MACHINE LEARNING CLASSIFICATION:
DETECTING WEAR ON A COMPUTER NUMERICALLY CONTROLLED MILL TOOL

METIS BOOTCAMP | July 9, 2021

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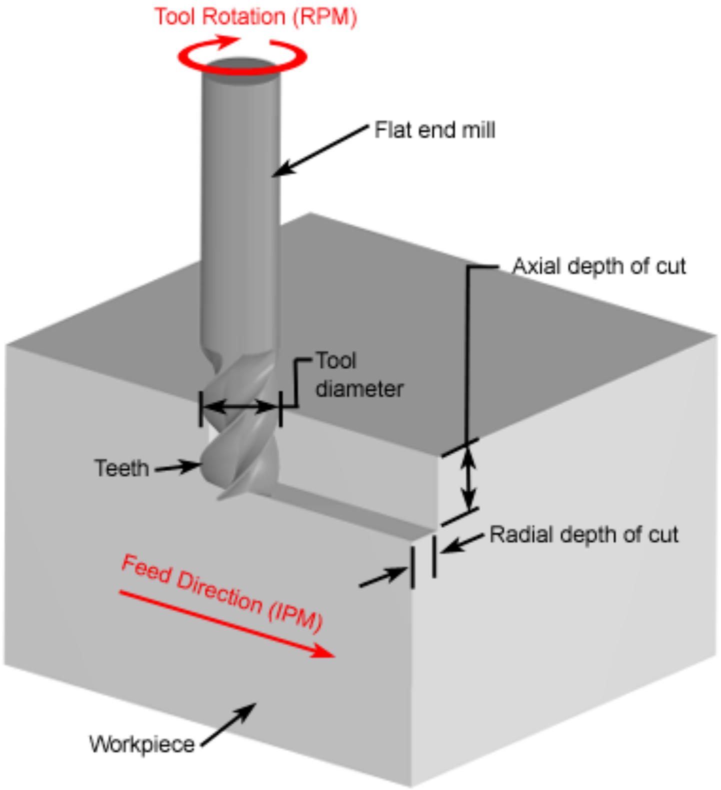
OUTLINE

- Problem Statement
- Dataset/EDA
- Baseline and Choice Model
- Recommendation

PROBLEM STATEMENT

Predict wear on a CNC milling tool so that the milling tool can be replaced before products are ruined.



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COMMON CAUSES OF MILL TOOL WEAR

- Feed Rate (low/high)
- Cutting Speed (low/high)
- Tool Grade (hard/soft)

DATASET

18 Experiments

10 Worn tools
8 unworn tools

Features

Position
Velocity
Acceleration
Feedrate
…

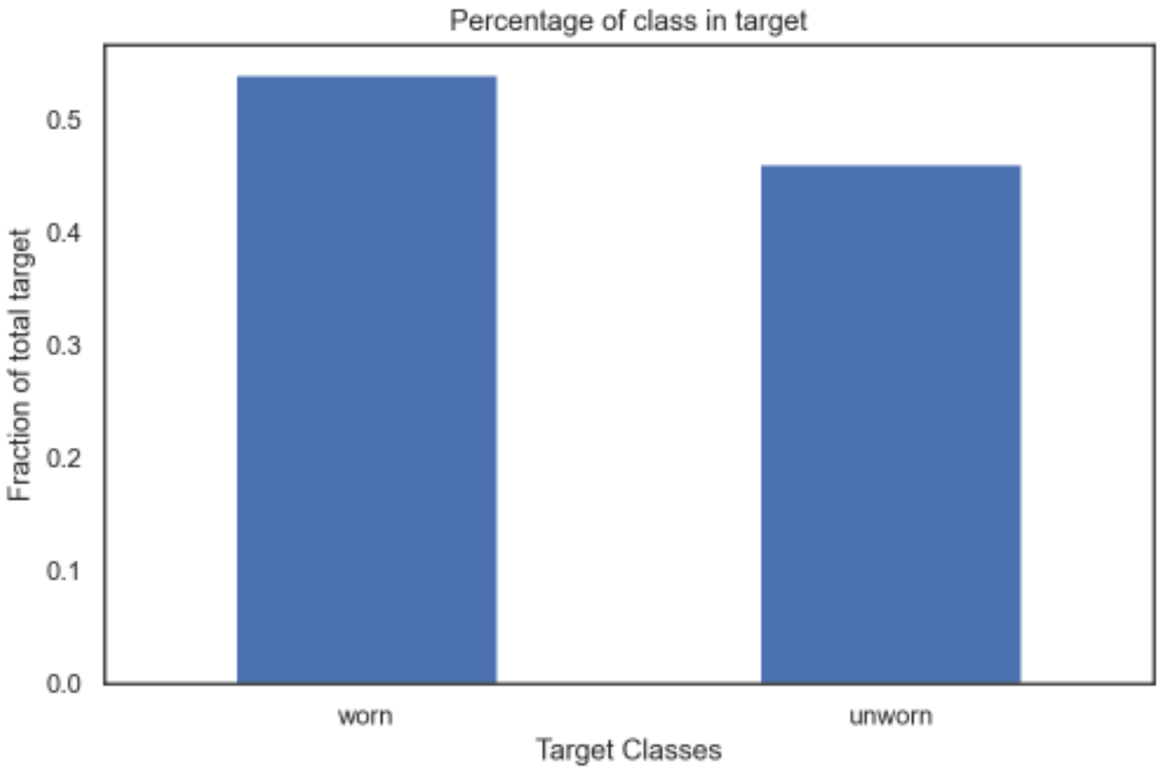
25286 Observations
52 Features

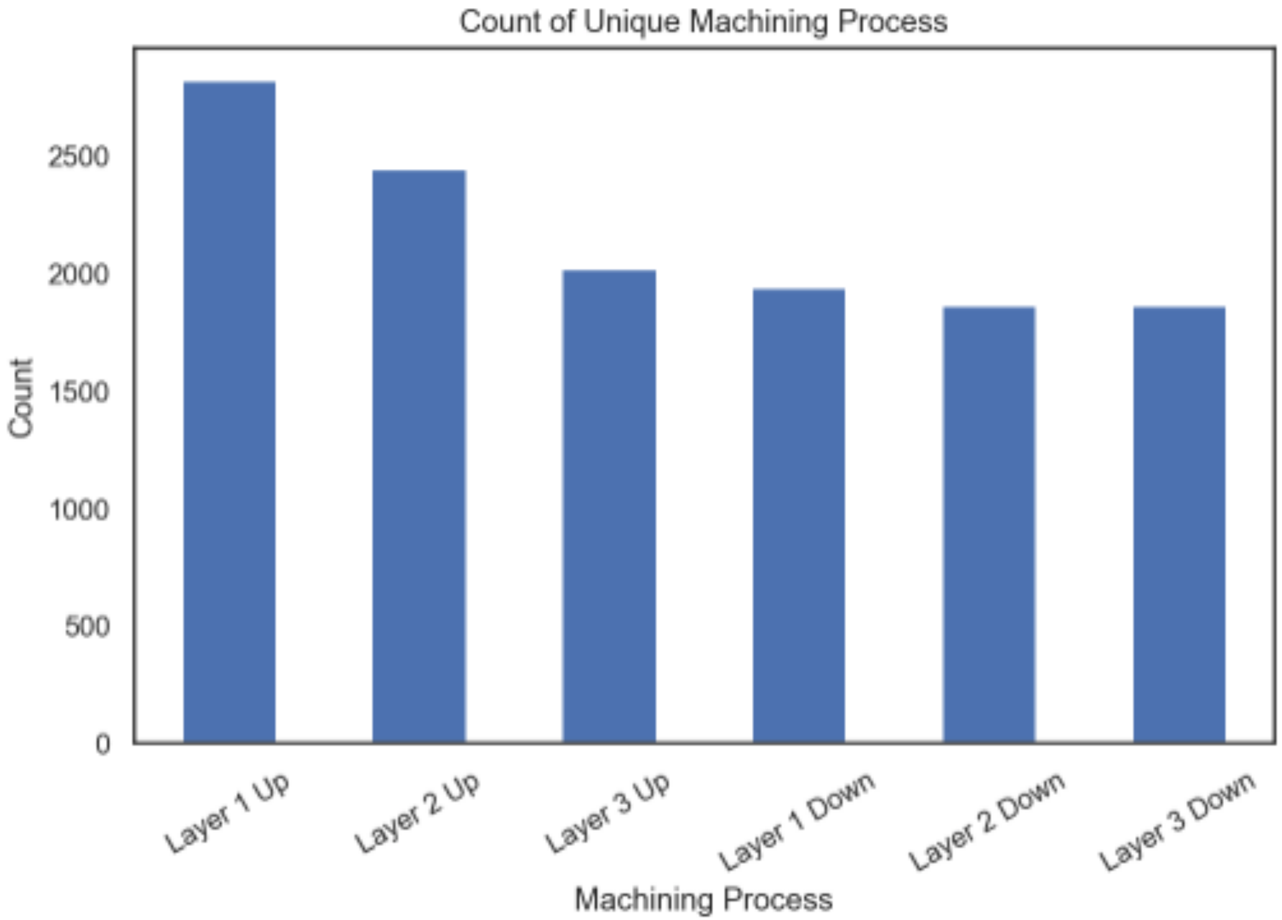
Data Cleaning

12943 Observations
43 Features

EDA

- Fairly Balanced Classes





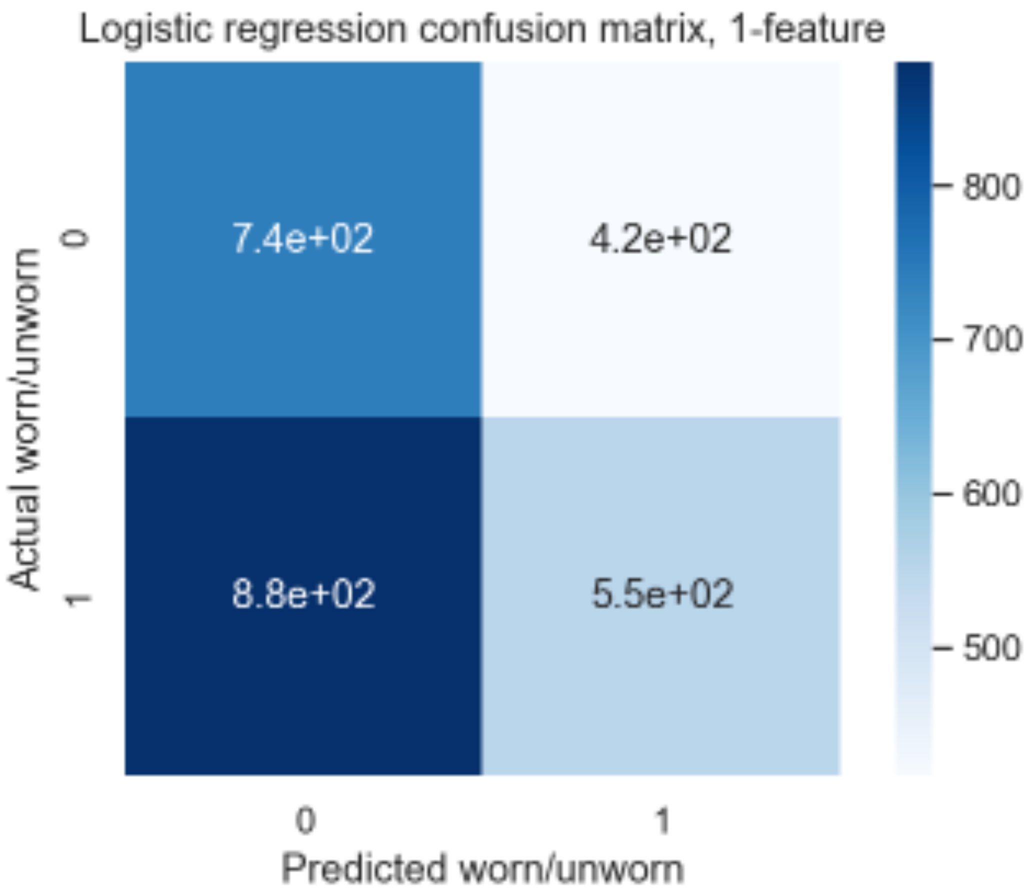
CLASSIFICATION METRICS

- Accuracy
- f_beta (beta = 2)
- AUC
- Confusion Matrix

BASELINE - LOGISTIC REGRESSION

Baseline Feature = FEED RATE

- C = 0.95
- Accuracy (Test Data)
  49.9 %

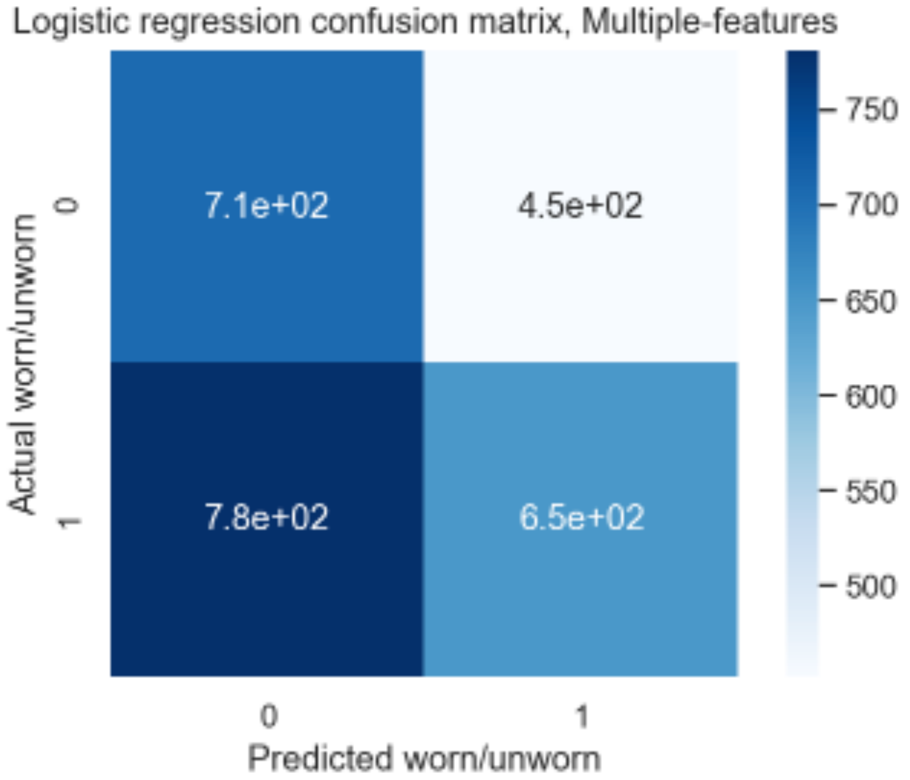


FEATURE ENGINEERING - CUTTING SPEED

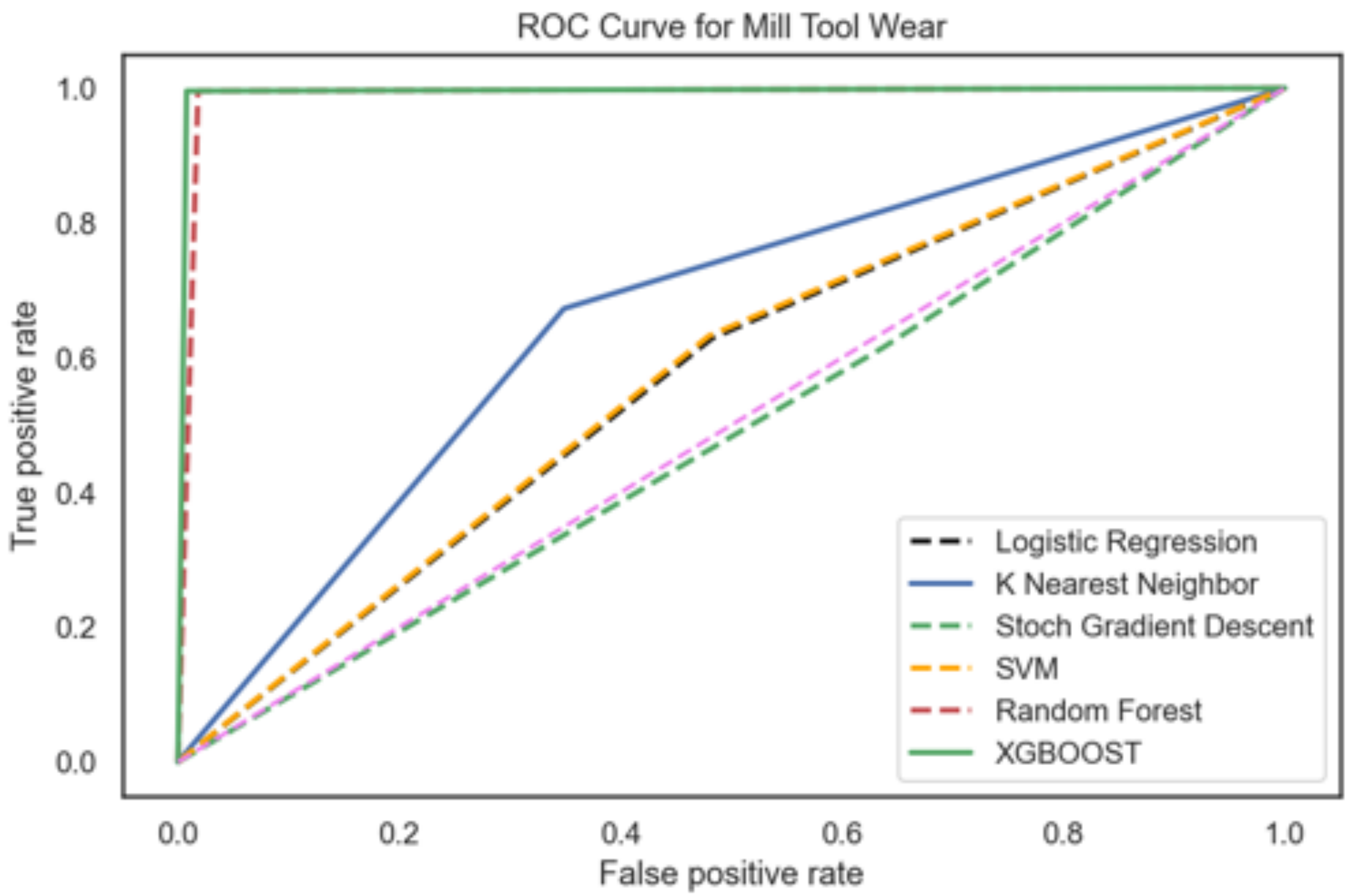
- Cutting Speed = *Pi x Tool Diameter x Spindle Speed*

Features = FEE DRATE, X-Acceleration, Cutting Speed

- Scaled
- C = 0.95
- Accuracy (Test Data)
  52.39 %



MODEL COMPARISON - ROC AUC

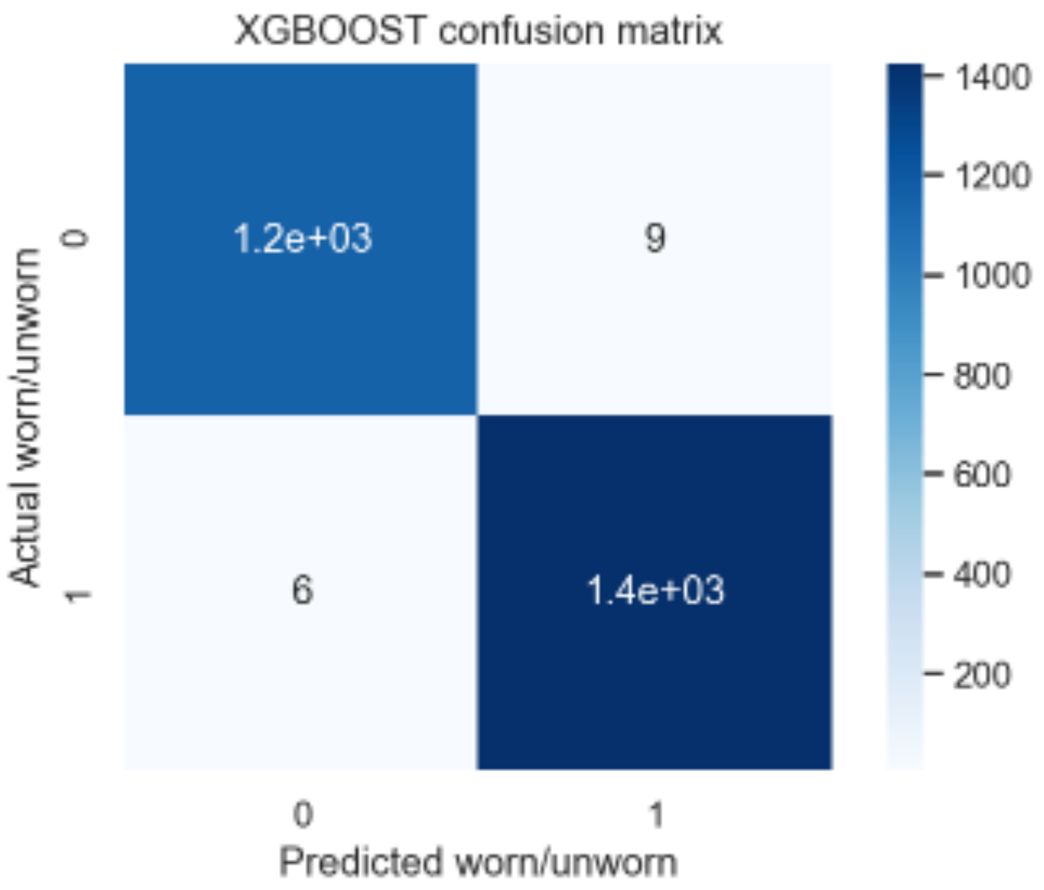


MODEL - XGBOOST

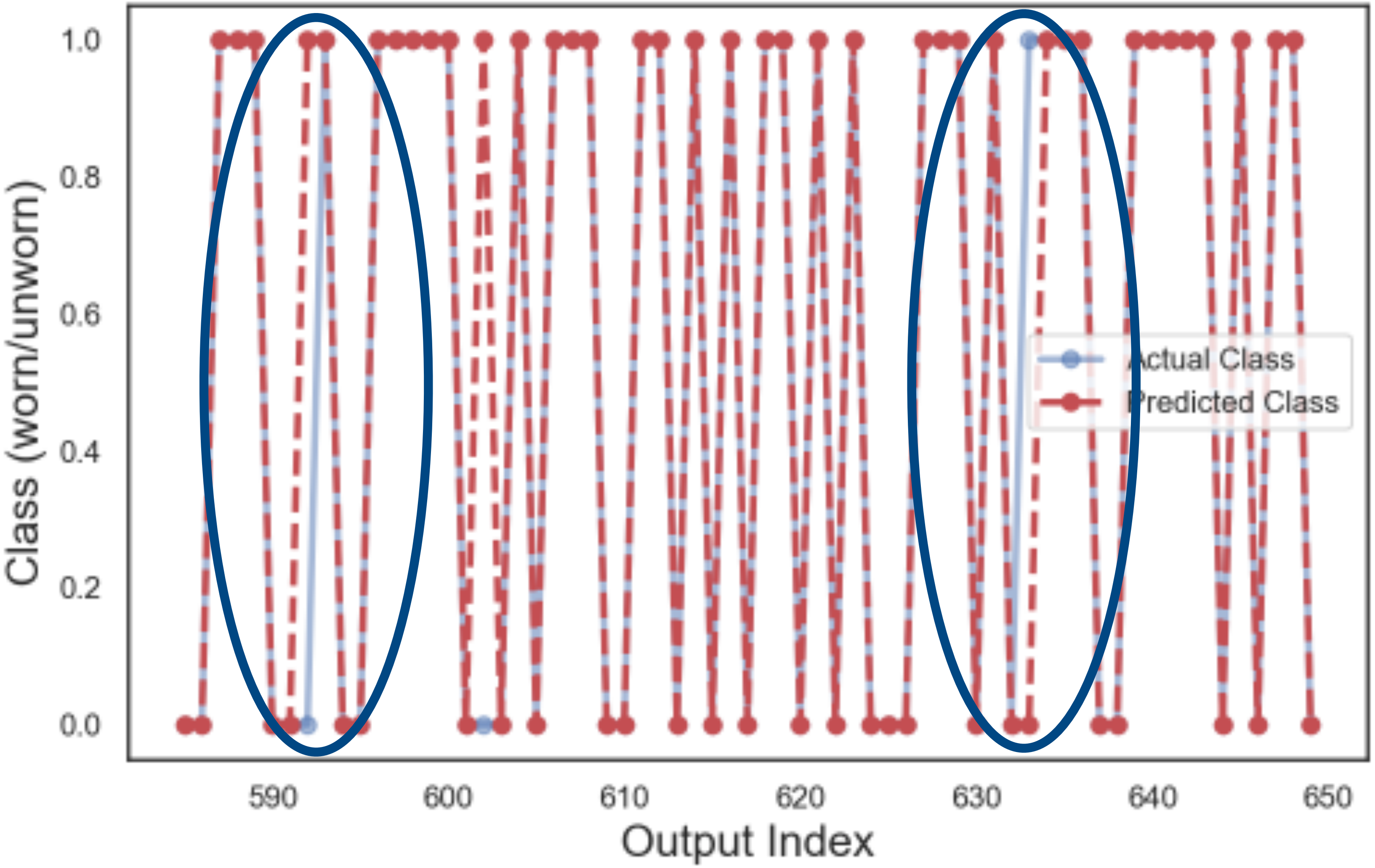
- ***Estimators = 100***
- ***Early Stopping = 50***
- ***Objective: Logistic***
- ***Learning Rate: 0.05***
- ***Sub Sampling: 0.8***
- ***Min Child Weight: 3***

- Threshold = 0.45
- Recall (0.9958 —> 0.9972)
- Accuracy (Test Data)

  99.42 %



XGBOOST - ACTUAL AND PREDICTED OUTPUT



RECOMMENDATIONS

- Accuracy and AUC are interpretable metrics for balanced datasets
- Reduce threshold to account for recall, ie penalize False negatives.
- Use XGBOOST for its optimal predictive ability when interpretability can be sacrificed.

APPENDIX - FLASK APP

Machine Learning Classification

Click to see plots on different pages

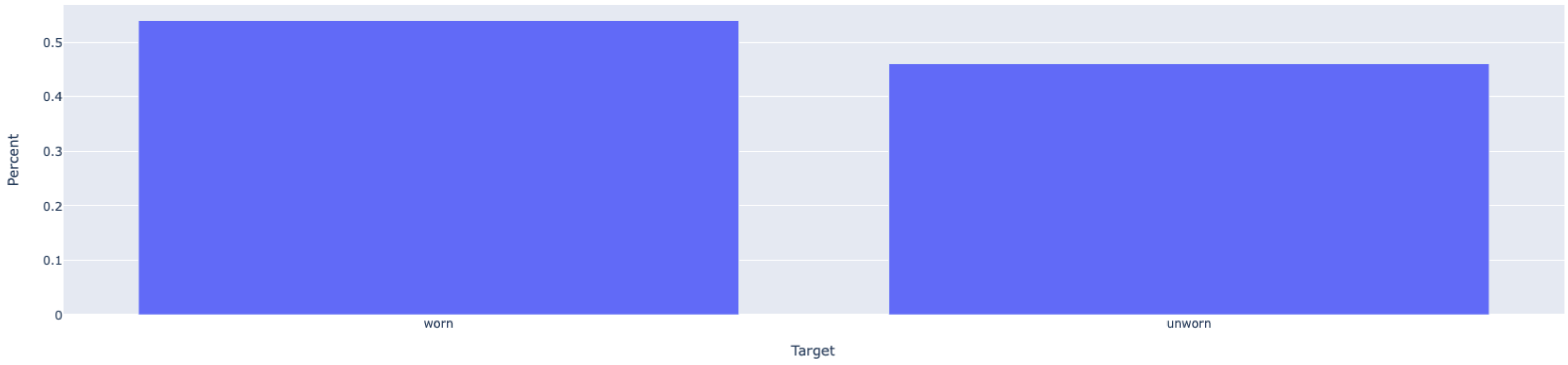
Dataset class distribution

AUC Comparison for models

APPENDIX - FLASK APP

Plotly chart

Return to index page



APPENDIX - FLASK APP

AUC comparison

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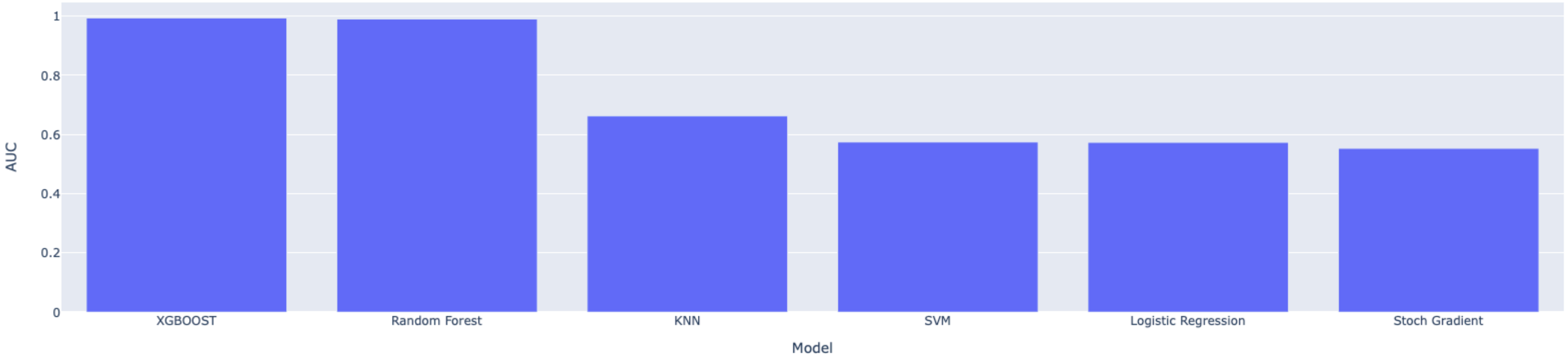
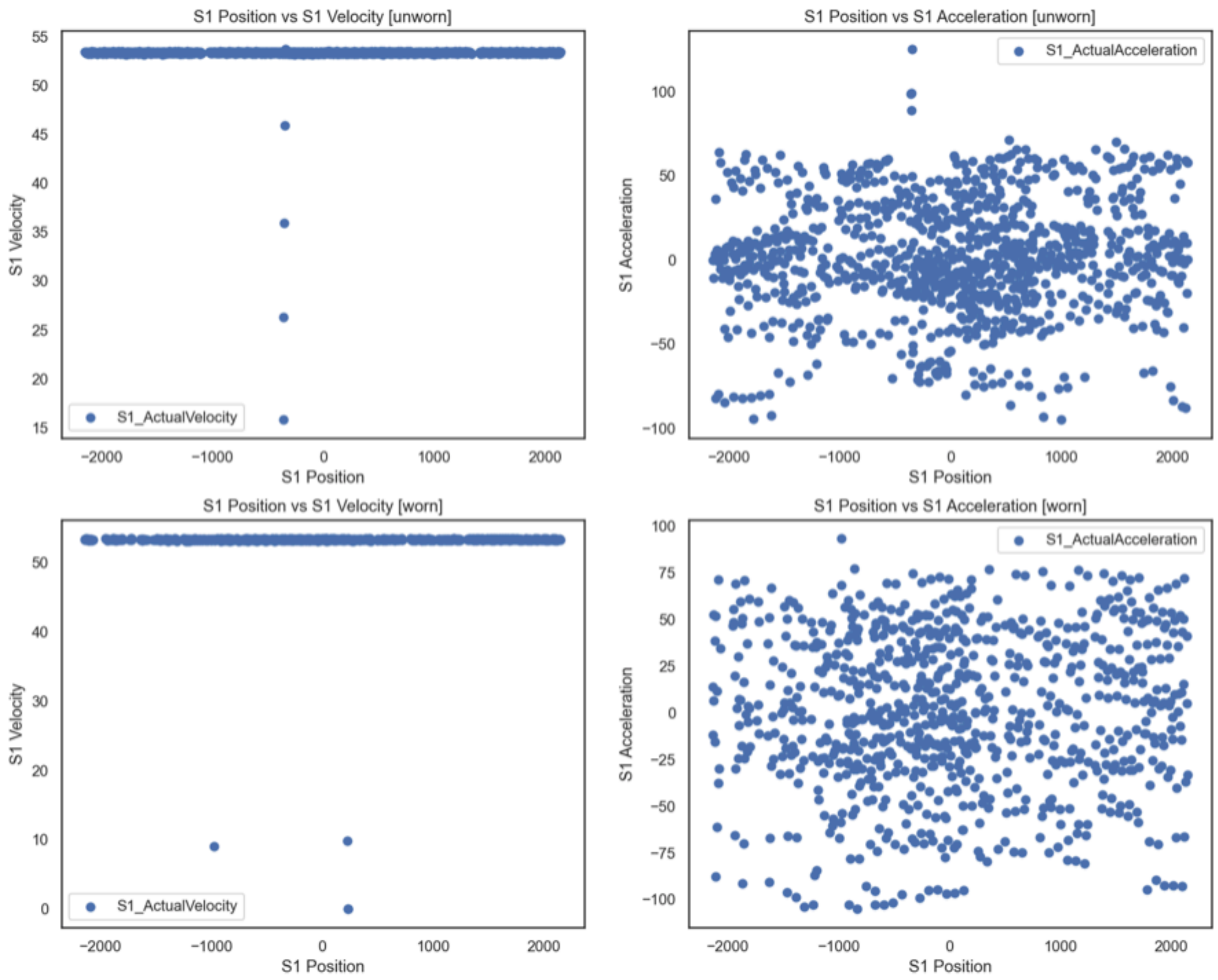
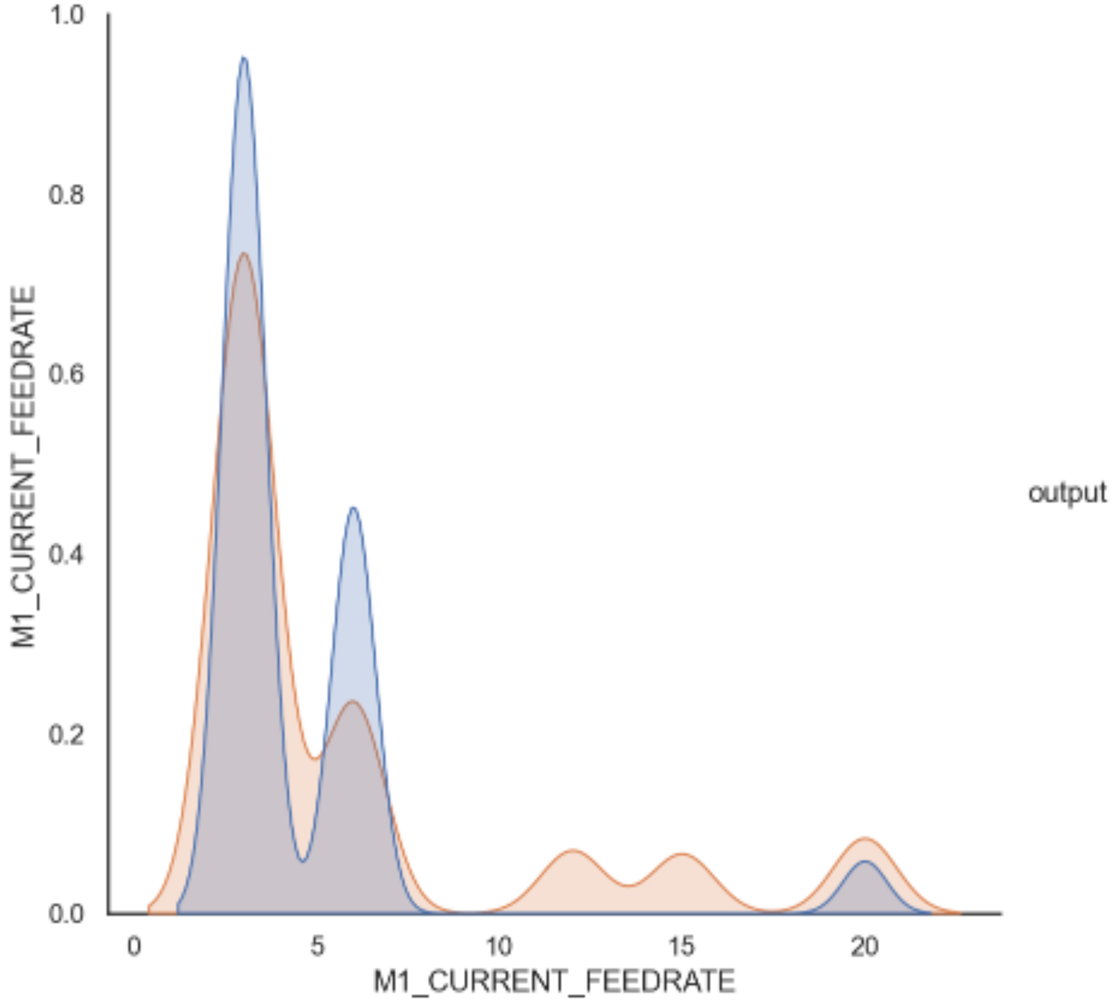


AUC gives the probability that the random actual positive is ranked higher than random actual negative. This is the probability that the classifier assigns high score to the worn class.

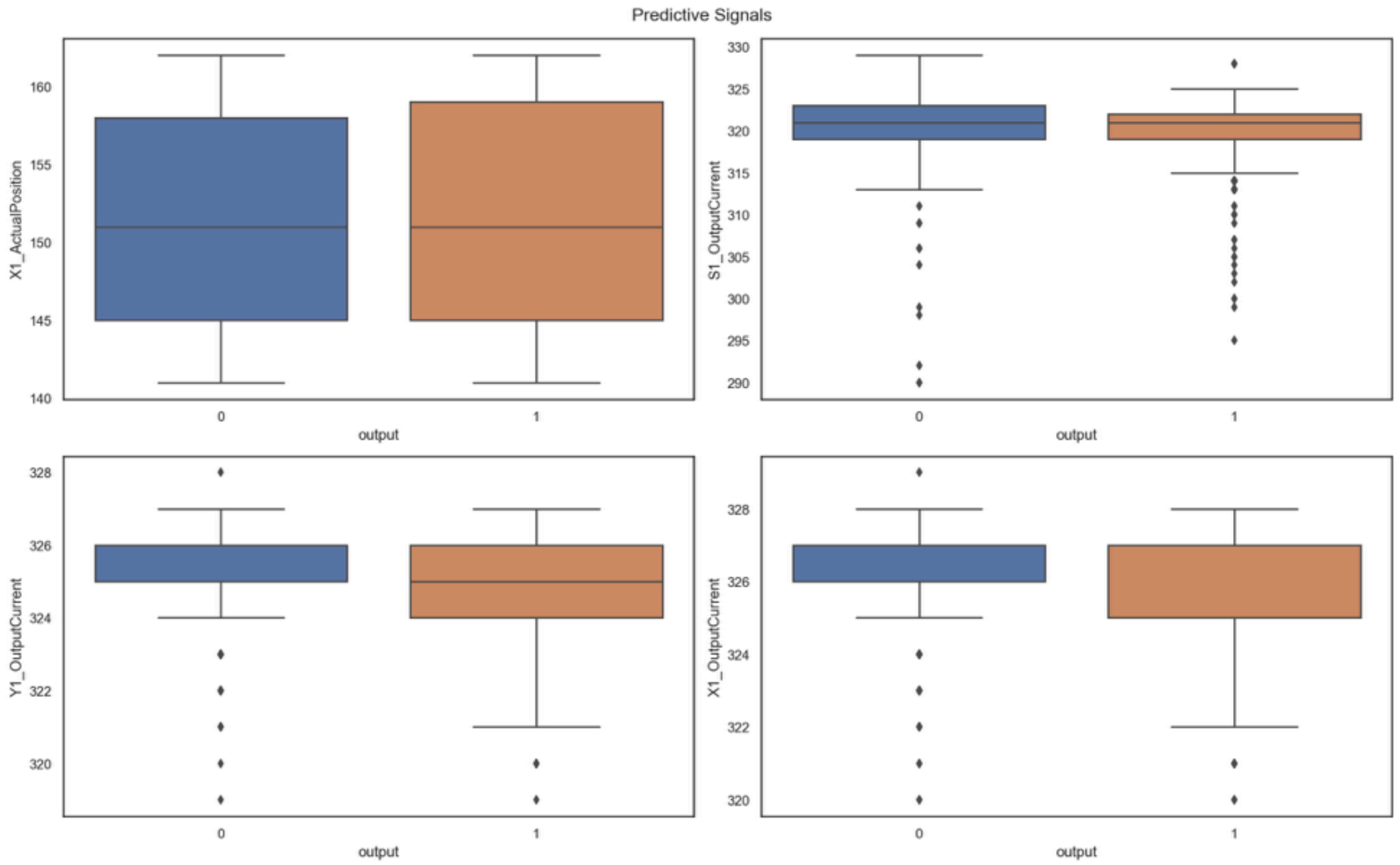
APPENDIX - EDA



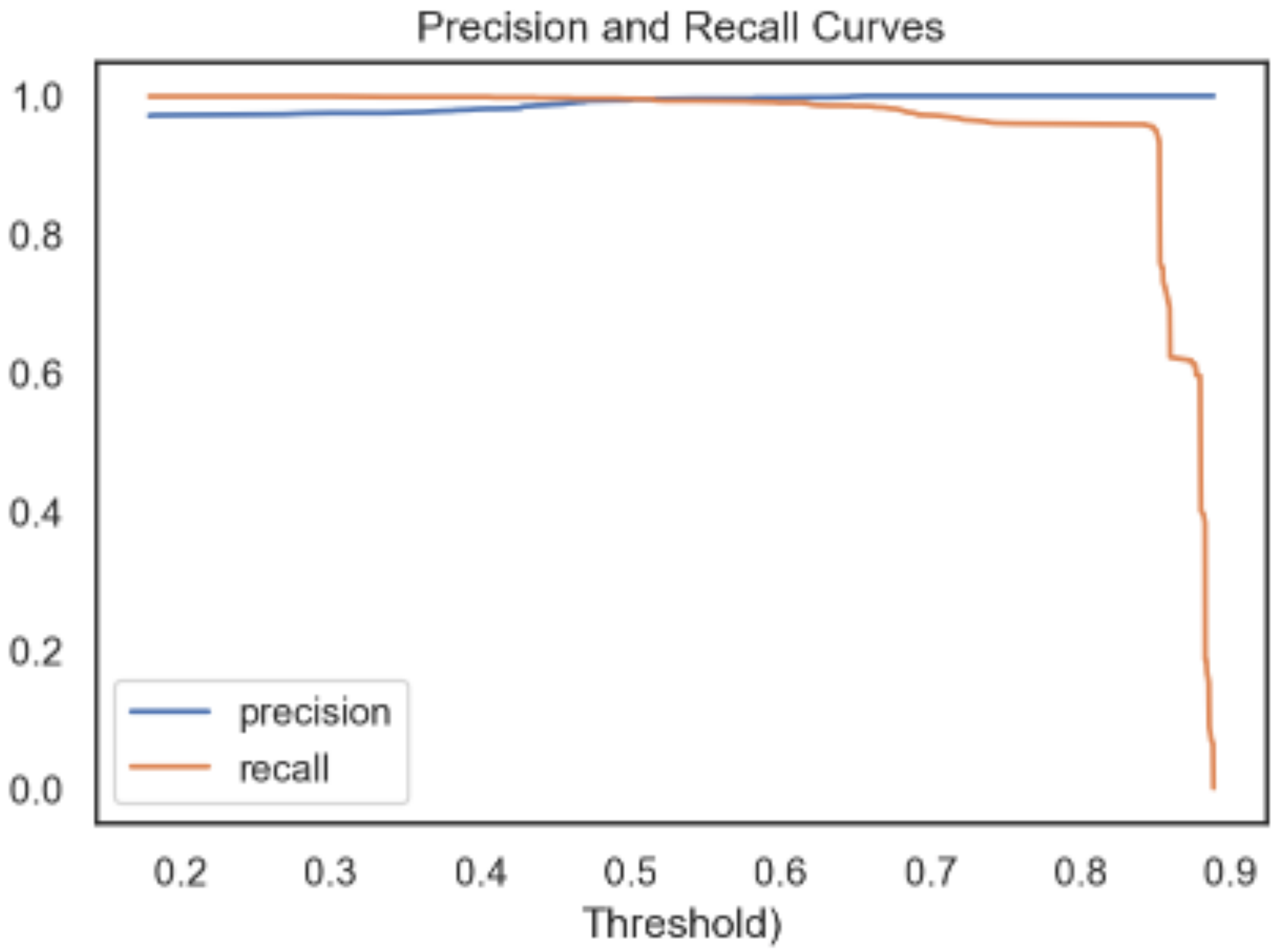
APPENDIX - FEEDRATE DISTRIBUTION



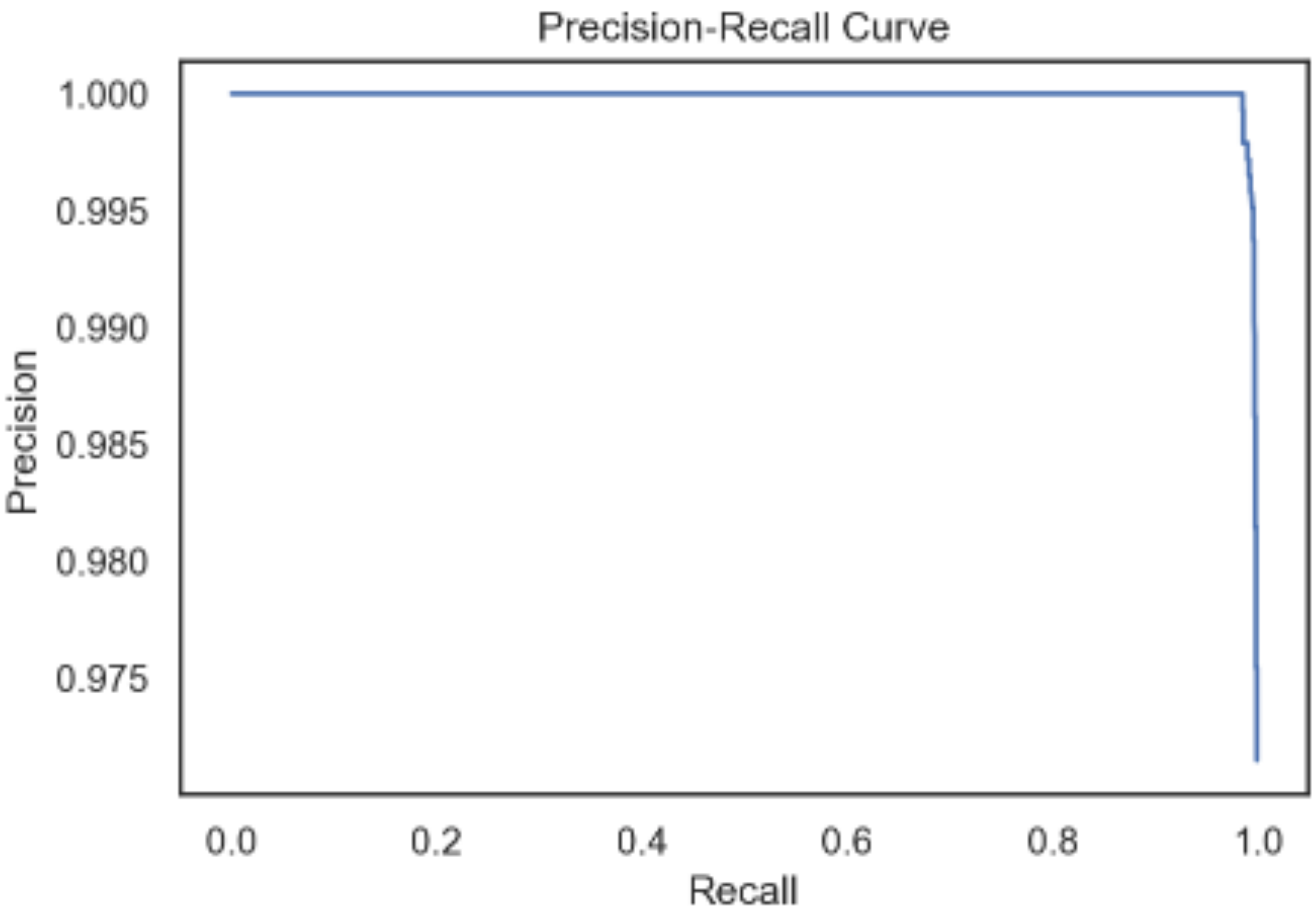
APPENDIX - PREDICTIVE SIGNALS



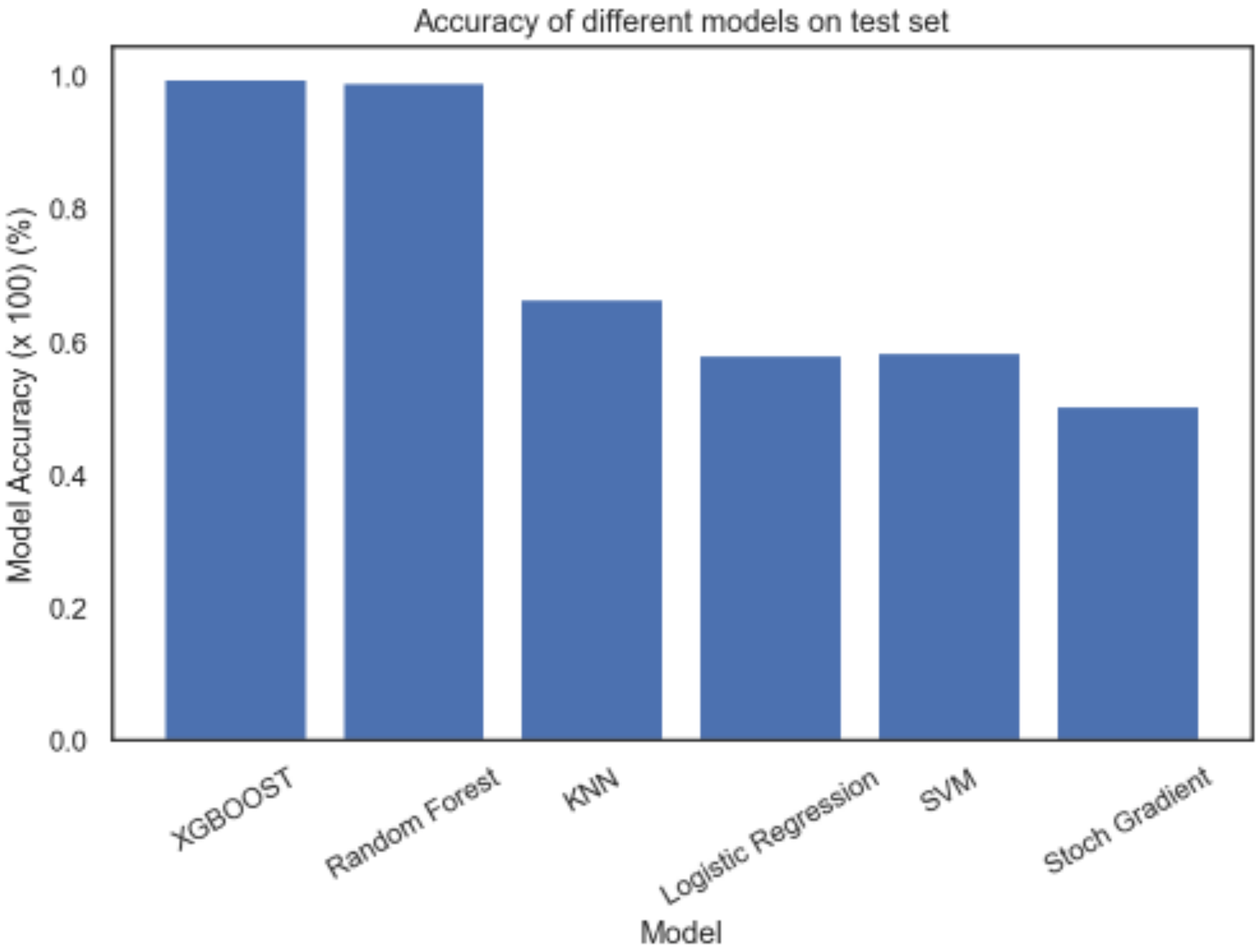
APPENDIX - XGBOOST



APPENDIX - XGBOOST



APPENDIX - ACCURACY COMPARISON



APPENDIX - AUC COMPARISON