

Machine Learning Evaluation Report

This document details the performance of six candidate models for semiconductor fault detection. Key focus areas include Recall (Safety), Precision, False Alarm Rate, G-Mean etc. and Feature Attribution (Explainability).

Summary:

Evaluation Objective:

In semiconductor manufacturing, a missed fault (False Negative) is costly, but excessive false alarms (False Positives) halt production. This analysis evaluates six machine learning models to find the optimal balance between Recall (Safety) and Precision (Efficiency).

Key Findings:

- The "Complexity Trap": Contrary to popular trends, complex ensemble models (XGBoost, Random Forest) underperformed due to signal dilution in high-dimensional noise.
- The "Golden Signal" Discovery: A single sensor was identified as a deterministic predictor of failure.
- The Champion Model: The Decision Tree emerged as the superior architecture, uniquely capable of isolating the non-normal "Golden Signal".

Logistic Classification



Fig 1a): Precision-Recall Curve

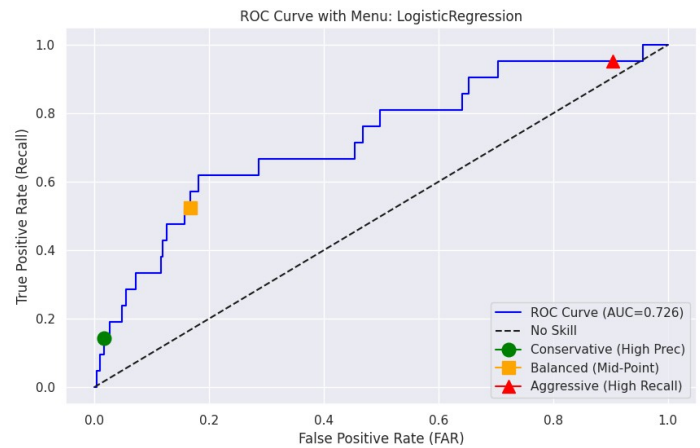


Fig 1b): ROC Curve for Logistic classification

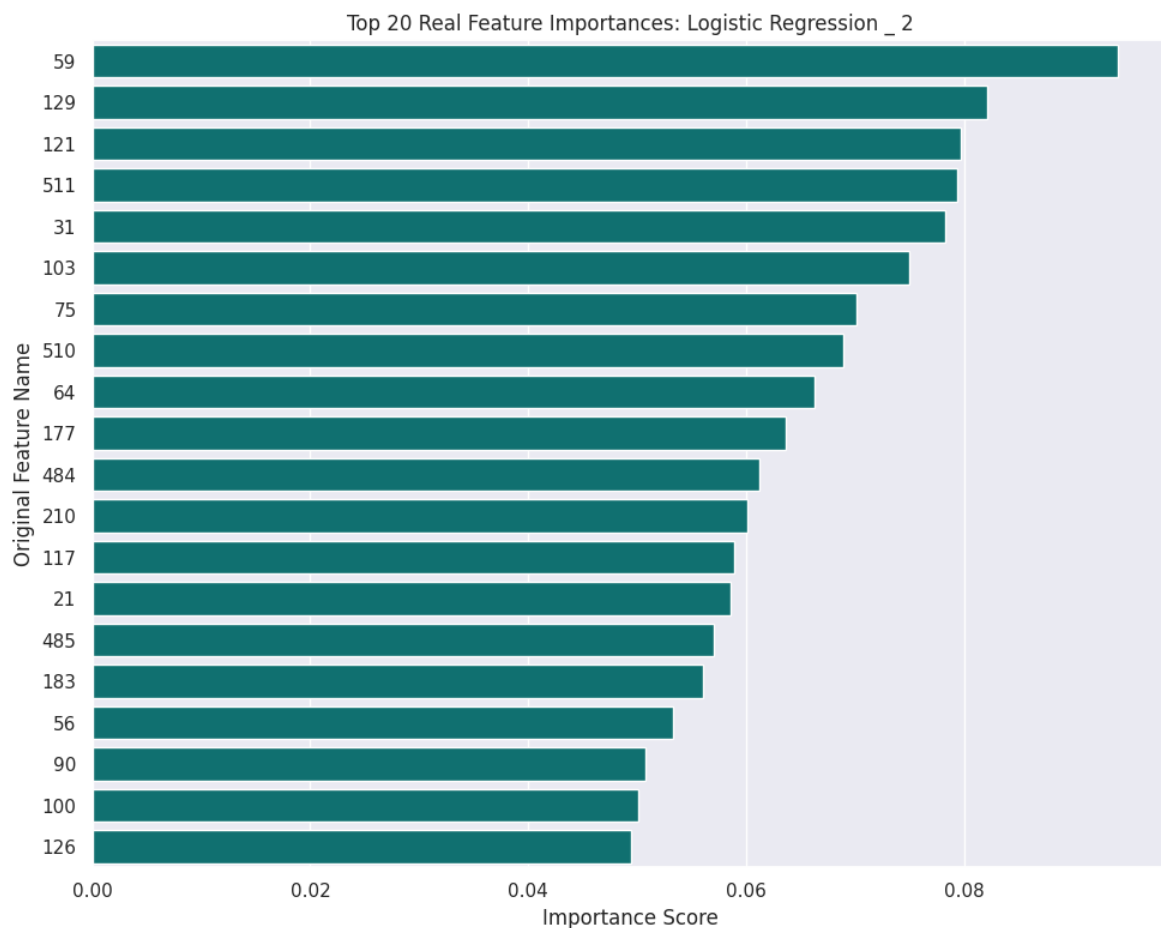


Fig 1c): Top 20 Features identified by Logistic classification model.

Logistic classification model successfully identified the trend but lacked the thresholding sharpness required for high-recall safety. It served as the first hint that the signal was linear but extreme.

Decision Tree (Champion)

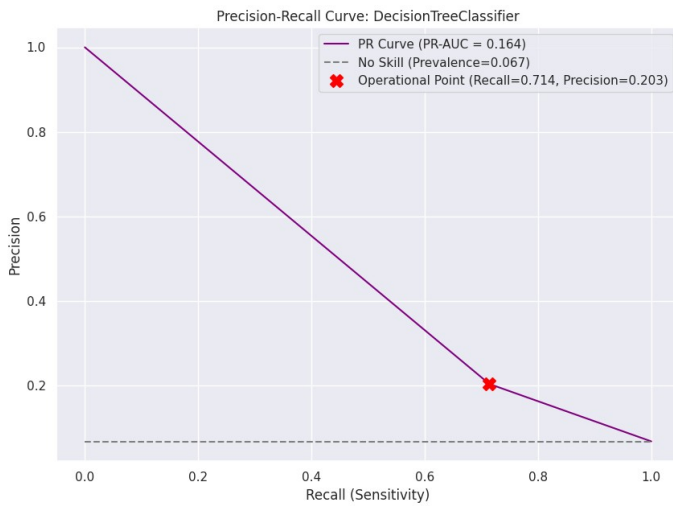


Fig 2a): Precision-Recall Curve

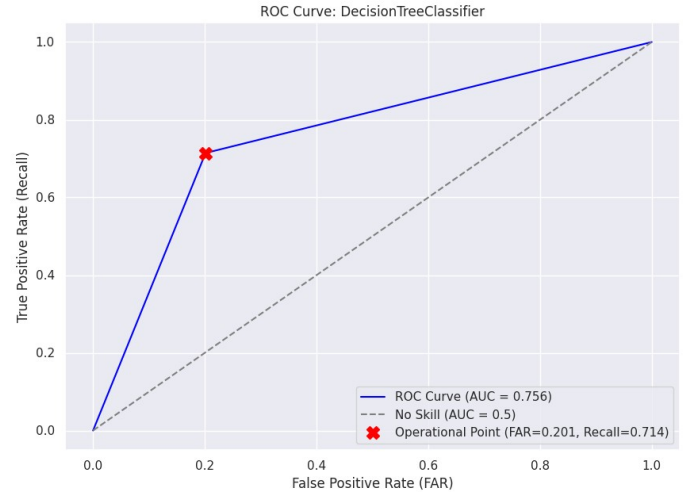


Fig 2b): ROC Curve for Decision Trees

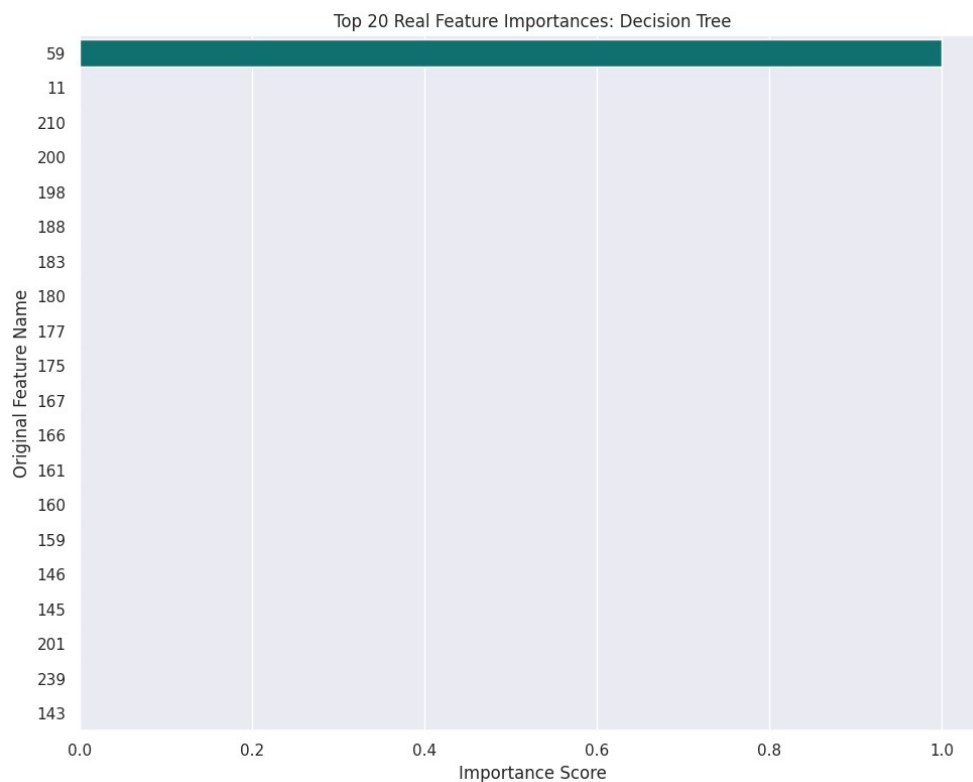


Fig 2c): Decision Tree Feature Importance. The model assigns >90% importance to a single feature (at index 59 – sensor 64), effectively ignoring 19 other available features.

- Decision Tree model identified sensor 64 (at 59 index) as the golden threshold signal that best classifies the failure wafer and the proper wafer.
- Decision Tree is the champion model as majority of the metrics for this model outperform the other models.

Random Forest

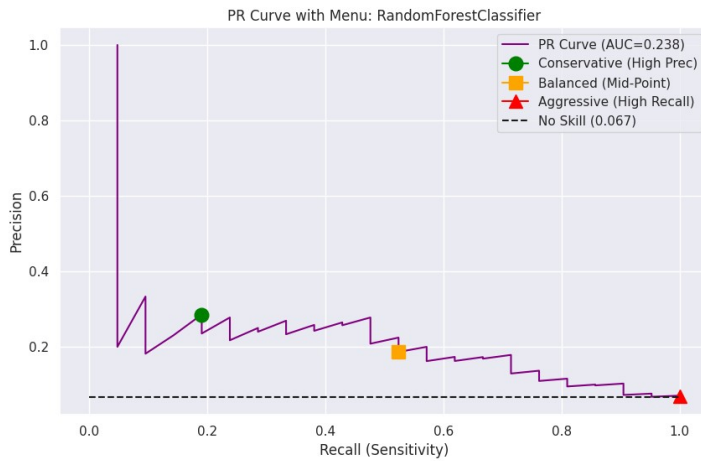


Fig 3a): Precision-Recall Curve

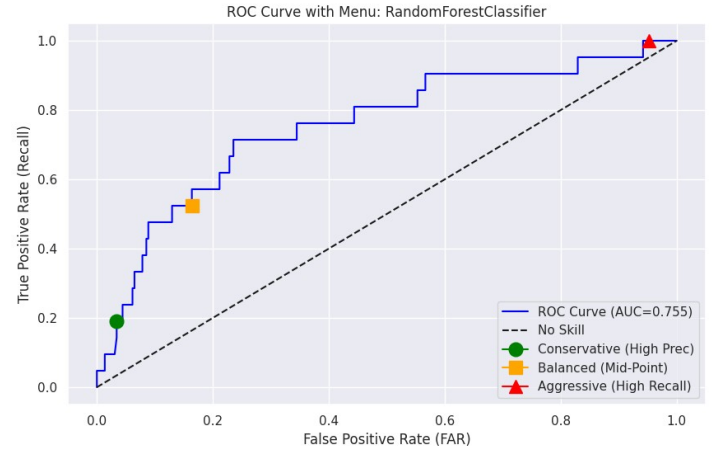


Fig 3b): ROC Curve for Random Forest

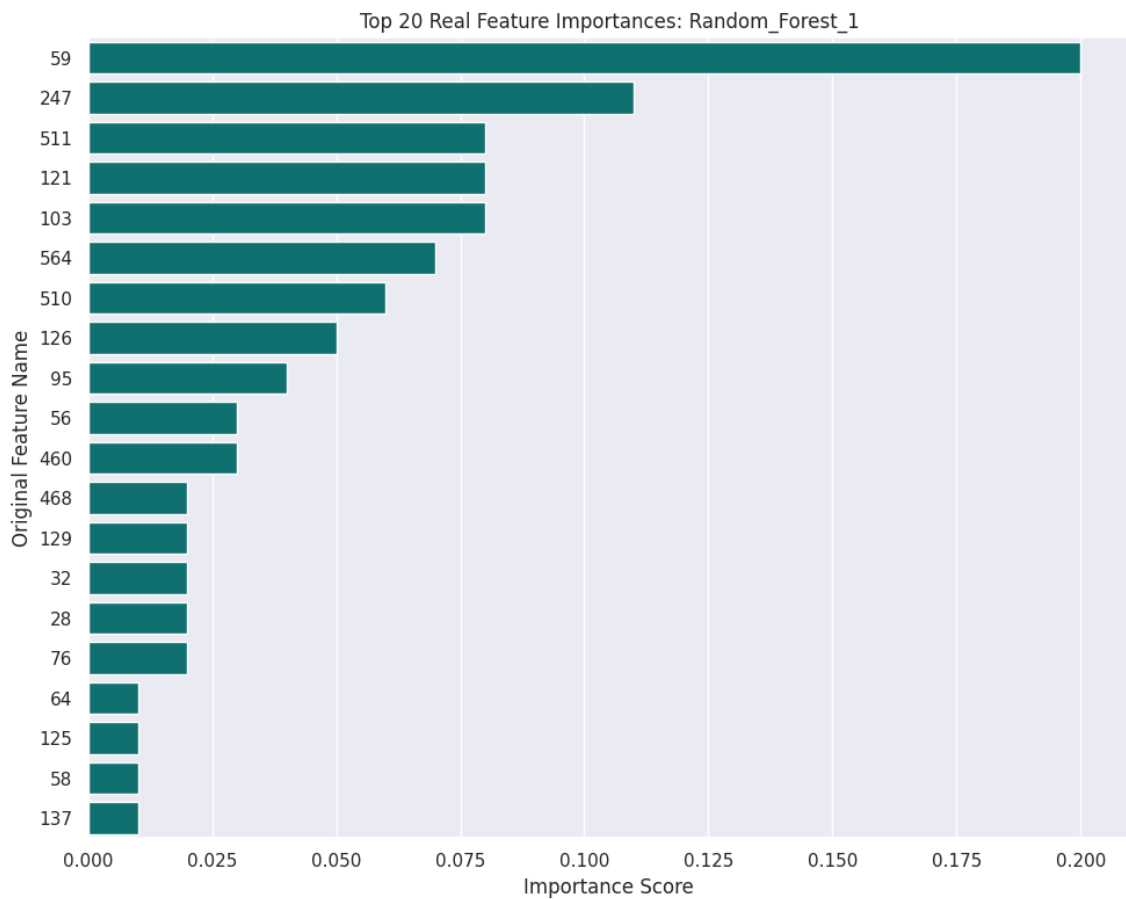


Fig 3c): Top 20 Features identified by Random Forest model.

Random Forest model is expected to be the top performer but suffered from "Feature Dilution."

XGB

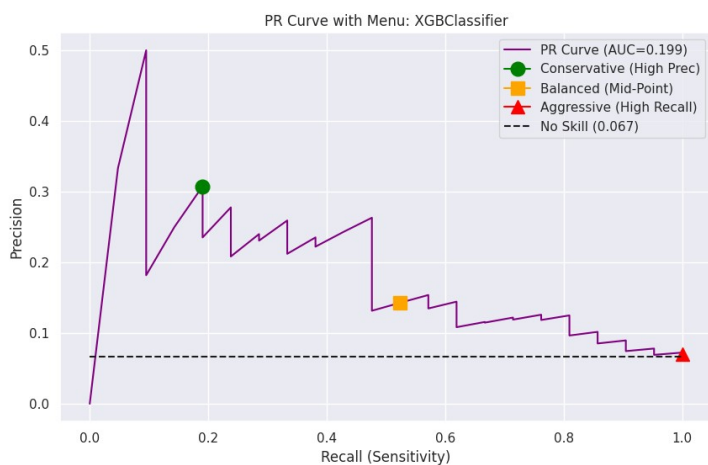


Fig 4a): Precision-Recall Curve

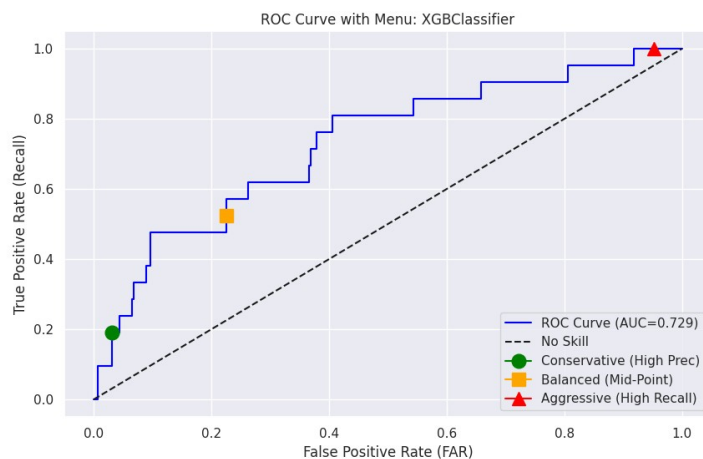


Fig 4b): ROC Curve for XGB

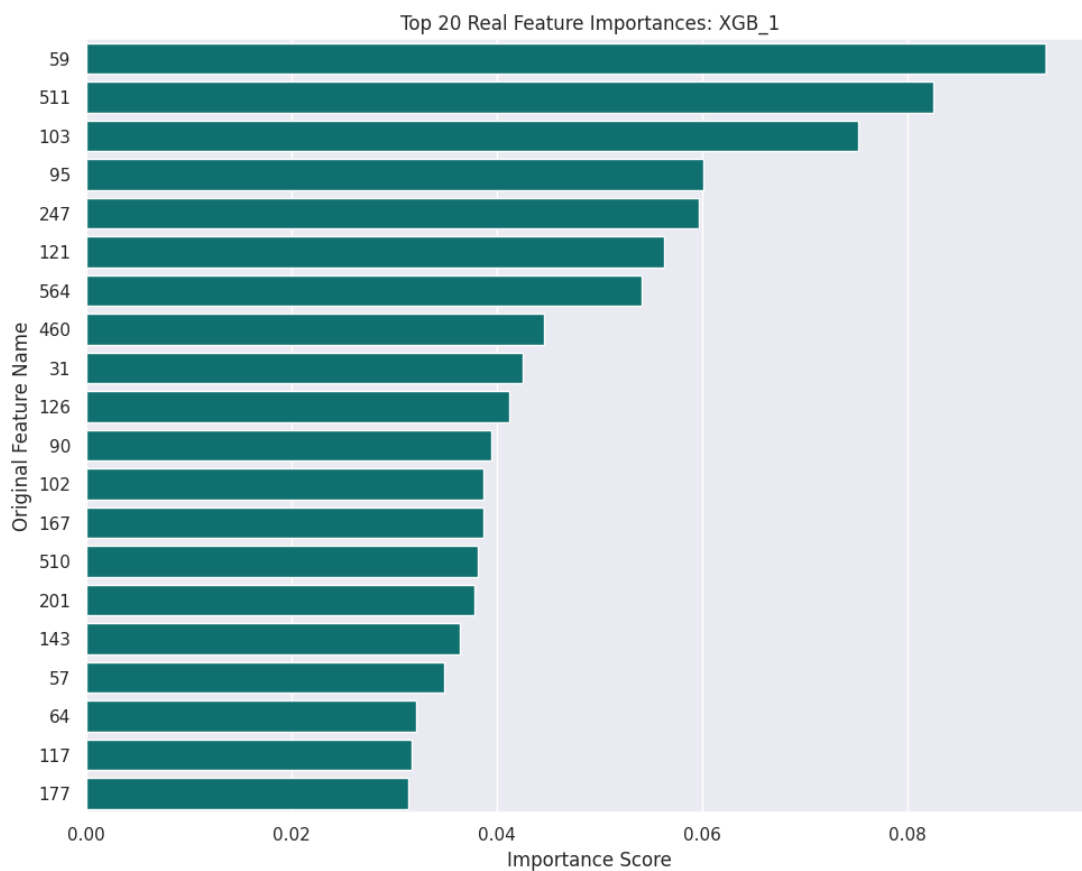


Fig 4c): Top 20 Features identified by XGB model.

XGB is a powerful gradient boosting engine that "tried too hard."

Naive Bayes

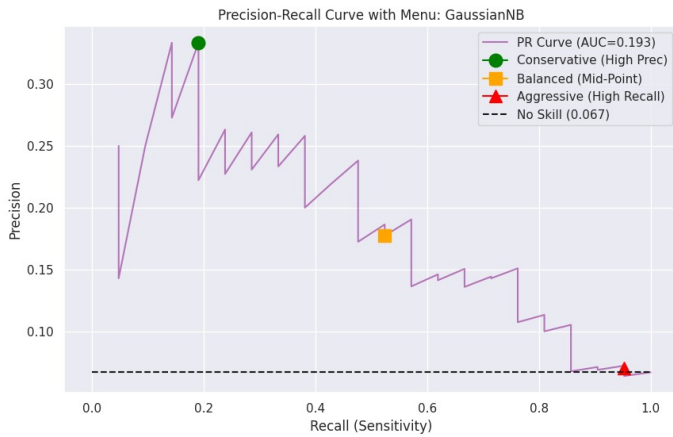


Fig 5a): Precision-Recall Curve

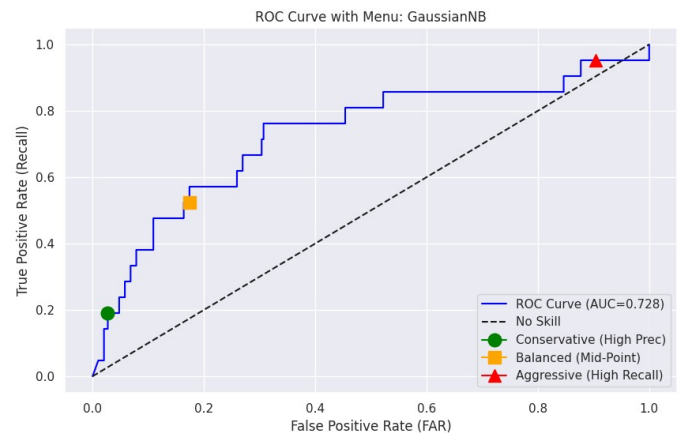


Fig 5b): ROC Curve for Naive Bayes

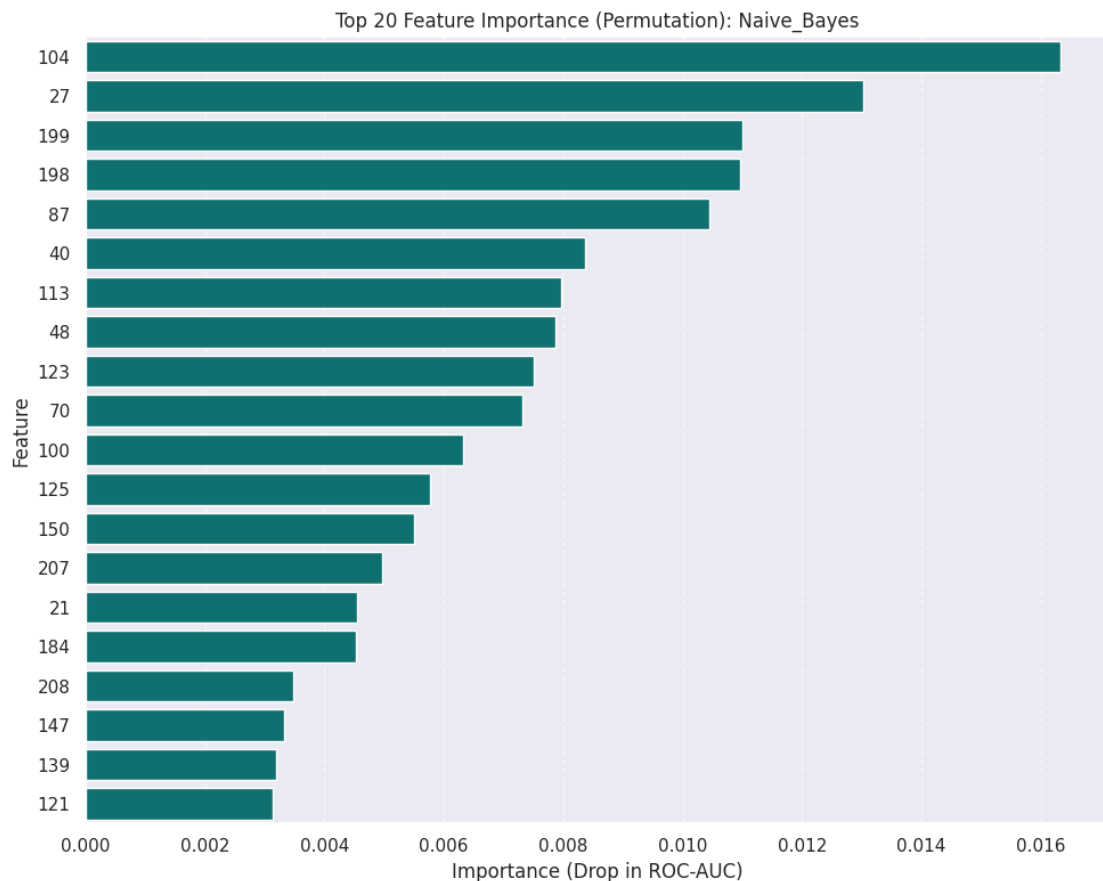


Fig 5c: Top 20 Features identified by Naive Bayes model

Naive Bayes treated the critical signal as a statistical anomaly rather than a predictor, effectively filtering it out.

KNN

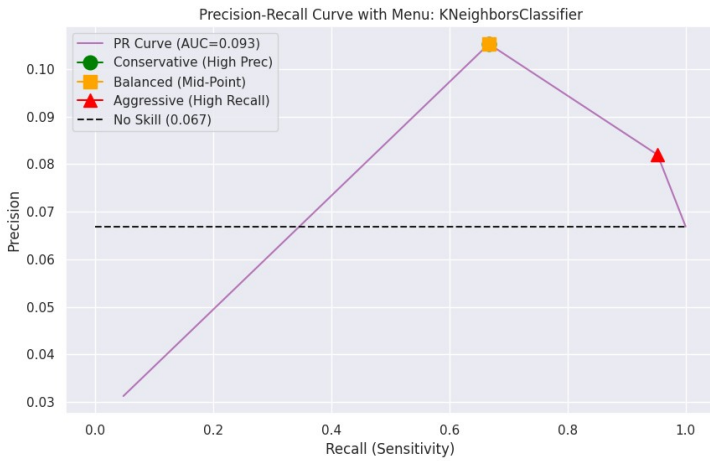


Fig 6a): Precision-Recall Curve

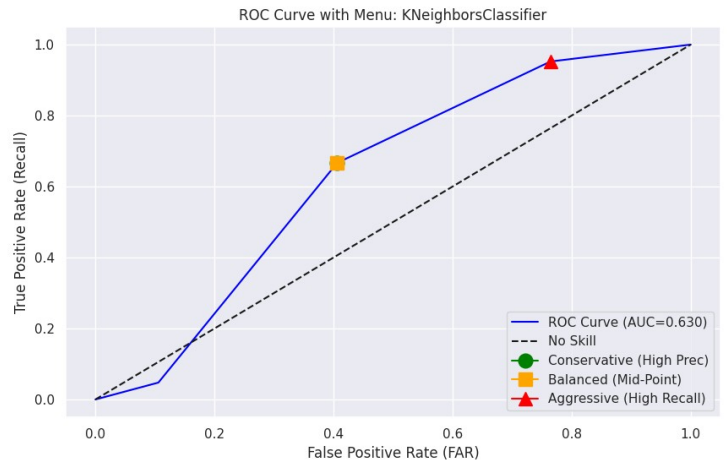


Fig 6b): ROC Curve for KNN

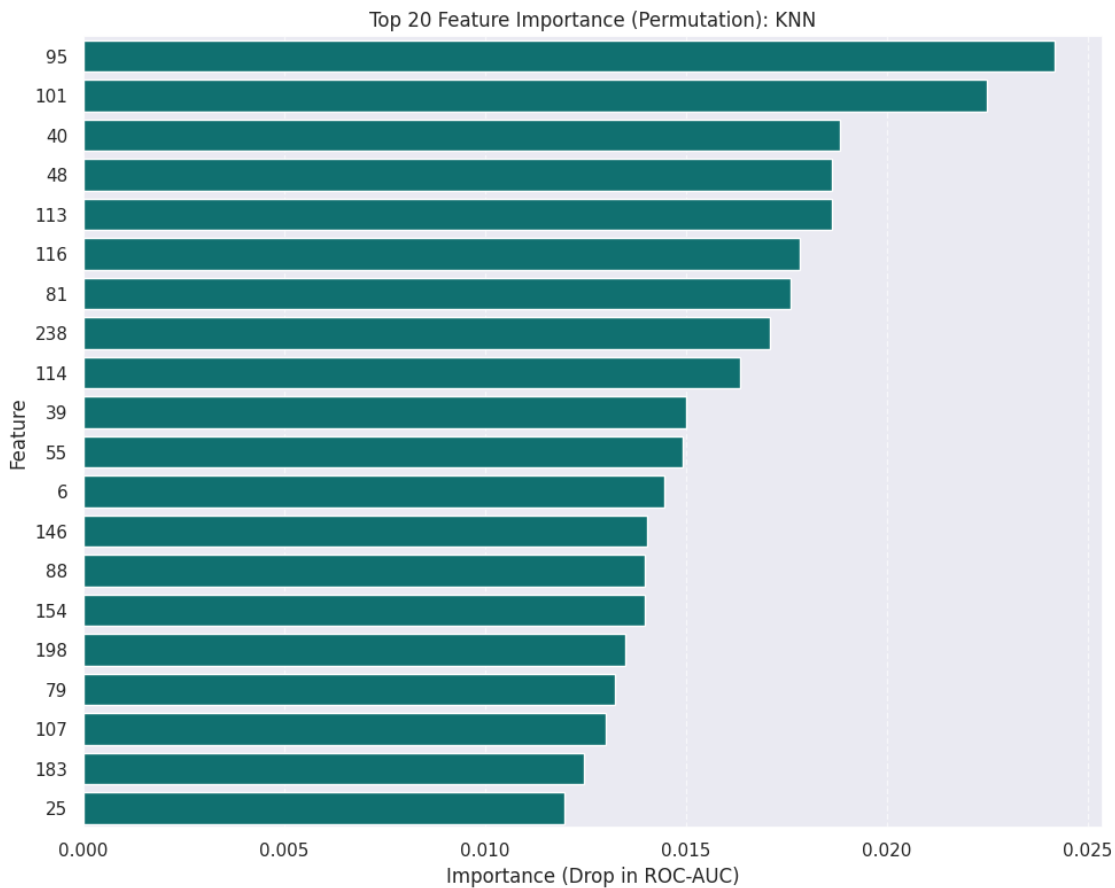


Fig 6c): Top 20 Features identified by KNN model

KNN a distance-based algorithm, failed to detect the fault because the "distance" created by the single important sensor was overwhelmed by the accumulated small distances of noisy sensors.

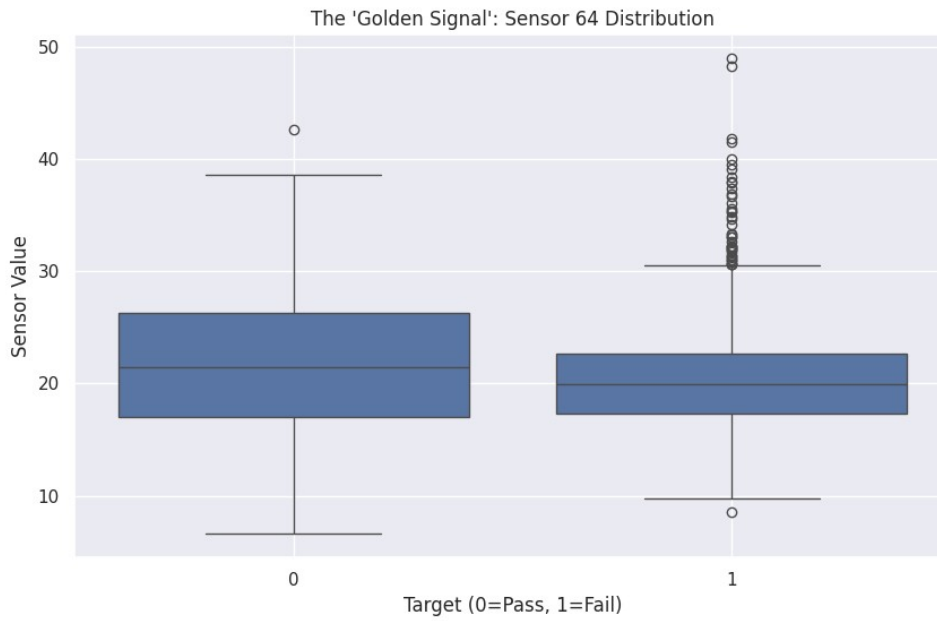


Fig 7: Golden sensor – feature at 59, box plot for class – 0 – Majority class and class – 1 - Minority class

Table 1. Various metrics for different models

Model Type	Thres hold Type	Thres hold	F2-Score	Recall	Preci sion	G-Mean	Specif icity	Accur acy	ROC -AUC	False Alarm Rate	PR-AUC
KNN	DT	0.50	0.32	0.67	0.11	0.63	0.59	0.60	0.63	0.41	0.09
NB	T T	0.00	0.41	0.76	0.15	0.72	0.68	0.68	0.73	0.32	0.19
LR	DT	0.50	0.43	0.62	0.19	0.71	0.81	0.80	0.73	0.19	0.21
LR	T T	0.36	0.34	0.81	0.10	0.62	0.48	0.50	0.73	0.52	0.21
DT_1	DT	0.50	0.47	0.71	0.20	0.76	0.80	0.79	0.76	0.20	0.16
DT_2	T T	0.61	0.45	0.62	0.21	0.72	0.84	0.82	0.73	0.16	0.16
RF	DT	0.50	0.42	0.67	0.17	0.72	0.77	0.76	0.75	0.23	0.24
XGB	T T	0.35	0.35	0.71	0.12	0.66	0.61	0.61	0.73	0.39	0.19

DT: Default Threshsold

TT: Tuned Threshold