Transparent Credit Scoring Using Explainable Machine Learning

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Introduction

Introduction

- **What is credit scoring?**
- **Why is it important in FinTech?**
- **Why is transparency essential?**

Goal — **Predict creditworthiness using machine learning in a transparent and fair way.**

Data Preprocessing

02

Dataset Overview

Types of features (Age, income, balance, outstanding debt, etc.)

Target variables – Credit_Score (Good, Standard, Poor)

Reference: https://www.kaggle.com/datasets/parisrohan/credit-score-classification/data

Data Preprocessing

Handling missing value

Feature Engineering

Encoding categorical variables

Scaling

03

Modeling Approaches

Modeling Approaches

Logistic Regression

✅ Interpretable
✅ Fast
✅ Decent when features have linear relationships

Random Forest

✅ Handles non-linearity
✅ Robust to outliers
✅ Ignore irrelevant features

XGBoost

✅ Efficient
✅ Handles missing data internally
✅ Prevent overfitting

Model Evaluation Metrics

04

Model Evaluation Metrics

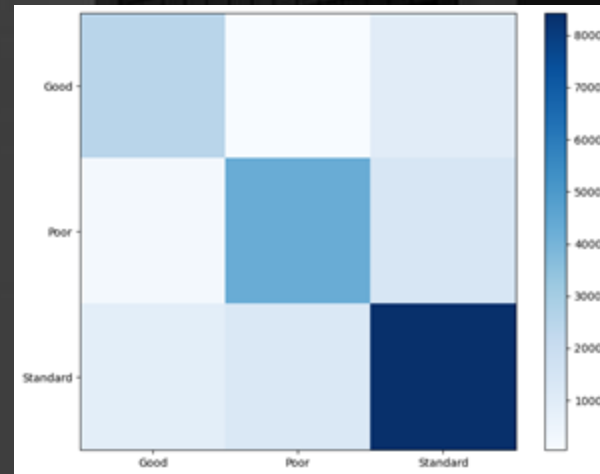|	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.6049	0.59	0.52	0.54
Random Forest	0.8013	0.79	0.79	0.79
XGBoost	0.7599	0.75	0.74	0.74

Confusion Matrix
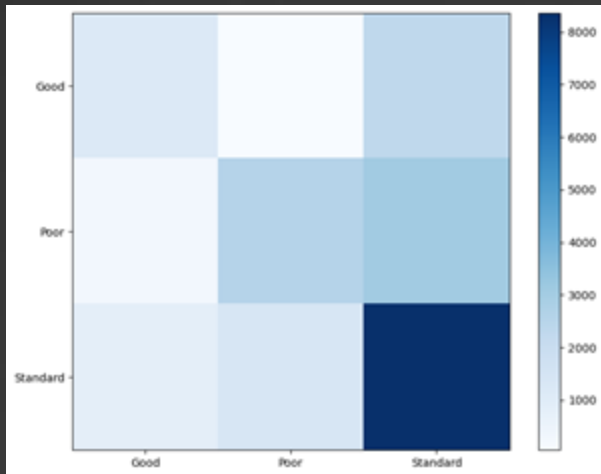
Logistic
Regression
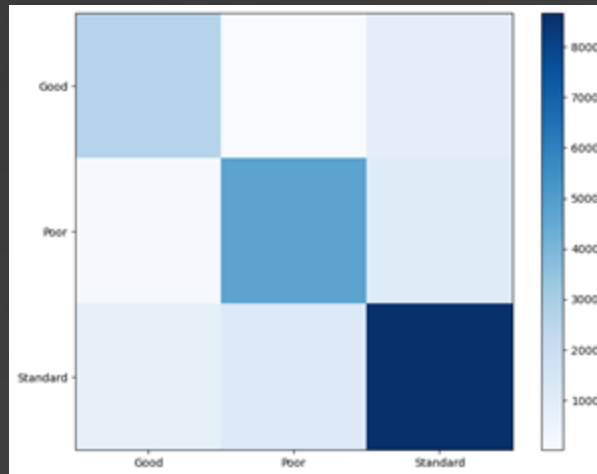
Random Forest

XGBoost

05

**ROC-AUC
Curve**

ROC Curves

ROC = Receiver Operating Characteristic

AUC = Area Under the Curve

Logistic Regression	0.7661
Random Forest	0.9228
XGBoost	0.9008
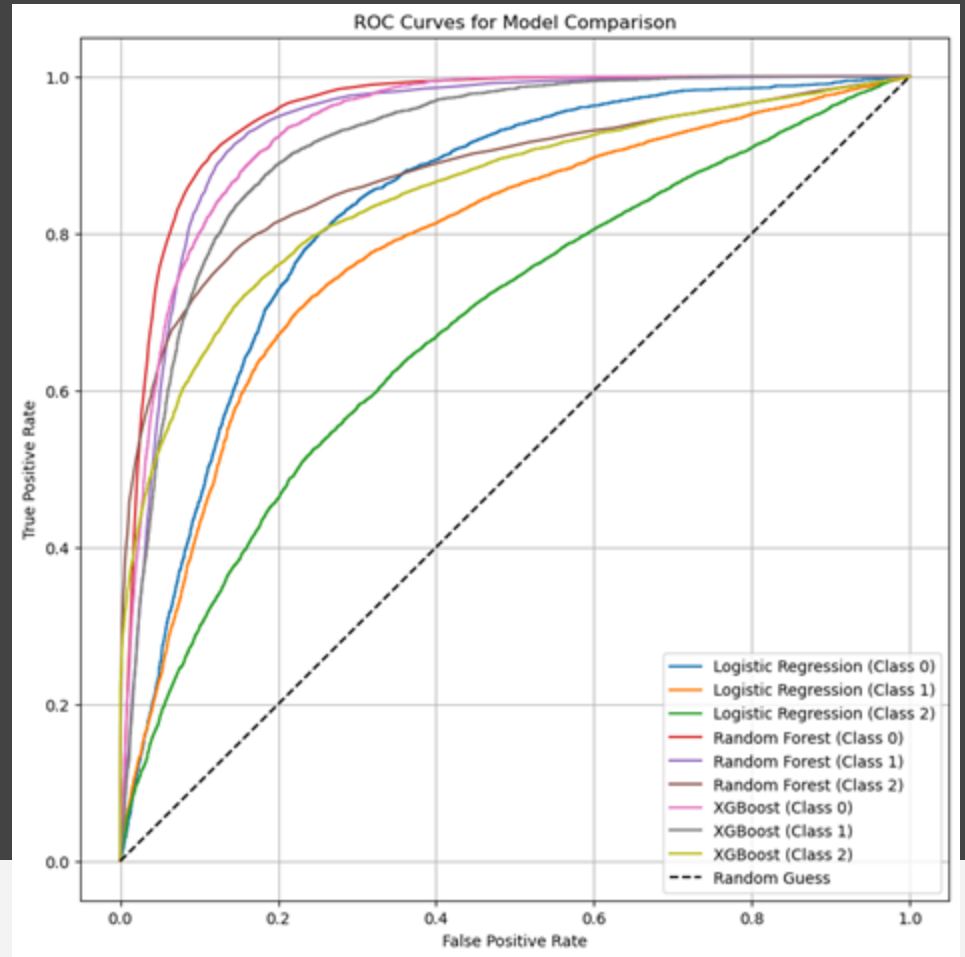
ROC Curves for Model Comparison

SHAP

06

SHAP (SHapley Additive exPlanations)

Logistic Regression

Random Forest

XGBoost
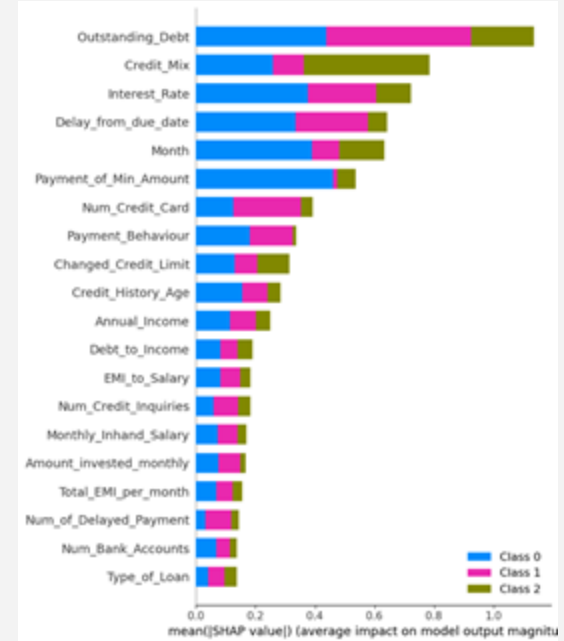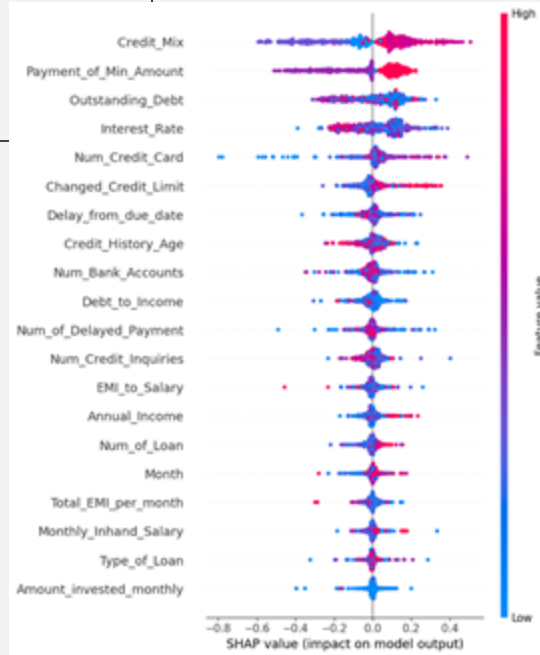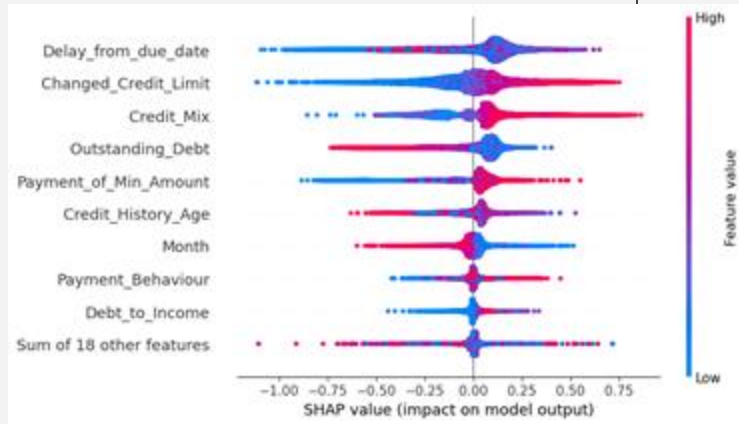
07

Final Model

Final Model — Random Forest

High accuracy
Achieved 80.1% accuracy

Balanced metrics
Precision, recall, F1-score
are highest

Handles non-linearity
Captures complex relationships
and interactions

Robustness
Less sensitive to noise
and outliers

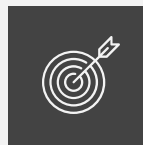## Explainability
SHAP works well with
tree based models

08
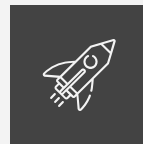
Challenges

Challenges
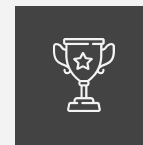
SHAP runtime

Sampling 500 data

Model explainability

Learned how to use SHAP for different model types

Overfitting risk

Used validation set performance and metrics like macro F1 for generalization
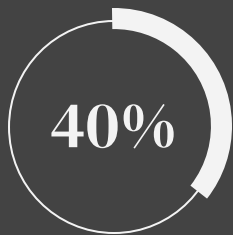
Feature availability

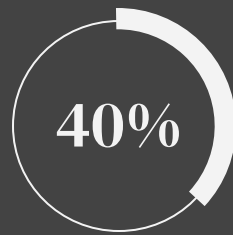Implemented robust error handling and fallback imputation methods

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Conclusion

My Findings

40%

Built a model

Transparent and high
performing credit
scoring model

40%

SHAP and ROC

For interpretability
and validation

20%

AI in FinTech

Ethical and
responsible

Thanks

Q&A