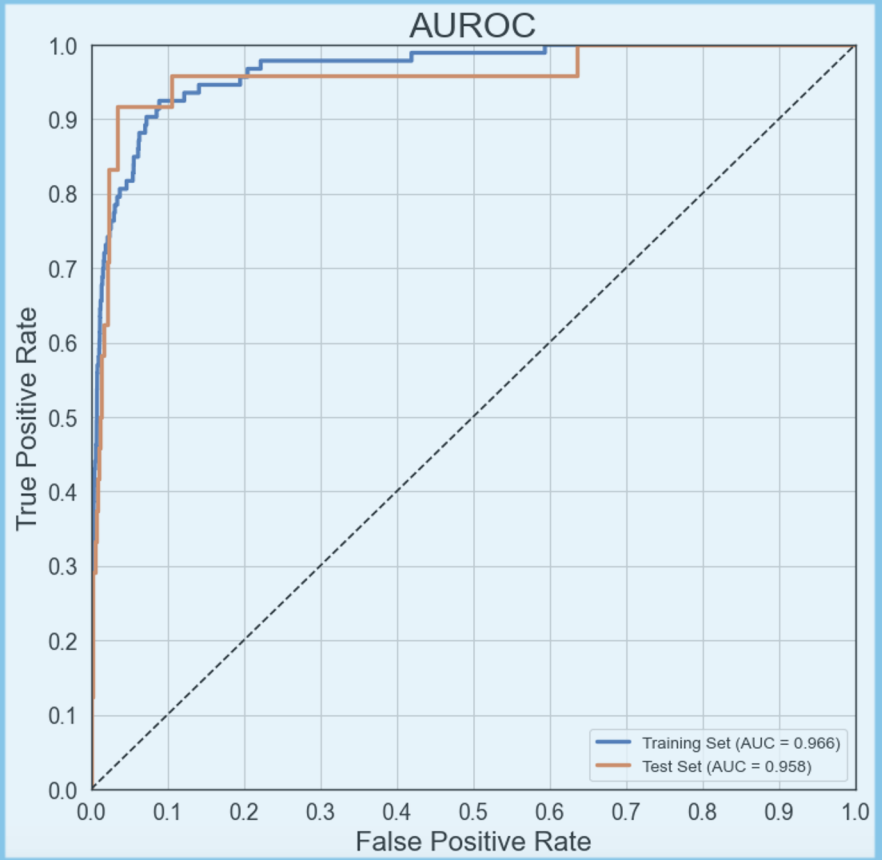


Sixth Individual Model Developed

XGBoost

(Regularization parameters optimized to AUC)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.105 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)

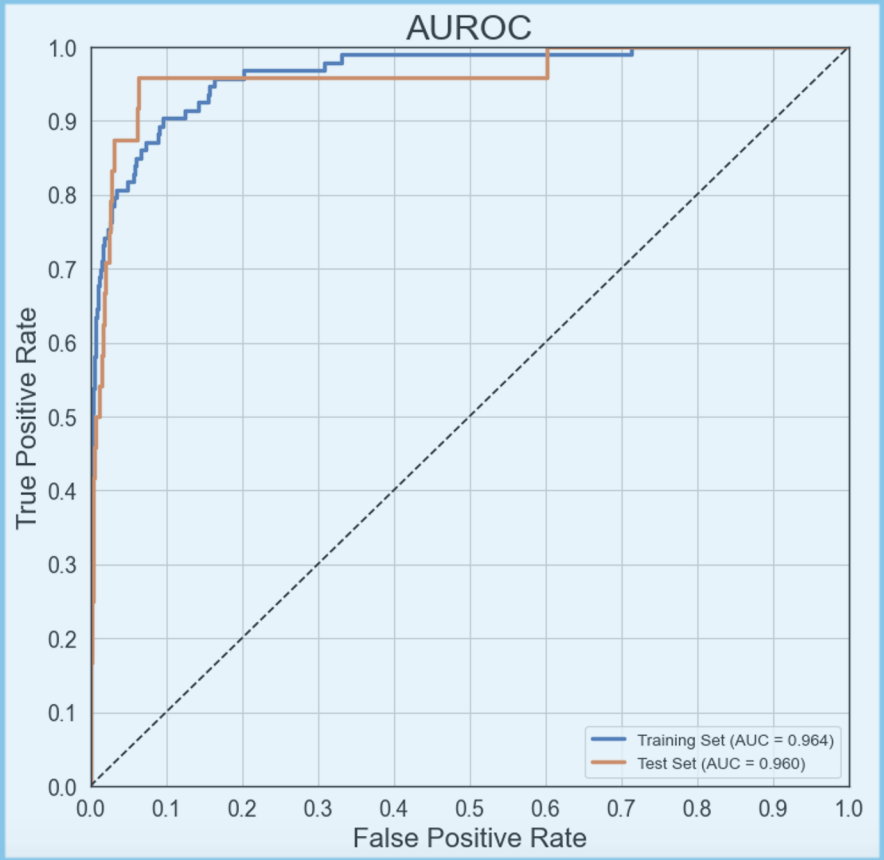


First Ensemble Model Developed

Voting Classifier

(Includes all six individual models)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.063 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)

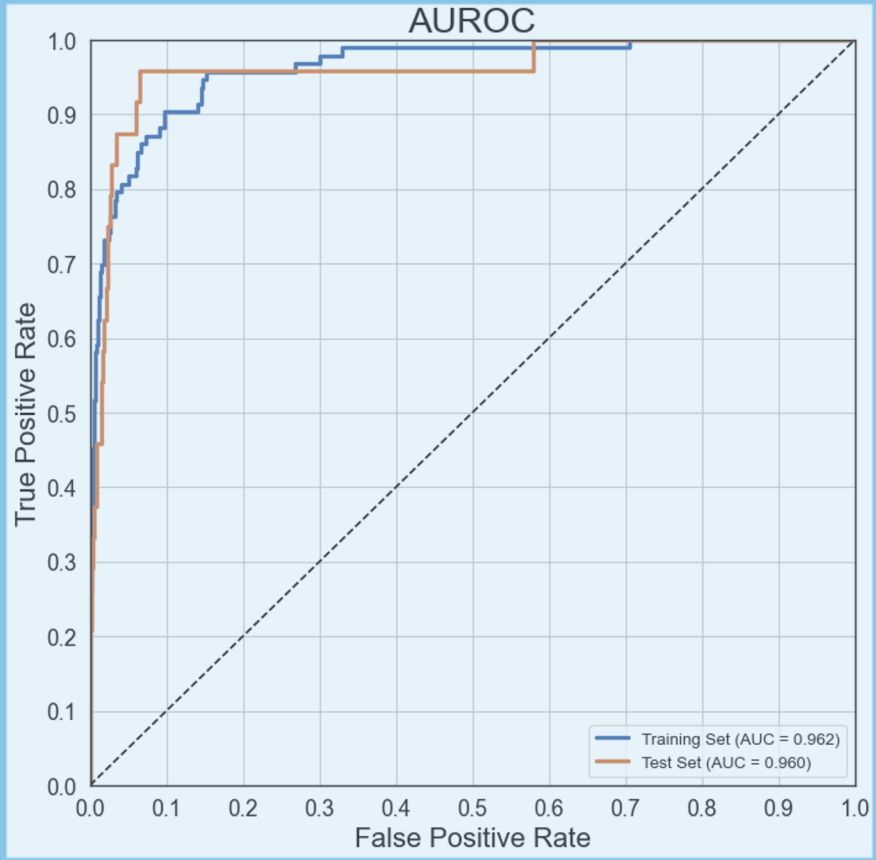


Second Ensemble Model Developed

Voting Classifier

(LR + RF + XGBoost models, optimized to AUC)

- TPR = 0.958 achievable (same as final model)
- FPR = 0.065 for TPR = 0.958
  → Not as good as the final model (FPR = 0.048)



Third Ensemble Model Developed

Voting Classifier

(LR + XGBoost models, optimized to AUC)

- TPR = 0.958
- FPR = 0.048

  → **Best Model**