Credit Card Fraud Detection: Model Evaluation Report

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Project: Grow Link Data Science Assignment  
Task: Credit Card Fraud Detection(5)

# 1. Objective

The primary goal of this project is to build and evaluate multiple machine learning models to detect fraudulent credit card transactions, a typical case of highly imbalanced binary classification.

# 2. Dataset Overview

- Source: Credit card transactions dataset with 31 columns including Time, Amount, anonymized features V1 to V28, and the target variable Class.  
- Target: `Class` — 0 (Non-fraud), 1 (Fraud)  
- Imbalance Issue: Fraudulent transactions are significantly fewer than normal ones.

# 3. Preprocessing

- Dropped low-correlation features (< 0.10 with target) to reduce noise.  
- Missing values in the Class column were handled using dropna().  
- Stratified sampling ensured proportional representation of classes.  
- Performed under-sampling (RandomUnderSampler) and over-sampling (SMOTE) to balance the dataset for training.

# 4. Modeling Techniques

Models Trained:  
1. Random Forest  
2. XGBoost  
3. AdaBoost  
4. Gradient Boosting  
5. Voting Classifier (Ensemble of Random Forest and XGBoost)

Metrics Evaluated:  
- Accuracy  
- Precision (Weighted & Macro)  
- Recall (Weighted & Macro)  
- F1-score (Weighted & Macro)  
- ROC AUC

# 5. Results Summary

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy | F1 (Weighted) | ROC AUC | F1 (Macro) |
| Random Forest | 97.65% | 98.56% | 0.9880 | 59.63% |
| XGBoost | 99.61% | 99.68% | 0.9645 | 80.41% |
| AdaBoost | 89.38% | 94.09% | 0.9402 | 49.88% |
| Gradient Boosting | 89.36% | 94.08% | 0.9398 | 49.87% |
| Voting Classifier | 99.80% | 99.82% | 0.9727 | 87.45% |

Best model by ROC AUC: Random Forest  
Best overall performance (accuracy, F1): Voting Classifier

# 6. Visualization Highlights

- ROC Curves: Demonstrated strong separability of the best models.  
- Confusion Matrices: Clear understanding of prediction errors for each model.  
- Probability Distributions: Separated class predictions validate model confidence.

# 7. Conclusion

The project effectively handled class imbalance through resampling and evaluated a suite of ensemble models. Despite the Voting Classifier achieving superior F1 scores and accuracy, the Random Forest model stood out for its ROC AUC score, suggesting reliable fraud detection capabilities with minimal false positives.

# 8. Recommendations

- Consider hyperparameter tuning for top models to further improve performance.  
- Evaluate models with cost-sensitive metrics (e.g., cost of false negatives).  
- Deploy the best model using an API for real-time fraud detection.