Predictive Model Plan: Forecasting Customer Delinquency

This document outlines the proposed methodology for building, justifying, and evaluating a machine learning model to predict the likelihood of customer delinquency for Geldium. The plan was conceptualized using Google Gemini to scaffold the model logic, refine the justification, and structure the evaluation framework.

Step 1: Generated Model Logic

For this task, I would use a **Gradient Boosting Machine (GBM)**, such as an XGBoost or LightGBM implementation. This ensemble model builds decision trees sequentially, with each new tree correcting the errors of the previous one, resulting in a highly accurate and robust predictive tool. The model would ingest cleaned customer data, process it through the trained trees, and output a risk score between 0 and 1, indicating the probability of a customer becoming delinquent.

My top 5 input features, based on insights from the initial Exploratory Data Analysis (EDA), would be:

1. **no_of_past_due:** The strongest historical indicator of future payment problems.
2. **credit_score:** A comprehensive measure of a customer's creditworthiness.
3. **credit_utilization:** A key indicator of financial strain; high utilization is a significant risk factor.
4. **debt_to_income_ratio:** Measures a customer's ability to manage their debt payments relative to their income.
5. **monthly_income:** Represents the customer's capacity to service their debt obligations.

Step 2: Model Justification

The selection of a Gradient Boosting Machine is a strategic choice that balances high predictive accuracy with manageable interpretability, directly aligning with Geldium's primary goal of minimizing financial losses from delinquencies. While simpler models like logistic regression offer high transparency, they often fail to capture the complex, non-linear interactions between financial variables that GBMs excel at identifying. This superior accuracy means a more effective allocation of resources, allowing Geldium to focus interventions on the highest-risk customers. To address the "black box" nature of GBMs and satisfy regulatory needs for transparency, we will implement **SHAP (SHapley Additive exPlanations)**. This technique provides clear, human-readable explanations for each individual prediction, ensuring that we can justify any decision made based on the model's output, thus meeting both business performance and compliance requirements.

Step 3: Model Performance Evaluation Strategy

A multi-faceted evaluation strategy is crucial to ensure the model is not only accurate but also reliable and fair. Since delinquency is often a rare event, the dataset will be imbalanced, making standard accuracy a misleading metric.

My evaluation strategy is therefore focused on the following key metrics:

- **Accuracy & Reliability Metrics:**
    - **AUC (Area Under the ROC Curve):** This will be my primary metric for overall model performance. It measures the model's ability to correctly distinguish between delinquent and non-delinquent customers across all probability thresholds. An AUC closer to 1.0 indicates a highly effective model.
    - **F1-Score:** This metric provides a balance between Precision (minimizing false positives) and Recall (minimizing false negatives). It's crucial for finding an optimal probability threshold that effectively identifies at-risk customers (high Recall) without incorrectly flagging too many creditworthy customers (high Precision).
- **Fairness & Bias Checks:**
    - **Fairness Checks:** To ensure the model does not unfairly penalize specific customer segments, I will conduct a bias assessment. The core metric for this will be **Equalized Odds**. This involves checking that the model's true positive rate and false positive rate are consistent across different groups (e.g., customers from different income brackets or with different loan term lengths). Significant deviations would indicate bias and require model retraining or the application of mitigation techniques.

By interpreting these metrics together, we can confidently deploy a model that is not only a powerful predictor of risk but also a fair and responsible tool for the business.