Credit Fraud Detection Report

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1- About the Report

This report focuses on credit fraud detection. I will present all the techniques used to address the challenges of this imbalanced dataset(using classical machine learning techniques) and improve model performance. Each experiment is explained in detail, showing how different models performed with different strategies.

This report is designed not only to document my process and findings but also to serve as a practical guide for anyone working on similar machine learning projects, especially those dealing with imbalanced classification problems.

2- Why Are Imbalanced Datasets a Challenge in Fraud Detection?

Imbalanced datasets are very common in fraud detection problems, where fraud cases make up only a small percentage of all transactions. This creates several challenges:

- **Biased predictions**:
  If we train a model on the imbalanced data as it is, the model may learn to always predict the majority class (e.g., "not fraud"). This can result in high accuracy but poor fraud detection, because most fraud cases will be missed.

- **Mismatch with real-world data**:
  Resampling techniques like oversampling or undersampling change the class distribution in the training set. For example, turning 1% fraud cases into 35% changes the nature of the data(in real life). This can help the model learn to detect fraud better, but it no longer reflects the true distribution seen in real-world scenarios.

- **Performance depends on the dataset**:
  While techniques like oversampling can improve results, they don’t always work well on every dataset. Their success depends on the data characteristics and the models used.

In this report, I will explain the different techniques I used to handle the imbalanced data and show how they affected the performance of various machine learning models.

3. Models and Techniques Used to Handle Class Imbalance

In this section, I describe the techniques and machine learning models I used to address the challenge of class imbalance in fraud detection.

Techniques:

To handle the imbalance between the majority (non-fraud) and minority (fraud) classes, I applied the following strategies:

1. **Undersampling** – Reducing the number of majority class samples to balance the dataset.

2. **Oversampling using SMOTE (Synthetic Minority Oversampling Technique)** – Generating synthetic examples for the minority class to increase its representation.

3. **Combined Sampling** – Applying both oversampling and undersampling to create a more balanced dataset.

4. **Cost-Sensitive Learning** – Assigning a higher cost to misclassifying fraud cases to force the model to focus more on the minority class.

5. **Using the Data As-Is** – Training the model on the original imbalanced dataset to serve as a baseline and see if the resampling techniques will improve the performance or harm it.

Models:

I experimented with a variety of machine learning algorithms to evaluate how well they perform with different sampling strategies:

1. **Logistic Regression**

2. **Random Forest**

3. **XGBoost (Extreme Gradient Boosting)**

4. **CatBoost**

5. **MLP (Multi-Layer Perceptron)**

4- Analysis of All Models Across All Experiments

For all models, RandomizedSearchCV with StratifiedKFold cross-validation was applied to select optimal hyperparameters. Each model's performance is evaluated using both default and optimized thresholds.

4.1 Logistic Regression

Default Threshold Performance:

- Raw data (with/without scaling): Model performed poorly, indicating underfitting (F1_train = 0.0682, F1_val = 0.0616).
- Cost-sensitive learning (with/without scaling): Similar underfitting behavior observed
- Resampling techniques: High overfitting, with a large gap between training and validation F1 scores.

Best Threshold Performance:

- Raw data: Significant improvement with threshold 0.99 (f_score_train = 0.7931, f_score_val = 0.7932)
- Cost-sensitive learning: Maintained good performance with optimized threshold(like performance with raw data)
- Resampling techniques: Overfitting still happened, even after changing the threshold

Key Observation:

Logistic Regression performs best with raw data and improves a lot when the threshold is tuned. Resampling methods usually cause overfitting, so they’re not a good choice for this model.

4.2 Random Forest Classifier

Default Threshold Performance:

- Raw data (with/without scaling): Best performance achieved with no overfitting or underfitting
- Resampling techniques: High overfitting, with a large gap between training and validation F1 scores.

Best Threshold Performance:

- Raw data: Performance did not improve with optimized threshold (0.336), and the optimized threshold indicates lower model confidence
- Resampling techniques: Overfitting still happened, even after changing the threshold, and the gap between training and validation F1_score increased, except for cost-sensitive learning, where gaps remained constant
- Overall: The Default threshold generally outperformed the optimized threshold

Key Observation:

Random Forest achieves optimal performance with raw, unprocessed data using the default threshold. Increasing **(min_samples_leaf)** and setting **(class_weight = None**) helps to prevent **overfitting** by limiting tree complexity and also using regularization techniques.

4.3 XGBoost and CatBoost Classifiers

Default and Best Threshold Performance:

- All experiments: Both models showed consistent overfitting, regardless of whether scaling or regularization techniques were applied.
- Scaling effect: No noticeable improvement in performance.
- Threshold optimization: Did not reduce overfitting.

Key Observation:
XGBoost and CatBoost consistently overfit in all scenarios. Since they degraded the performance, they were removed from the final voting classifier.

4.4 Multi-Layer Perceptron (MLP) Classifier

Default Threshold Performance:

- Raw data with scaling: Delivered the best results among all individual models.
- Raw data without scaling: Performed poorly, confirming the need for scaling.
- Resampling techniques and cost-sensitive learning: Led to overfitting.
- Early stopping: Helped reduce overfitting when tuned correctly.

Best Threshold Performance:

- Optimized threshold (0.8712): Results were similar to the default threshold.
- Confidence: Model showed higher prediction confidence at the optimized threshold.

Key Observation:
The MLP Classifier was the top-performing individual model, working best with scaled data. Early stopping improves generalization, and threshold tuning boosts confidence without changing overall performance.

4.5 Voting Classifier

Configuration 1 – All Models

- Models included: Logistic Regression, Random Forest, XGBoost, CatBoost, MLP (scaled data).
- Performance: Overfitted in all experiments.
- Root cause:
    - XGBoost and CatBoost consistently overfitted in all settings, which negatively impacted the ensemble.
    - Resampling techniques (undersampling, oversampling, oversampling and undersampling) further increased overfitting since most models also overfitted under these methods.

Configuration 2 – Selected Models

- Models included: Logistic Regression, Random Forest, MLP (scaled data).
- Best performance:
    - Raw data: Achieved best results with optimized threshold (0.7861).
    - Scores: f_score_train = 0.84, f_score_val = 0.82.
- Resampling techniques: still overfitting.
- Other experiments: Performed well with raw data (scaled/unscaled) and cost-sensitive learning (scaled/unscaled).

Key Observation:
The best ensemble setup used the Voting Classifier with Logistic Regression, Random Forest, and MLP on raw scaled data. This configuration balanced performance and generalization, while avoiding the overfitting issues introduced by XGBoost and CatBoost.

5- Best Model

Criteria Considered
In real-world projects, the “best” model depends on the business’s priorities—such as agreed performance targets and acceptable error trade-offs. In this project, my primary selection metric was the F1-score.

Since two models achieved the same F1-score, I applied additional considerations :

- Cost of Missing Fraud vs Cost of False Alarms
- Customer Experience (too many blocks = angry customers)
- Investigation Capacity (Can your team handle 1000 alerts/day?)

Top two models

Two models stood out during evaluation:

- Random Forest (raw data or raw data with scaling)
- MLPClassifier (scaled data)

After comparing both, the MLPClassifier with scaled data is the best choice for me but You can use either the best MLPClassifier model or the best RandomForest model, but I will use the MLPClassifier for the final deployment..

MLPClassifier Results

Default Threshold (0.5):

- F1_train = 0.8301
- F1_val = 0.8323

train classification report for default threshold :

	precision	recall	f1-score	support
0	0.9996	0.9998	0.9997	170579
1	0.8910	0.7770	0.8301	305
accuracy			0.9994	170884
macro avg	0.9453	0.8884	0.9149	170884
weighted avg	0.9994	0.9994	0.9994	170884

val classification report for default threshold :

	precision	recall	f1-score	support
0	0.9997	0.9998	0.9997	56870
1	0.8675	0.8000	0.8324	90
accuracy			0.9995	56960
macro avg	0.9336	0.8999	0.9161	56960
weighted avg	0.9995	0.9995	0.9995	56960

Optimized Threshold (0.8712):

- F1_train = 0.8389
- F1_val = 0.8353

train classification report for the best threshold :

	precision	recall	f1-score	support
0	0.9996	0.9999	0.9997	170579
1	0.9115	0.7770	0.8389	305
accuracy			0.9995	170884
macro avg	0.9556	0.8885	0.9193	170884
weighted avg	0.9994	0.9995	0.9994	170884

val classification report for the best threshold :

	precision	recall	f1-score	support
0	0.9997	0.9998	0.9998	56870
1	0.8875	0.7889	0.8353	90
accuracy			0.9995	56960
macro avg	0.9436	0.8944	0.9175	56960
weighted avg	0.9995	0.9995	0.9995	56960

Why is MLPClassifier the Best Model?

1- Consistent Precision and Balanced Recall

At its best threshold (0.87), the MLPClassifier achieves a strong balance:

- Precision: 88.8%
- Recall: 78.9%

This means positive predictions are highly reliable, reducing unnecessary false alarms while still capturing the majority of fraudulent cases.

2- Stable Performance Across Thresholds

The performance difference between the default threshold (0.5) and the best threshold (0.87) is minimal:

- Default (0.5): F1_train = 0.8301, F1_val = 0.8323
- Best (0.87): F1_train = 0.8389, F1_val = 0.8353

This small improvement (+0.0088 train, +0.0030 val) shows the MLPClassifier is not overly sensitive to threshold tuning, indicating a confident decision boundary.

3- Lower False Positive Rate

In the validation set, confusion matrices:

- MLP Best (0.87): FP = 9, FN = 19
- RandomForest Best (0.36): FP = 9, FN = 19
- MLP Default (0.5): FP = 11, FN = 18
- RandomForest Default (0.5): FP = 6, FN = 21

Both MLP (0.87) and Random Forest (0.36) have the same FP and FN counts at their best thresholds. However:

- MLP achieves this at a much higher threshold (0.87), meaning its positive predictions are made with greater confidence.
- Random Forest only achieves its best results by lowering the threshold to 0.36, which increases the chance of making uncertain predictions on new data.

Conclusion

The MLPClassifier with a best threshold of 0.87 delivers:

- **Balanced precision and recall**
- **Robustness to threshold changes**
- **Competitive false positive rates without aggressive threshold lowering**
- **MLPClassifier is the recommended model for general deployment due to its stability, high-confidence predictions, and consistent performance across thresholds.**

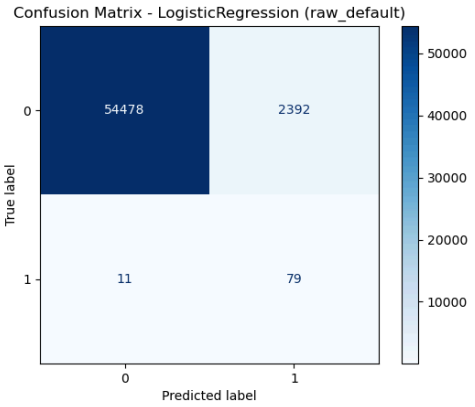
6- side notes

The best threshold greatly improved Logistic Regression’s performance across all experiments and reduced false positive alarms.

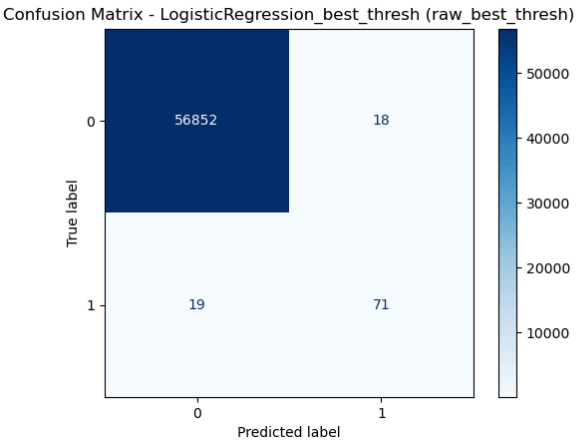
1- logistics regression with raw data :

model	f1_train	f1_val	f1_train_a	f1_val_at_	pr_auc_va	best_threshold
LogisticRe	0.068293	0.061695	0.793103	0.793296	0.717582	0.999988

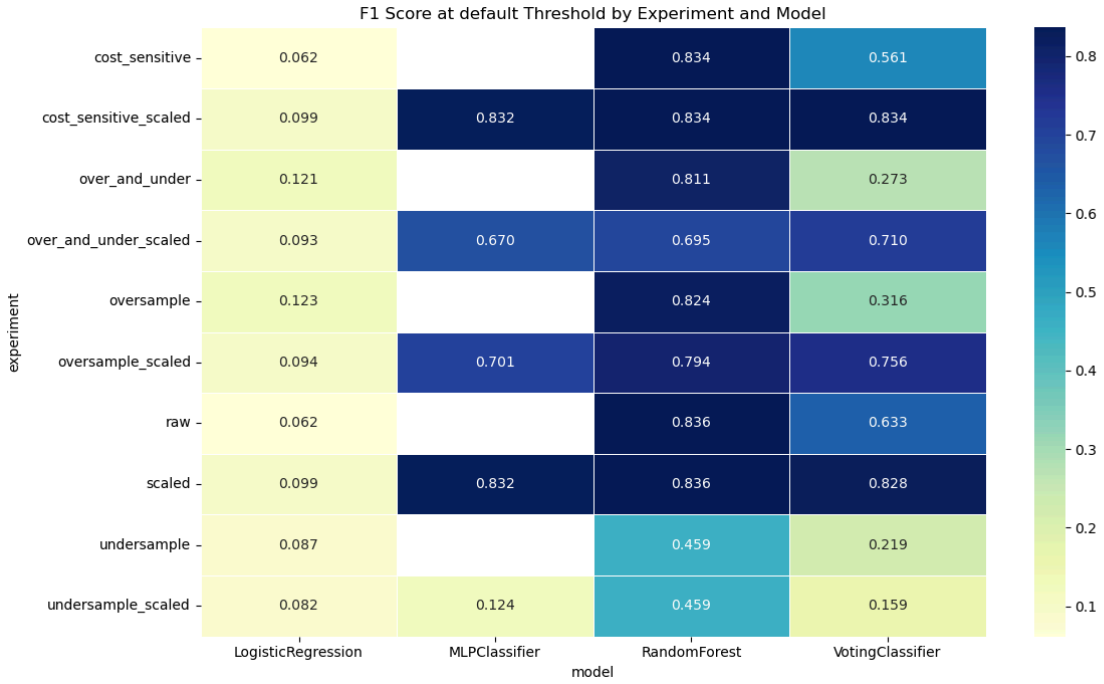
- **confusion matrix for default threshold (0.5) :**



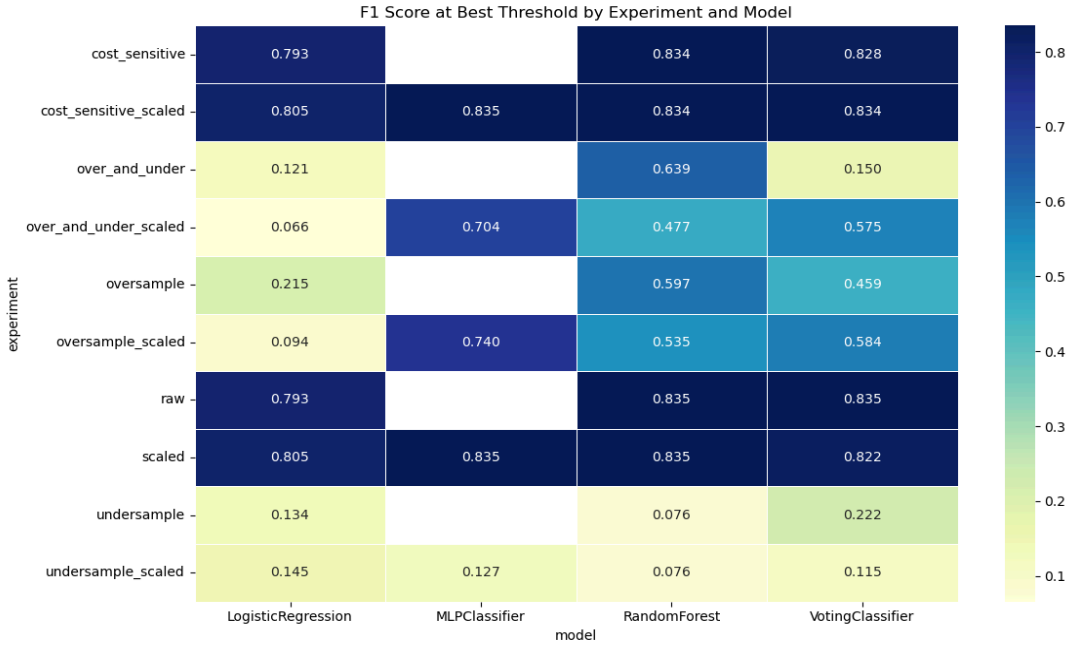
- **confusion matrix for default threshold (0.999) :**



7- Results for all models and experiments are based on the default threshold applied to the validation dataset.



8- Results for all models and experiments are based on the optimized threshold applied to the validation dataset.



9- Conclusion

1- Sampling techniques are useless in this project, and they harm the model performance more than improve it, especially (undersampling)

2- You should apply (RandomizedSearchCV) to determine the best parameters for your models. This will help you get the best performance