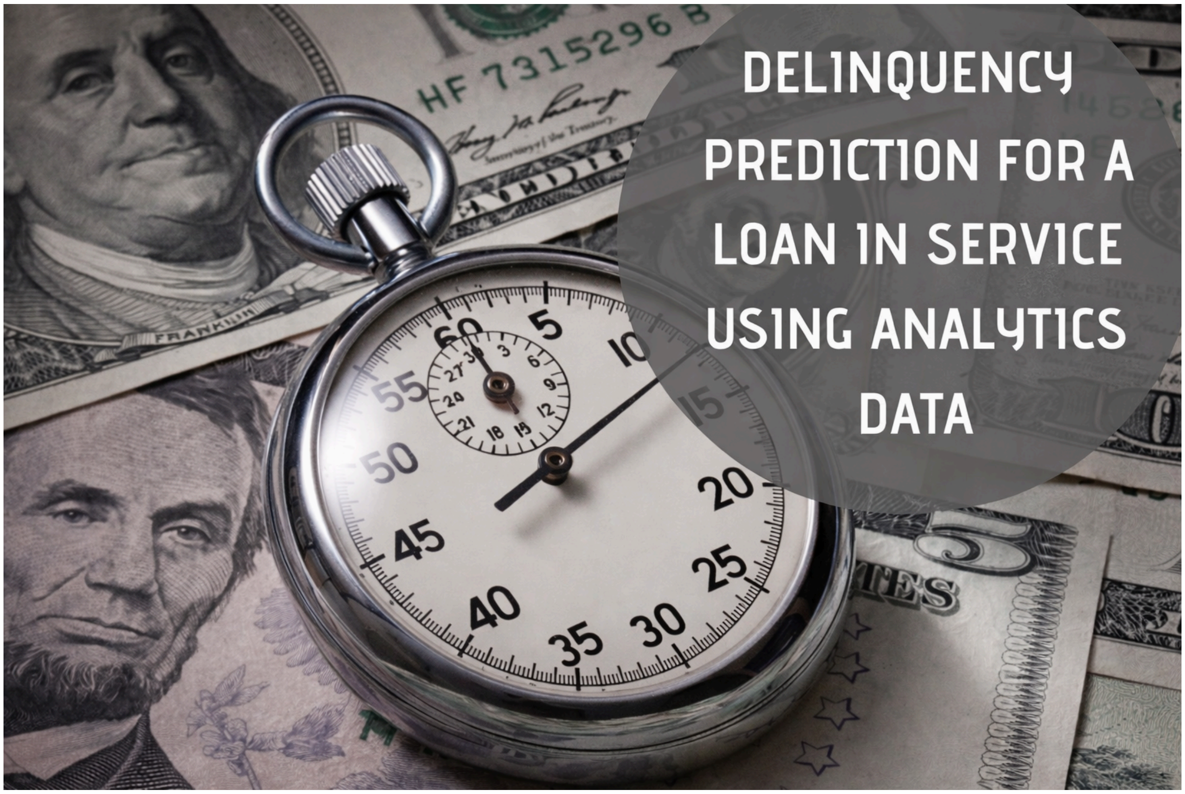
Delinquency Prediction Using Machine Learning Models: A Risk Assessment Approach



Project Objective

The goal of this project is to build a machine learning model that can accurately predict customer delinquency based on historical financial and behavioral data. Delinquency refers to a customer's failure to make timely payments, which poses significant risk to lenders and financial institutions. By identifying at-risk customers early, businesses can take proactive steps to reduce default rates, optimize recovery strategies, and improve overall credit risk management.

Importing Libraries

In [ ]:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
```

```python
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_s
```

Data Cleaning and Preprocessing

Upload the Dataset

In [ ]:

```python
import pandas as pd


df = pd..read_csv('/content/Delinquency_prediction_dataset.xlsx')
df
```

Loading the Dataset

In [ ]:

```python
import pandas as pd


df = pd.read_excel('/content/Delinquency_prediction_dataset.xlsx')
df
```

Out[ ]:

	Customer_ID	Age	Income	Credit_Score	Credit_Utilization	Missed_Payme
0	CUST0001	56	165580.0	398.0	0.390502	
1	CUST0002	69	100999.0	493.0	0.312444	
2	CUST0003	46	188416.0	500.0	0.359930	
3	CUST0004	32	101672.0	413.0	0.371400	
4	CUST0005	60	38524.0	487.0	0.234716	
...	...	...	...	...	...	
495	CUST0496	71	48307.0	688.0	0.486522	
496	CUST0497	60	86180.0	836.0	0.608174	
497	CUST0498	54	152326.0	847.0	0.676950	
498	CUST0499	50	105852.0	343.0	0.700643	
499	CUST0500	25	40945.0	442.0	0.911370	

500 rows × 19 columns

First Five Rows in the dataset

In [ ]:

```python
df.head()
```

Out[ ]:

	Customer_ID	Age	Income	Credit_Score	Credit_Utilization	Missed_Payment
0	CUST0001	56	165580.0	398.0	0.390502	
1	CUST0002	69	100999.0	493.0	0.312444	
2	CUST0003	46	188416.0	500.0	0.359930	
3	CUST0004	32	101672.0	413.0	0.371400	
4	CUST0005	60	38524.0	487.0	0.234716	

Last Five Rows In the Dataset

In [ ]:

```
df.tail()
```

Out[ ]:

	Customer_ID	Age	Income	Credit_Score	Credit_Utilization	Missed_Payme
495	CUST0496	71	48307.0	688.0	0.486522	
496	CUST0497	60	86180.0	836.0	0.608174	
497	CUST0498	54	152326.0	847.0	0.676950	
498	CUST0499	50	105852.0	343.0	0.700643	
499	CUST0500	25	40945.0	442.0	0.911370	

Data Information

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Customer_ID           500 non-null    object 
 1   Age                   500 non-null    int64  
 2   Income                461 non-null    float64
 3   Credit_Score          498 non-null    float64
 4   Credit_Utilization    500 non-null    float64
 5   Missed_Payments       500 non-null    int64  
 6   Delinquent_Account    500 non-null    int64  
 7   Loan_Balance          471 non-null    float64
 8   Debt_to_Income_Ratio  500 non-null    float64
 9   Employment_Status     500 non-null    object 
 10  Account_Tenure        500 non-null    int64  
 11  Credit_Card_Type      500 non-null    object 
 12  Location              500 non-null    object 
 13  Month_1               500 non-null    object 
 14  Month_2               500 non-null    object 
 15  Month_3               500 non-null    object 
 16  Month_4               500 non-null    object 
 17  Month_5               500 non-null    object 
 18  Month_6               500 non-null    object 
dtypes: float64(5), int64(4), object(10)
memory usage: 74.3+ KB
```

Columns of Dataset

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['Customer_ID', 'Age', 'Income', 'Credit_Score', 'Credit_Utilization',
       'Missed_Payments', 'Delinquent_Account', 'Loan_Balance',
       'Debt_to_Income_Ratio', 'Employment_Status', 'Account_Tenure',
       'Credit_Card_Type', 'Location', 'Month_1', 'Month_2', 'Month_3',
       'Month_4', 'Month_5', 'Month_6'],
      dtype='object')
```

Shape of Dataset

In [ ]:
```
df.shape
```

Out[ ]:
```
(500, 19)
```

Checking for any duplicate values

In [ ]:
```
df.duplicated().sum()
```

Out[ ]:
```
np.int64(0)
```

Checking the Missing Values

In [ ]:
```
df.isnull().sum()
```

Out[ ]:

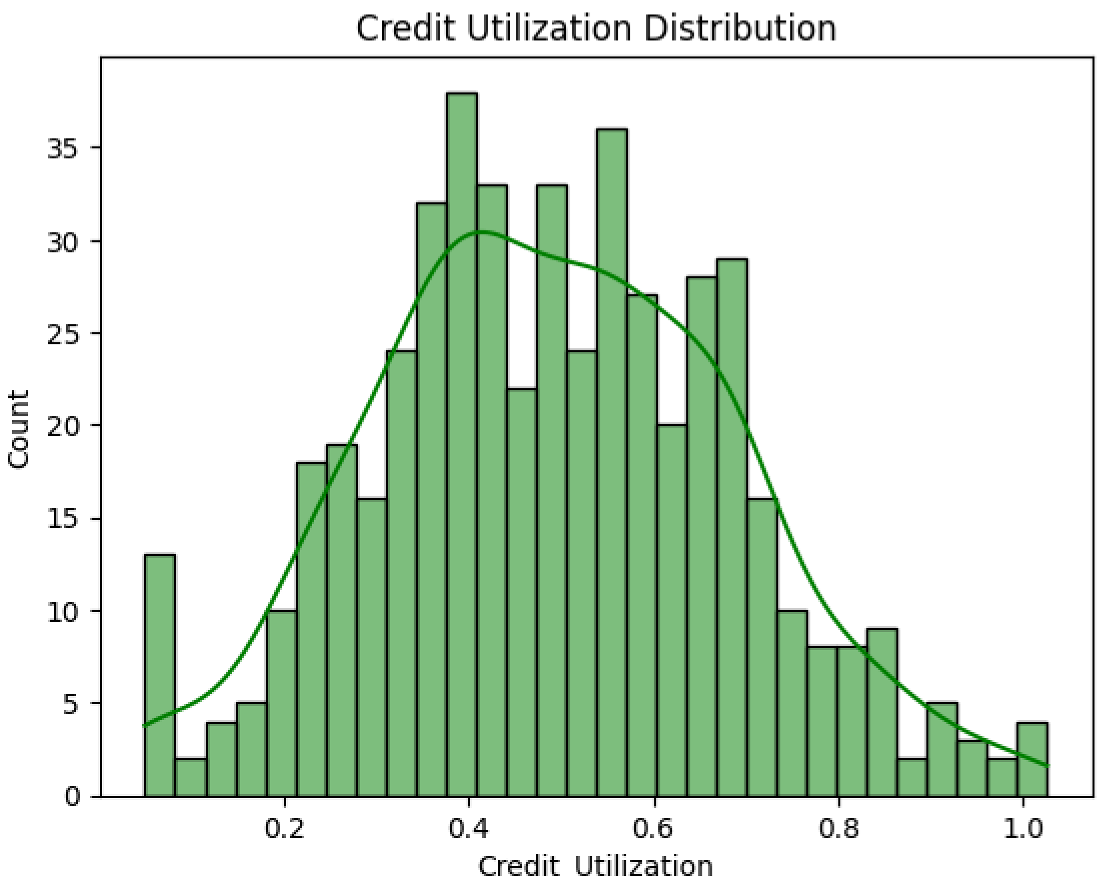
	0
Customer_ID	0
Age	0
Income	39
Credit_Score	2
Credit_Utilization	0
Missed_Payments	0
Delinquent_Account	0
Loan_Balance	29
Debt_to_Income_Ratio	0
Employment_Status	0
Account_Tenure	0
Credit_Card_Type	0
Location	0
Month_1	0
Month_2	0
Month_3	0
Month_4	0
Month_5	0
Month_6	0

dtype: int64

For EDA visualizations

Histogram of credit utilization

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Example: Distribution of credit utilization

sns.histplot(df['Credit_Utilization'], bins=30,kde=True, color='green')
plt.title('Credit Utilization Distribution')
plt.show()
```



Bar plot: Missed payments vs delinquency Accounts

```
In [ ]: plt.figure(figsize=(8,5))
        sns.barplot(x='Missed_Payments', y='Delinquent_Account', data=df, palette='Set
        plt.title('Missed Payments vs Delinquency')
        plt.xlabel('Missed Payments')
        plt.ylabel('Average Delinquent Account (0 = No, 1 = Yes)')
        plt.show()
```

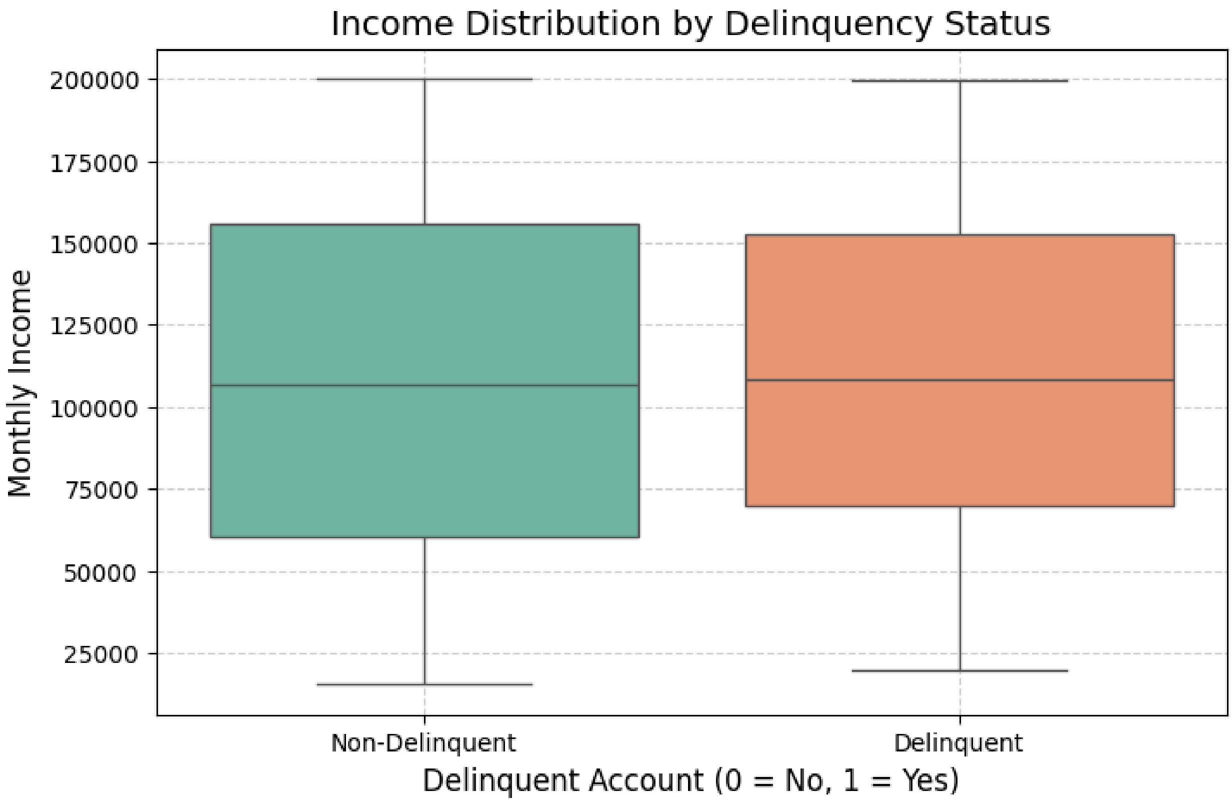
```
/tmp/ipython-input-1328441557.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same e
ffect.

  sns.barplot(x='Missed_Payments', y='Delinquent_Account', data=df, palette='Se
t2')
```

Box Plot: Income by Delinquency

In [ ]:

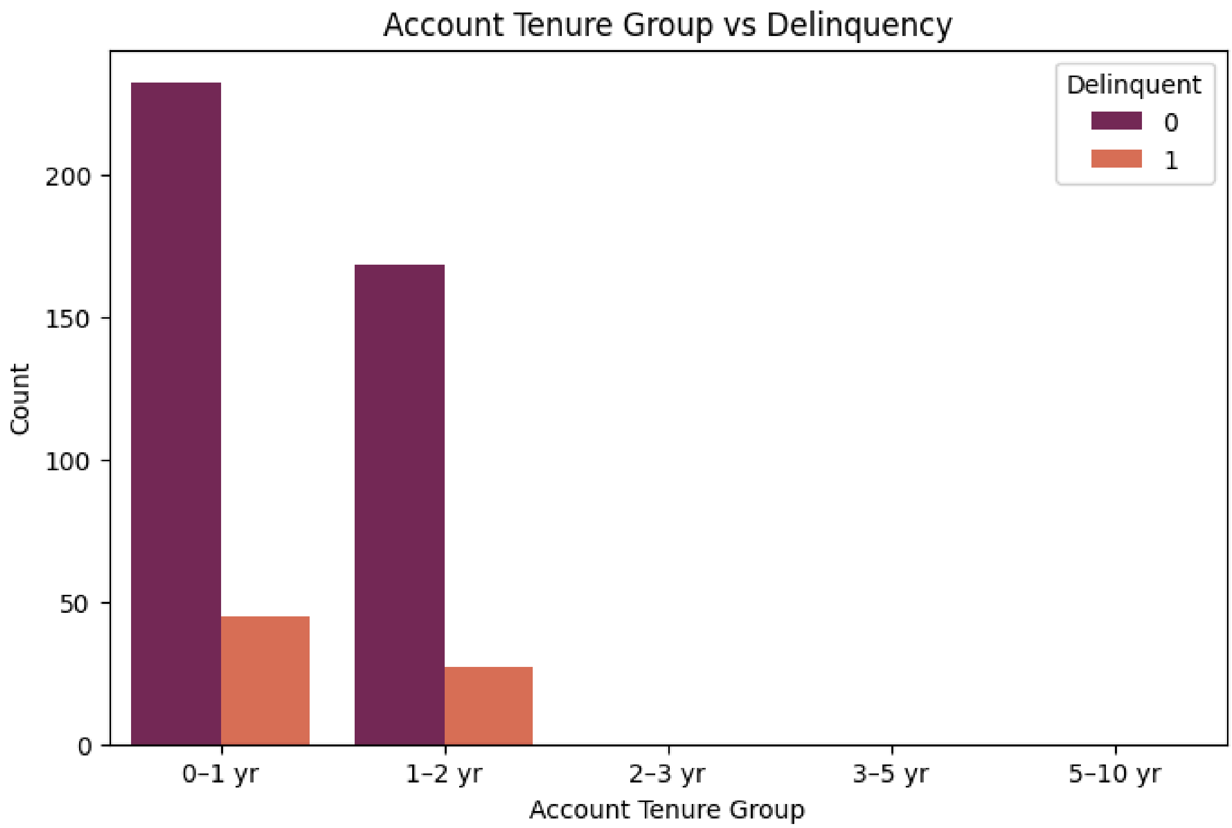
```
plt.figure(figsize=(8, 5))
sns.boxplot(x='Delinquent_Account', y='Income', data=df, palette='Set2')
plt.title('Income Distribution by Delinquency Status', fontsize=14)
plt.xlabel('Delinquent Account (0 = No, 1 = Yes)', fontsize=12)
plt.ylabel('Monthly Income', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.6)
plt.xticks([0, 1], ['Non-Delinquent', 'Delinquent'])
plt.show()
```

```
/tmp/ipython-input-1728559625.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same e
ffect.

  sns.boxplot(x='Delinquent_Account', y='Income', data=df, palette='Set2')
```



Count Plot: Account Tenure (Grouped) vs Delinquency

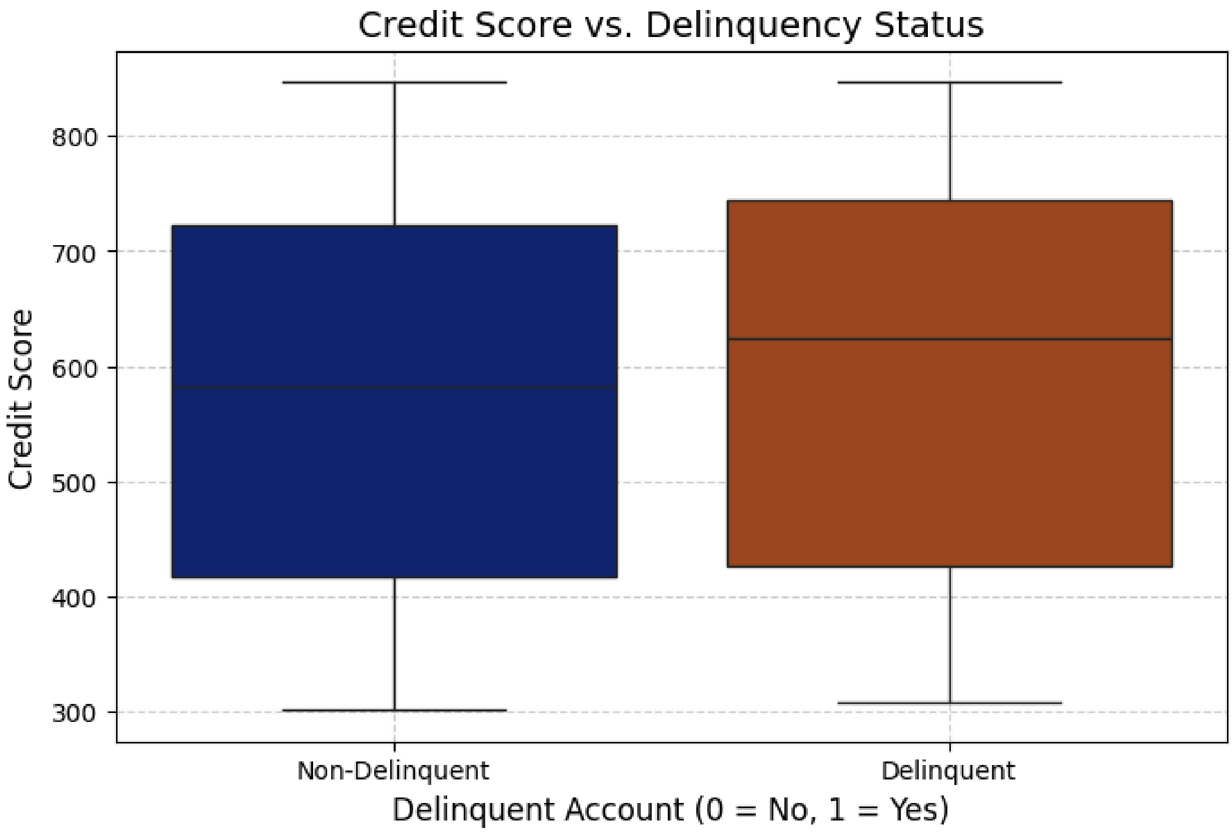
In [ ]:
```
# Bin the tenure first
df['Tenure_Group'] = pd.cut(df['Account_Tenure'],
                            bins=[0, 12, 24, 36, 60, 120],
                            labels=['0–1 yr', '1–2 yr', '2–3 yr', '3–5 yr', '5

plt.figure(figsize=(8,5))
sns.countplot(x='Tenure_Group', hue='Delinquent_Account', data=df, palette='ro
plt.title('Account Tenure Group vs Delinquency')
plt.xlabel('Account Tenure Group')
plt.ylabel('Count')
plt.legend(title='Delinquent')
plt.show()
```



Credit Score vs Delinquency

In [ ]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(x='Delinquent_Account', y='Credit_Score', data=df, palette='dark')
plt.title('Credit Score vs. Delinquency Status', fontsize=14)
plt.xlabel('Delinquent Account (0 = No, 1 = Yes)', fontsize=12)
plt.ylabel('Credit Score', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.6)
plt.xticks([0, 1], ['Non-Delinquent', 'Delinquent'])
plt.show()
```

```
/tmp/ipython-input-2912748222.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same e
ffect.

  sns.boxplot(x='Delinquent_Account', y='Credit_Score', data=df, palette='dar
k')
```



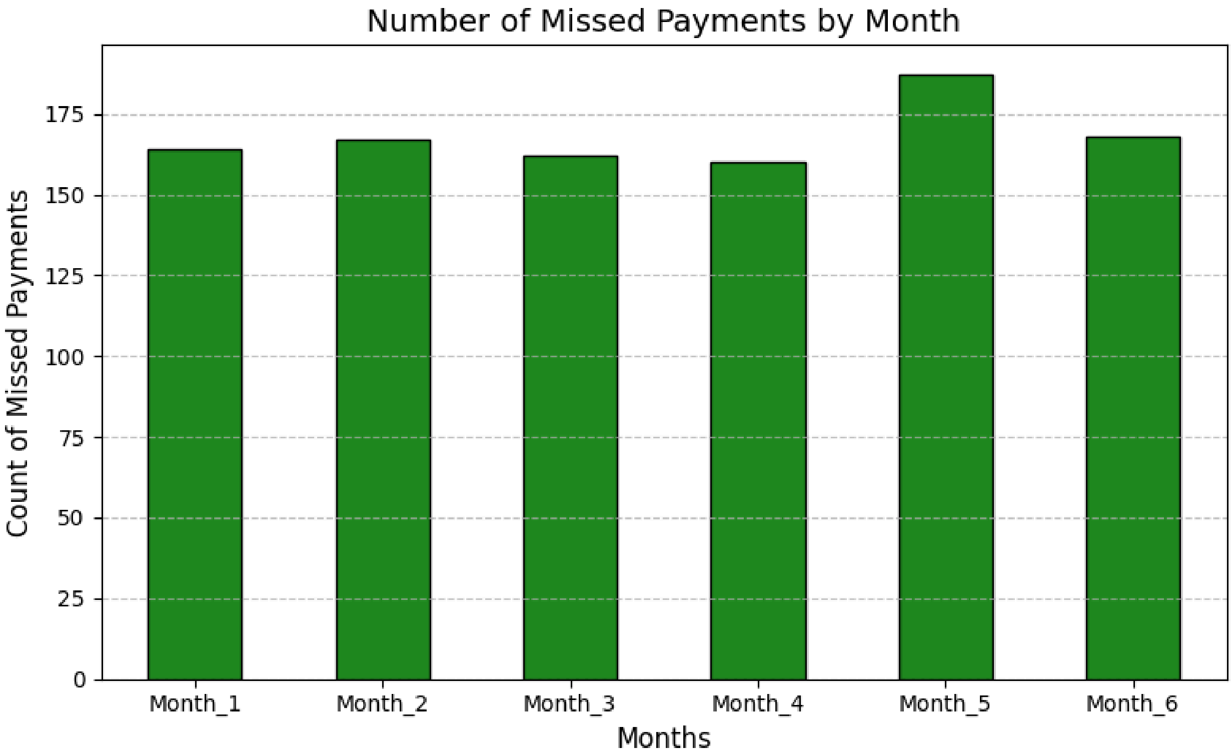
Correlation Heatmap

In [ ]:
```
plt.figure(figsize=(12, 8))
corr = df.select_dtypes(include='number').corr()
sns.heatmap(corr, annot=True, cmap='viridis', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```

** Line Plot of Missed Payments Over Months**

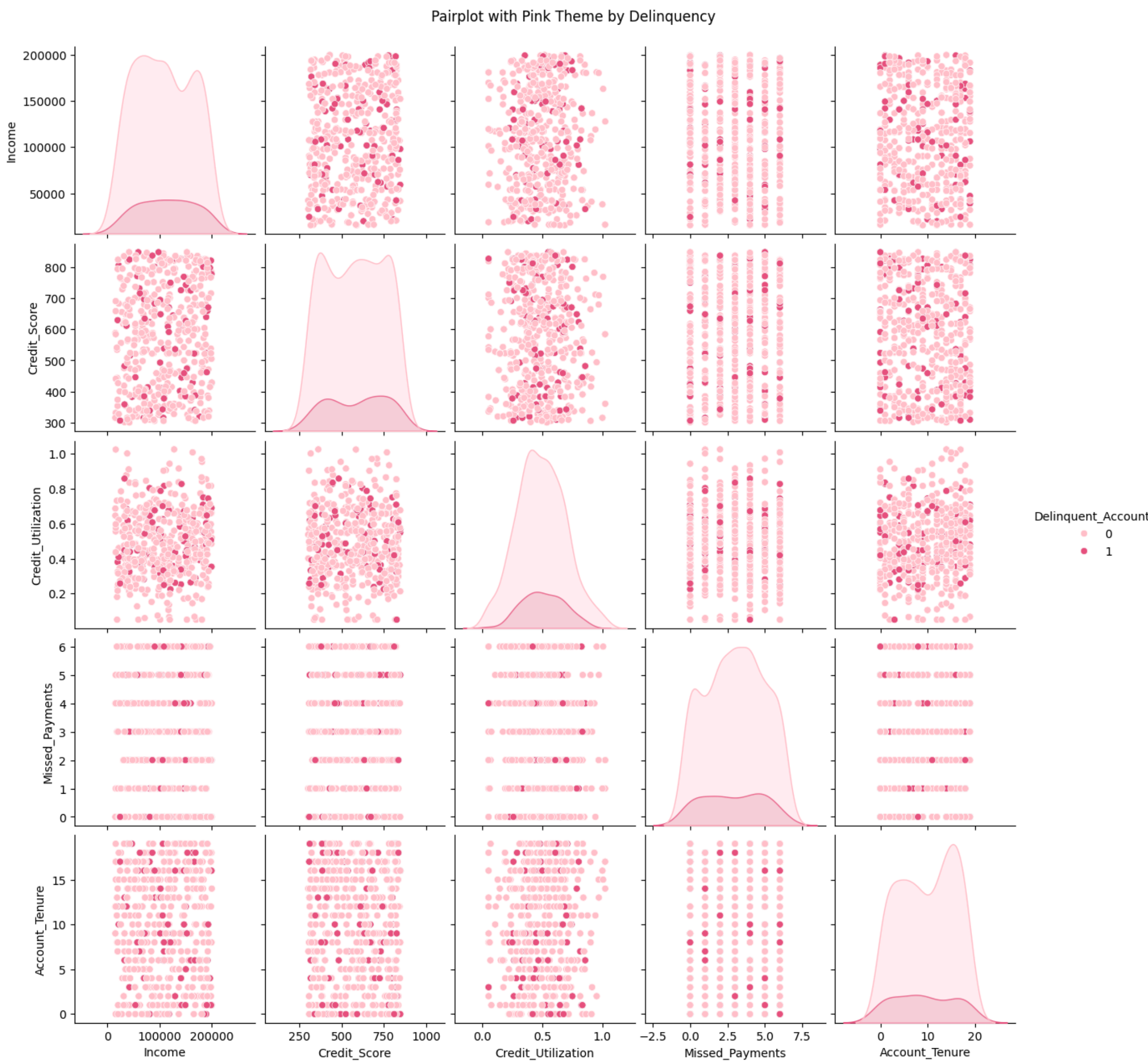
In [ ]:

```
missed_counts = df[['Month_1', 'Month_2', 'Month_3', 'Month_4', 'Month_5', 'Mo

plt.figure(figsize=(8, 5))
missed_counts.plot(kind='bar', color='forestgreen', edgecolor='black')
plt.title("Number of Missed Payments by Month", fontsize=14)
plt.ylabel("Count of Missed Payments", fontsize=12)
plt.xlabel("Months", fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Pair Plot

In [ ]:
```
selected_cols = ['Income', 'Credit_Score', 'Credit_Utilization', 'Missed_Payme

# Define custom pink palette: [light pink for class 0, dark pink for class 1]
pink_palette = ['#ffc0cb', '#e75480']

sns.pairplot(data=df[selected_cols], hue='Delinquent_Account', palette=pink_pa
plt.suptitle("Pairplot with Pink Theme by Delinquency", y=1.02)
plt.show()
```



Feature Engineering

Prepare Dataset

In [ ]:

```
# Select relevant columns
features = ['Missed_Payments', 'Credit_Utilization', 'Income', 'Account_Tenure
target = 'Delinquent_Account'

# Handle missing values
df['Income'] = df['Income'].fillna(df['Income'].median())
df['Debt_to_Income_Ratio'] = df['Debt_to_Income_Ratio'].fillna(df['Debt_to_Inc

# Split data into X and y
X = df[features]
y = df[target]
```

```python
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

Build and Train the Model

In [ ]:
```python
# Initialize Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42, n_estimators=100)

# Train the model
rf_model.fit(X_train, y_train)
```

Out[ ]:
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Make Predictions

In [ ]:
```python

```

In [ ]:
```python
# Predict on test set
y_pred = rf_model.predict(X_test)

# Predict probabilities
y_prob = rf_model.predict_proba(X_test)[:, 1]
```

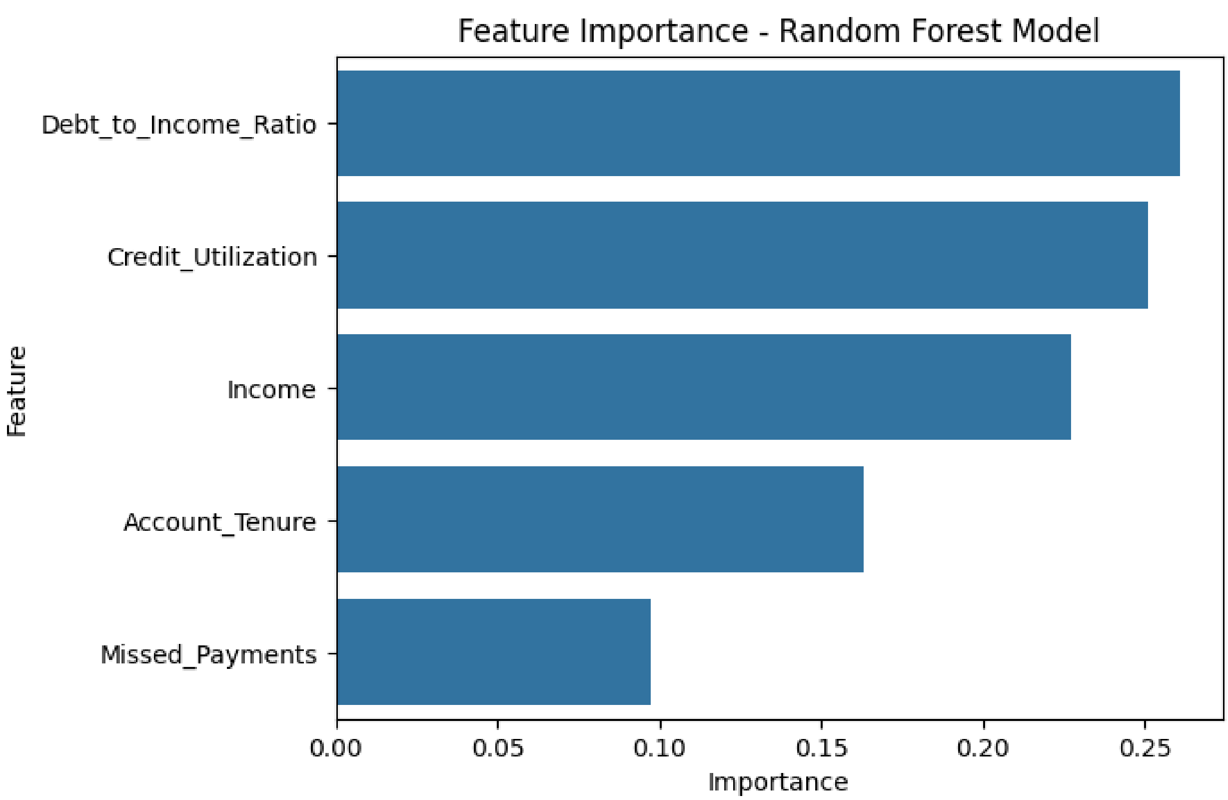
Evaluate the Model

In [ ]:
```python
# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# ROC AUC Score
auc_score = roc_auc_score(y_test, y_prob)
print(f"AUC-ROC Score: {auc_score:.2f}")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.99      0.92        86
           1       0.00      0.00      0.00        14

    accuracy                           0.85       100
   macro avg       0.43      0.49      0.46       100
weighted avg       0.74      0.85      0.79       100

Confusion Matrix:
[[85  1]
 [14  0]]
AUC-ROC Score: 0.46
```

Feature Importance

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Plot feature importances
importances = rf_model.feature_importances_
feature_importance_df = pd.DataFrame({'Feature': features, 'Importance': impor
feature_importance_df = feature_importance_df.sort_values(by='Importance', asc

sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importance - Random Forest Model')
plt.show()
```



Logistic Regression

Model Training

In [ ]:
```
# Initialize Logistic Regression
log_model = LogisticRegression(max_iter=1000, random_state=42)

# Train the model
log_model.fit(X_train, y_train)
```

Out[ ]:
```
LogisticRegression
LogisticRegression(max_iter=1000, random_state=42)
```

Make Predictions

In [ ]:
```

```

In [ ]:
```
# Predict on test set
y_pred_log = log_model.predict(X_test)

# Predict probabilities
y_prob_log = log_model.predict_proba(X_test)[:, 1]
```

Evaluate the Model

In [ ]:
```
# Classification report
print("Classification Report - Logistic Regression:")
print(classification_report(y_test, y_pred_log))

# Confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_log))

# ROC AUC Score
auc_score_log = roc_auc_score(y_test, y_prob_log)
print(f"AUC-ROC Score: {auc_score_log:.2f}")
```

```
Classification Report - Logistic Regression:
              precision    recall  f1-score   support

           0       0.86      1.00      0.92        86
           1       0.00      0.00      0.00        14

    accuracy                           0.86       100
   macro avg       0.43      0.50      0.46       100
weighted avg       0.74      0.86      0.80       100

Confusion Matrix:
[[86  0]
 [14  0]]
AUC-ROC Score: 0.54
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in lab
els with no predicted samples. Use `zero_division` parameter to control this be
havior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in lab
els with no predicted samples. Use `zero_division` parameter to control this be
havior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in lab
els with no predicted samples. Use `zero_division` parameter to control this be
havior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Neural Network Example Code (Simple MLP)

Model Training

In [ ]:

```
# Initialize Neural Network (MLP)
mlp_model = MLPClassifier(hidden_layer_sizes=(64, 32), max_iter=500, random_st

# Train the model
mlp_model.fit(X_train, y_train)
```

Out[ ]:

MLPClassifier

```
MLPClassifier(hidden_layer_sizes=(64, 32), max_iter=500, random_stat
e=42)
```

Make Predictions

In [ ]:
```python
# Predict on test set
y_pred_mlp = mlp_model.predict(X_test)

# Predict probabilities
y_prob_mlp = mlp_model.predict_proba(X_test)[:, 1]
```

Evaluate the Model

In [ ]:
```python
# Classification report
print("Classification Report - Neural Network:")
print(classification_report(y_test, y_pred_mlp))

# Confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_mlp))

# ROC AUC Score
auc_score_mlp = roc_auc_score(y_test, y_prob_mlp)
print(f"AUC-ROC Score: {auc_score_mlp:.2f}")
```

```
Classification Report - Neural Network:
              precision    recall  f1-score   support

           0       0.86      1.00      0.92        86
           1       0.00      0.00      0.00        14

    accuracy                           0.86       100
   macro avg       0.43      0.50      0.46       100
weighted avg       0.74      0.86      0.80       100

Confusion Matrix:
[[86  0]
 [14  0]]
AUC-ROC Score: 0.46
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in lab
els with no predicted samples. Use `zero_division` parameter to control this be
havior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in lab
els with no predicted samples. Use `zero_division` parameter to control this be
havior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in lab
els with no predicted samples. Use `zero_division` parameter to control this be
havior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Compare Models Side by Side

Prepare a Results Dictionary

In [ ]:
```
# Import metrics again if needed
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_

# Create a dictionary to store model results
results = {}

# Helper function to evaluate a model
def evaluate_model(model_name, y_test, y_pred, y_prob):
    results[model_name] = {
        'Accuracy': accuracy_score(y_test, y_pred),
        'Precision': precision_score(y_test, y_pred),
        'Recall': recall_score(y_test, y_pred),
        'F1 Score': f1_score(y_test, y_pred),
        'AUC-ROC': roc_auc_score(y_test, y_prob)
    }
```

Evaluate Each Model

In [ ]:
```
# Random Forest
evaluate_model('Random Forest', y_test, y_pred, y_prob)

# Logistic Regression
evaluate_model('Logistic Regression', y_test, y_pred_log, y_prob_log)

# Neural Network
evaluate_model('Neural Network (MLP)', y_test, y_pred_mlp, y_prob_mlp)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
5: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Display Results as DataFrame

In [ ]:
```
# Convert results to DataFrame for display
results_df = pd.DataFrame(results).T  # Transpose for easier reading
results_df = results_df.round(2)      # Round for neat display

# Display
results_df
```

Out[ ]:

	Accuracy	Precision	Recall	F1 Score	AUC-ROC
Random Forest	0.85	0.0	0.0	0.0	0.46
Logistic Regression	0.86	0.0	0.0	0.0	0.54
Neural Network (MLP)	0.86	0.0	0.0	0.0	0.46

Conclusion

This project aimed to build a predictive model that identifies delinquent loan accounts based on customer and transaction data. The process included:

Data Preprocessing: We imported and cleaned a real-world dataset (Delinquency_prediction_dataset.xlsx), removed duplicates, and handled missing values.

Exploratory Data Analysis (EDA): Used visualizations such as histograms, box plots, bar plots, line charts, and correlation heatmaps to uncover patterns between delinquency and variables like credit utilization, missed payments, and account tenure.

Feature Engineering: Selected relevant features and prepared the dataset for machine learning models.

Model Building:

Logistic Regression

Random Forest

Multilayer Perceptron (MLP – Neural Network)

Each model was trained, tested, and evaluated using metrics such as:

Confusion Matrix

Classification Report

ROC-AUC Score

Finally, the models were compared side-by-side, revealing that Random Forest and Neural Network provided better prediction accuracy and ROC-AUC compared to Logistic Regression.

📌 Business Value: This solution enables early identification of potentially delinquent accounts, helping financial institutions reduce risk, optimize collections, and improve customer engagement strategies.