Detecting Fraudulent Transactions in Online Payments using Supervised Learning

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Data Mining and Machine Learning Project

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DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

Problem Description

Problem Overview

Online transactions are increasingly exposed to fraudulent activities, posing risks to both consumers and businesses.
Credit card fraud detection is critical in preventing unauthorized access and minimizing financial losses.

Relevance of DMML Techniques

The challenge is inherently a **binary classification** task (*fraudulent* vs. *legitimate* transactions). This calls for robust **supervised** machine learning methods, advanced feature engineering, and imbalance handling strategies.

Proposed Approach

- Compare multiple classification algorithms to identify the most effective model for fraud detection.
- Candidate models:
  - *KNN*
  - *Gaussian NaiveBayes*
  - *DecisionTree*
  - *RandomForest*
  - *AdaBoost*
  - *XGBoost*
- A set of evaluation metrics will be used to compare the classifiers and determine the **best-performing** model.

Dataset Description

Dataset Source

- Publicly available on Kaggle: IEEE-CIS Fraud Detection
- Originally provided by Vesta Corporation, a real-world e-commerce platform

Collection Details

The dataset contains historical online transaction data enriched by behavioral signals and device information.

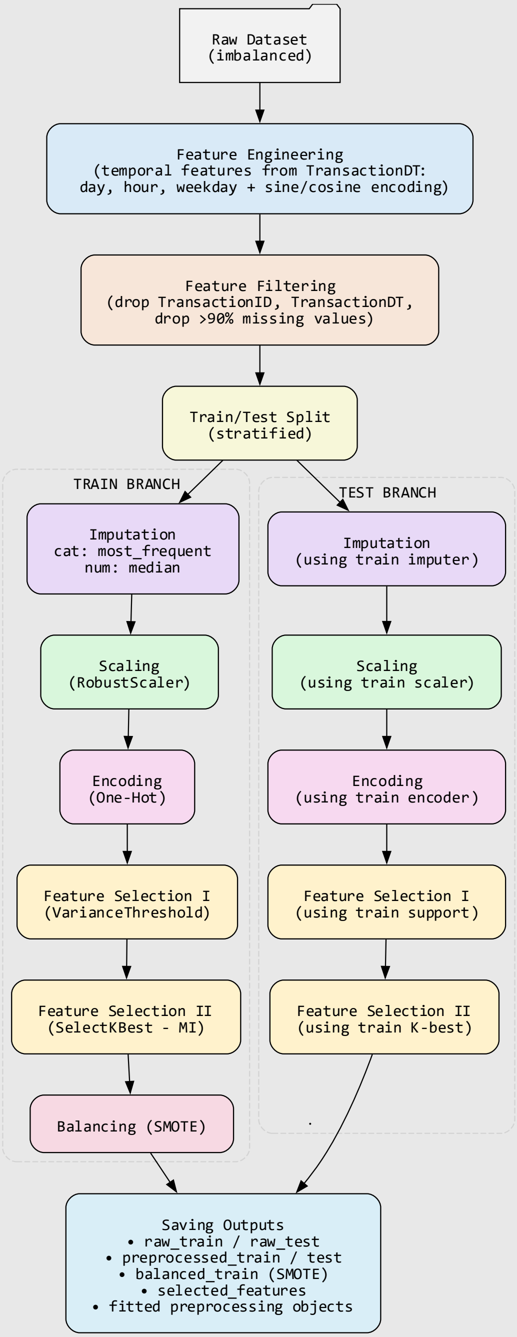
Dataset Properties:

- **Size**: 590,540 transactions (1.08 GB)
- **Fraudulent samples**: 20,663 (approx. 3.5%)
- **Columns**: 432 total columns including transaction details, card info, identity data, and 339 engineered Vesta features
- **Label**: `isFraud` (1 = fraudulent, 0 = normal)
- **Input/Output Format**:
    - Input: Multivariate features including TransactionAmt, card1–card6, addr1, D1, C1, M1, V1–V339, etc.
    - Output: Binary class label `isFraud` $\in \{0, 1\}$

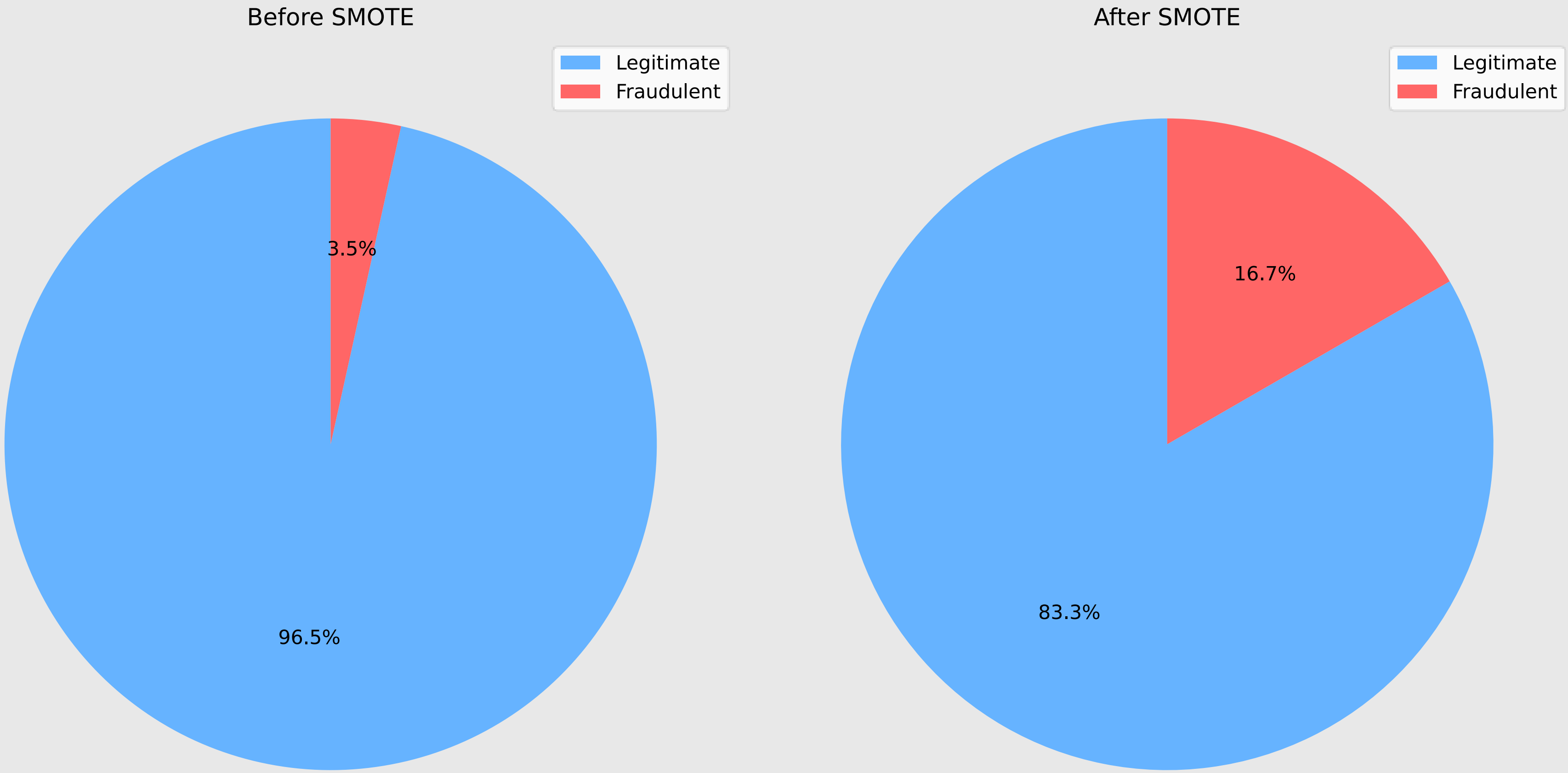
Preprocessing

Raw dataset cleaning

- **Feature engineering**: temporal features from `TransactionDT` → day, hour, weekday + cyclic encoding (sine/cosine).
- **Feature filtering**: removing *useless* or *non-informational* features.
- **Train/test split**: *stratified* sampling to preserve label distribution.
- **Imputation**: missing values replaced with *median* or *mode*.
- **Scaling**: `RobustScaler` to reduce outlier impact.
- **Encoding**: `OneHotEncoding` on categorical features.
- **Feature selection**:
  - ✓ Variance Threshold → remove low-variability features;
  - ✓ `SelectKBest` with Mutual Information → retain most informative features.
- Class imbalance handling: **SMOTE** applied only to training set only (*sampling strategy* set to 0.2 → fraud rate from 3.5% to 16.7%).



Preprocessing



Comparison of the class distribution in the training set before (left) and after (right) the application of **SMOTE**.

Training and Testing

Classifiers evaluated

- KNN (*K-Nearest Neighbors*)
- NB (*Gaussian NaiveBayes*)
- DT (*DecisionTree*)
- RF (*RandomForest*)
- ADA (*AdaBoost*)
- XGB (*XGBoost*)

Hyperparameter tuning

- **Grid Search** (`GridSearchCV`) with 5-fold CV
- Scoring metric: *f1-score* → balances *precision* & *recall* on imbalanced data
- Goal: find best hyperparameters for each classifier

Training & Testing

- Train on *SMOTE*-rebalanced train set
- 10-fold CV during training → robust validation metrics
- Test on imbalanced test set → evaluate predictions

Evaluation Metrics

Metrics used

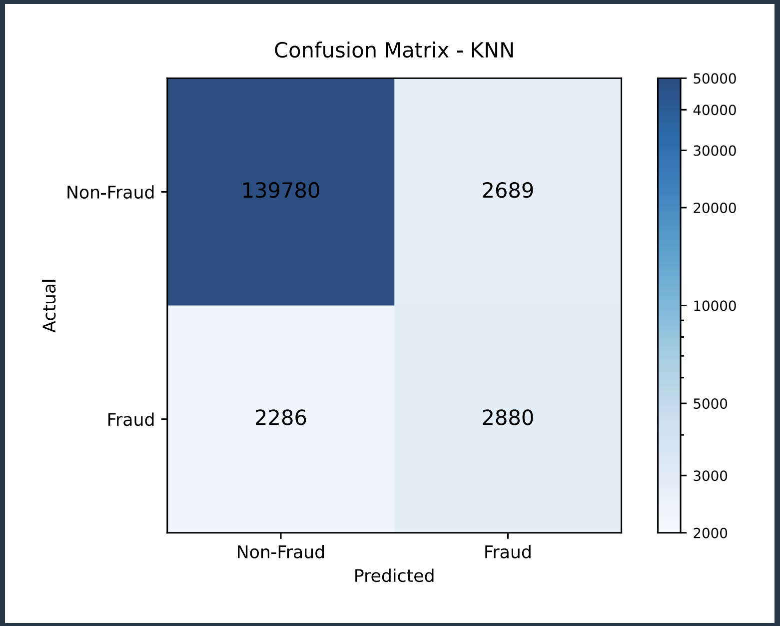
- *Confusion Matrix* → base for other metrics (TN, FP, FN, TP)
- *Precision & Recall* → focus
- *f1-score* → balances precision & recall (used in Grid Search)
- *Accuracy & Balanced Accuracy* → quick overview (the 2nd one robust to imbalanced datasets)
- Weighted versions → balancing the metrics between the 2 classes
- *ROC AUC & PR AUC* → compare overall classifier performance

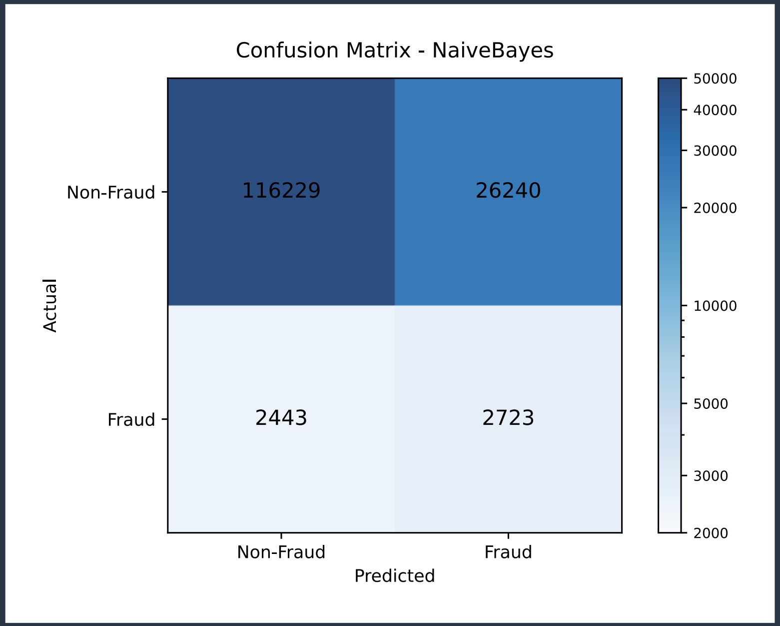
Acceptable Level of Performance (ALP)

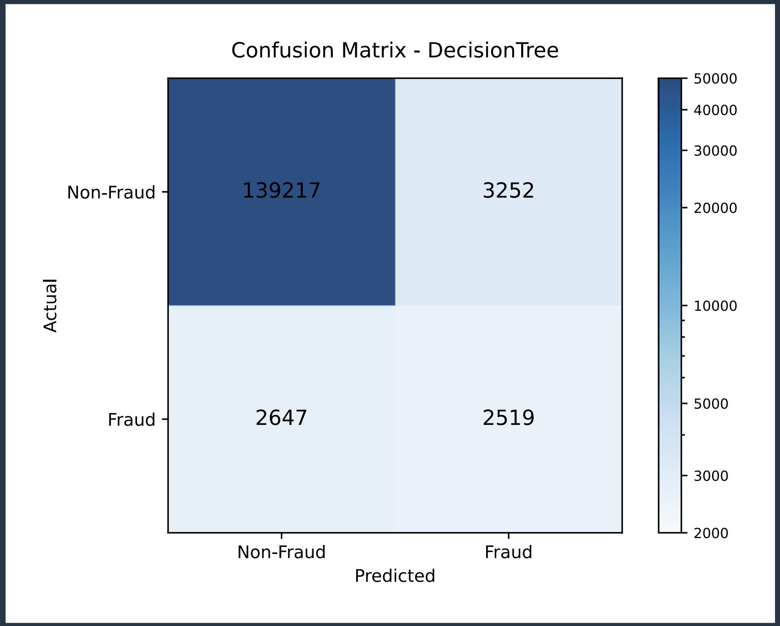
- Defined as TPR ≥ 0.8 → correctly identify ≥80% of frauds
- **ALP_threshold** → decision threshold where ALP is reached
- **ALP_FPR** → FPR when ALP is reached
- Analysis via ROC curves → identify best trade-off between TPR and FPR

Individual results

Confusion matrices

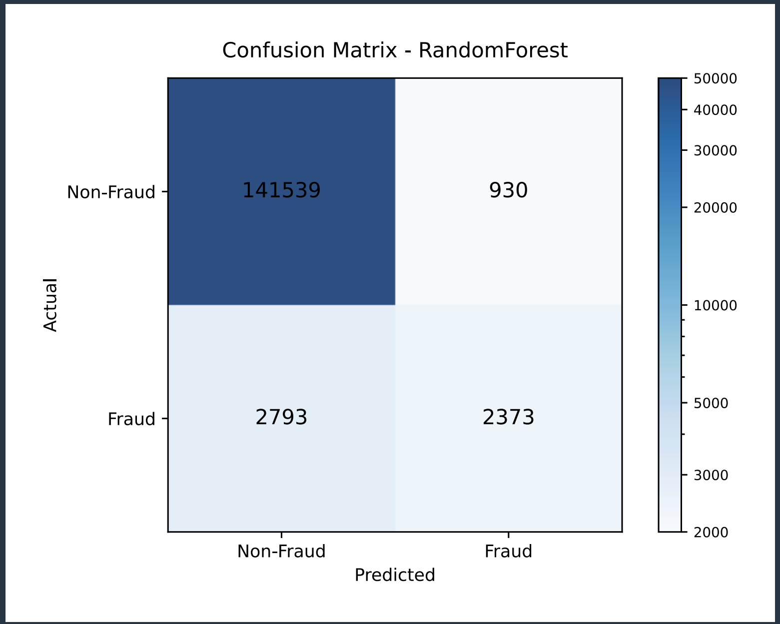


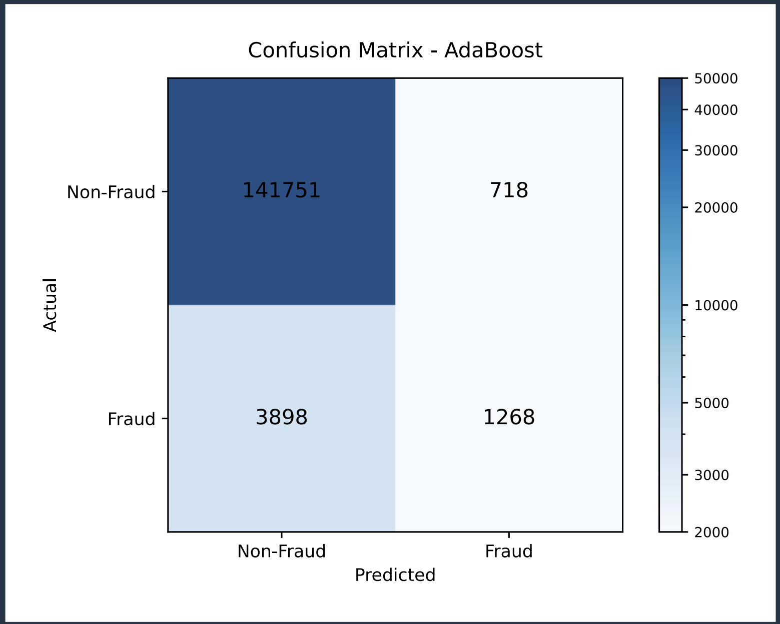


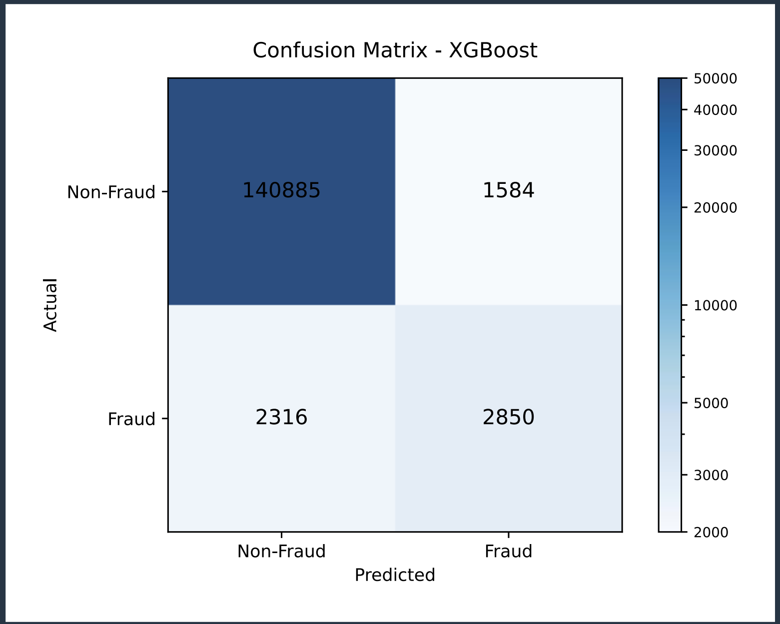


Individual results

Confusion matrices

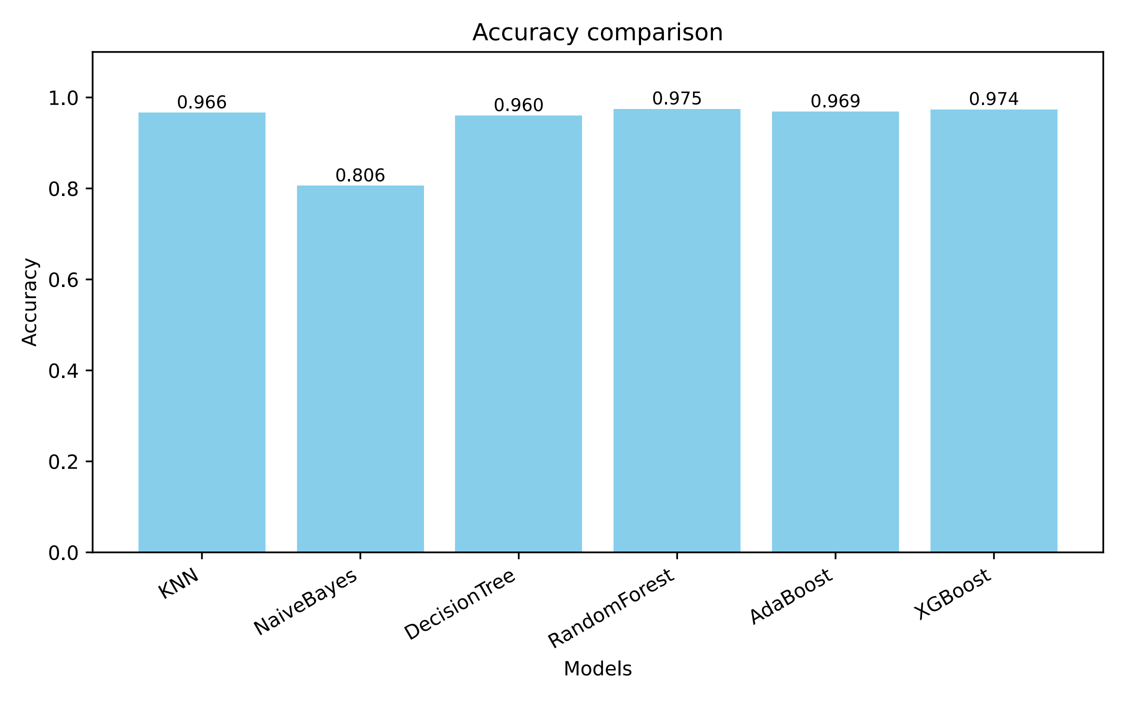


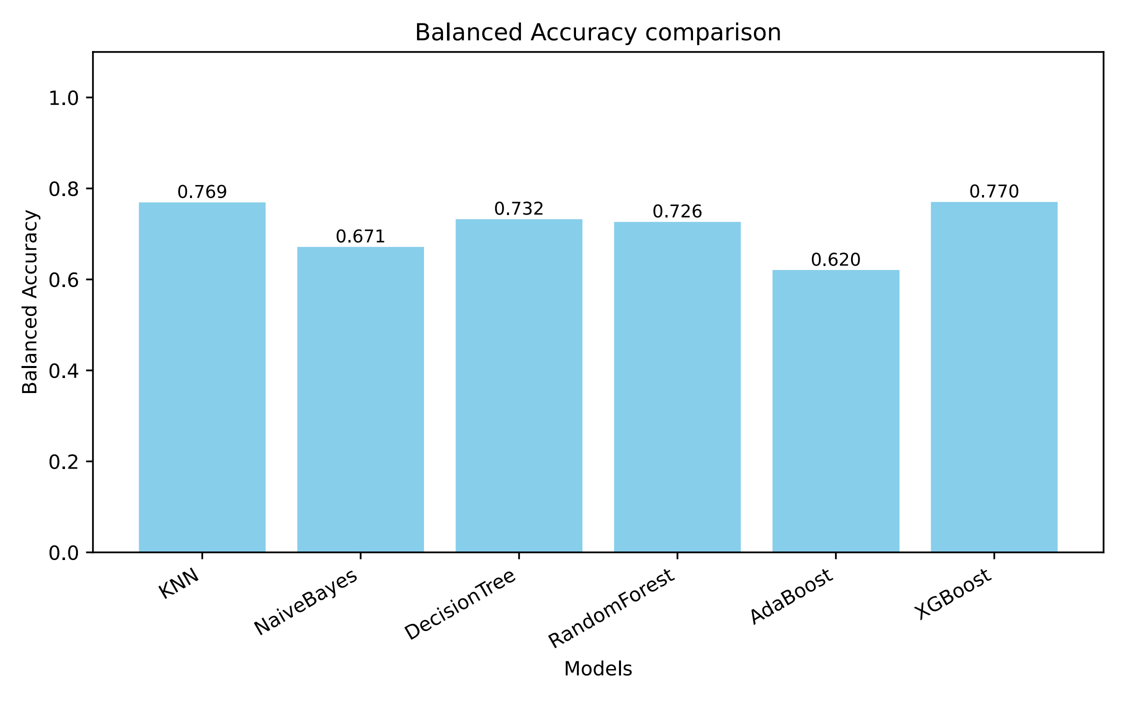




Model comparison

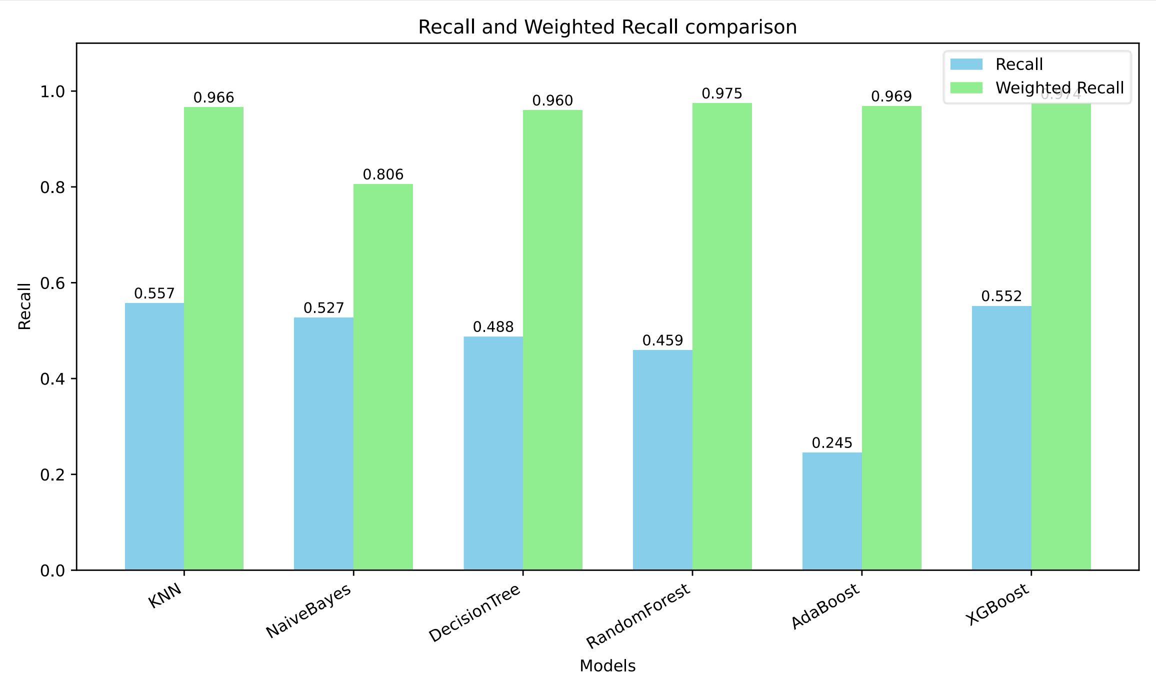
Accuracy & Balanced accuracy

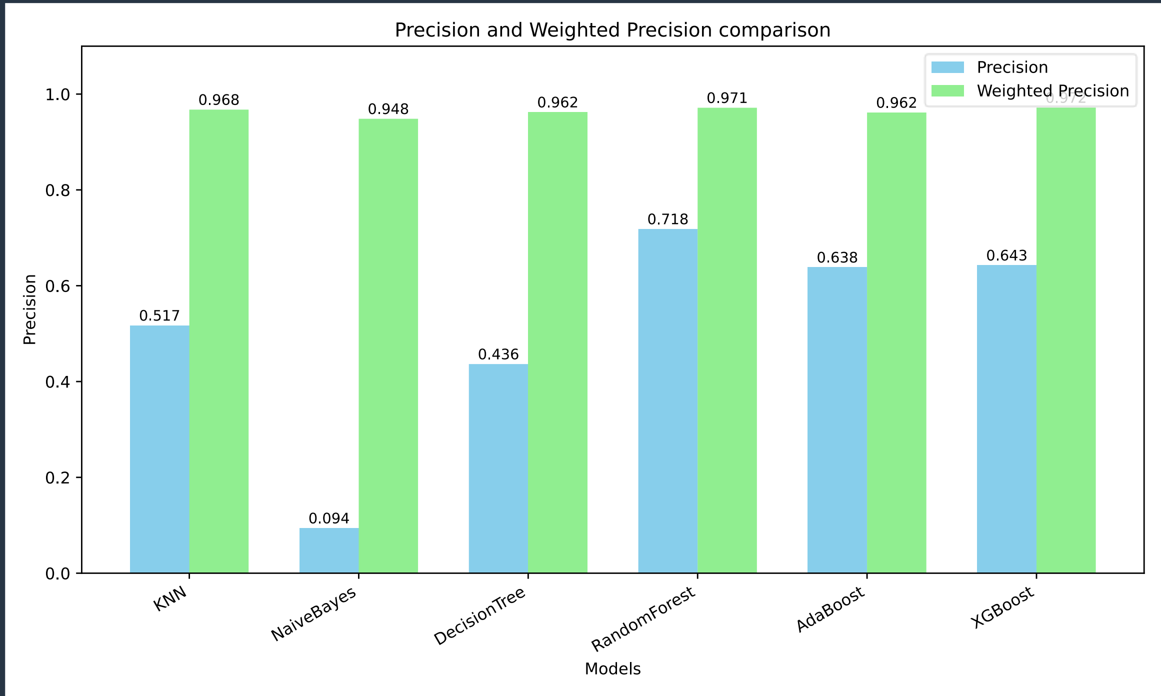




Model comparison

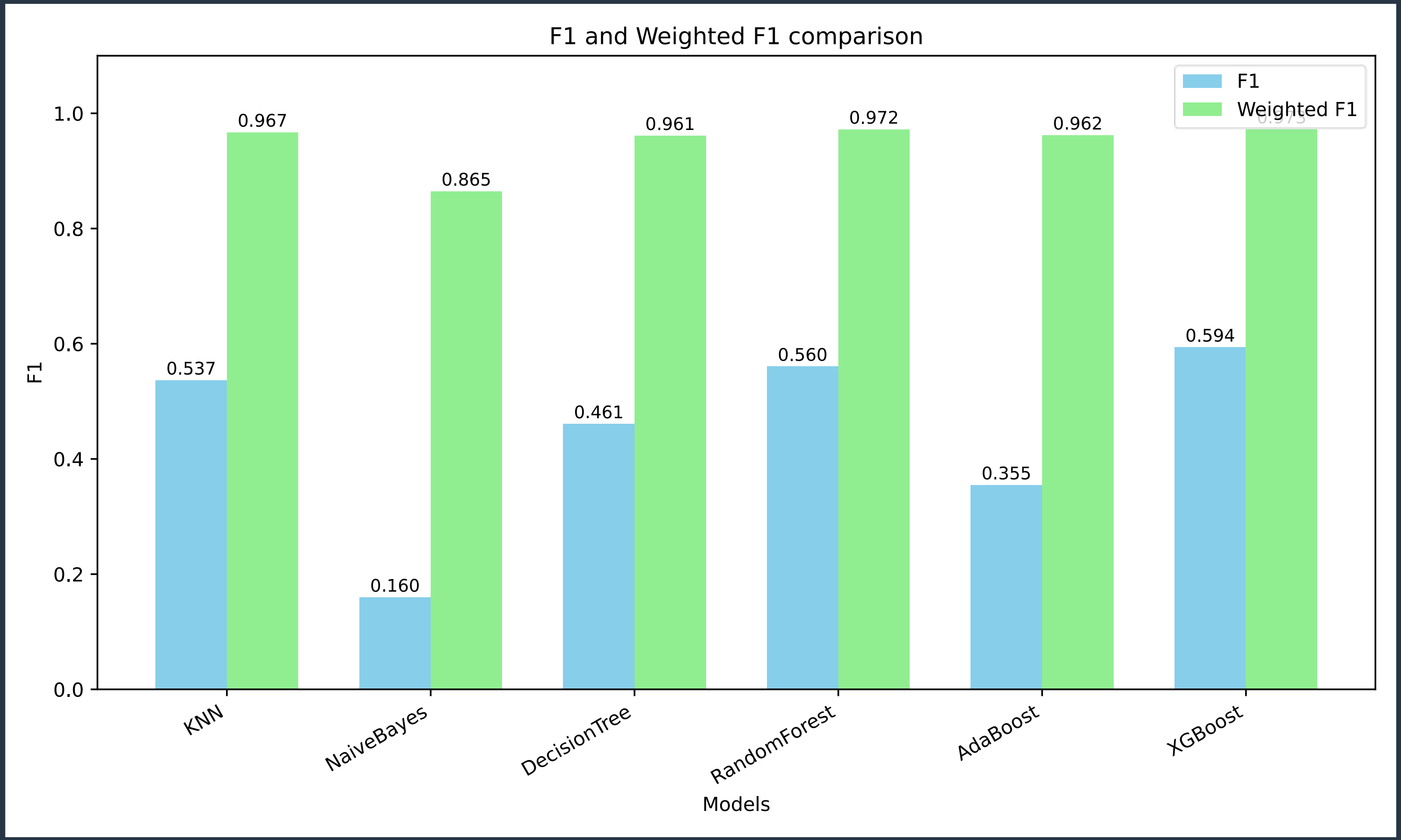
Recall & Precision





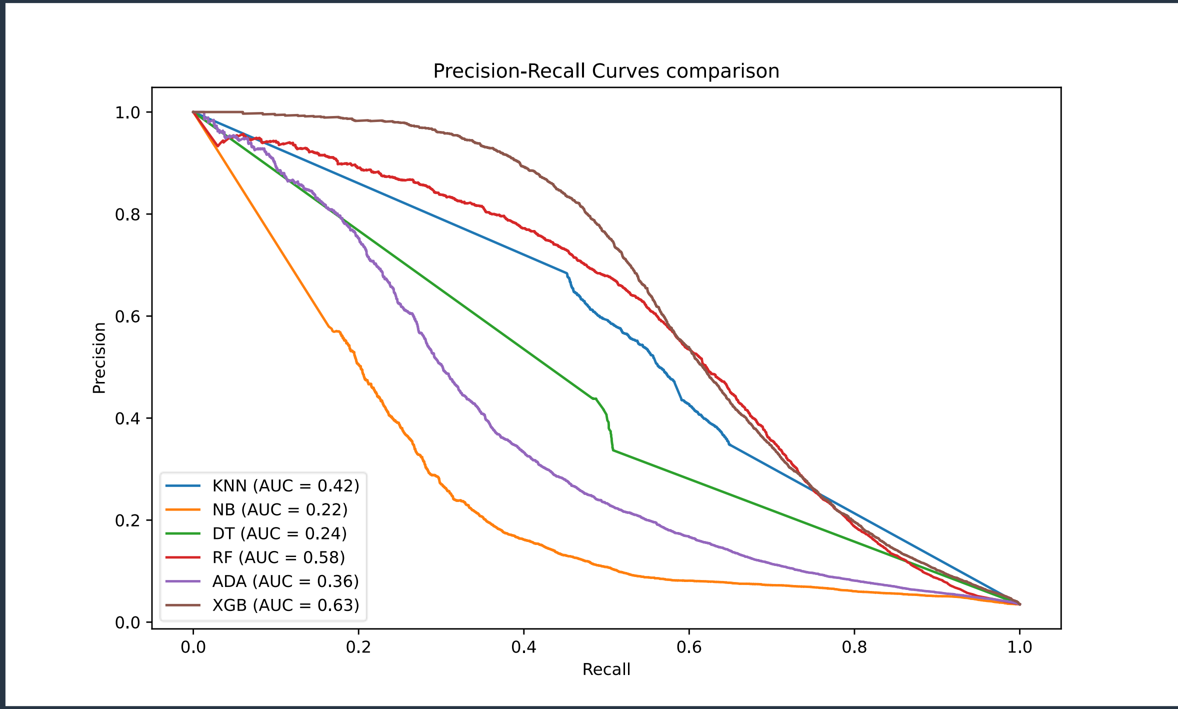
Model comparison

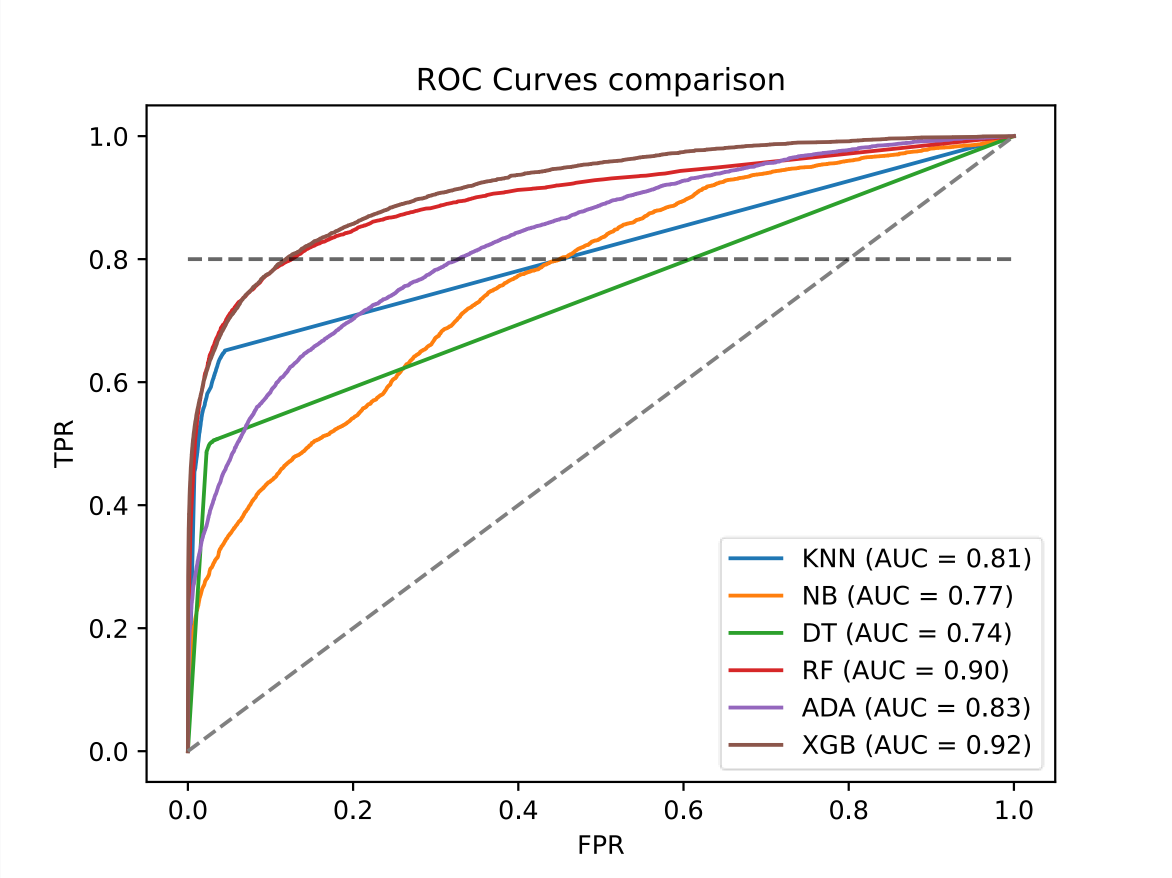
F1-score



Model comparison

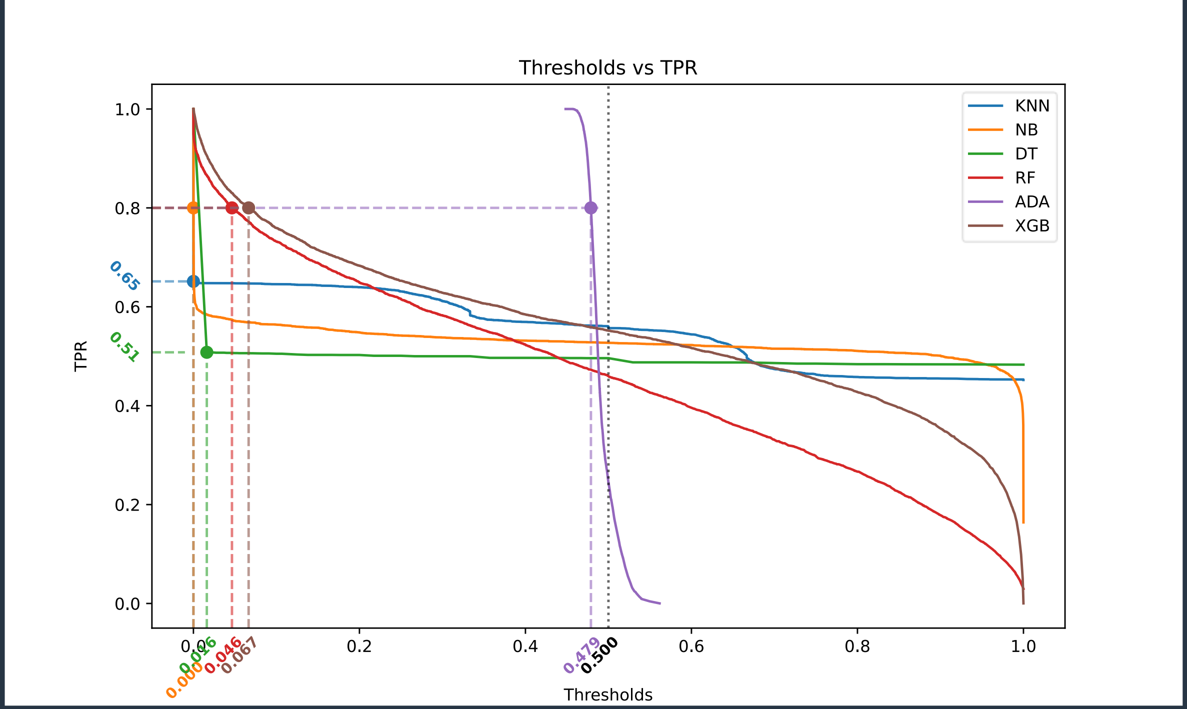
Precision-Recall & ROC

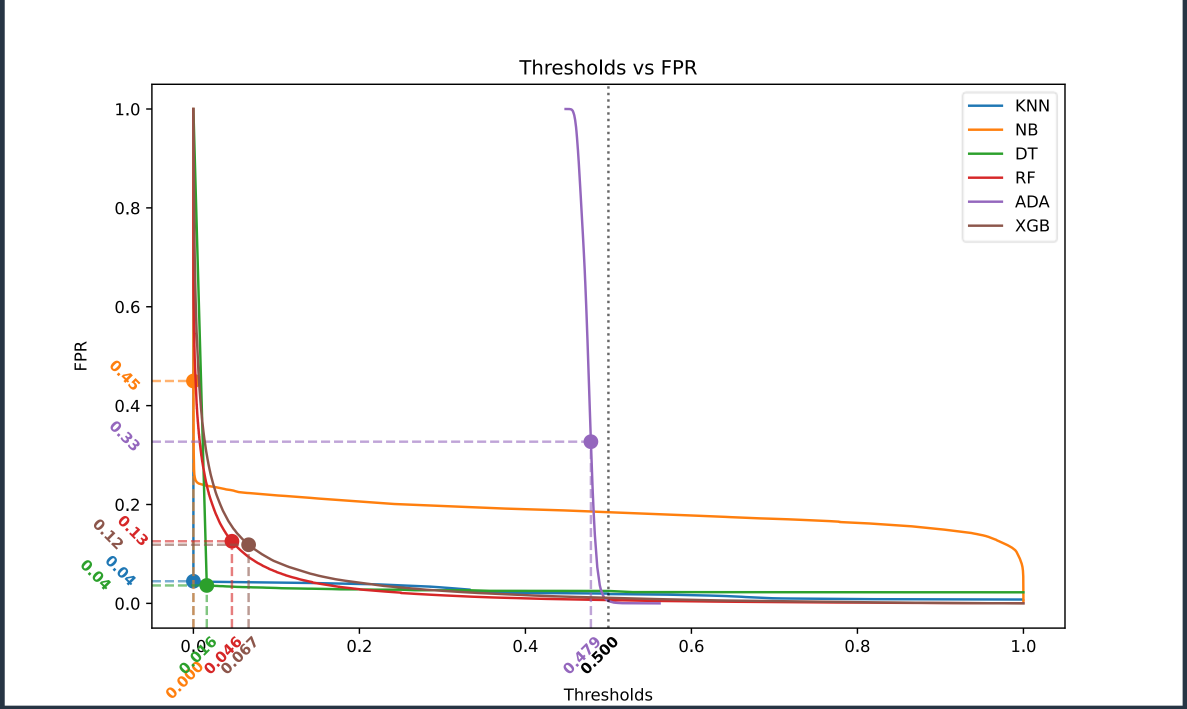




Model comparison

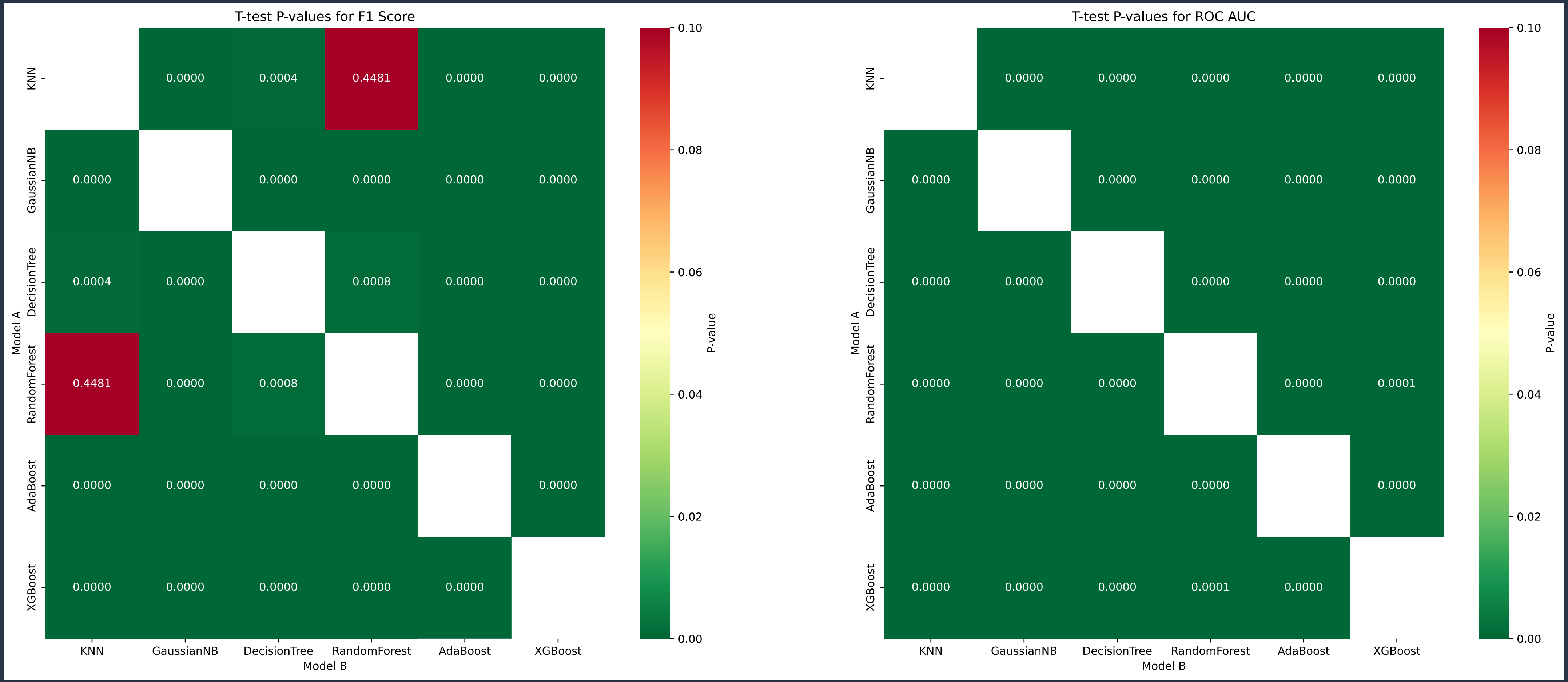
Threshold analysis





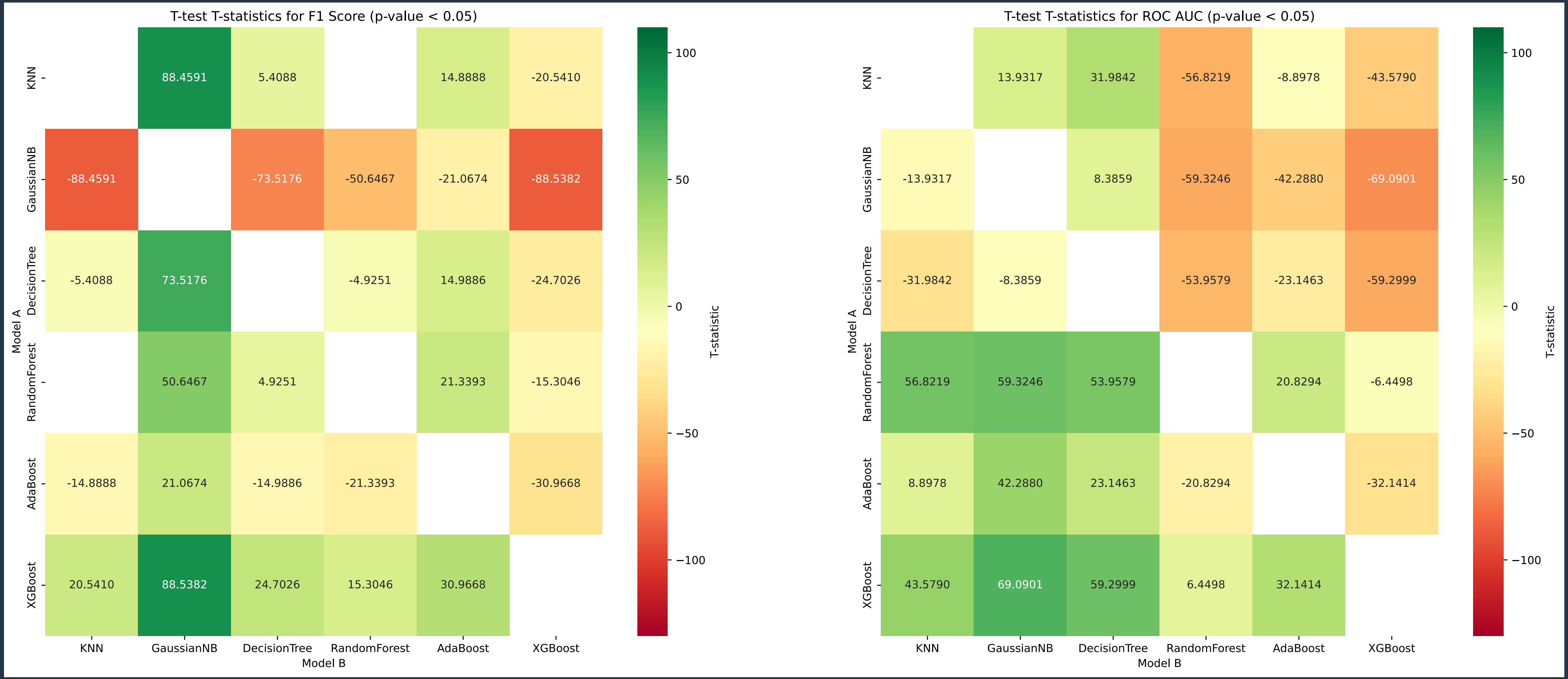
Statistical tests (*paired t-test*)

p-values



Statistical tests (*paired t-test*)

t-statistics



Model explainability

Goal

Understanding predictions & identifying influential features.

Feature Importances

- For DT, RF, ADA, XGB.
- Horizontal bar plots → top contributing features.

SHAP Values

- Quantify feature contribution for individual predictions.
- Summary plots → global feature impact.

Permutation Feature Importance

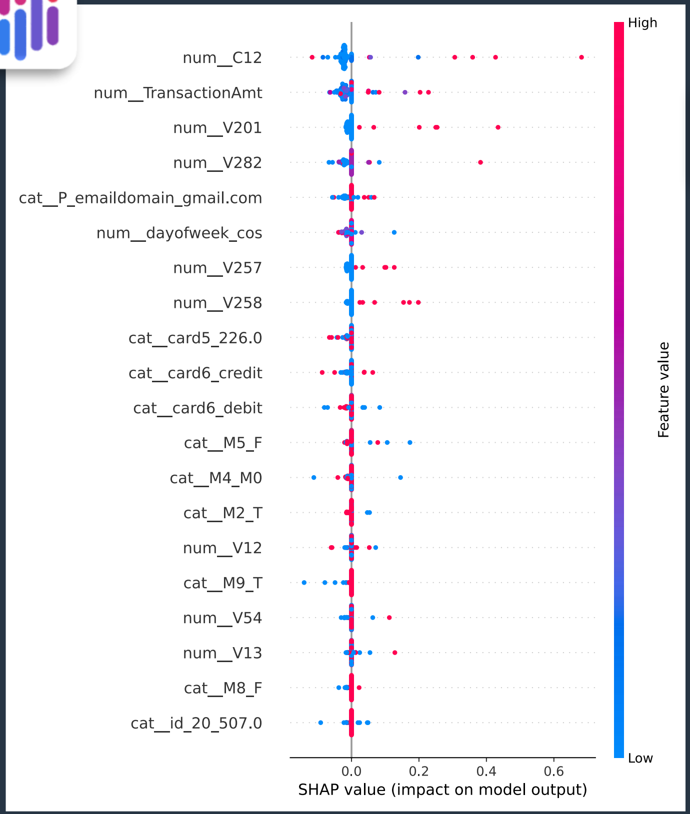
- Model-agnostic method.
- Measures decrease in performance when a feature is shuffled.

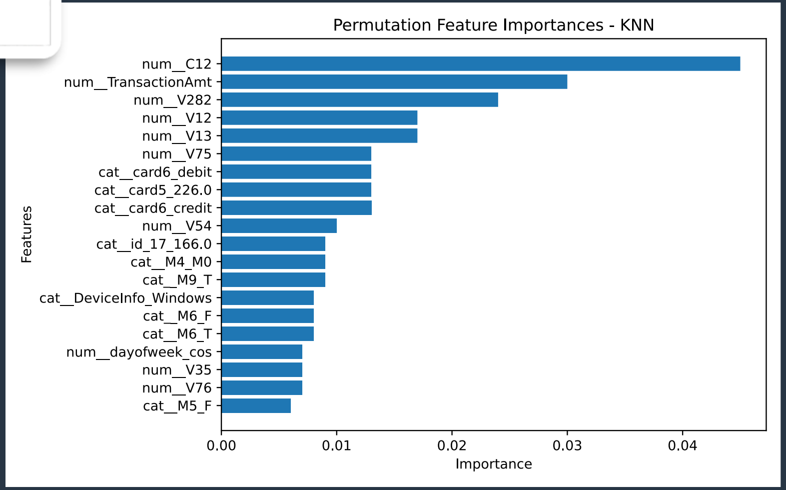
Rule Extraction via Surrogate Models

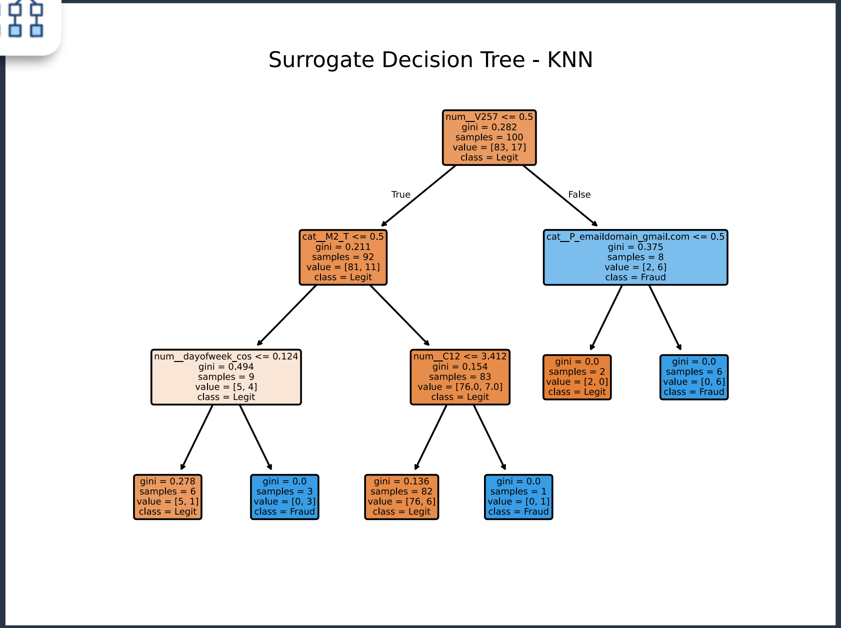
- Surrogate decision trees (`depth=3`).
- Extracts explicit, human-readable IF-THEN rules.

Explanations of the models

K-Nearest Neighbours

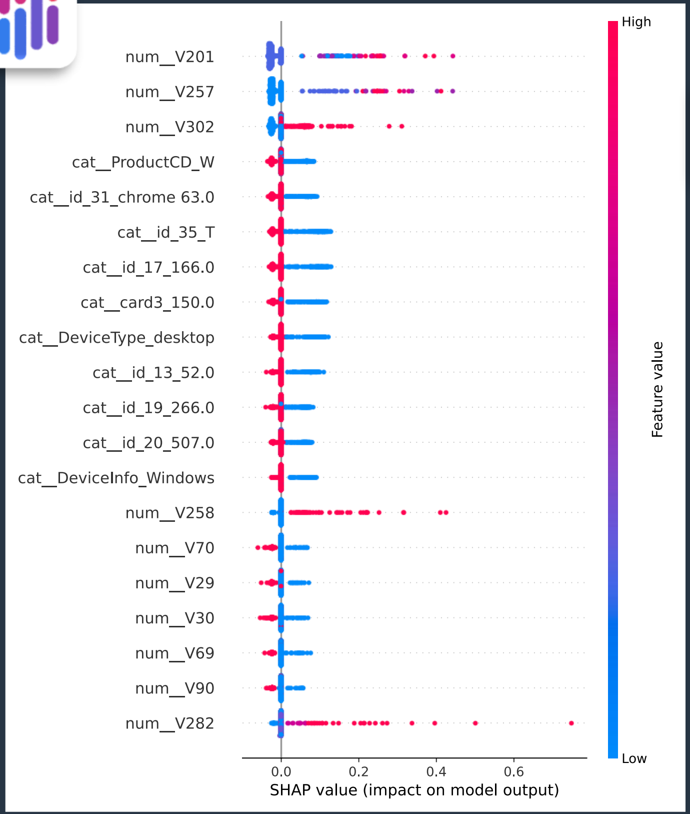


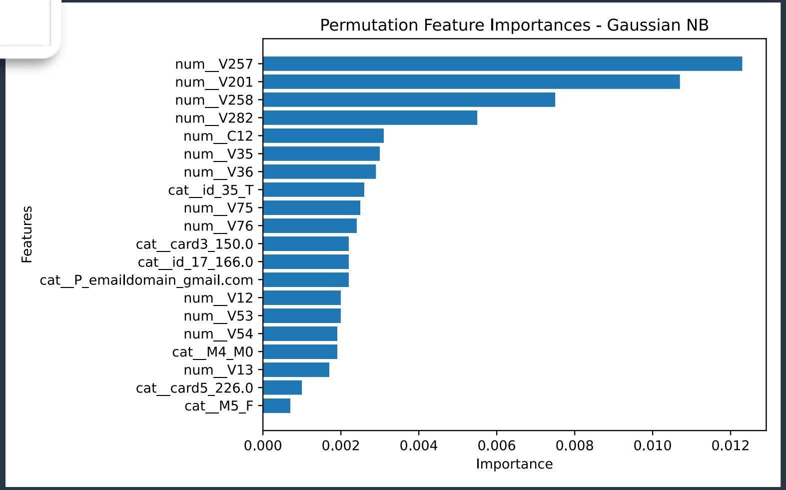


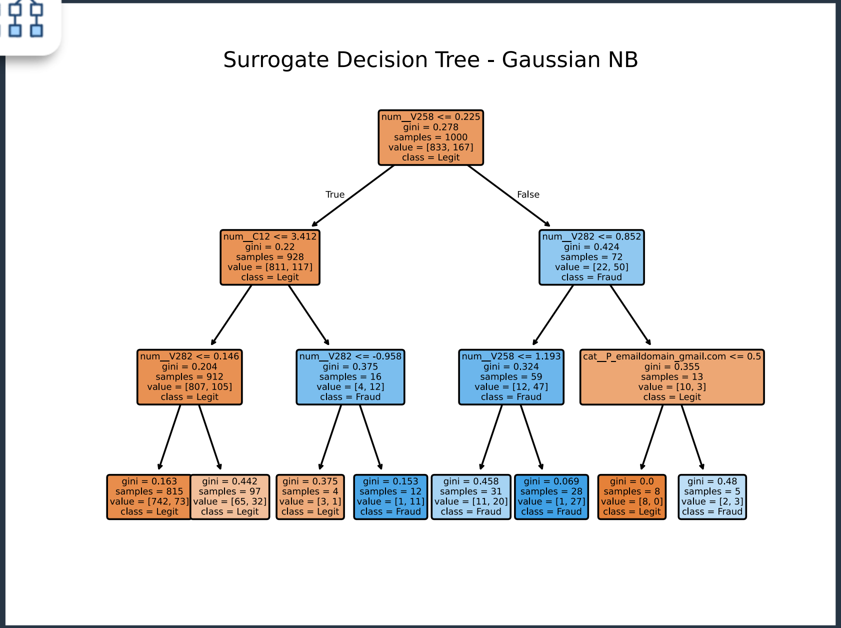


Explanations of the models

Gaussian NaiveBayes

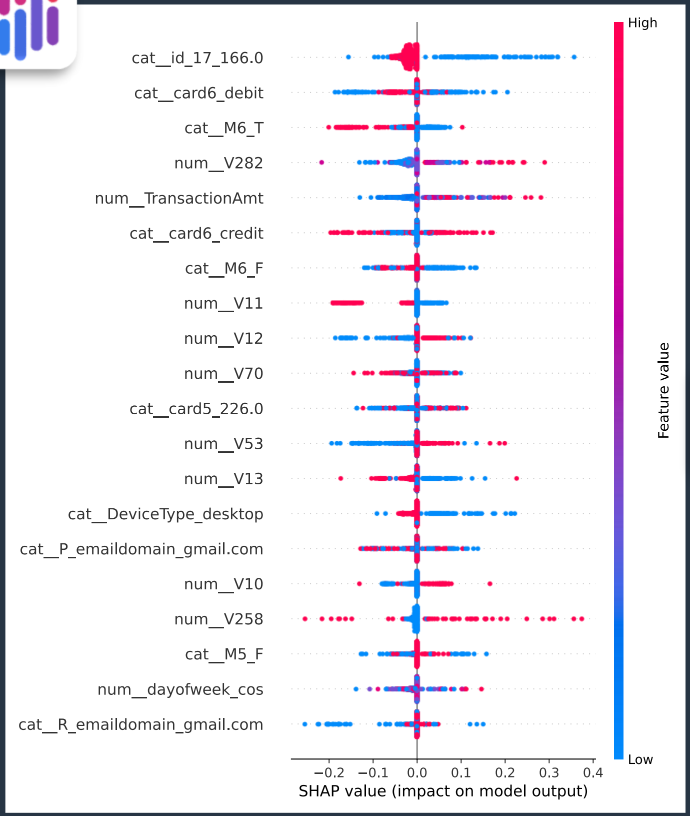


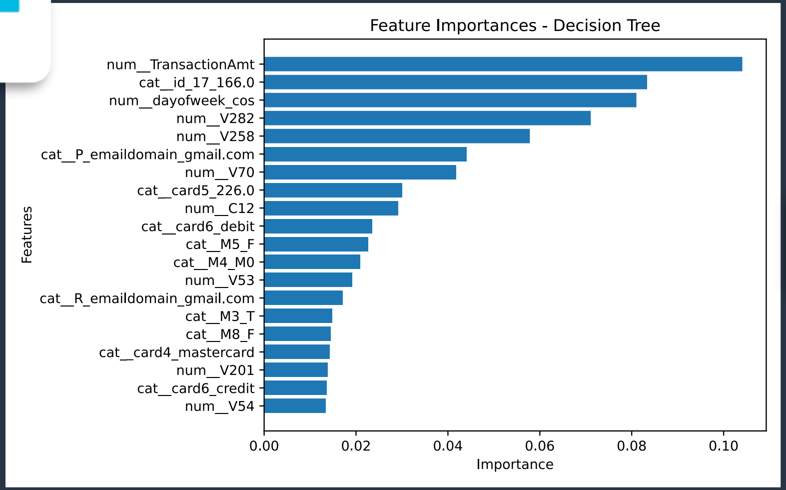


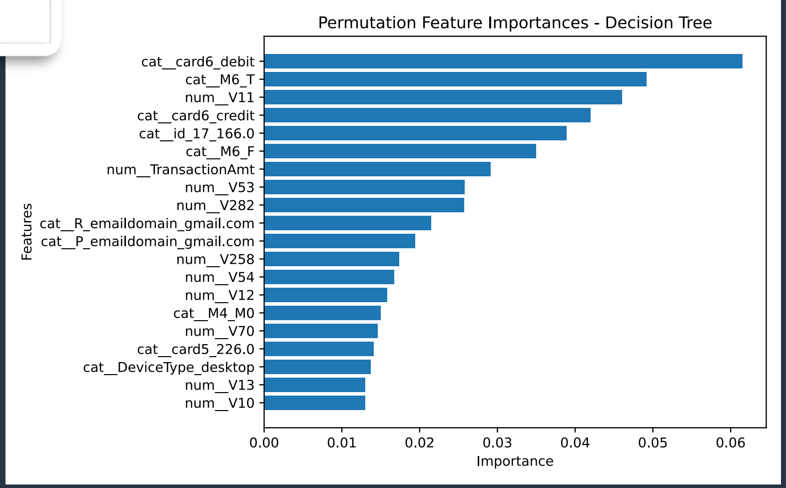


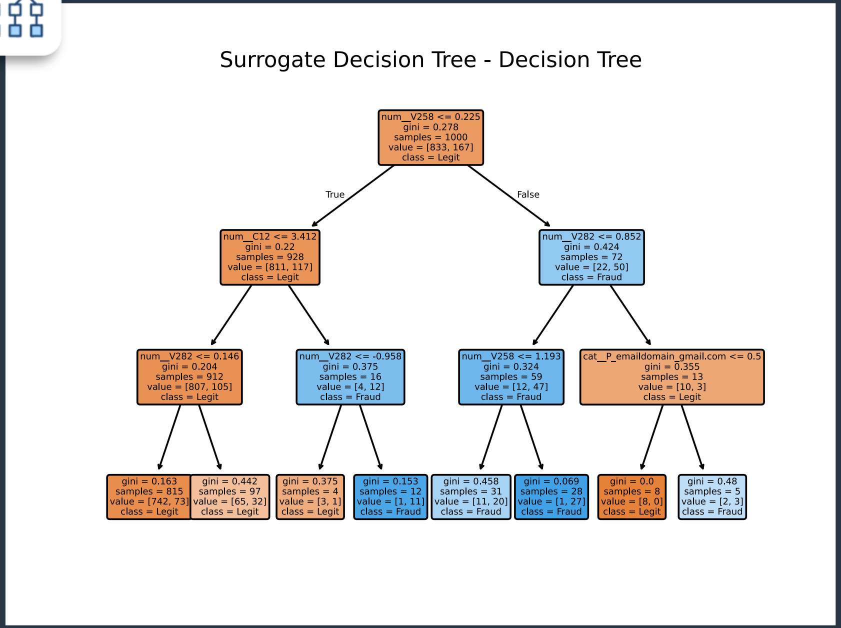
Explanations of the models

DecisionTree



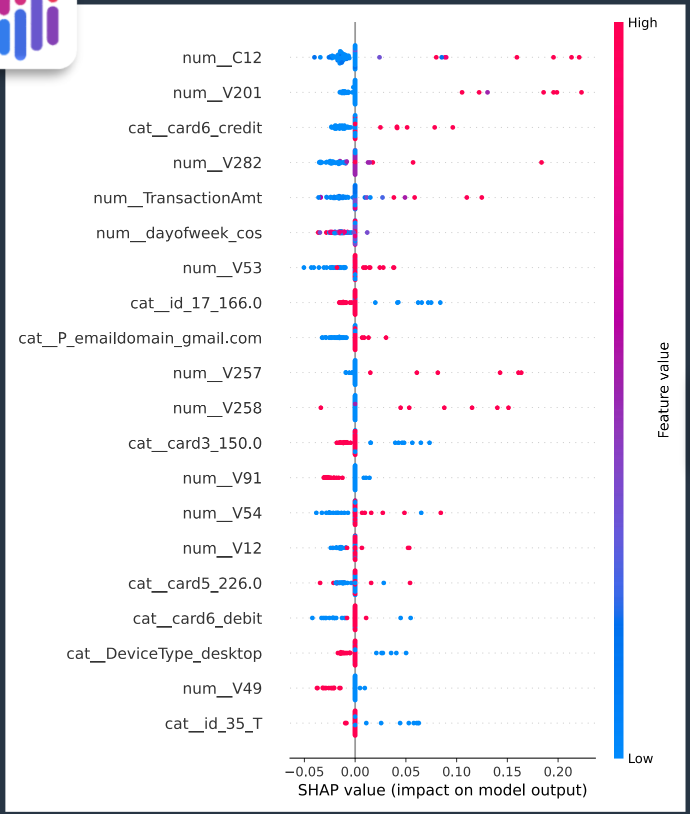


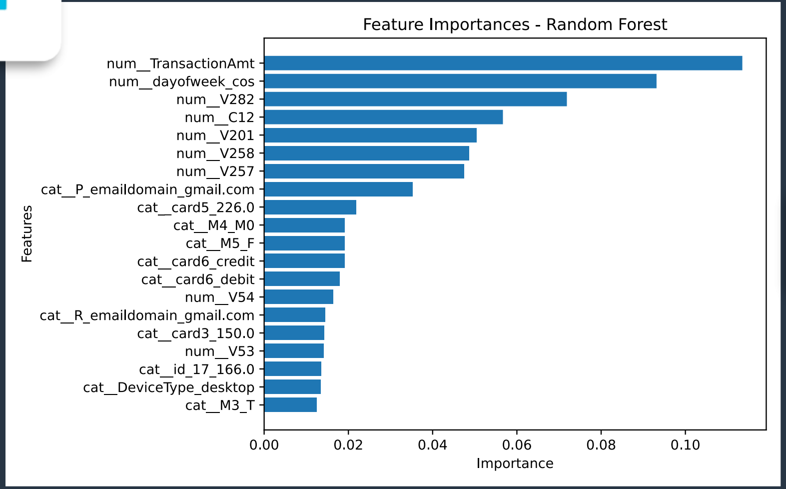


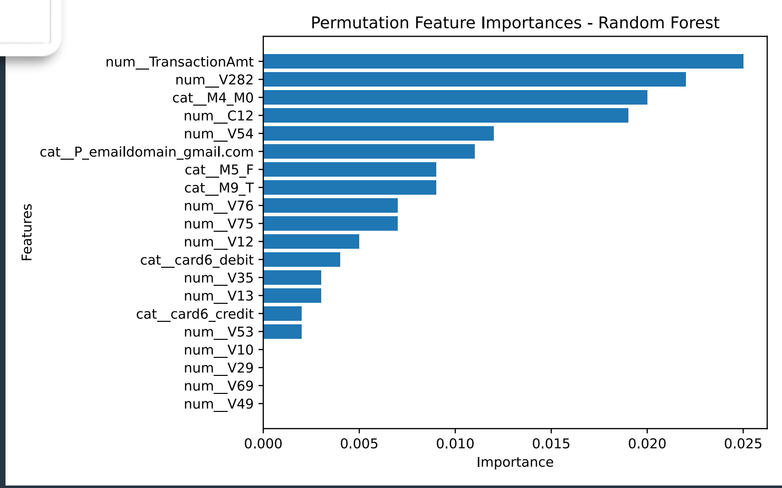


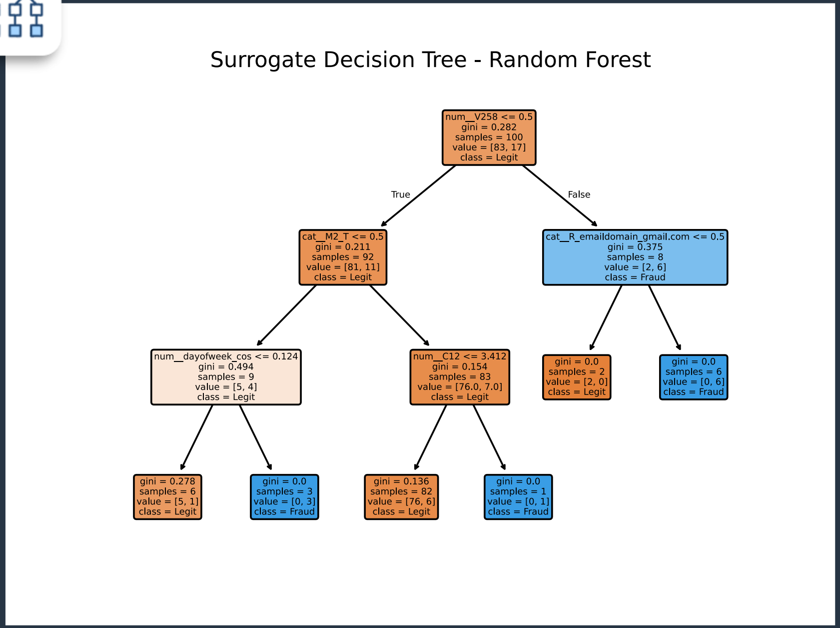
Explanations of the models

RandomForest



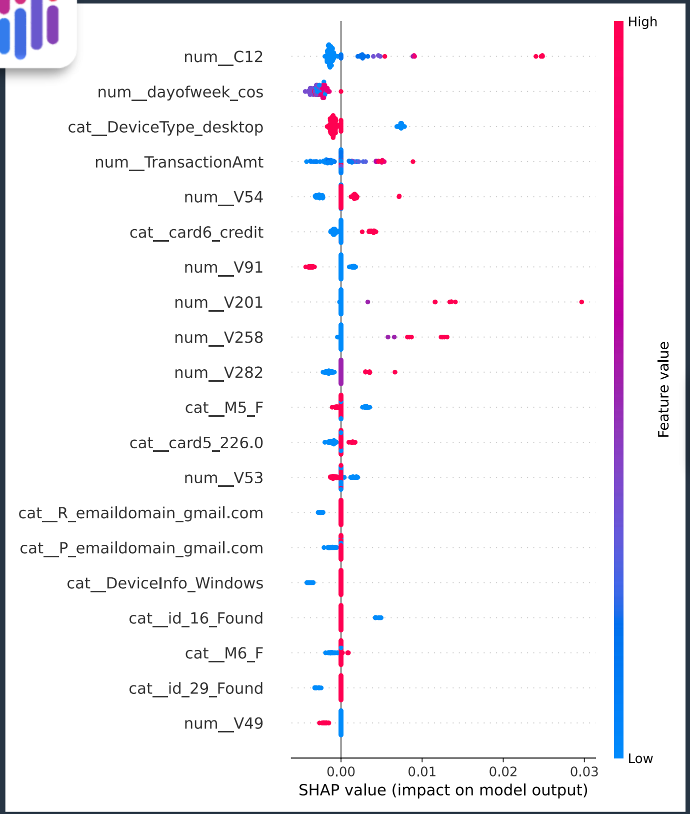


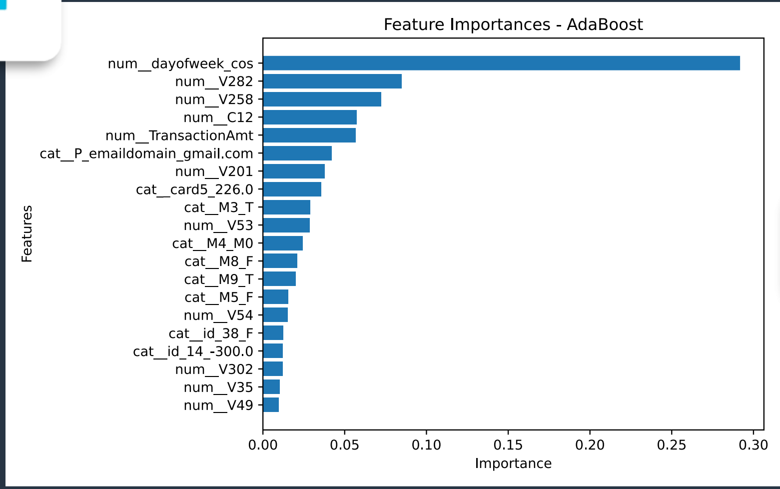


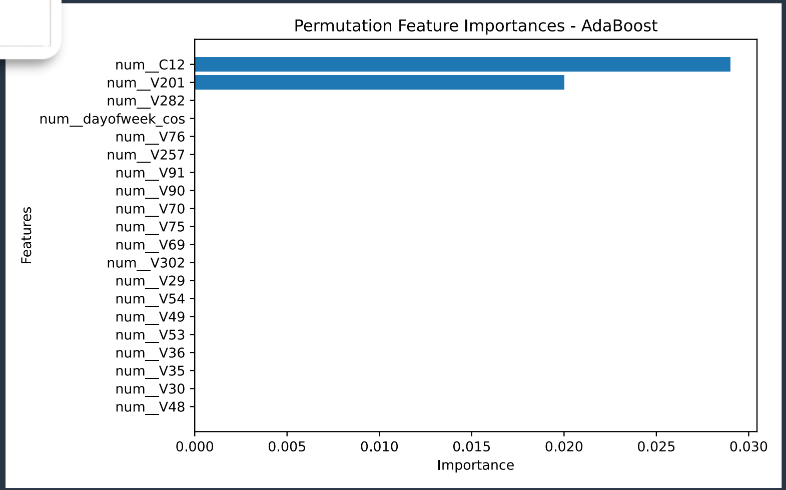


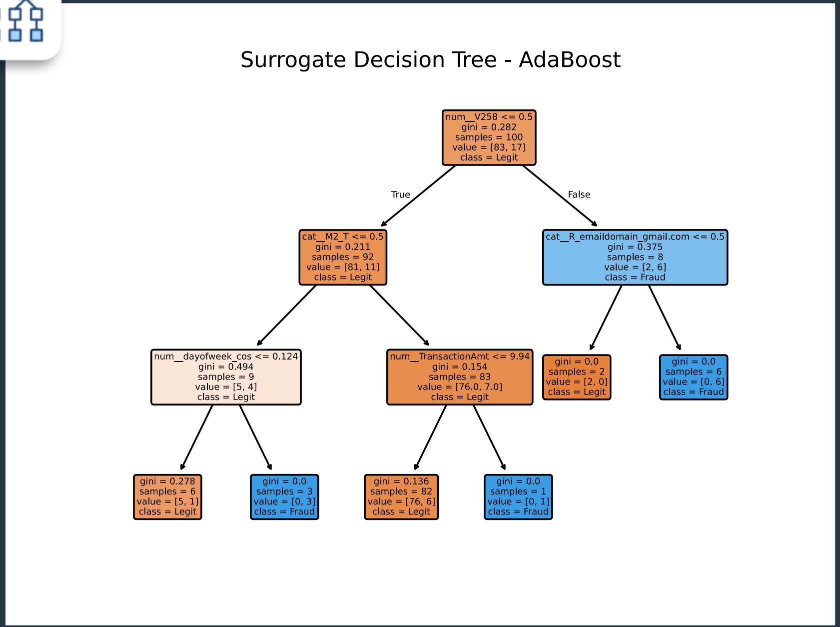
Explanations of the models

AdaBoost



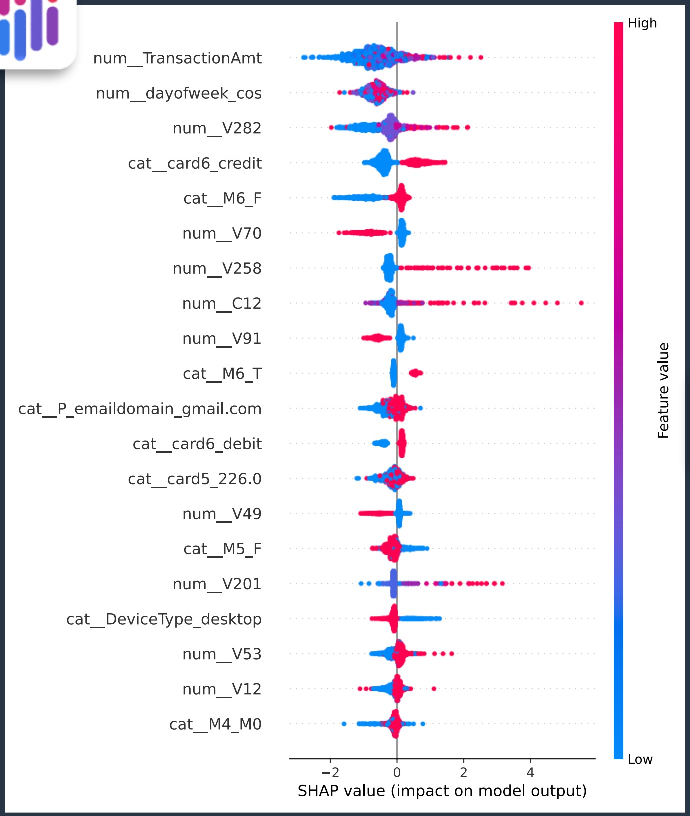


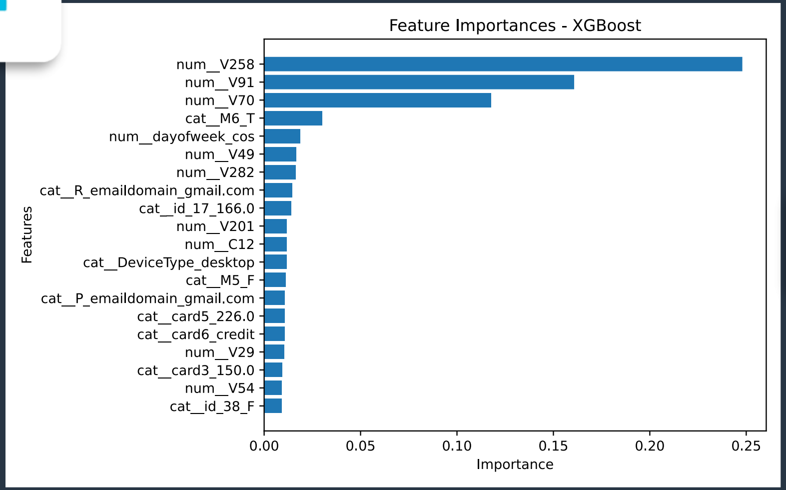


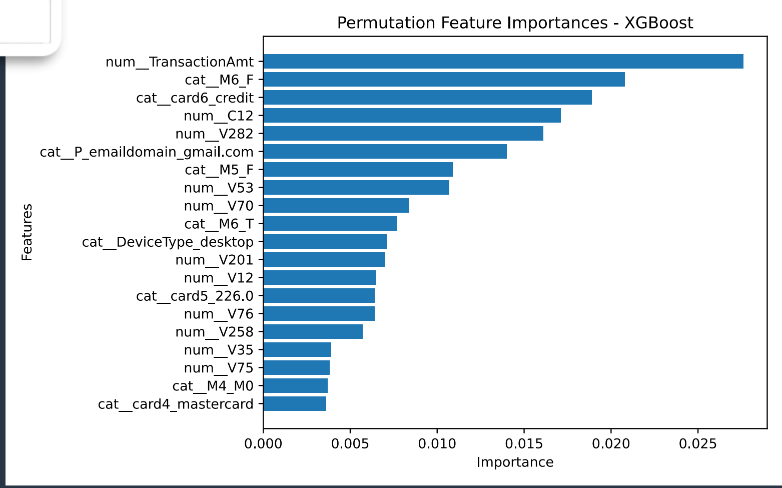


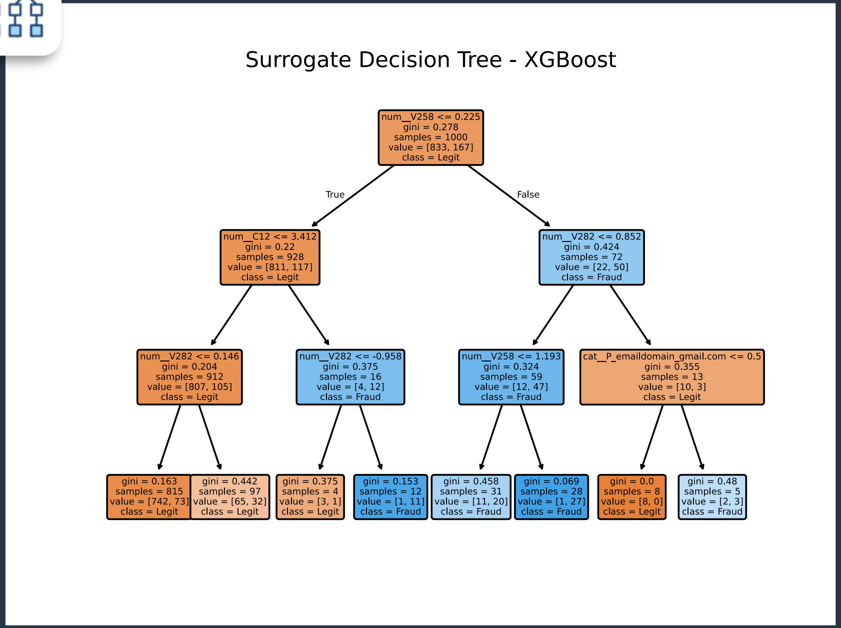
Explanations of the models

XGBoost









Real-world Application

Scenario

- Online payment systems → high risk of fraud
- Goal: real-time detection for banks, e-commerce, payment processors

Prototype

- Web interface built with *Streamlit*
- Users manually input transaction details

Pipeline

1. **Pre-processing**
   - Same as training: missing values, scaling, encoding, temporal features, feature selection
2. **Classification**
   - 6 classifiers: Decision Tree, Random Forest, Naive Bayes, KNN, AdaBoost, XGBoost
   - Output: Legitimate / Fraudulent
3. **Ensemble decision**
   - Majority voting for final prediction
4. **Explainability (XAI)**
   - Tree-based: SHAP values
   - AdaBoost: Kernel SHAP
   - Naive Bayes: posterior probabilities
   - KNN: nearest neighbors' examples

Real-world Application

Credit Card Fraud Detection

Insert a transaction to classify:

	TransactionID_x	TransactionDT	TransactionAmt	ProductCD	card1	card2
0	3457624	12153579	724	4	7826	481

Predict

Model Predictions:

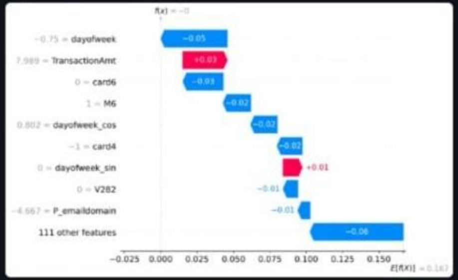
	Model	Prediction
0	Random Forest	Legitimate
1	XGBoost	Legitimate
2	Decision Tree	Legitimate
3	Gaussian NB	Legitimate
4	KNN	Legitimate
5	AdaBoost	Legitimate

Final Model Vote:

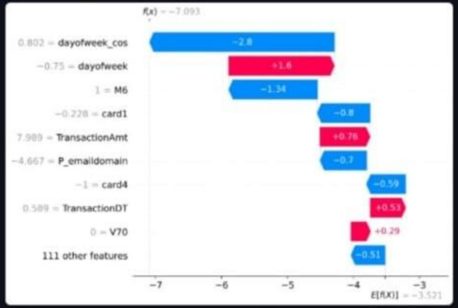
Transaction classified as Legitimate by 6/6 models!

Explanations (per model):

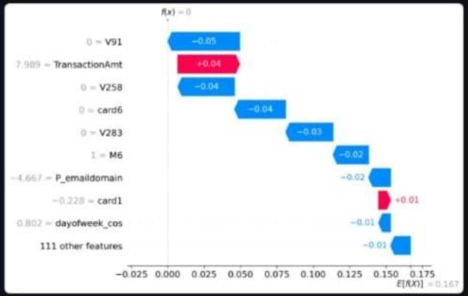
Explanation for Random Forest



Explanation for XGBoost



Explanation for Decision Tree



Explanation for Gaussian NB

Posterior probabilities (Legitimate vs Fraudulent): [0.98210872 0.01789128]

Transaction classified as **Legitimate** with probability 0.98

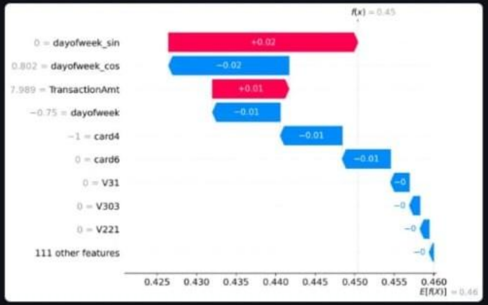
Explanation for KNN

The 3 most similar neighbors and their true labels:

	Index	Label
0	2680	Legitimate
1	86410	Legitimate
2	368395	Legitimate

Transaction classified as **Legitimate** because 0 of the 3 neighbors were Fraudulent.

Explanation for AdaBoost



Conclusions

Key Findings

Best performance

Ensemble models: ***XGBoost*** better even than *RandomForest* and *AdaBoost* (both *f1-score*, *ROC AUC*).

Acceptable Level of Performance (ALP)

Some models can correctly identify ≥80% frauds with limited false positives.

Threshold analysis

KNN & *DecisionTree* cannot match top performers.

AdaBoost → “conservative” (small threshold deviation), but high false positive rate.

Worst model: *Gaussian NaiveBayes*.

References

Related Work

- Cho Do Xuan, Dang Ngoc Phong, Nguyen Duy Phuong. *A new approach for detecting credit card fraud transaction*, International Journal of Nonlinear Analysis and Applications, Vol. 14 (2023), pp. 133–146.
  Available at: https://ijnaa.semnan.ac.ir/article_7623_b95b41b8707a1ba645b2ad938f3cd76f.pdf

Bibliography

- *Kaggle Dataset: IEEE-CIS Fraud Detection*
  Available at: https://www.kaggle.com/datasets/phambacong/ieee-cis-fraud-detection
- T. Chen and C. Guestrin, *XGBoost: A scalable tree boosting system* (2016).
  Available at: https://arxiv.org/abs/1603.02754
- C. Nadeau, Y. Bengio, *Inference for the Generalization Error* (2003).
  Available at: https://doi.org/10.1023/A:1024068626366
- Z. Hanusz, J. Tarasinska, and W.Zieliński, *Shapiro–wilk test with known mean* (2016).
  Available at: https://www.researchgate.net/publication/298706800_Shapiro-Wilk_test_with_known_mean

Thanks for your attention!

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