German Credit Risk Prediction: Comprehensive Model Analysis & Recommendations

1. Executive Summary

This report evaluates three machine learning models for predicting credit risk (Risk vs. No Risk) using the German credit dataset:

1. **Random Forest (RF) without SMOTE**
2. **Random Forest (RF) with SMOTE**
3. **Decision Tree (DT) with SMOTE & Boosting**

Key Findings:

- **Non-SMOTE RF** has the highest testing accuracy (**81.55%**) but suffers from severe **class imbalance**, detecting only **21.8% of "No Risk"** cases.
- **SMOTE-RF** improves balance (**No Risk detection: 25.6% vs. Risk: 69.5%**) but slightly reduces accuracy (**79.07%**).
- **SMOTE-DT** shows **severe overfitting** (96.15% training vs. 78.97% testing) and is **not recommended** for deployment.

Best Model:

- **If catching risky applicants is critical → Non-SMOTE RF** (high sensitivity, 85.4% Risk detection).
- **If balanced performance is needed → SMOTE-RF** (better equilibrium between Risk & No Risk predictions).

2. Business Problem Alignment

This section links the model performance evaluation to the core business challenges faced by financial institutions in credit risk management.

Business Problem 1: Reducing Financial Losses from Credit Card Defaults

Objective: Accurately identify and reject high-risk applicants to minimize default-related losses.

- **Best Model:** Random Forest (No SMOTE)

- **Justification:** This model delivered the highest True Positive Rate (TPR) for the "Risk" class (0.827) and strong overall testing accuracy (80.75%).

- **Business Value:** Effectively prevents issuing credit to high-risk individuals, reducing the chance of bad debt and write-offs.

Business Problem 2: Promoting Fair and Inclusive Lending

Objective: Improve approval rates for low-risk applicants while maintaining reasonable accuracy.

- **Best Model:** Random Forest with SMOTE
- **Justification:** SMOTE enhanced the model's ability to detect the "No Risk" class (0.256), creating a more balanced output and reducing false negatives.
- **Business Value:** Encourages financial inclusion by ensuring fewer low-risk applicants are unfairly rejected due to data imbalance.

Model to Avoid: Decision Tree with SMOTE

- **Reason:** Despite high training accuracy (96.15%), the model underperformed in testing (78.97%) and demonstrated classic signs of overfitting.
- **Impact:** Fails to generalize, leading to unreliable credit decisions in production environments.

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3. Detailed Model Performance Analysis

A. Random Forest (No SMOTE)

Training:

- **Accuracy:** 84.07%
- **Sensitivity (Risk Detection):** 97.2%
- **Specificity (No Risk Detection):** 21.7%

Testing:

- **Accuracy:** 81.55%
- **Sensitivity:** 85.4%
- **Specificity:** 21.8%

Key Insight:

- **Extremely biased toward "Risk" predictions** (misses many safe applicants).
- **Best for strict risk aversion** (e.g., banks prioritizing fraud prevention).

B. Random Forest (With SMOTE)

Training:

- **Accuracy:** 84.45%
- **Sensitivity:** 53.7%
- **Specificity:** 51.2%

Testing:

- **Accuracy:** 79.07%
- **Sensitivity:** 69.5%
- **Specificity:** 25.6%

Key Insight:

- **More balanced than Non-SMOTE RF** (fewer false positives).
- **Better for fair lending decisions** (fewer safe applicants wrongly rejected).

C. Decision Tree (With SMOTE & Boosting)

Training:

- **Accuracy:** 96.15% *(likely overfit)*
- **Sensitivity:** 66.2%
- **Specificity:** 64.6%

Testing:

- **Accuracy:** 78.97%
- **Sensitivity:** 71.0%
- **Specificity:** 24.1%

Key Insight:

- **Severe overfitting** (training accuracy unrealistic).
- **Not recommended for deployment** due to poor generalization.
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Why SMOTE Was Used

Addressing Class Imbalance

- During initial model evaluation, we identified a significant class imbalance in the dataset, with “Risk” cases occurring far more frequently than “No Risk” cases. This imbalance can bias models to favor the majority class, leading to:
- High overall accuracy but poor minority class detection
- Skewed predictions that neglect the importance of low-risk individuals

SMOTE: Synthetic Minority Oversampling Technique

To address this, we applied SMOTE, which generates synthetic samples of the minority class ("No Risk") by interpolating between existing instances. Unlike random oversampling, SMOTE introduces new, realistic data points rather than duplicating existing records.

Purpose and Benefits

- The primary goals of using SMOTE were:
- Enhance class balance to allow models to better learn from "No Risk" cases
- Improve fairness and recall for the minority class
- Reduce model bias and assess the trade-off between balanced performance and majority class accuracy

4. Comparative Summary

Metric	Non-SMOTE RF	SMOTE-RF	SMOTE-DT
Testing Accuracy	**81.55%**	79.07%	78.97%
Risk Detection (Sensitivity)	**85.4%**	69.5%	71.0%
No Risk Detection (Specificity)	21.8%	**25.6%**	24.1%
Overfitting Risk	Low	Moderate	**High**

4. Recommendations

Best Model Selection

Use Case	Recommended Model	Why?

Strict Risk Avoidance (e.g., fraud prevention)	**Non-SMOTE RF**	Highest Risk detection (85.4%)
Balanced Decision-Making (fair lending)	**SMOTE-RF**	Better No Risk detection (25.6%)
Avoid	SMOTE-DT	Overfits, unreliable generalization

6. Conclusion

- **Non-SMOTE RF is best for maximizing Risk detection** but penalizes safe applicants.
- **SMOTE-RF is better for balanced lending decisions** but misses some risky cases.
- **Avoid SMOTE-DT due to overfitting.**

Final Recommendation:

- **Deploy SMOTE-RF** if fairness is a priority.
- **Use Non-SMOTE RF** if minimizing risk exposure is critical.
- **Monitor model performance** and refine thresholds based on business needs.