Credit Card Default Prediction

Insight Report for XYZ Bank

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Client: XYZ Bank

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Project Overview

XYZBank seeks to reduce loan and credit losses by identifying customers likely to default on credit card payments within the next month4before missed payments occur.

Current Challenge

Defaults detected only after missed payments, resulting in revenue loss, elevated collection costs, and cash flow disruption.

Strategic Objective

Use historical data to predict defaulters in advance, enabling early payment reminders, risk-based credit limit adjustments, and enhanced overall risk management.

Data Overview

Dataset Specifications

Source: UCI Credit Card Default Dataset (Taiwan)

Record Count: 30,000 customer profiles

Target Variable: DEFAULT (1 = Default, 0 = No Default)

Key Features

- **LIMIT_BAL:** Customer credit limit
- **AGE:** Customer age
- **BILL_AMT1:** Current month bill
- **PAY_AMT1:** Last month payment
- **PAY_0:** Payment delay (months)

Key Insights from Data Analysis

Age Profile Risk

Customers under30 are **1.4× more likely** to default than older demographics. Consider smaller credit limits or co-signer requirements.

Payment Behavior

Lowpayment-to-billratio (<40%) indicates poor repayment capacity. These customers warrant early payment reminders and enhanced monitoring.

Payment History

Three or more pastpayment delays is a strong predictive indicator. High-risk group requiring credit limit reduction or additional collateral.

Power BI Visualization Approach

Interactivedashboardscombiningmultiplevisualizationtechniquestosurfaceactionable credit risk insights across customer segments.

Comparative Analysis

Bar and column charts comparing default rates by age, education, and payment behavior segments.

Trend Monitoring

Line charts tracking monthly payment patterns and default trends across the six-month observation window.

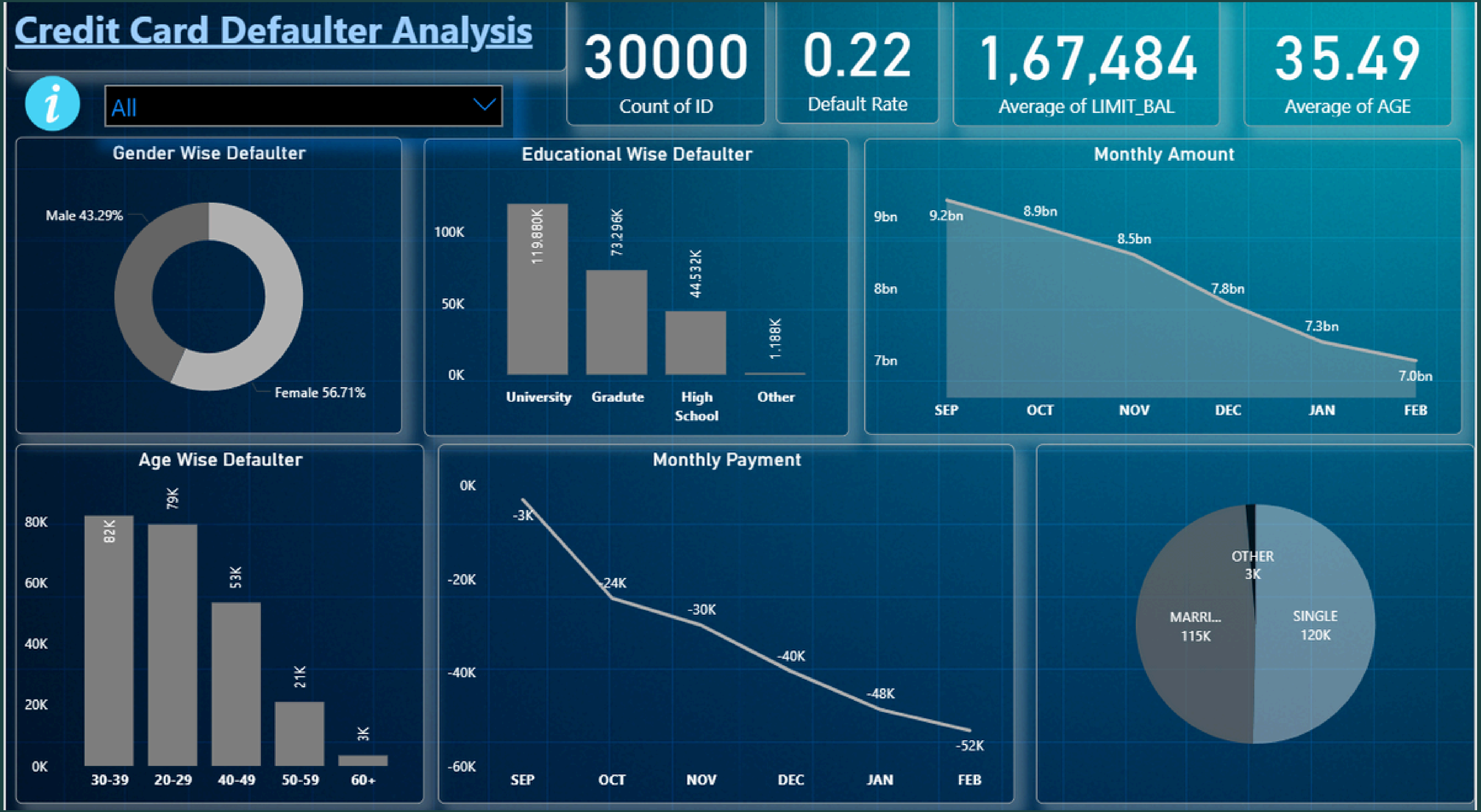
Segment Distribution

Pie and donut charts displaying category proportions including marital status, education, and payment behavior classifications.

Key Metrics

KPI cards highlighting total customers, overall default rate, average credit limit, and average customer age for quick reference.

Dashboard



Credit Card Defaulter Analysis
All
30000
Count of ID
0.22
Default Rate
1,67,484
Average of LIMIT_BAL
35.49
Average of AGE
Gender Wise Defaulter
Male 43.29%
Female 56.71%
Educational Wise Defaulter
100K
50K
0K
119.880K
73.296K
44.532K
1.188K
University
Gradute
High School
Other
Monthly Amount
9bn
8bn
7bn
9.2bn
8.9bn
8.5bn
7.8bn
7.3bn
7.0bn
SEP
OCT
NOV
DEC
JAN
FEB
Age Wise Defaulter
80K
60K
40K
20K
0K
82K
79K
53K
21K
3K
30-39
20-29
40-49
50-59
60+
Monthly Payment
0K
-20K
-40K
-60K
-3K
-24K
-30K
-40K
-48K
-52K
SEP
OCT
NOV
DEC
JAN
FEB
OTHER
3K
MARRI...
115K
SINGLE
120K

Default Rate Analysis

Python Analytics Results: Ageand Payment Behavior Insights

25%

Highest Risk

Younger customers (20-30 years) show peak default rates.

3X

Payment Ratio Impact

Customers paying <40% of bills are significantly more likely to default.

78%

Model Accuracy

Predictive model achieves approximately 78% accuracy in default identification.

Business Recommendations

Strategic interventions across credit policy,customer engagement,and collections to reduce default rates and optimize risk management.

1

Credit Policy

Reduce credit limits for customers with repeated payment delays or low payment-to-bill ratios.

Expected Impact: 15320% reduction in credit losses

2

Customer Engagement

Deploy SMS/email payment reminders 3 days before due dates for high-risk customer segments.

Expected Impact: -10% increase in on-time payments

3

Collections Optimization

Prioritize collection calls using predicted defaulter list for efficient resource allocation.

Expected Impact: Improved recovery rates and efficiency

4

Product Innovation

Offer EMI-based repayment plans for high-risk customers to improve affordability.

Expected Impact: Higher customer retention and reduced defaults

Model Deployment Plan

Five-step implementation road mapenablingreal-timedefault prediction and continuous monitoring.

Export Model

Serialize trained model (model.pkl) from Python environment.

Dashboard Integration

Integrate model into bank's CRM or analytics dashboard for accessibility.

Automated Updates

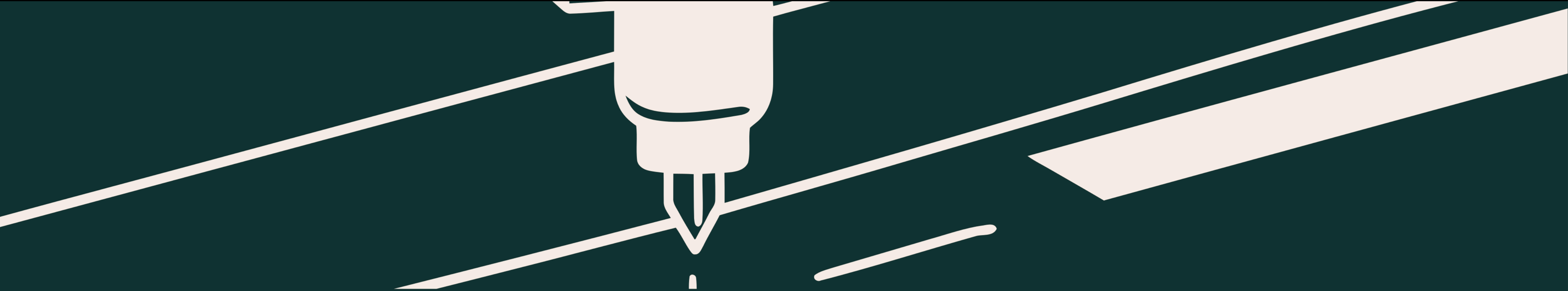
Configure auto-refresh predictions every billing cycle.

Data Storage

Store predictions in database for audit trail and monitoring.

Real-Time Capability

Enable seamless prediction updates as new customer data arrives monthly.



Limitations & Future Enhancement

Currentmodelconstraintsandrecommendednextstepstoimprovepredictiveaccuracy and operational utility.

Current Limitations

- Only 5 feature used
- Model is logical regression
- Accuracy < 85%
- Dataset static

Recommended Enhancements

- Add more behaviour data (income, transections)
- Test with Random Forest for better accuracy
- Optimize sample data for balance
- Connect to live pipeline fir real_time prediction

Executive Summary

78% Predictive Accuracy

Successfully identified customers likely to defaulton credit card payments with in one month using historical credit data and advanced analytics.

Risk Reduction

Up to 20% potential reduction in bad debt exposure through proactive intervention.

Early Detection

High-risk customer profiles identified in advance before payment disruption occurs.

Strategic Optimization

Enhanced credit policies and collections strategies based on predictive insights.