Finclub Summer Project 2 (2025) Report

Title: Credit Card Behaviour Score Prediction Using Classification and Risk-Based Techniques

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1. Project Overview

This report presents a credit card behaviour score prediction model designed to identify potential defaulters using behavioural data. The primary objective is to build a binary classification model using financial variables to predict whether a customer will default in the next billing cycle. This approach allows the bank to proactively manage risk exposure.

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2. Data Loading and Cleaning

- Training and test datasets were loaded using pandas.
- Missing values were imputed using the **median** of each column.
- Data types were confirmed, and irrelevant columns (e.g., BILL_AMT series) were removed due to high correlation with other features.

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3. Exploratory Data Analysis (EDA)

Several plots and analyses were conducted:

- **Sex vs Default:** Females showed a slightly higher default rate than males.
- **Age vs Default:** Younger customers had a higher likelihood of defaulting.
- **Limit Balance by Default Status & Sex:** A violin plot revealed that defaulters generally had lower credit limits.
- **Payment Delays:** PAY_0 to PAY_6 values were analyzed; defaulters exhibited frequent delays.
- **Repayment Consistency:** Irregular payment behaviour was common among defaulters.
- **Feature Correlation:** Features like BILL_AMT1 to BILL_AMT6 were highly correlated and thus removed.

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4. Feature Engineering

Custom financial features were created to enhance predictive power:

- **Credit Utilization Ratio**: Ratio of average bill amount to credit limit.
- **Maximum & Average Delay**: From PAY_0 to PAY_6.
- **Delinquency Streaks**: Number of consecutive months with overdue payments.

These engineered features captured customer behaviour patterns better than raw variables.

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5. Data Preprocessing

- **Scaling**: StandardScaler was used for all numerical features.
- **Balancing**: Addressed class imbalance using **SMOTE** to synthesize minority (defaulter) samples.
- **Splitting**: The training data was split into 80% train and 20% validation sets.

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6. Model Training and Evaluation

Five models were trained and evaluated:

Logistic Regression

- Performed moderately with balanced precision and recall.

Decision Tree

- Captured non-linear trends but prone to overfitting.

Support Vector Machine (SVM)

- More accurate but computationally expensive.

XGBoost

- High accuracy and recall captured complex interactions well.

Neural Network (Dense Layers)

- A shallow feed-forward neural net performed decently but required tuning.

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7. Final Model: Ensemble Approach

The final prediction model was an **ensemble of SVM, XGBoost, and Neural Network**. Each model contributed to the final prediction via soft voting based on predicted probabilities. This ensemble leveraged:

- SVM's robustness to high-dimensional spaces
- XGBoost's performance in handling tabular and imbalanced data
- Neural Network's ability to capture non-linear patterns

This combined approach yielded the best generalization and balance of performance.

Key metrics on the validation set:

- **Accuracy**: ~93.21%
- **Precision**: 0.8876
- **Recall**: 0.9894

- **F1 Score**: 0.9358
- **F2 Score**: 0.9672
- **AUC-ROC**: 0.9862

The classification threshold was tuned to **0.37** to prioritize recall over precision, minimizing missed defaulters.

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8. Financial Insights

Financial analysis revealed significant trends and behavioural indicators linked to default risk:

- **Overdue Payments (PAY_0 to PAY_6):** Strong predictors of future default. Customers with values ≥1 in recent months were much more likely to default.
- **Repayment Behaviour:** Irregular or minimum-only payments suggest credit stress and increase default likelihood.
- **Credit Utilization:** High utilization ratios implied that customers were heavily dependent on credit, often correlating with repayment issues.
- **Delinquency Patterns:** Consecutive overdue months (streaks) were common among defaulters and proved to be a critical derived feature.
- **PAY_TO_BILL Ratio:** Low ratio indicated either low repayment capacity or intention, both indicative of high risk.

These financial behaviours not only helped improve model accuracy but also provided explainable, actionable insights for credit risk teams.

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9. Evaluation Methodology

The model was evaluated using multiple metrics on a validation split from the training set:

- **Accuracy** captured overall performance.
- **Precision** highlighted how many of the flagged defaulters were correct.
- **Recall** emphasized the model's ability to catch actual defaulters.
- **F1 Score** balanced precision and recall.
- **F2 Score** (weighted towards recall) was prioritized, aligning with the business goal of minimizing missed defaults.

We used an **80-20 split** for train-validation and tuned the classification threshold to **0.37** using grid search to maximize the F2.

This threshold optimization directly influenced recall, allowing the model to detect more actual defaulters while keeping false positives in check.

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10. Business Implications

- **True Positives** (correctly identified defaulters): Allow early risk mitigation actions.
- **False Positives**: May inconvenience some customers but acceptable in conservative credit management.
- **False Negatives**: Pose significant financial risks; thus, threshold was optimized to reduce them.

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11. Summary and Learnings

- Feature engineering with financial insight significantly boosted model performance.
- SMOTE effectively addressed class imbalance without overfitting.
- The ensemble model outperformed individual classifiers in generalization.
- Metric selection (F2 Score) was aligned with credit risk priorities.
- Threshold tuning enhanced the model's operational value.

Final Submission Includes:

- Submission_22323025.csv
- Cleaned Jupyter notebook
- This descriptive report

End of Report