PROJECT TITLE: PREDICTING LOAN DEFAULTERS

PROBLEM STATEMENT:

Financial institutions face significant challenges in accurately assessing loan default risk. Traditional methods often fall short in today's complex financial landscape.

In response to this problem, we will develop a robust machine learning pipeline to predict loan default risk, enabling better credit decisions and minimizing financial losses.

Methodology

This study will adopt a supervised machine learning approach to address the problem. The process will begin with data understanding, EDA, data preprocessing, including handling missing values, duplicates, deriving insights, encoding categorical variables, and scaling numerical features to ensure comparability across different ranges.

Several supervised learning algorithms will be tested, including Support Vector Machines (SVM), Random Forest, Gradient Boosting, and Logistic Regression among others. Each model will be trained and validated using stratified k-fold cross-validation to ensure robustness and to account for class imbalance. Performance will be evaluated using multiple metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.

Feature engineering will be applied to derive new variables (e.g., borrower behavior categories) to improve predictive power. Feature importance analysis will also be conducted to identify the most influential predictors of loan default.

The final model will undergo hyperparameter tuning (via grid search) to optimize generalization performance. Lastly, the selected model will be evaluated on a held-out test set to provide an unbiased assessment of real-world predictive capability.

In [ ]:
```python
# IMPORTING LIBRARIES FOR ANALYSIS
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
```

In [ ]:
```python
cus_data = pd.read_csv('https://raw.githubusercontent.com/Oyeniran20/axia_cohort_8/
loan_hist = pd.read_csv('https://raw.githubusercontent.com/Oyeniran20/axia_cohort_8
loan_curr = pd.read_csv('https://raw.githubusercontent.com/Oyeniran20/axia_cohort_8
```

Customer Data

This data contains customer's personal information

The data will be cleaned in preparation for prediction and insights will be derived from it

In [ ]:
```
cus_data.head()
```

Out[ ]:

	customerid	birthdate	bank_account_type	longitude_gps
0	8a858e135cb22031015cbafc76964ebd	1973-10-10 00:00:00.000000	Savings	3.319219
1	8a858e275c7ea5ec015c82482d7c3996	1986-01-21 00:00:00.000000	Savings	3.325598
2	8a858e5b5bd99460015bdc95cd485634	1987-04-01 00:00:00.000000	Savings	5.746100
3	8a858efd5ca70688015cabd1f1e94b55	1991-07-19 00:00:00.000000	Savings	3.362850
4	8a858e785acd3412015acd48f4920d04	1982-11-22 00:00:00.000000	Savings	8.455332

In [ ]:
```
cus_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4346 entries, 0 to 4345
Data columns (total 9 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   customerid                  4346 non-null   object 
 1   birthdate                   4346 non-null   object 
 2   bank_account_type           4346 non-null   object 
 3   longitude_gps               4346 non-null   float64
 4   latitude_gps                4346 non-null   float64
 5   bank_name_clients           4346 non-null   object 
 6   bank_branch_clients         51 non-null     object 
 7   employment_status_clients   3698 non-null   object 
 8   level_of_education_clients  587 non-null    object 
dtypes: float64(2), object(7)
memory usage: 305.7+ KB
```

In [ ]:
```
cus_data.isna().sum()
```

Out[ ]:

	0
customerid	0
birthdate	0
bank_account_type	0
longitude_gps	0
latitude_gps	0
bank_name_clients	0
bank_branch_clients	4295
employment_status_clients	648
level_of_education_clients	3759

dtype: int64

Note: Bank_branch_client, employment_status_clients and Level_of_education has a lot of missing data

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

Out[ ]:
```
np.int64(12)
```

Note: Data has 12 duplicates

Data Cleaning

In [ ]:
```
#dropping columns with too much missing data
cus_data.drop(columns=['bank_branch_clients', 'level_of_education_clients'], inplac
```

The customer bank branch and education level columns were dropped due to excessive missing data (over 50%), which would have compromised both the quality of insights and the accuracy of predictive models.

In [ ]:
```
# filling missing employment status with not provided
cus_data['employment_status_clients'] = cus_data['employment_status_clients'].filln
```

A small number of records in the customer employment status column were missing. Given the importance of employment information in studying loan defaulters, these null values were imputed with 'Not Provided'. In addition, if missing columns were to be dropped, we will be left with little data for prediction as 648 will be gone

In [ ]:
```
#converting brithdate to datetime
cus_data['birthdate'] = pd.to_datetime(cus_data['birthdate'], errors='coerce')
```

In [ ]:
```
cus_data.drop_duplicates(inplace=True)
```

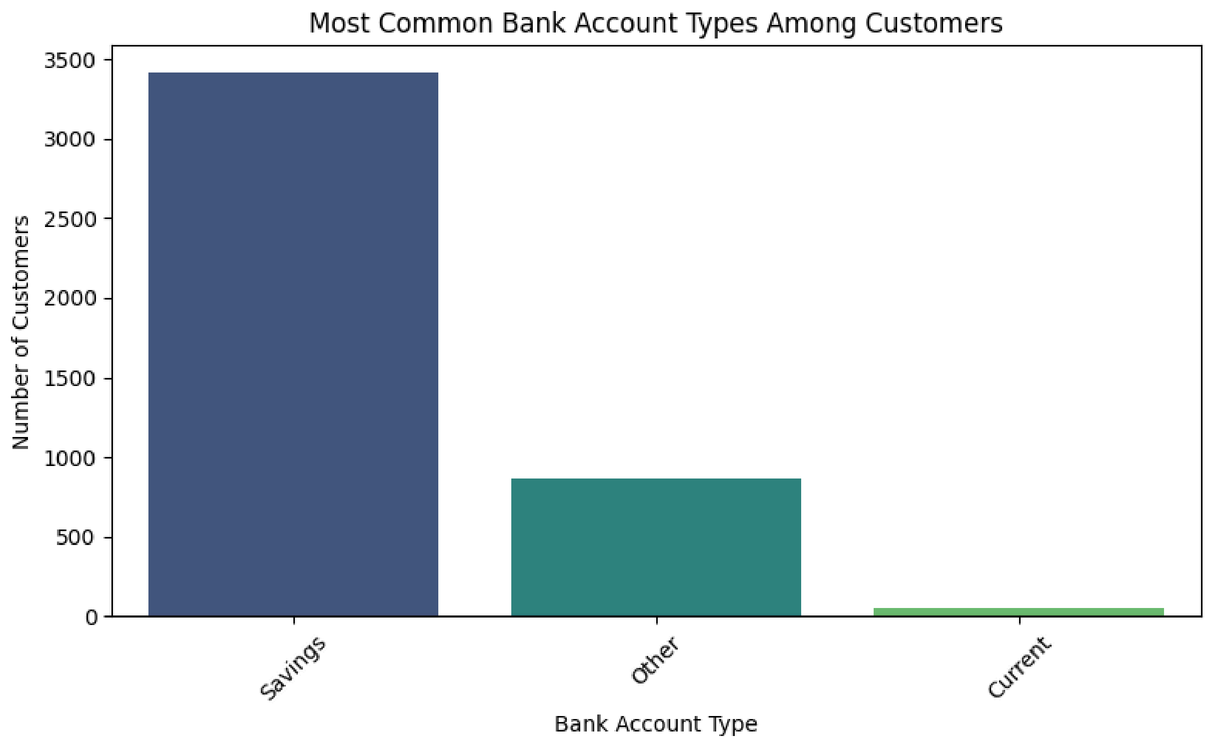
In [ ]:
```
cus_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 4334 entries, 0 to 4345
Data columns (total 7 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   customerid                 4334 non-null   object
 1   birthdate                  4334 non-null   datetime64[ns]
 2   bank_account_type          4334 non-null   object
 3   longitude_gps              4334 non-null   float64
 4   latitude_gps               4334 non-null   float64
 5   bank_name_clients          4334 non-null   object
 6   employment_status_clients  4334 non-null   object
dtypes: datetime64[ns](1), float64(2), object(4)
memory usage: 270.9+ KB
```

INSIGHTS

In [ ]:
```
#Common bank account type amongst clients

# Count plot for bank account types
plt.figure(figsize=(8, 5))
sb.countplot(data=cus_data, x='bank_account_type', order=cus_data['bank_account_typ

plt.title('Most Common Bank Account Types Among Customers')
plt.xlabel('Bank Account Type')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-3896620443.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sb.countplot(data=cus_data, x='bank_account_type', order=cus_data['bank_account_ty
pe'].value_counts().index, palette='viridis')
```



In [ ]:

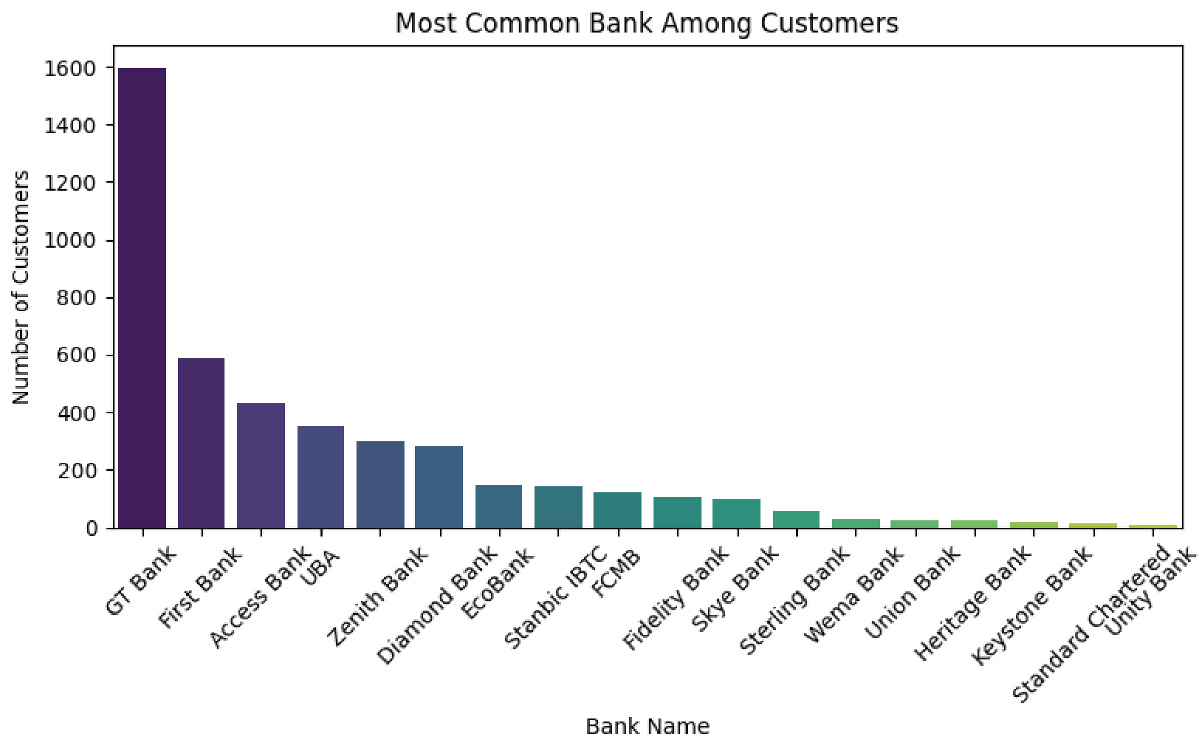
```
# Customer Location Map
import folium
from folium.plugins import MarkerCluster

map_center = [cus_data['latitude_gps'].mean(), cus_data['longitude_gps'].mean()]
customer_map = folium.Map(
    location=map_center,
    zoom_start=6,
    tiles='cartodbpositron',
    control_scale=True
)

# Add a marker cluster
marker_cluster = MarkerCluster(
    show_coverage_on_hover=True,
    zoom=10,
    maxClusterRadius=50
).add_to(customer_map)

# Add customer markers with custom icons and popups
for _, row in cus_data.iterrows():
    folium.Marker(
        location=[row['latitude_gps'], row['longitude_gps']],
        popup=folium.Popup(row['bank_name_clients'], max_width=200),
        icon=folium.Icon(color='blue', icon='university', prefix='fa')  # Bank icon
    ).add_to(marker_cluster)

# Add a layer control for interactivity
folium.LayerControl().add_to(customer_map)

# If running in a Jupyter notebook, display the map
customer_map
```

Out[ ]:

In [ ]:

```
#Client Bank
plt.figure(figsize=(8, 5))
sb.countplot(data=cus_data, x='bank_name_clients', order=cus_data['bank_name_client

plt.title('Most Common Bank Among Customers')
plt.xlabel('Bank Name')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

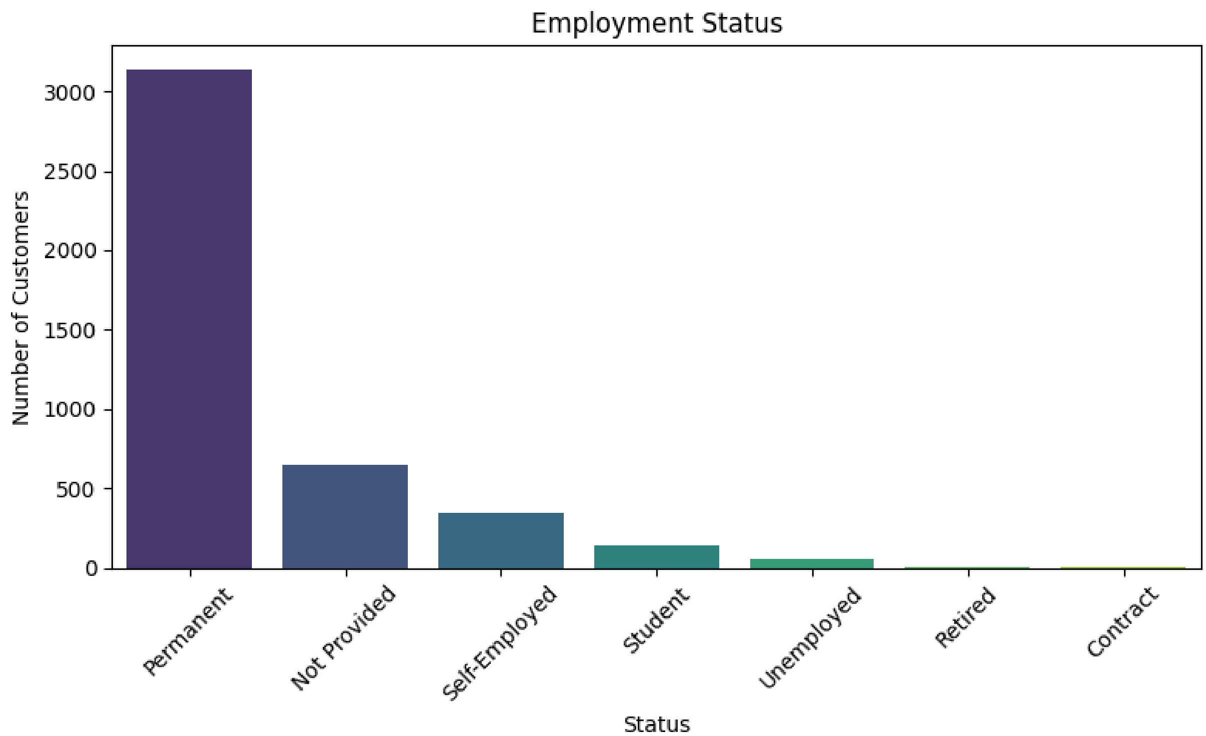
```
/tmp/ipython-input-2745858733.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sb.countplot(data=cus_data, x='bank_name_clients', order=cus_data['bank_name_clien
ts'].value_counts().index, palette='viridis')
```



In [ ]:

```
#client employment
plt.figure(figsize=(8, 5))
sb.countplot(data=cus_data, x='employment_status_clients', order=cus_data['employme

plt.title('Employment Status')
plt.xlabel('Status')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-3649671441.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sb.countplot(data=cus_data, x='employment_status_clients', order=cus_data['employm
ent_status_clients'].value_counts().index, palette='viridis')
```



Findings

- The majority of customers hold savings accounts.
- A large proportion of customers are based in Nigeria (4,311).
- GT Bank is the most commonly used bank among customers.
- Regarding employment: the majority are permanent staff, followed by self-employed customers. A smaller segment did not provide their employment status.

Loan History

This contains data regarding customer's loans

In [ ]:
```
loan_hist.head()
```

Out[ ]:

	customerid	systemloanid	loannumber	approveddate	creati
0	8a2a81a74ce8c05d014cfb32a0da1049	301682320	2	2016-08-15 18:22:40.000000	201(17:22:32.
1	8a2a81a74ce8c05d014cfb32a0da1049	301883808	9	2017-04-28 18:39:07.000000	201 17:38:53.
2	8a2a81a74ce8c05d014cfb32a0da1049	301831714	8	2017-03-05 10:56:25.000000	201 09:56:19.
3	8a8588f35438fe12015444567666018e	301861541	5	2017-04-09 18:25:55.000000	201 17:25:42.
4	8a85890754145ace015429211b513e16	301941754	2	2017-06-17 09:29:57.000000	201 08:29:50.

In [ ]:
```
loan_hist.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18183 entries, 0 to 18182
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   customerid       18183 non-null  object
 1   systemloanid     18183 non-null  int64
 2   loannumber       18183 non-null  int64
 3   approveddate     18183 non-null  object
 4   creationdate     18183 non-null  object
 5   loanamount       18183 non-null  float64
 6   totaldue         18183 non-null  float64
 7   termdays         18183 non-null  int64
 8   closeddate       18183 non-null  object
 9   referredby       1026 non-null   object
 10  firstduedate     18183 non-null  object
 11  firstrepaiddate  18183 non-null  object
dtypes: float64(2), int64(3), object(7)
memory usage: 1.7+ MB
```

Dates are not in correct data type

In [ ]:
```
loan_hist.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%
systemloanid	18183.0	3.018395e+08	93677.672704	301600134.0	301776577.0	301854965.0
loannumber	18183.0	4.189353e+00	3.249490	1.0	2.0	3.0
loanamount	18183.0	1.650124e+04	9320.547516	3000.0	10000.0	10000.0
totaldue	18183.0	1.957320e+04	10454.245277	3450.0	11500.0	13000.0
termdays	18183.0	2.669279e+01	10.946556	15.0	15.0	30.0

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

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

In [ ]:
```
#returning customers
loan_hist.customerid.duplicated().sum()
```

Out[ ]:
```
np.int64(13824)
```

customerid has duplicates as this data contains all loans collected by each customer

While the referredby column has some missing values, these nulls actually represent customers who were not referred. Thus, the column continues to offer valuable information for analysis.

In [ ]:
```
loan_hist.referredby.isna().sum()
```

Out[ ]:
```
np.int64(17157)
```

Data Cleaning

In [ ]:
```
#transforming referred by column by filling null with not referred and the ones ref
loan_hist['referredby'] = loan_hist['referredby'].fillna('Not Referred')
loan_hist['referredby'] = loan_hist['referredby'].apply(lambda x: 'Referred' if x !
```

In [ ]:
```
# converting dates to datetime
date_columns = ['approveddate', 'creationdate', 'closeddate', 'firstduedate', 'firs
for col in date_columns:
    loan_hist[col] = pd.to_datetime(loan_hist[col])
```

In [ ]:
```
loan_hist.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18183 entries, 0 to 18182
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   customerid       18183 non-null  object
 1   systemloanid     18183 non-null  int64
 2   loannumber       18183 non-null  int64
 3   approveddate     18183 non-null  datetime64[ns]
 4   creationdate     18183 non-null  datetime64[ns]
 5   loanamount       18183 non-null  float64
 6   totaldue         18183 non-null  float64
 7   termdays         18183 non-null  int64
 8   closeddate       18183 non-null  datetime64[ns]
 9   referredby       18183 non-null  object
 10  firstduedate     18183 non-null  datetime64[ns]
 11  firstrepaiddate  18183 non-null  datetime64[ns]
dtypes: datetime64[ns](5), float64(2), int64(3), object(2)
memory usage: 1.7+ MB
```

In [ ]:

```
loan_hist.describe()
```

Out[ ]:

	systemloanid	loannumber	approveddate	creationdate	loanamount	
count	1.818300e+04	18183.000000	18183	18183	18183.000000	18
mean	3.018395e+08	4.189353	2017-02-25 09:59:36.147390464	2017-02-25 08:55:29.725677824	16501.237420	19
min	3.016001e+08	1.000000	2016-01-15 08:53:28	2016-01-15 07:53:17	3000.000000	3
25%	3.017766e+08	2.000000	2016-12-19 16:13:04.500000	2016-12-19 15:12:53.500000	10000.000000	1
50%	3.018550e+08	3.000000	2017-04-04 16:44:44	2017-04-04 15:44:31	10000.000000	13
75%	3.019197e+08	6.000000	2017-05-27 15:07:16	2017-05-27 14:07:06.500000	20000.000000	24
max	3.020003e+08	26.000000	2017-07-28 10:47:43	2017-07-28 09:46:34	60000.000000	68
std	9.367767e+04	3.249490	NaN	NaN	9320.547516	10

From date information:

- Difference between first due date and first repaid date – captures how promptly a customer makes their first repayment, which is critical for identifying potential defaulters.

- Difference between closed date and approved date (loan duration) – measures the actual duration of the loan, useful for assessing repayment behavior and loan management.

Derived from loan amount, total due, term days, and loan duration:

- Interest rate – percentage of interest charged on the loan; important for evaluating loan profitability and customer cost burden.
- Repayment multiple – the ratio of total repayment to principal; helps assess if customers are over-repaying or under-repaying relative to the loan amount.
- Difference between planned term and actual loan duration – indicates deviations in repayment schedules, highlighting potential repayment issues.
- Number of days between consecutive loans – shows customer borrowing frequency, which can signal risk patterns or over-leveraging.

In [ ]:
```
#calculating actual loan duration in days
loan_hist['loan_duration'] = (loan_hist['closeddate'] - loan_hist['approveddate']).
```

In [ ]:
```
# calculating difference between first repaid date and first due date in days
loan_hist['first_repayment_diff_days'] = (loan_hist['firstrepaiddate'] - loan_hist[
```

In [ ]:
```
#calculating difference between bank stated term days and the actual loan duration
loan_hist['overall_repayment_diff_days'] = loan_hist['loan_duration'] - loan_hist['
```

In [ ]:
```
#Interest rate
loan_hist['interest_rate'] = (loan_hist['totaldue']-loan_hist['loanamount']) / loan
```

In [ ]:
```
#repayment multiple
loan_hist['repayment_multiple'] = loan_hist['totaldue']/loan_hist['loanamount']
```

In [ ]:
```
# Calculating difference in days between consecutive loans per customer
loan_hist = loan_hist.sort_values(['customerid', 'approveddate'])
loan_hist['days_between_loans'] = loan_hist.groupby('customerid')['approveddate'].d
```

In [ ]:
```
loan_hist.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 18183 entries, 1893 to 1216
Data columns (total 18 columns):
 #   Column                       Non-Null Count  Dtype         
---  ------                       --------------  -----         
 0   customerid                   18183 non-null  object        
 1   systemloanid                 18183 non-null  int64         
 2   loannumber                   18183 non-null  int64         
 3   approveddate                 18183 non-null  datetime64[ns]
 4   creationdate                 18183 non-null  datetime64[ns]
 5   loanamount                   18183 non-null  float64       
 6   totaldue                     18183 non-null  float64       
 7   termdays                     18183 non-null  int64         
 8   closeddate                   18183 non-null  datetime64[ns]
 9   referredby                   18183 non-null  object        
 10  firstduedate                 18183 non-null  datetime64[ns]
 11  firstrepaiddate              18183 non-null  datetime64[ns]
 12  loan_duration                18183 non-null  int64         
 13  first_repayment_diff_days    18183 non-null  int64         
 14  overall_repayment_diff_days  18183 non-null  int64         
 15  interest_rate                18183 non-null  float64       
 16  repayment_multiple           18183 non-null  float64       
 17  days_between_loans           13824 non-null  float64       
dtypes: datetime64[ns](5), float64(5), int64(6), object(2)
memory usage: 2.6+ MB
```

In [ ]:

```
loan_hist.head()
```

Out[ ]:

	customerid	systemloanid	loannumber	approveddate	crea
1893	8a1088a0484472eb01484669e3ce4e0b	301960241	1	2017-07-02 19:19:01	20
5216	8a1a1e7e4f707f8b014f797718316cad	301620412	1	2016-05-13 15:29:37	20
17546	8a1a1e7e4f707f8b014f797718316cad	301632940	2	2016-06-15 11:22:38	20
7999	8a1a1e7e4f707f8b014f797718316cad	301916386	3	2017-05-23 14:21:42	20
16602	8a1a1e7e4f707f8b014f797718316cad	301947045	4	2017-06-21 22:09:51	20

In [ ]:

```
loan_hist.describe()
```

Out[ ]:

	systemloanid	loannumber	approveddate	creationdate	loanamount	
count	1.818300e+04	18183.000000	18183	18183	18183.000000	18
mean	3.018395e+08	4.189353	2017-02-25 09:59:36.147390464	2017-02-25 08:55:29.725677824	16501.237420	19
min	3.016001e+08	1.000000	2016-01-15 08:53:28	2016-01-15 07:53:17	3000.000000	3
25%	3.017766e+08	2.000000	2016-12-19 16:13:04.500000	2016-12-19 15:12:53.500000	10000.000000	1
50%	3.018550e+08	3.000000	2017-04-04 16:44:44	2017-04-04 15:44:31	10000.000000	13
75%	3.019197e+08	6.000000	2017-05-27 15:07:16	2017-05-27 14:07:06.500000	20000.000000	24
max	3.020003e+08	26.000000	2017-07-28 10:47:43	2017-07-28 09:46:34	60000.000000	68
std	9.367767e+04	3.249490	NaN	NaN	9320.547516	10

Insights

In [ ]:
```
# Select only numeric columns (excluding datetime)
numeric_cols = loan_hist.select_dtypes(include=['number'])

# Get describe and filter only mean, min, max
summary = numeric_cols.describe().loc[['mean', 'min', 'max']]
summary
```

Out[ ]:

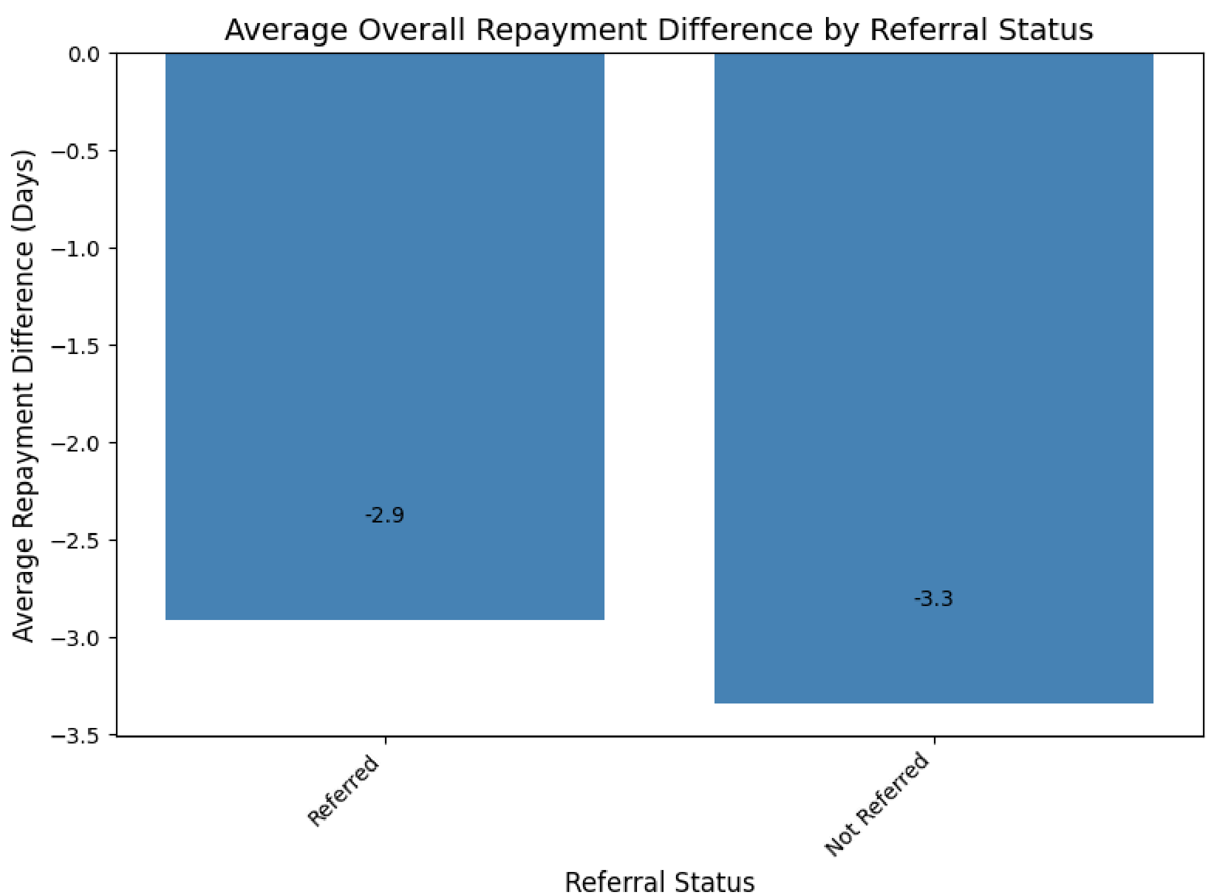
	systemloanid	loannumber	loanamount	totaldue	termdays	loan_duration	firs
mean	3.018395e+08	4.189353	16501.23742	19573.202931	26.69279	23.38041	
min	3.016001e+08	1.000000	3000.00000	3450.000000	15.00000	0.00000	
max	3.020003e+08	26.000000	60000.00000	68100.000000	90.00000	380.00000	

In [ ]:
```
# Total loan given out
total_loan = loan_hist['loanamount'].sum()

# Total interest gotten
total_interest = (loan_hist['totaldue'] - loan_hist['loanamount']).sum()

print(f"Total loan amount lent out is ₦{total_loan:,.2f}")
print(f"Total company profit is ₦{total_interest:,.2f}")
```

```
profit_margin = (total_interest / total_loan) * 100
print(f"Profit margin: {profit_margin:.2f}%")
```

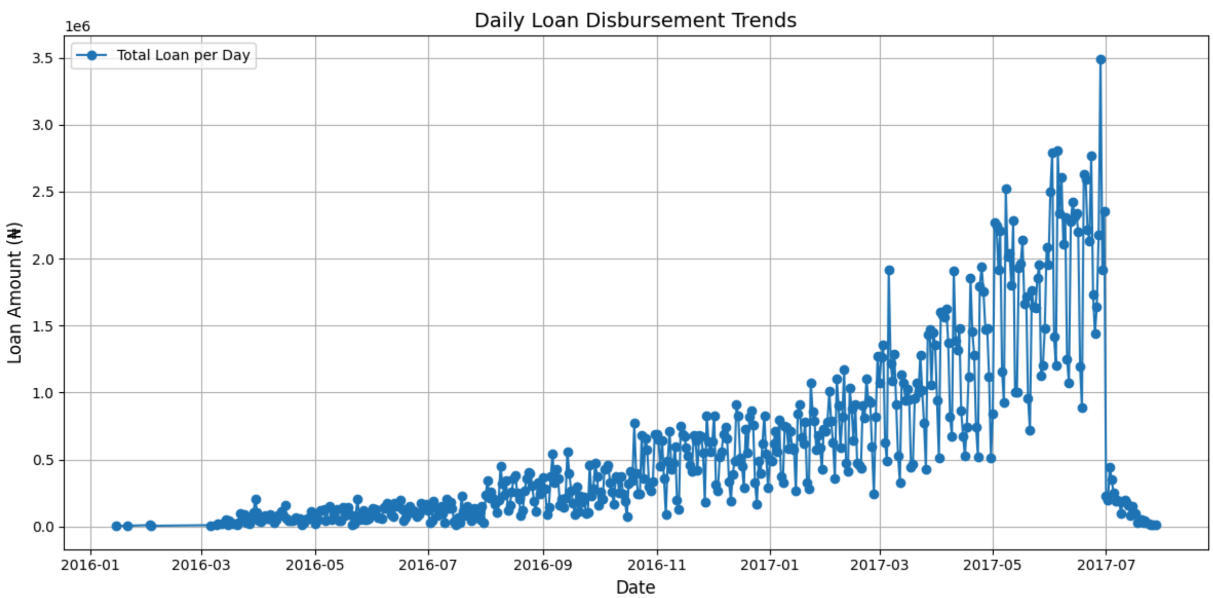
```
Total loan amount lent out is ₦300,042,000.00
Total company profit is ₦55,857,548.90
Profit margin: 18.62%
```

In [ ]:
```
# Group by referral status and calculate average repayment difference
referral_avg = loan_hist.groupby("referredby")["overall_repayment_diff_days"].mean(

# Sort values for nicer plotting
referral_avg = referral_avg.sort_values("overall_repayment_diff_days", ascending=Fa

# Plot
plt.figure(figsize=(8,6))
plt.bar(referral_avg["referredby"], referral_avg["overall_repayment_diff_days"], co

plt.title("Average Overall Repayment Difference by Referral Status", fontsize=14)
plt.xlabel("Referral Status", fontsize=12)
plt.ylabel("Average Repayment Difference (Days)", fontsize=12)
plt.xticks(rotation=45, ha="right")

# Add value labels on top of bars
for i, v in enumerate(referral_avg["overall_repayment_diff_days"]):
    plt.text(i, v + 0.5, f"{v:.1f}", ha="center", fontsize=10)

plt.tight_layout()
plt.show()
```



In [ ]:
```
# Group by date to get total loan amount and average loan per day
loan_by_date = loan_hist.groupby(loan_hist["approveddate"].dt.date).agg(
    total_loan=("loanamount", "sum"),
    avg_loan=("loanamount", "mean"),
    count=("loanamount", "count")
).reset_index()

# Find the date with the highest total loan
top_date = loan_by_date.loc[loan_by_date["total_loan"].idxmax()]

print("Date with the highest total loan disbursed:")
print(f"Date: {top_date['approveddate']}, Total Loan: ₦{top_date['total_loan']:,.2f
      f"Average Loan: ₦{top_date['avg_loan']:,.2f}, Number of Loans: {top_date['cou

# Plot trend of total loans disbursed over time
plt.figure(figsize=(12,6))
plt.plot(loan_by_date["approveddate"], loan_by_date["total_loan"], marker="o", labe

plt.title("Daily Loan Disbursement Trends", fontsize=14)
plt.xlabel("Date", fontsize=12)
plt.ylabel("Loan Amount (₦)", fontsize=12)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Date with the highest total loan disbursed:
Date: 2017-06-28, Total Loan: ₦3,490,000.00, Average Loan: ₦18,663.10, Number of Loa
ns: 187
```



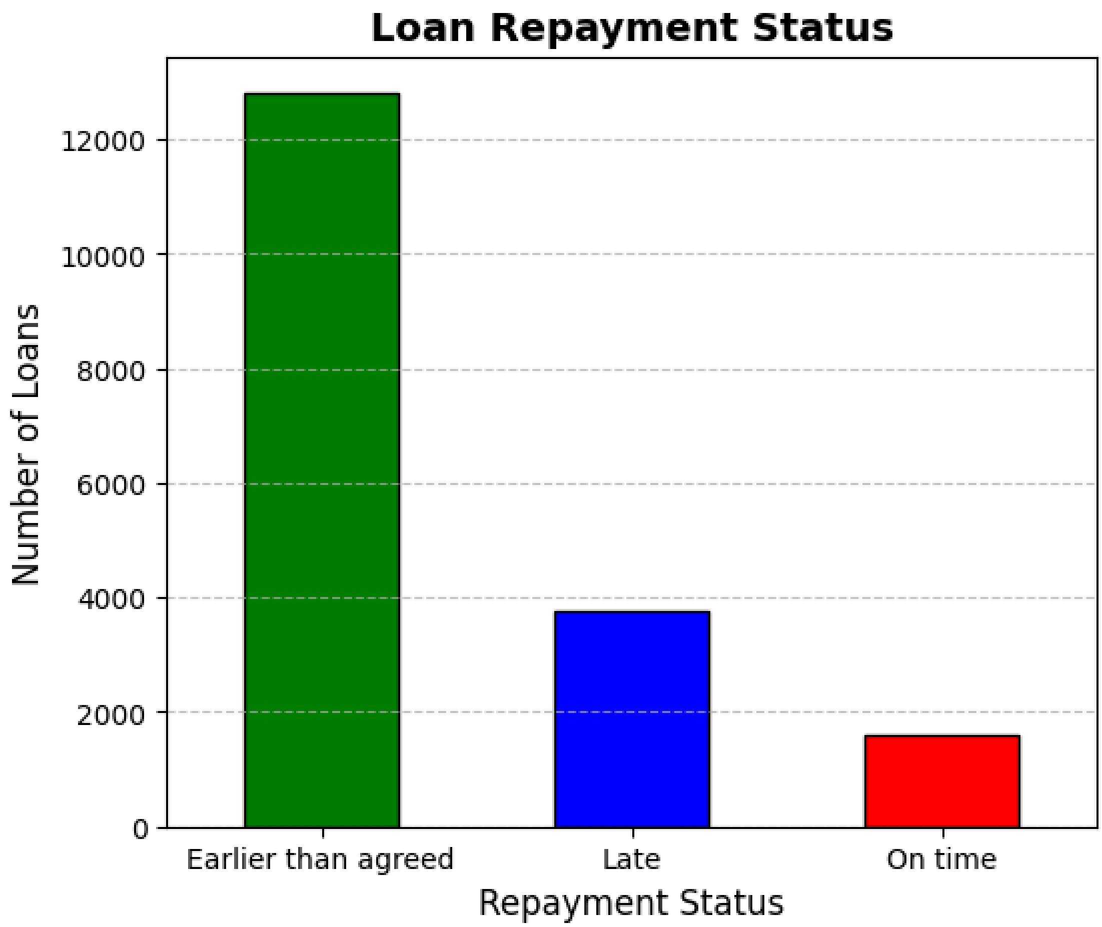
In [ ]:
```
# Filter loans borrowed on June 28
june28_loans = loan_hist[loan_hist["approveddate"].dt.date == pd.to_datetime("2017-

# Average repayment difference (days)
avg_repayment_june28 = june28_loans["overall_repayment_diff_days"].mean()

# Classify repayment behavior
if avg_repayment_june28 < 0:
```

```
    status = "earlier than agreed"
elif avg_repayment_june28 == 0:
    status = "on time"
else:
    status = "later than agreed"

print(f"On June 28 2017, the average repayment difference was {avg_repayment_june28
```

```
On June 28 2017, the average repayment difference was -4.51 days, meaning customers
repaid earlier than agreed.
```

In [ ]:

```
# Creating a new variable for repayment status
def repayment_status(x):
    if x < 0:
        return "Earlier than agreed"
    elif x == 0:
        return "On time"
    else:
        return "Late"

repayment_status_var = loan_hist["overall_repayment_diff_days"].apply(repayment_sta

# Count each repayment status
status_counts = repayment_status_var.value_counts()

# Plot
plt.figure(figsize=(6, 5))
status_counts.plot(kind="bar", color=["green", "blue", "red"], edgecolor="black")

plt.title("Loan Repayment Status", fontsize=14, weight="bold")
plt.xlabel("Repayment Status", fontsize=12)
plt.ylabel("Number of Loans", fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis="y", linestyle="--", alpha=0.7)

plt.show()
```



Key Insights

The company has disbursed ₦300.04 million in loans, generating a profit of ₦55.86 million, which corresponds to an overall profit margin of approximately 18.6%, indicating that the loan portfolio is profitable.

On average, customers borrow around ₦16,500 and repay approximately 1.2 times the loan amount, with interest rates averaging 20%.

Customers who were not referred tend to repay earlier than those who were referred.

The highest loan disbursement occurred on June 28th, even though it was not a holiday. This could be influenced by end-of-month financial pressures, or operational factors such as batch processing or marketing campaigns. Interestingly, on this date, customers on average repaid earlier than agreed.

Most customers repaid earlier than agreed, followed by those who repaid late, highlighting generally strong repayment behavior.

Customer Repayment Profile

To create the customer repayment profile, loan history will be aggregated for each individual.

In [ ]:

```

```

In [ ]:

```
# Aggregating customer profile
customer_profile = loan_hist.groupby("customerid").agg({
    "systemloanid": "count",              # total number of loans
    "loanamount": "mean",                 # avg loan amount
    "totaldue": "mean",                   # avg total due
    "termdays": "mean",                   # avg loan term
    "loan_duration": "mean",              # avg loan duration
    "first_repayment_diff_days": "mean", # avg first repayment diff
    "overall_repayment_diff_days": "mean", # avg repayment diff
    "interest_rate": "mean",              # avg interest rate
    "repayment_multiple": "mean",         # avg repayment multiple
    "days_between_loans": "mean"          # avg days between loans
}).reset_index()

# Renaming for clarity
customer_profile = customer_profile.rename(columns={
    "systemloanid": "total_loans",
    "loanamount": "avg_loan_amount",
    "totaldue": "avg_total_due",
    "termdays": "avg_term_days",
    "loan_duration": "avg_loan_duration",
    "first_repayment_diff_days": "avg_first_repay_diff",
    "overall_repayment_diff_days": "avg_overall_repay_diff",
    "interest_rate": "avg_interest_rate",
    "repayment_multiple": "avg_repayment_multiple",
    "days_between_loans": "avg_days_between_loans"
})
```

In [ ]:

```
customer_profile.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4359 entries, 0 to 4358
Data columns (total 11 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   customerid              4359 non-null   object 
 1   total_loans             4359 non-null   int64  
 2   avg_loan_amount         4359 non-null   float64
 3   avg_total_due           4359 non-null   float64
 4   avg_term_days           4359 non-null   float64
 5   avg_loan_duration       4359 non-null   float64
 6   avg_first_repay_diff    4359 non-null   float64
 7   avg_overall_repay_diff  4359 non-null   float64
 8   avg_interest_rate       4359 non-null   float64
 9   avg_repayment_multiple  4359 non-null   float64
 10  avg_days_between_loans  2966 non-null   float64
dtypes: float64(9), int64(1), object(1)
memory usage: 374.7+ KB
```

Note: Average days between loans has missing values

Feature Engineering

- Borrower type – derived from the days between loans. This helps classify customers based on borrowing frequency, which can indicate financial behavior and potential risk.
- Repayment behavior category – created as Early, On-time, or Late. This is crucial for identifying repayment patterns, detecting high-risk borrowers, and informing credit decisions.

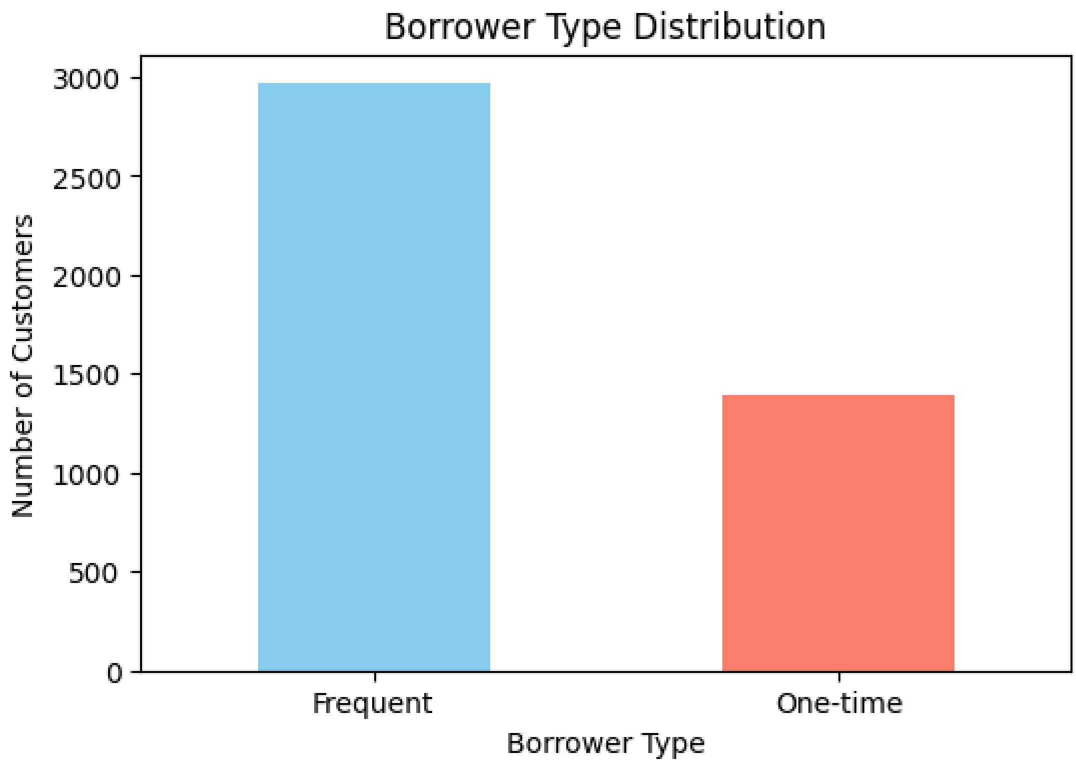
In [ ]:
```
# Create new column for borrower type
customer_profile["borrower_type"] = np.where(
    customer_profile["avg_days_between_loans"].isna(),
    "One-time",
    "Frequent"
)
```

In [ ]:
```
customer_profile["avg_days_between_loans"] = customer_profile["avg_days_between_loa
```

Nulls in the average days between loans column were replaced with -1 rather than dropped. This is because they correspond to customers who borrowed only once, and retaining this information is important for both insight generation and predictive modeling.

In [ ]:
```
# Defining a function to categorize customer's repayment behaviour
def categorize_repayment(x):
    if x < 0:
        return "Early"
    elif x == 0:
        return "On-time"
    else:
        return "Late"

# Apply to both columns
customer_profile["first_repay_category"] = customer_profile["avg_first_repay_diff"]
customer_profile["overall_repay_category"] = customer_profile["avg_overall_repay_di
```

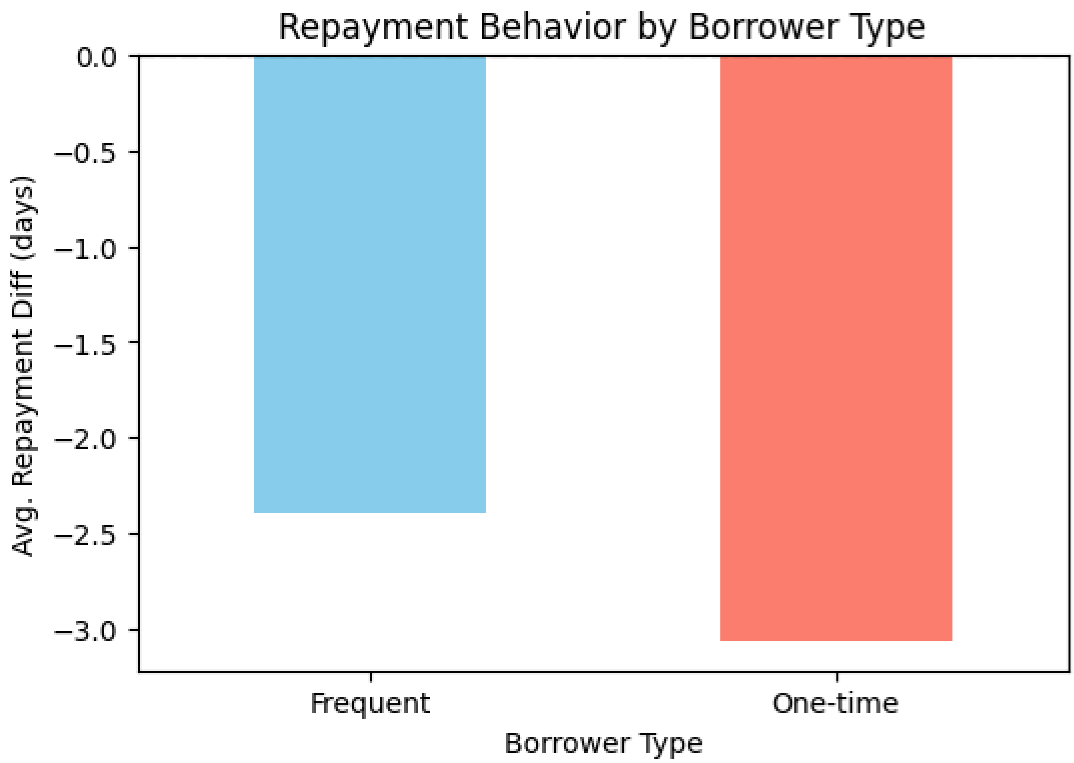
In [ ]:
```
# Count borrower types
borrower_counts = customer_profile["borrower_type"].value_counts()

# Plot
plt.figure(figsize=(6,4))
borrower_counts.plot(kind="bar", color=["skyblue", "salmon"])

plt.title("Borrower Type Distribution")
plt.xlabel("Borrower Type")
plt.ylabel("Number of Customers")
plt.xticks(rotation=0)
plt.show()
```



In [ ]:

```
import matplotlib.pyplot as plt

# Group by borrower type and take mean repayment diff
repayment_behavior = customer_profile.groupby("borrower_type")["avg_overall_repay_d

print("Average repayment diff (days):")
print(repayment_behavior)

# Plot
plt.figure(figsize=(6,4))
repayment_behavior.plot(kind="bar", color=["skyblue", "salmon"])

plt.axhline(0, color="black", linestyle="--")  # Line at 0 = on time
plt.title("Repayment Behavior by Borrower Type")
plt.ylabel("Avg. Repayment Diff (days)")
plt.xlabel("Borrower Type")
plt.xticks(rotation=0)
plt.show()
```

```
Average repayment diff (days):
borrower_type
Frequent    -2.393403
One-time    -3.061019
Name: avg_overall_repay_diff, dtype: float64
```



One-time borrowers tend to repay earlier than frequent borrowers, who show more variable repayment patterns.

Overall, there are more frequent borrowers which we can classify as more returning customers

Current loan data

In [ ]:
```
#data properties
loan_curr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4368 entries, 0 to 4367
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   customerid     4368 non-null   object 
 1   systemloanid   4368 non-null   int64  
 2   loannumber     4368 non-null   int64  
 3   approveddate   4368 non-null   object 
 4   creationdate   4368 non-null   object 
 5   loanamount     4368 non-null   float64
 6   totaldue       4368 non-null   float64
 7   termdays       4368 non-null   int64  
 8   referredby     587 non-null    object 
 9   good_bad_flag  4368 non-null   object 
dtypes: float64(2), int64(3), object(5)
memory usage: 341.4+ KB
```

In [ ]:
```
#missing data
```

```
loan_curr.referredby.isna().sum()
```

Out[ ]: `np.int64(3781)`

In [ ]:
```
#transforming referred by column by filling null with not referred and the ones ref
loan_curr['referredby'] = loan_curr['referredby'].fillna('Not Referred')
loan_curr['referredby'] = loan_curr['referredby'].apply(lambda x: 'Referred' if x !
```

In [ ]:
```
# converting dates to datetime
date_columns = ['approveddate', 'creationdate']
for col in date_columns:
    loan_curr[col] = pd.to_datetime(loan_curr[col])
```

In [ ]:
```
#deriving interest rate from loanamount and totaldue data
#Interest rate
loan_curr['interest_rate'] = (loan_curr['totaldue']-loan_curr['loanamount']) / loan
```

Merging

Reasoning

The predictive approach of relying solely on past closed loans to determine whether a customer will default has significant limitations. This is because repayment history is only available for returning customers, leaving new customers without any behavioral data. If the model is trained exclusively on past loans, it introduces a bias—it will perform well on customers with previous records but completely fail to generalize to first-time borrowers.

Moreover, attempting to merge the dataset of past loans with the dataset containing the current good_bad_flag introduces a logical inconsistency. The good_bad_flag attached to the current loan reflects the outcome of that specific loan only; it cannot retroactively represent the performance of previous loans. For example, a customer might have repaid their earlier loans on time (good) but later defaulted on their current loan (bad). If past and present records are merged without careful separation, the model could mistakenly learn misleading relationships, effectively "contaminating" the historical data with information from the future.

This highlights a crucial data integrity principle: labels must remain temporally consistent with the features they describe. In other words, we should not apply a label from a future loan to past loans unless those past loans originally carried their own good_bad_flag. Had the historical dataset included outcomes for each past loan, those could have been valid training examples.

Given these realities, the more reliable approach is to train the model primarily on current active loans, where the good_bad_flag correctly reflects repayment outcomes, while also engineering features that capture customer behavior patterns, financial attributes, and loan dynamics. This ensures that the model remains robust and fair for both new and returning customers, without compromising on data integrity.

In [ ]:
```
loan_curr.head()
```

Out[ ]:

	customerid	systemloanid	loannumber	approveddate	creationd
0	8a2a81a74ce8c05d014cfb32a0da1049	301994762	12	2017-07-25 08:22:56	2017-07 07:2
1	8a85886e54beabf90154c0a29ae757c0	301965204	2	2017-07-05 17:04:41	2017-07 16:0
2	8a8588f35438fe12015444567666018e	301966580	7	2017-07-06 14:52:57	2017-07 13:5
3	8a85890754145ace015429211b513e16	301999343	3	2017-07-27 19:00:41	2017-07 18:0
4	8a858970548359cc0154883481981866	301962360	9	2017-07-03 23:42:45	2017-07 22:4

In [ ]:
```
loan_hist[loan_hist['customerid'].astype(str) == "8a8588f35438fe12015444567666018e"
```

Out[ ]:

	customerid	systemloanid	loannumber	approveddate	creatic
59	8a8588f35438fe12015444567666018e	301775359	1	2016-12-17 05:14:12	2016 0
1144	8a8588f35438fe12015444567666018e	301787809	2	2017-01-05 16:40:20	2017 1
1143	8a8588f35438fe12015444567666018e	301807034	3	2017-01-31 13:22:46	2017 1
1745	8a8588f35438fe12015444567666018e	301811670	4	2017-02-07 10:56:32	2017 0
3	8a8588f35438fe12015444567666018e	301861541	5	2017-04-09 18:25:55	2017 1
58	8a8588f35438fe12015444567666018e	301901083	6	2017-05-11 12:07:29	2017 1

The above lines of code shows that customer (8a8588f35438fe12015444567666018e) has 6 previous loan, making his/her current loan 7....

we do not know if the customer defaulted in the past or not. we only know that they did not default on the 7th loan.

Now merging will cause us to assume all the past loans were good too, which is not a good approach for prediction.

Therefore for thia prediction, only the current loan and customer information will be used.

In [ ]:
```
#merging dataset on customerID
merged_df = loan_curr.merge(
    cus_data,
    on="customerid",
    how="inner"
)
```

In [ ]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3269 entries, 0 to 3268
Data columns (total 17 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   customerid                 3269 non-null   object
 1   systemloanid               3269 non-null   int64
 2   loannumber                 3269 non-null   int64
 3   approveddate               3269 non-null   datetime64[ns]
 4   creationdate               3269 non-null   datetime64[ns]
 5   loanamount                 3269 non-null   float64
 6   totaldue                   3269 non-null   float64
 7   termdays                   3269 non-null   int64
 8   referredby                 3269 non-null   object
 9   good_bad_flag              3269 non-null   object
 10  interest_rate              3269 non-null   float64
 11  birthdate                  3269 non-null   datetime64[ns]
 12  bank_account_type          3269 non-null   object
 13  longitude_gps              3269 non-null   float64
 14  latitude_gps               3269 non-null   float64
 15  bank_name_clients          3269 non-null   object
 16  employment_status_clients  3269 non-null   object
dtypes: datetime64[ns](3), float64(5), int64(3), object(6)
memory usage: 434.3+ KB
```

Feature Engineering

In [ ]:
```
#customer age
merged_df['customer_age'] = ((merged_df['creationdate'] - merged_df['birthdate']).d
```

In [ ]:
```
#age category
bins = [18, 24, 39, 59]
labels = ['Youth', 'Adult', 'Middle Age']

# Apply cut
merged_df['age_category'] = pd.cut(merged_df['customer_age'], bins=bins, labels=lab
```

In [ ]:
```
merged_df["Loan_Term_Category"] = np.where(
    (merged_df["termdays"] >= 15) & (merged_df["termdays"] <= 30),
    "Short Term",
    "Long Term"
)
```

In [ ]:
```
merged_df.head()
```

Out[ ]:

	customerid	systemloanid	loannumber	approveddate	creationd
0	8a2a81a74ce8c05d014cfb32a0da1049	301994762	12	2017-07-25 08:22:56	2017-07 07:22
1	8a85886e54beabf90154c0a29ae757c0	301965204	2	2017-07-05 17:04:41	2017-07 16:04
2	8a8588f35438fe12015444567666018e	301966580	7	2017-07-06 14:52:57	2017-07 13:52
3	8a85890754145ace015429211b513e16	301999343	3	2017-07-27 19:00:41	2017-07 18:00
4	8a858970548359cc0154883481981866	301962360	9	2017-07-03 23:42:45	2017-07 22:42

In [ ]:

Exploratory Data *Analysis*

In [ ]:

```
#dropping columns not necessary for prediction
new = merged_df.drop(columns=['customerid', 'systemloanid','creationdate', 'approve
```

The New data contains only columns relevant for prediction, the date, IDs, customer bank name, lat and long are not features important for *prediction*

In [ ]:

```
#encoding the target column as 0 and 1 (i.e Good-1, Bad-0) as model cannot predict
new['target'] = (new['good_bad_flag'] == 'Good').astype(int)
```

In [ ]:

```
new.target.value_counts()
```

Out[ ]:

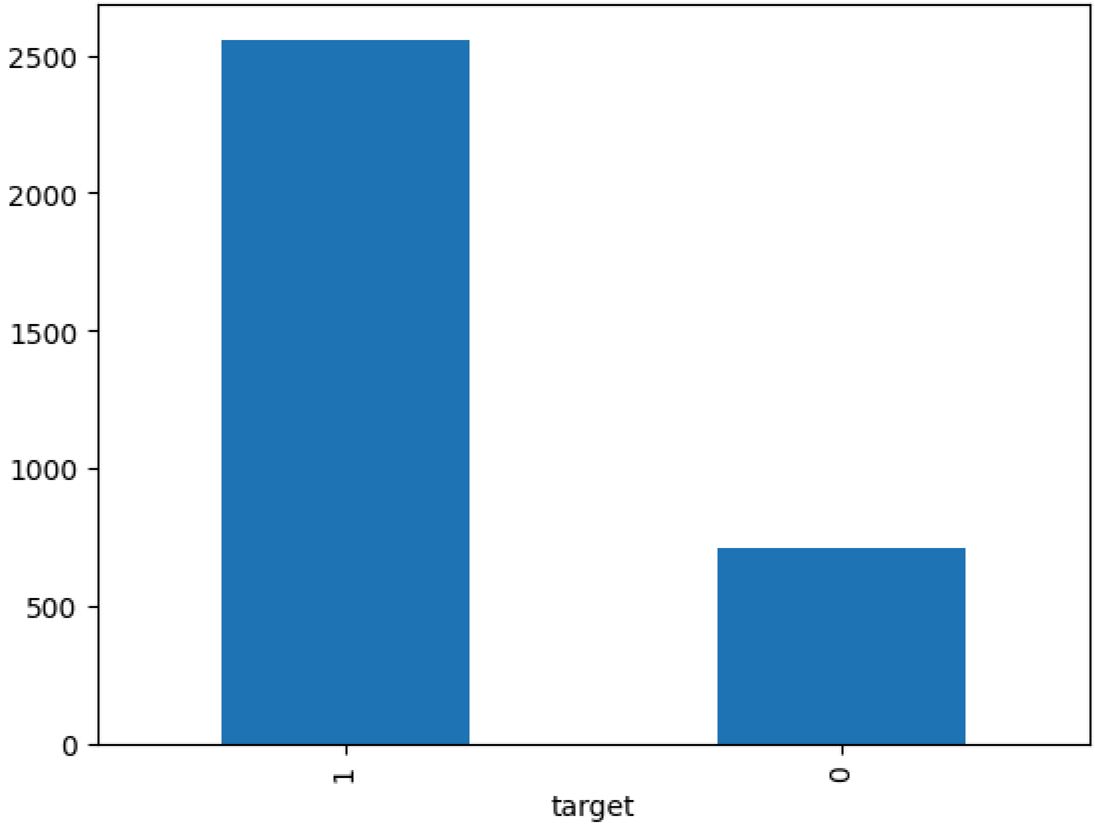
target	count
1	2556
0	713

dtype: int64

In [ ]:

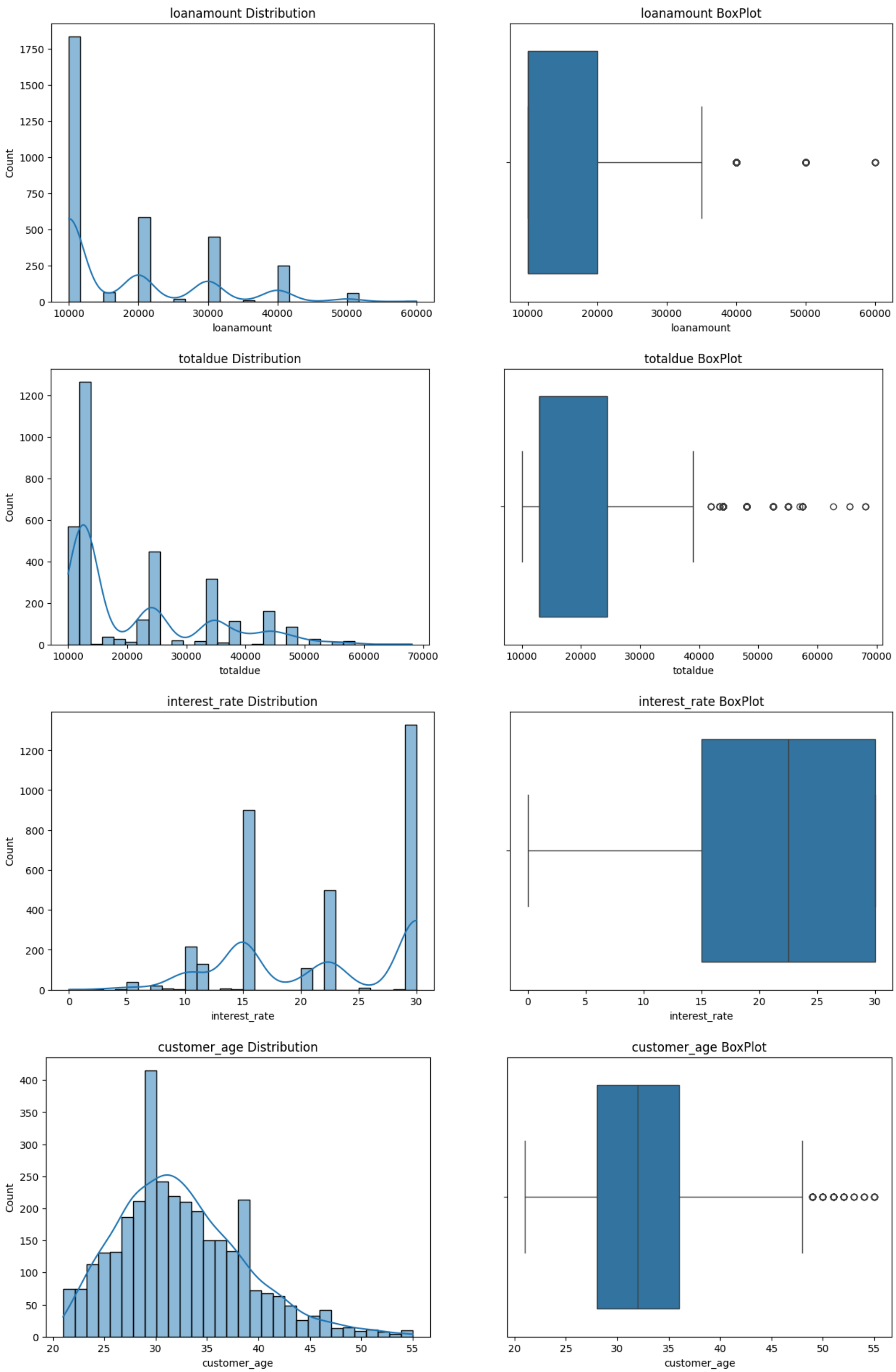
```
new.target.value_counts().plot(kind='bar')
```

Out[ ]: <Axes: xlabel='target'>



In [ ]:
```
num_cols = ['loanamount', 'totaldue','interest_rate','customer_age']

cat_cols = ['referredby', 'bank_account_type','employment_status_clients', 'age_cat
```

In [ ]:
```
# checking distribution
for col in num_cols:
    plt.figure(figsize=(15,5))
    # Histogram
    plt.subplot(1, 2, 1)
    sb.histplot(data=new[col], kde=True, bins=30)
    plt.title(f'{col} Distribution')

    #boxplot
    plt.subplot(1,2,2)
    sb.boxplot(x=new[col])
    plt.title(f'{col} BoxPlot')
    plt.show()
```

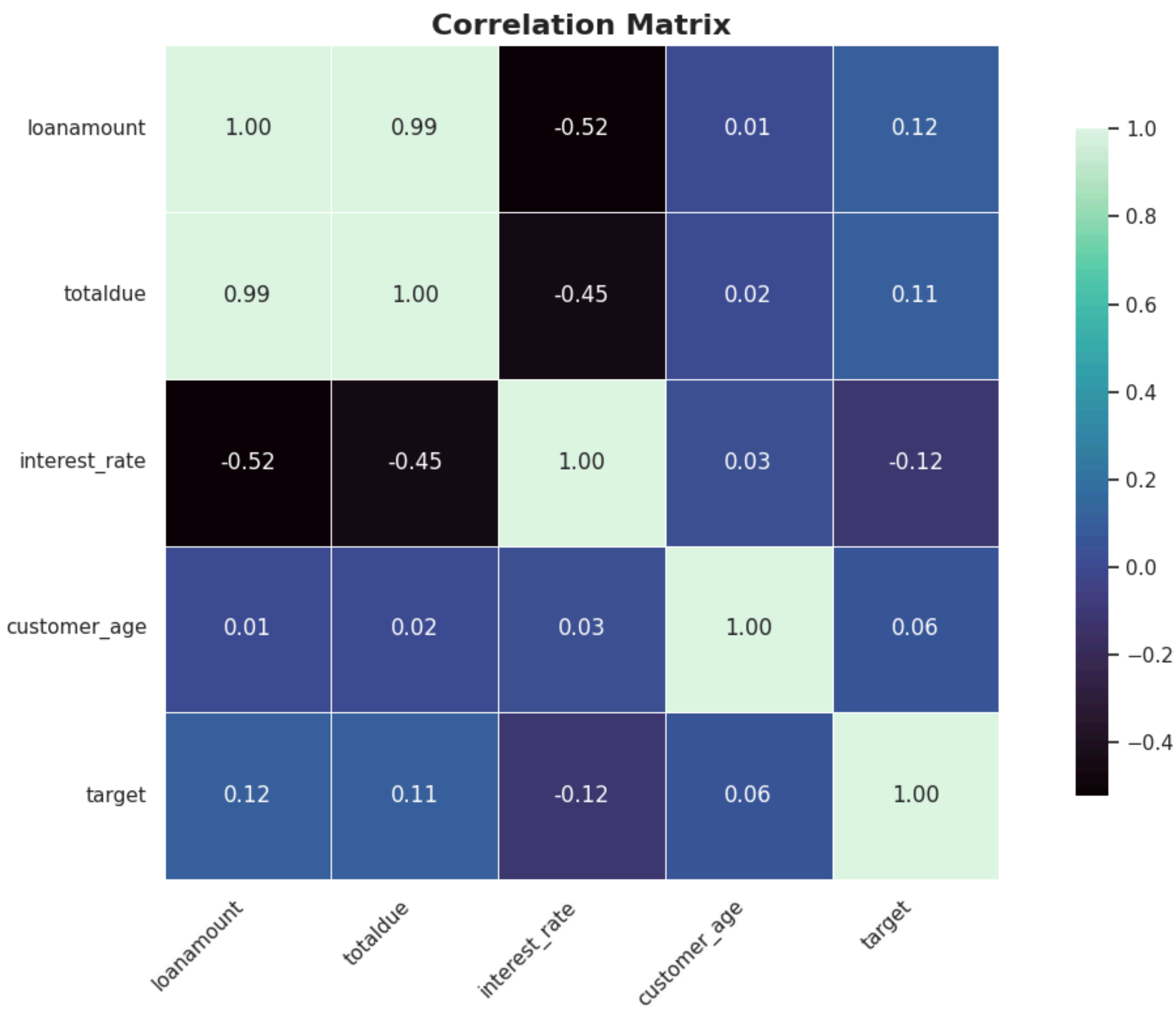

loanamount Distribution
Count
loanamount
loanamount BoxPlot
loanamount
totaldue Distribution
Count
totaldue
totaldue BoxPlot
totaldue
interest_rate Distribution
Count
interest_rate
interest_rate BoxPlot
interest_rate
customer_age Distribution
Count
customer_age
customer_age BoxPlot
customer_age

- Most Customers borrowed 10,000 naira just a few borrowed as high 60,000
- A Large amount of interest rate fall within 30%
- Most of the customers are 29 years old

In [ ]:
```
target_col = 'target'

# Compute correlation matrix between numeric columns and target
corr_matrix = new[num_cols + [target_col]].corr()

# Show correlation of all numeric cols with target
corr_with_target = corr_matrix[target_col].sort_values(ascending=False)
print(corr_with_target)
```

```
target           1.000000
loanamount       0.117787
totaldue         0.112080
customer_age     0.061760
interest_rate   -0.121834
Name: target, dtype: float64
```

In [ ]:
```
#plot correlation matrix
plt.figure(figsize=(12, 8))
sb.set(style="white")

# Plot the heatmap
sb.heatmap(
    corr_matrix,
    cmap="mako",
    annot=True,
    fmt=".2f",
    linewidths=0.5,
    cbar_kws={"shrink": 0.8},
    square=True
)

plt.title("Correlation Matrix", fontsize=16, weight='bold')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



It is important to note that the correlation between features and the target variable is generally low, indicating that these features are not strong predictors for identifying loan defaulters.

Feature selection

In [ ]:
```
new.head()
```

Out[ ]:

	loanamount	totaldue	termdays	referredby	good_bad_flag	interest_rate	bank_accoun
0	30000.0	34500.0	30	Not Referred	Good	15.00	
1	15000.0	17250.0	30	Not Referred	Good	15.00	S
2	20000.0	22250.0	15	Not Referred	Good	11.25	
3	10000.0	11500.0	15	Not Referred	Good	15.00	S
4	40000.0	44000.0	30	Not Referred	Good	10.00	

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
```

In [ ]:

```
ft = new.copy()
```

In [ ]:

```
ft.head()
```

Out[ ]:

	loanamount	totaldue	termdays	referredby	good_bad_flag	interest_rate	bank_accoun
0	30000.0	34500.0	30	Not Referred	Good	15.00	
1	15000.0	17250.0	30	Not Referred	Good	15.00	S
2	20000.0	22250.0	15	Not Referred	Good	11.25	
3	10000.0	11500.0	15	Not Referred	Good	15.00	S
4	40000.0	44000.0	30	Not Referred	Good	10.00	

With Chi-Square

In [ ]:

```
for col in ft.columns:
  le = LabelEncoder()
  ft[col] = le.fit_transform(ft[col])
ft.head()
```

Out[ ]:

	loanamount	totaldue	termdays	referredby	good_bad_flag	interest_rate	bank_account
0	4	30	1	0	1	12	
1	1	14	1	0	1	12	
2	2	21	0	0	1	8	
3	0	6	0	0	1	12	
4	6	37	1	0	1	7	

In [ ]:

```
from sklearn.feature_selection import chi2
```

In [ ]:

```
A = ft.drop(columns =['good_bad_flag', 'target', 'termdays'])
b = ft['target']
```

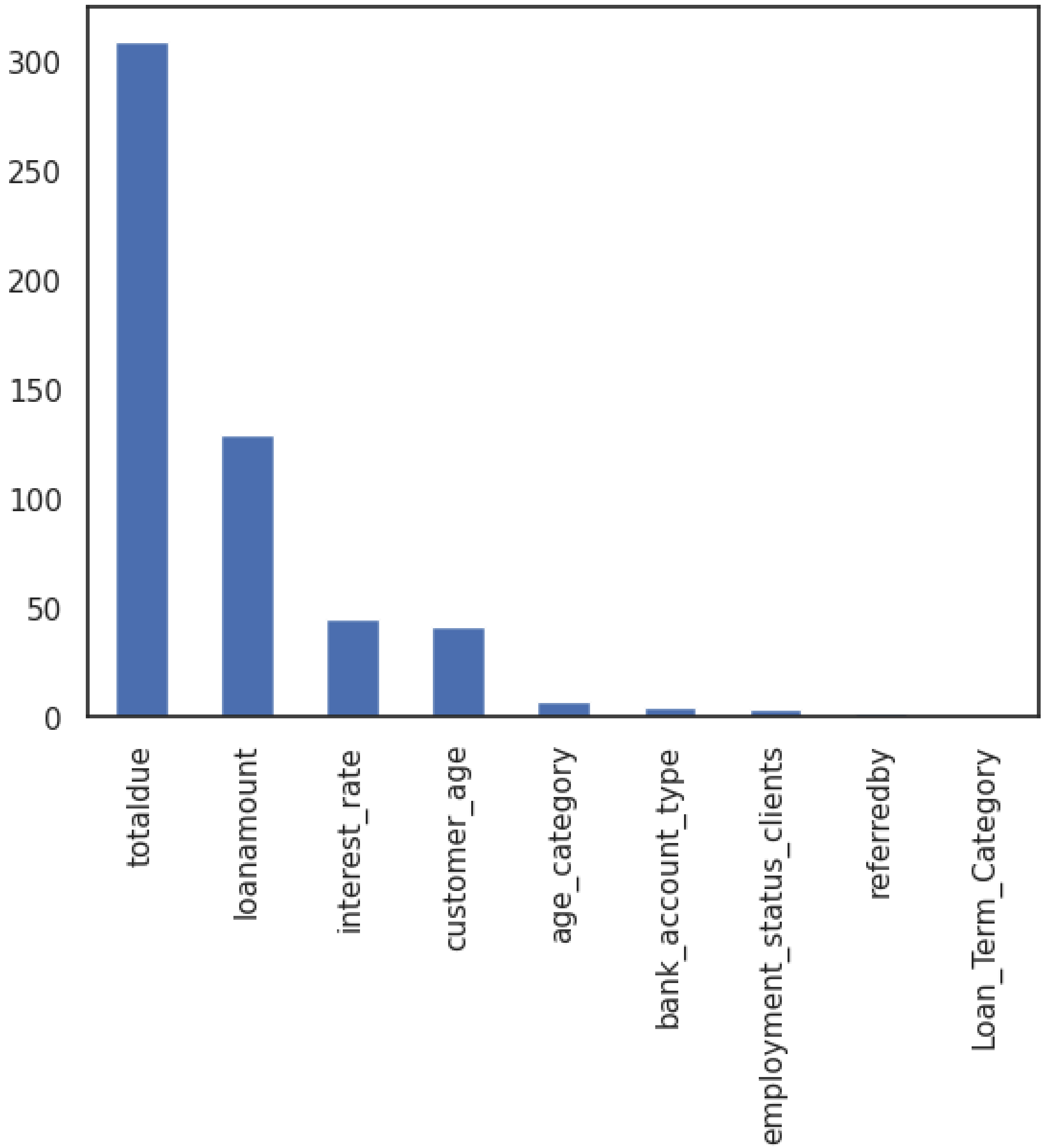
In [ ]:

```
chi_scores = chi2(A,b)
```

In [ ]:

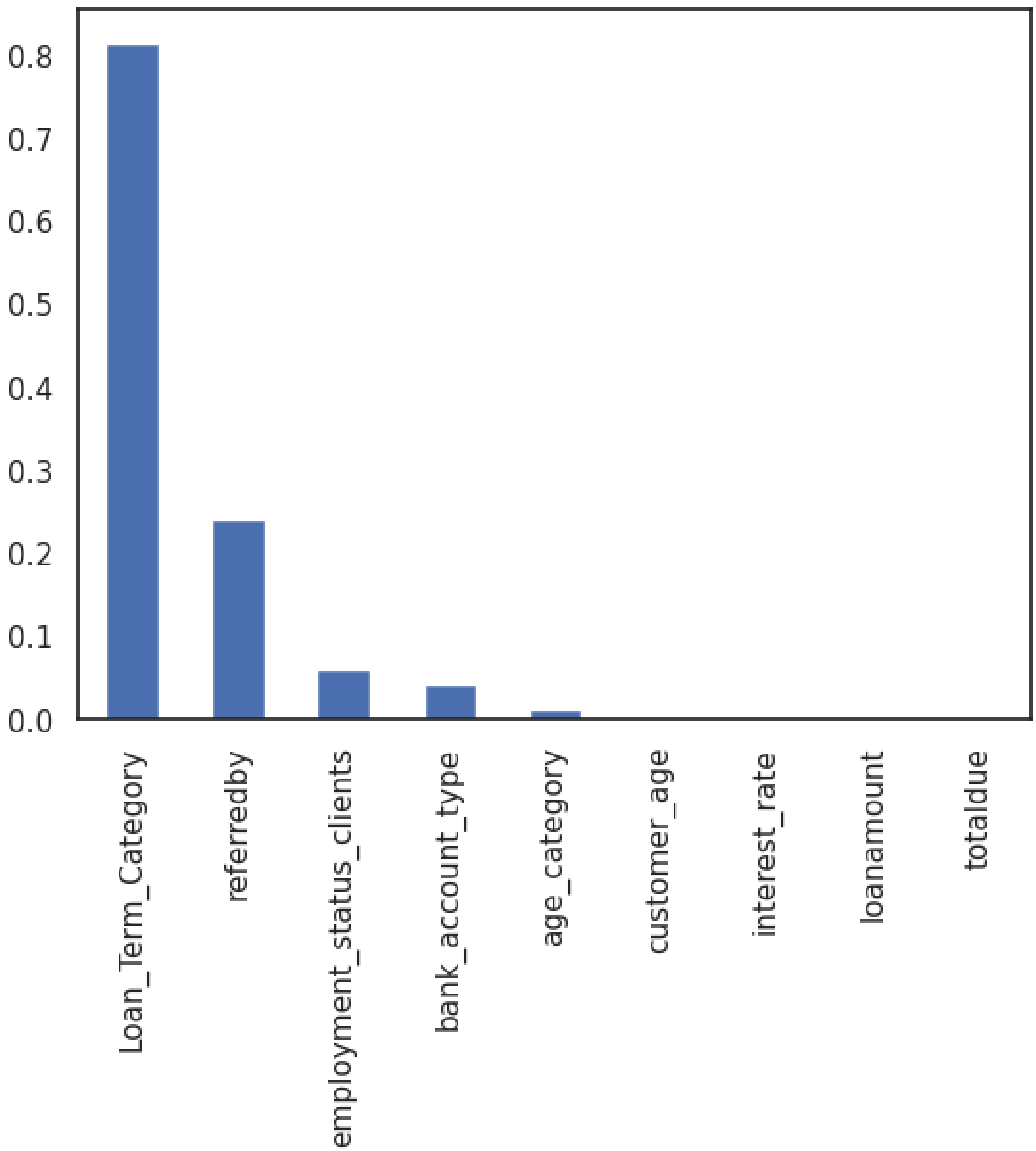
```
chi_values =  pd.Series(chi_scores[0], index = A.columns)
chi_values.sort_values(ascending = False, inplace=True)
chi_values.plot.bar()
```

Out[ ]: <Axes: >



In [ ]:
```
p_values =  pd.Series(chi_scores[1], index = A.columns)
p_values.sort_values(ascending = False, inplace=True)
p_values.plot.bar()
```

Out[ ]: <Axes: >



Top Important Features are Totaldue, LoanAmount, InterestRate, CustomerAge, AgeCategory, BankAccountType and Employment Status.

With RFE(Repercusive Feature Elimination)

In [ ]:
```
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier
```

In [ ]:
```
estimator = DecisionTreeClassifier(random_state=42)

# Pass the instance into RFE
rfe = RFE(estimator=estimator, n_features_to_select=5)

# Fit on your data
rfe.fit(A, b)
```

Out[ ]:

```
RFE
estimator: DecisionTreeClassifier
DecisionTreeClassifier
```

In [ ]:

```
for i, col in zip(range (A.shape[1]), A.columns):
  print(f'{col} selected = {rfe.support_[i]} ranking = {rfe.ranking_[i]}')
```

```
loanamount selected = False ranking = 2
totaldue selected = True ranking = 1
referredby selected = True ranking = 1
interest_rate selected = True ranking = 1
bank_account_type selected = False ranking = 3
employment_status_clients selected = True ranking = 1
customer_age selected = True ranking = 1
age_category selected = False ranking = 4
Loan_Term_Category selected = False ranking = 5
```

With RFE, top features are TotalDue, Referredby, InterestRate, Employment Status and customer Age

Conclusion

Both Chi-Square and RFE identified TotalDue, InterestRate, CustomerAge, and Employment Status as key features, indicating strong and consistent predictive power. Chi-Square additionally highlighted LoanAmount, AgeCategory, and BankAccountType, while RFE identified ReferredBy as important. This implies that while the consistently overlapping features should be prioritized, the additional features suggested by each method may still contribute depending on the modeling approach.

In [ ]:

```

```

Data Preprocessing

Note: Without Application of Feature Selection

In [ ]:

```
#defining x and y
X= new.drop(columns=['good_bad_flag', 'target', 'termdays']) #dropping term days as
y= new['target']
```

In [ ]:

```
#splitting data into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_st
```

In [ ]:

```
#Importing libraries foe encoding and scaling categorical and numerical columns rep
from sklearn.preprocessing import StandardScaler,OneHotEncoder
```

```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

In [ ]:
```
#create a pipeline for preprocessing
num_pipeline = Pipeline(steps=[
    ('scaler', StandardScaler())
])

cat_pipeline = Pipeline(steps=[
    ('encoder', OneHotEncoder(sparse_output= False, handle_unknown ='ignore'))
])
```

In [ ]:
```
#apply preprocessing
preprocessor = ColumnTransformer(transformers=[
    ('num', num_pipeline, num_cols),
    ('cat', cat_pipeline, cat_cols)
])
```

Model Training

In [ ]:
```
!pip install catboost
```

```
Requirement already satisfied: catboost in /usr/local/lib/python3.12/dist-packages
(1.2.8)
Requirement already satisfied: graphviz in /usr/local/lib/python3.12/dist-packages
(from catboost) (0.21)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dist-packages
(from catboost) (3.10.0)
Requirement already satisfied: numpy<3.0,>=1.16.0 in /usr/local/lib/python3.12/dist-
packages (from catboost) (2.0.2)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.12/dist-packag
es (from catboost) (2.2.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-packages (fro
m catboost) (1.16.1)
Requirement already satisfied: plotly in /usr/local/lib/python3.12/dist-packages (fr
om catboost) (5.24.1)
Requirement already satisfied: six in /usr/local/lib/python3.12/dist-packages (from
catboost) (1.17.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/d
ist-packages (from pandas>=0.24->catboost) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packag
es (from pandas>=0.24->catboost) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-pack
ages (from pandas>=0.24->catboost) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.12/dist-pa
ckages (from matplotlib->catboost) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.12/dist-packag
es (from matplotlib->catboost) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.12/dist-p
ackages (from matplotlib->catboost) (4.59.1)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.12/dist-p
ackages (from matplotlib->catboost) (1.4.9)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.12/dist-pac
kages (from matplotlib->catboost) (25.0)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.12/dist-packages
(from matplotlib->catboost) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.12/dist-pa
ckages (from matplotlib->catboost) (3.2.3)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.12/dist-pac
kages (from plotly->catboost) (8.5.0)
```

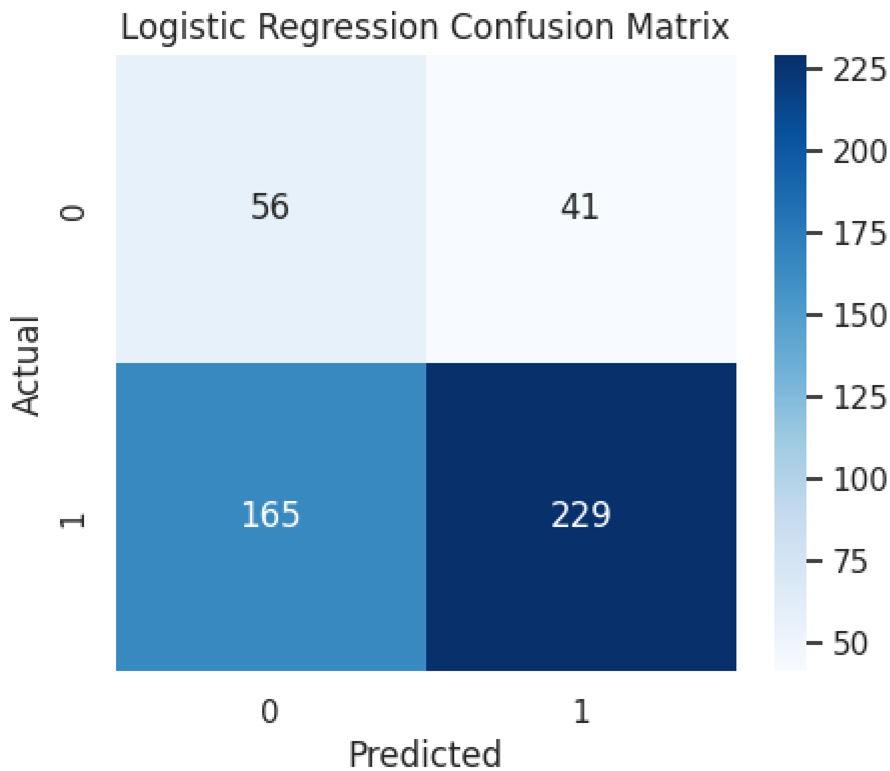
In [ ]:

```
#importing models and evaluation metrics required for prediction
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from catboost import CatBoostClassifier
from imblearn.ensemble import BalancedRandomForestClassifier, EasyEnsembleClassifie
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000, class_weight="balanced
    "Random Forest": RandomForestClassifier(n_estimators=200, random_state=42, clas
    "XGBoost": XGBClassifier(n_estimators=300, learning_rate=0.1, max_depth=5, rand
    "SVM": SVC(probability=True, class_weight="balanced", random_state=42),
    "Neural Net": MLPClassifier(hidden_layer_sizes=(64,32), max_iter=500, random_st
```

```python
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=200, random_state=
    "CatBoost": CatBoostClassifier(iterations=200, verbose=0, random_state=42),
    "Easy Ensemble": EasyEnsembleClassifier(n_estimators=50, random_state=42),
    "Decision Tree": DecisionTreeClassifier(criterion="gini", max_depth=5, random_s
}
```

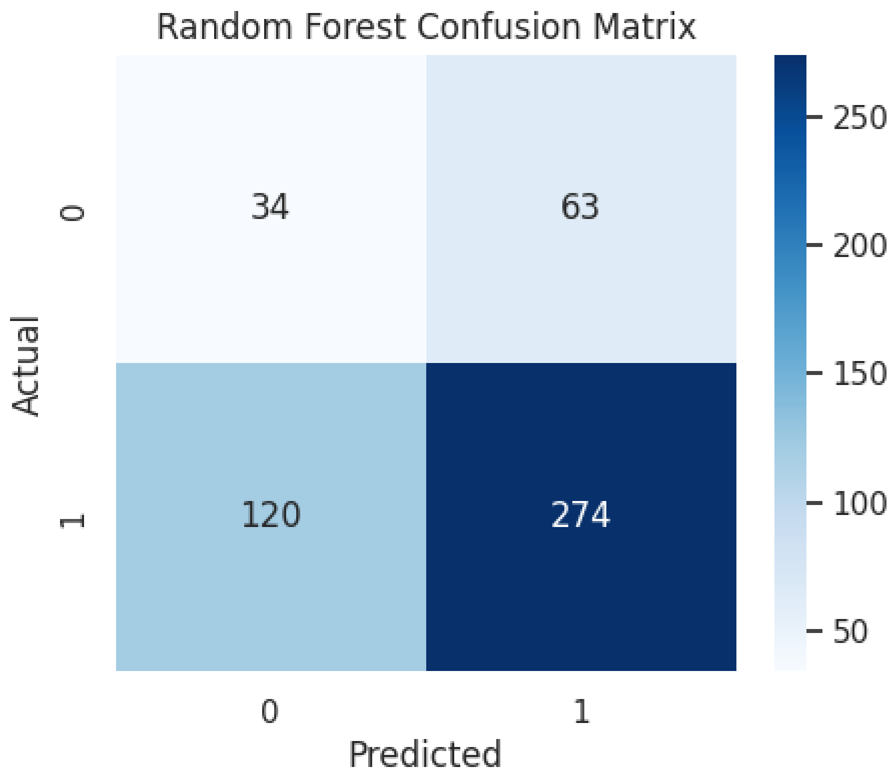
In [ ]:

```python
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE

results = {}

# loop through models
for name, model in models.items():
    pipeline = ImbPipeline(steps=[
        ('preprocessor', preprocessor),
        ('smote', SMOTE(random_state=42)),
        ('model', model)
    ])

    # fit model
    pipeline.fit(X_train, y_train)

    # predictions
    train_pred = pipeline.predict(X_train)
    test_pred = pipeline.predict(X_test)

    # probabilities (for ROC AUC)
    test_proba = pipeline.predict_proba(X_test)[:, 1]

    # metrics
    results[name] = {
        "Train Accuracy": accuracy_score(y_train, train_pred),
        "Test Accuracy": accuracy_score(y_test, test_pred),
        "Recall": recall_score(y_test, test_pred),
        "Precision": precision_score(y_test, test_pred),
        "F1 Score": f1_score(y_test, test_pred),
        "ROC AUC": roc_auc_score(y_test, test_proba),
        "Confusion Matrix": confusion_matrix(y_test, test_pred).tolist()  # stored
    }

    # Plot confusion matrix
    plt.figure(figsize=(5,4))
    sb.heatmap(results[name]["Confusion Matrix"], annot=True, fmt='d', cmap='Blues'
    plt.title(f'{name} Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    # Print classification report
    print(f"\n{name} Classification Report:\n")
    print(classification_report(y_test, test_pred))

# Convert to DataFrame (without confusion matrix column)
metrics1 = pd.DataFrame(results).T.drop(columns=["Confusion Matrix"])
```



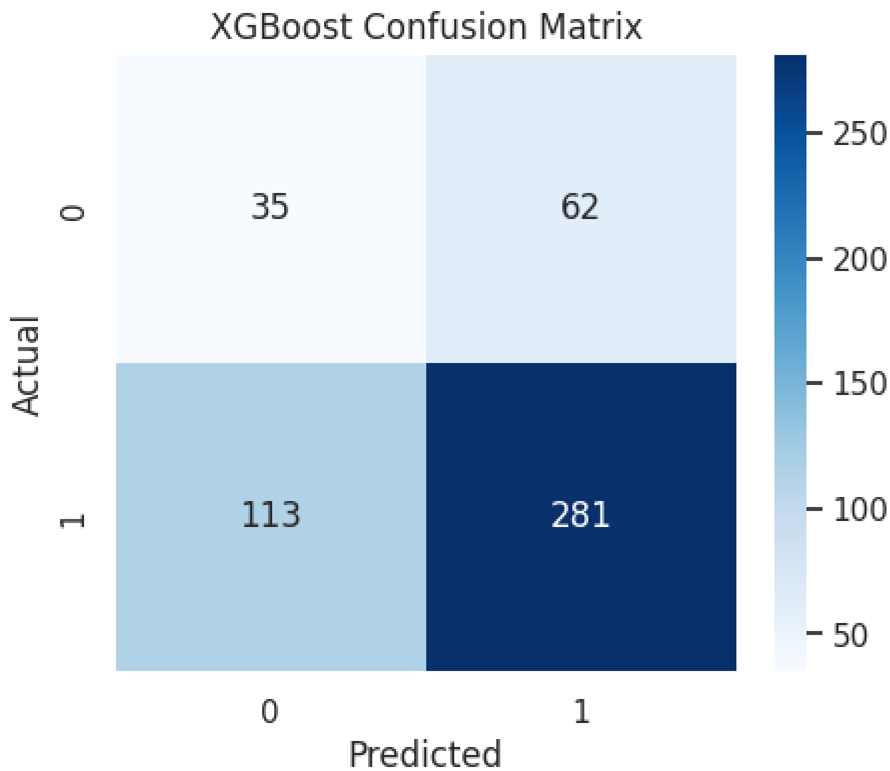
Logistic Regression Classification Report:

	precision	recall	f1-score	support
0	0.25	0.58	0.35	97
1	0.85	0.58	0.69	394
accuracy			0.58	491
macro avg	0.55	0.58	0.52	491
weighted avg	0.73	0.58	0.62	491



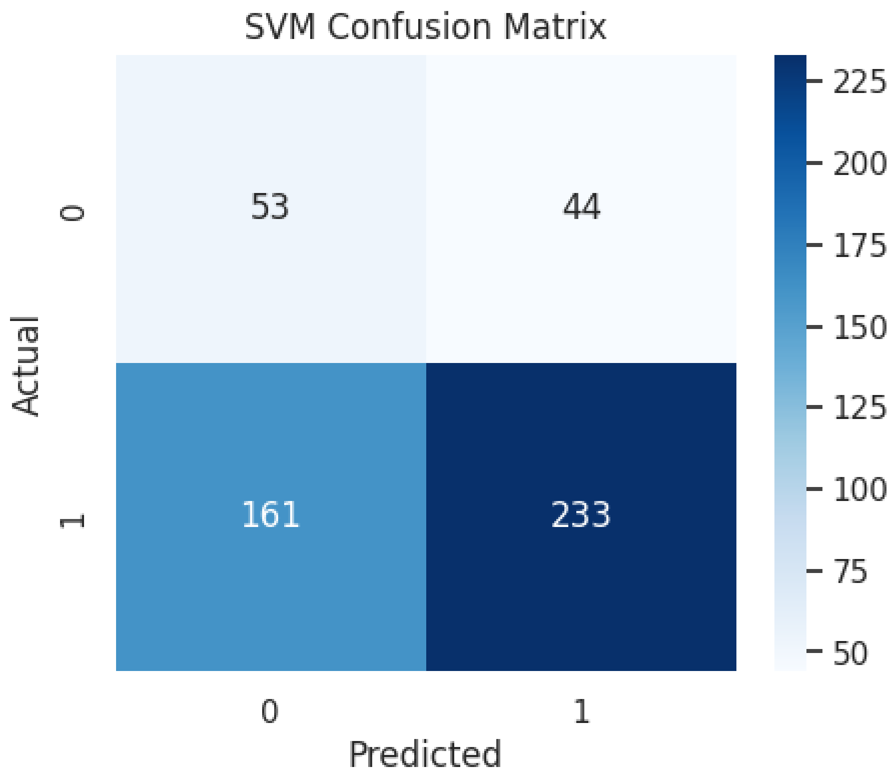

```
Random Forest Classification Report:

              precision    recall  f1-score   support

           0       0.22      0.35      0.27        97
           1       0.81      0.70      0.75       394

    accuracy                           0.63       491
   macro avg       0.52      0.52      0.51       491
weighted avg       0.70      0.63      0.66       491
```

```
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [23:0
8:36] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```



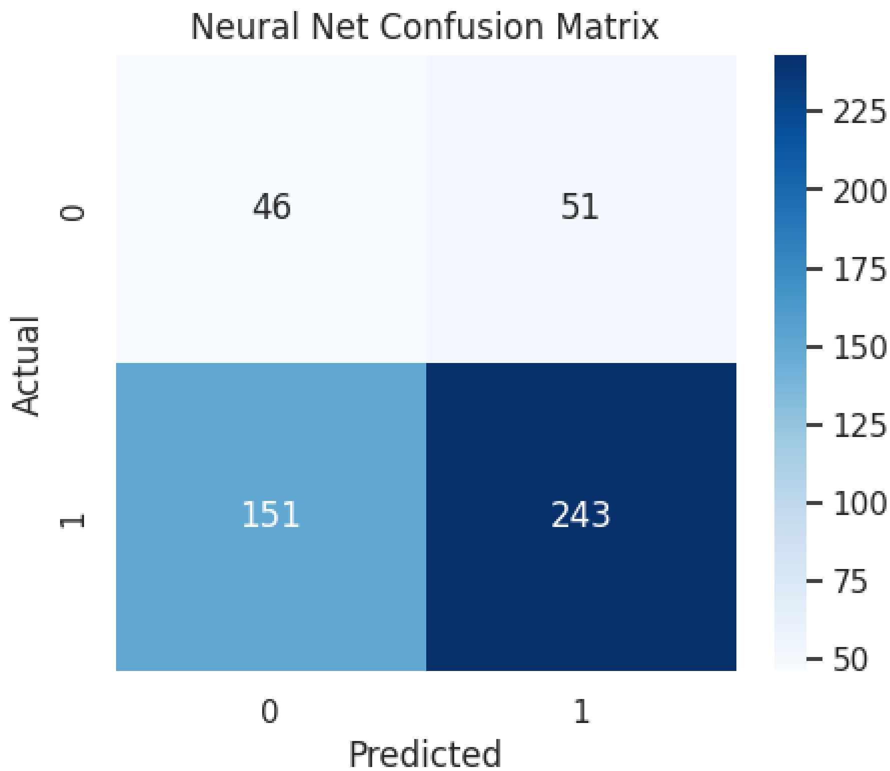
XGBoost Classification Report:

	precision	recall	f1-score	support
0	0.24	0.36	0.29	97
1	0.82	0.71	0.76	394
accuracy			0.64	491
macro avg	0.53	0.54	0.52	491
weighted avg	0.70	0.64	0.67	491



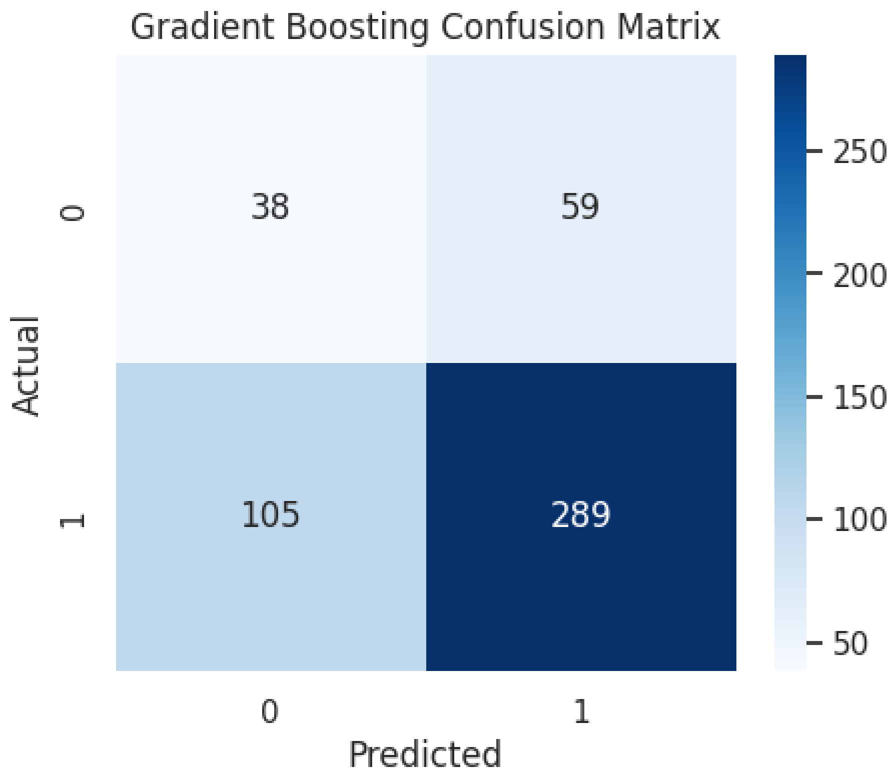
SVM Classification Report:

	precision	recall	f1-score	support
0	0.25	0.55	0.34	97
1	0.84	0.59	0.69	394
accuracy			0.58	491
macro avg	0.54	0.57	0.52	491
weighted avg	0.72	0.58	0.62	491



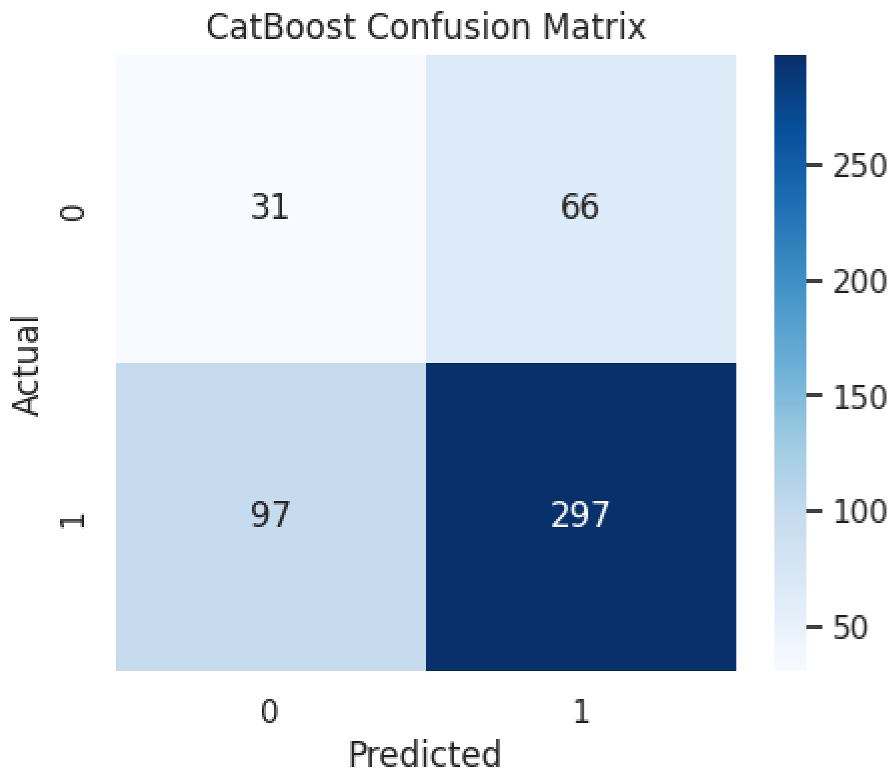
Neural Net Classification Report:

	precision	recall	f1-score	support
0	0.23	0.47	0.31	97
1	0.83	0.62	0.71	394
accuracy			0.59	491
macro avg	0.53	0.55	0.51	491
weighted avg	0.71	0.59	0.63	491



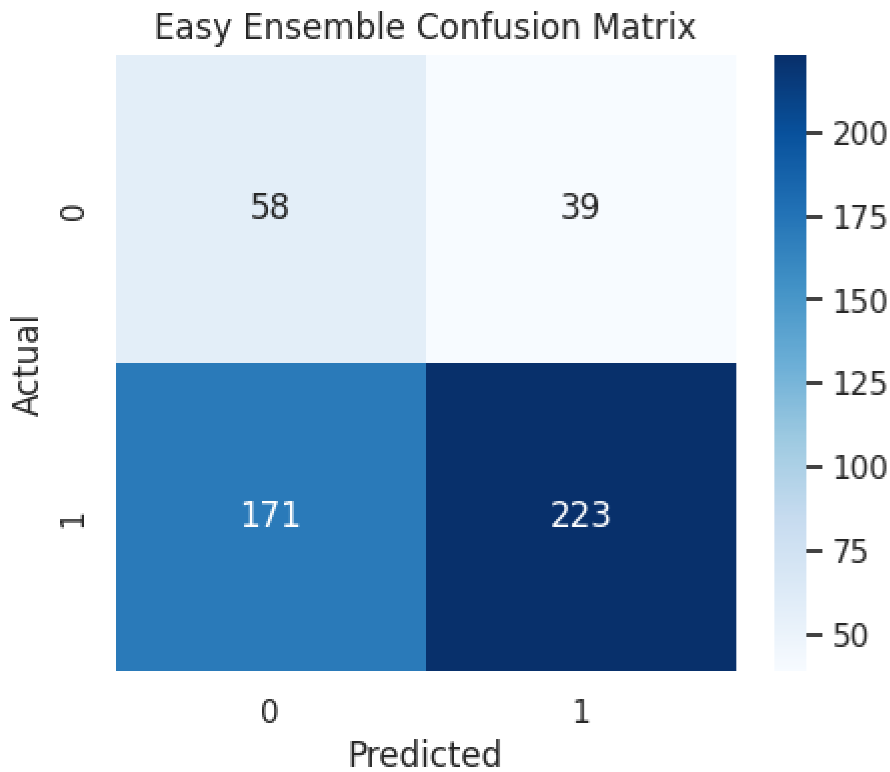
Gradient Boosting Classification Report:

	precision	recall	f1-score	support
0	0.27	0.39	0.32	97
1	0.83	0.73	0.78	394
accuracy			0.67	491
macro avg	0.55	0.56	0.55	491
weighted avg	0.72	0.67	0.69	491



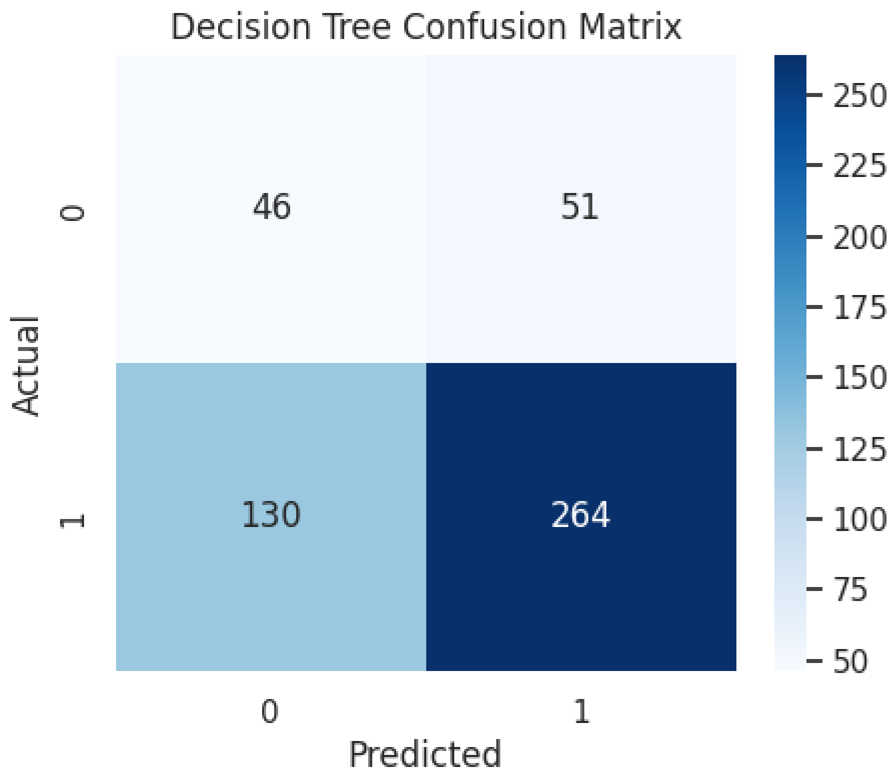
CatBoost Classification Report:

	precision	recall	f1-score	support
0	0.24	0.32	0.28	97
1	0.82	0.75	0.78	394
accuracy			0.67	491
macro avg	0.53	0.54	0.53	491
weighted avg	0.70	0.67	0.68	491



Easy Ensemble Classification Report:

	precision	recall	f1-score	support
0	0.25	0.60	0.36	97
1	0.85	0.57	0.68	394
accuracy			0.57	491
macro avg	0.55	0.58	0.52	491
weighted avg	0.73	0.57	0.62	491




```
Decision Tree Classification Report:

              precision    recall  f1-score   support

           0       0.26      0.47      0.34        97
           1       0.84      0.67      0.74       394

    accuracy                           0.63       491
   macro avg       0.55      0.57      0.54       491
weighted avg       0.72      0.63      0.66       491
```

In [ ]:

```
metrics1
```

Out[ ]:

	Train Accuracy	Test Accuracy	Recall	Precision	F1 Score	ROC AUC
Logistic Regression	0.589633	0.580448	0.581218	0.848148	0.689759	0.603943
Random Forest	0.771778	0.627291	0.695431	0.813056	0.749658	0.505011
XGBoost	0.736141	0.643585	0.713198	0.819242	0.762551	0.556976
SVM	0.605472	0.582485	0.591371	0.841155	0.694486	0.581467
Neural Net	0.672426	0.588595	0.616751	0.826531	0.706395	0.570268
Gradient Boosting	0.716343	0.665988	0.733503	0.83046	0.778976	0.56336
CatBoost	0.734701	0.668024	0.753807	0.818182	0.784676	0.578275
Easy Ensemble	0.580994	0.572301	0.56599	0.851145	0.679878	0.603158
Decision Tree	0.645428	0.631365	0.670051	0.838095	0.744711	0.594066

Summary

While boosting models like CatBoost and XGBoost show higher overall performance, they are biased toward the majority class (good loans). This makes them appear strong but weak at identifying defaulters — the class that truly matters in loan prediction. In contrast, SVM, Easy Ensemble, and Decision Tree maintain a better balance between predicting good and bad loans. Their lower scores reflect the real challenge of detecting defaulters, giving a more honest view of model performance. For credit risk, these balanced models are more reliable because they reduce the risk of approving bad loans.

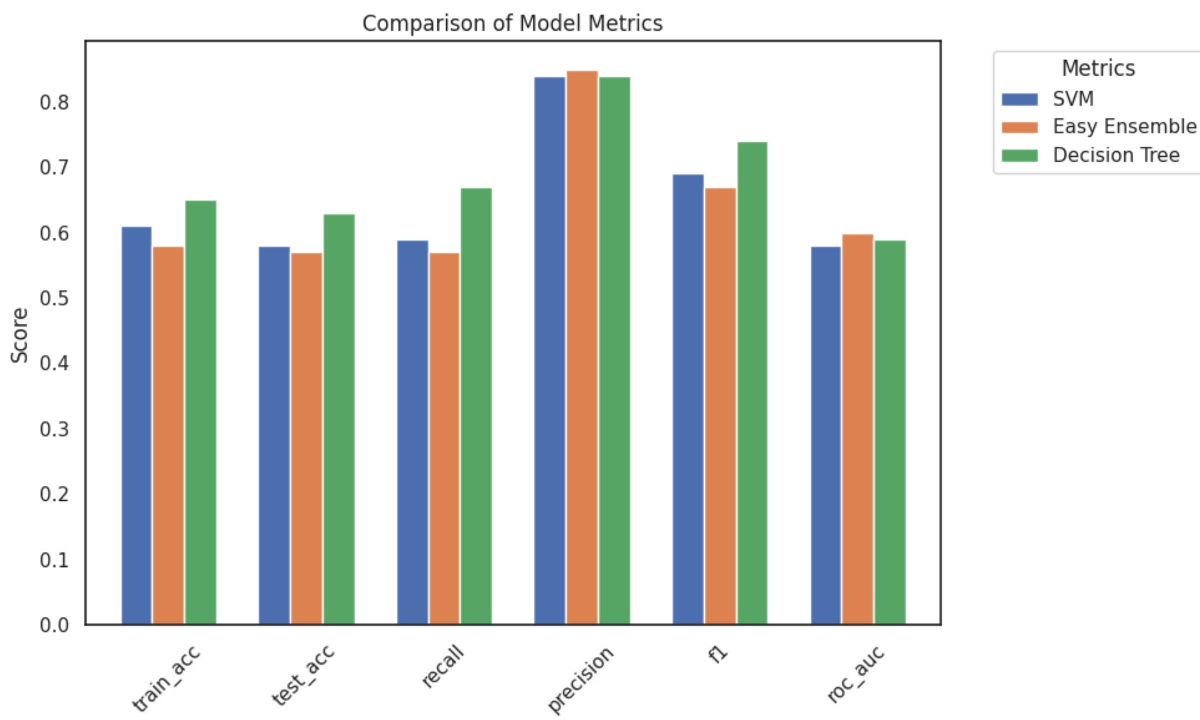
In [ ]:

```
#Top model Result comparison
results = {
    "SVM": {
        "train_acc": 0.61,
        "test_acc": 0.58,
        "recall": 0.59,
        "precision": 0.84,
        "f1": 0.69,
        "roc_auc": 0.58
    },
    "Easy Ensemble": {
        "train_acc": 0.58,
        "test_acc": 0.57,
        "recall": 0.57,
        "precision": 0.85,
        "f1": 0.67,
        "roc_auc": 0.60
    },
    "Decision Tree":{
```

```
        'train_acc': 0.65,
        'test_acc': 0.63,
        'recall': 0.67,
        'precision': 0.84,
        'f1': 0.74,
        'roc_auc': 0.59
    }
}

df_results = pd.DataFrame(results)
print(df_results)
```

```
            SVM  Easy Ensemble  Decision Tree
train_acc  0.61           0.58           0.65
test_acc   0.58           0.57           0.63
recall     0.59           0.57           0.67
precision  0.84           0.85           0.84
f1         0.69           0.67           0.74
roc_auc    0.58           0.60           0.59
```

In [ ]:
```
df_results.plot(kind="bar", figsize=(10,6), width=0.7)
plt.title("Comparison of Model Metrics")
plt.ylabel("Score")
plt.xticks(rotation=45)
plt.legend(title="Metrics", bbox_to_anchor=(1.05,1), loc="upper left")
plt.tight_layout()
plt.show()
```

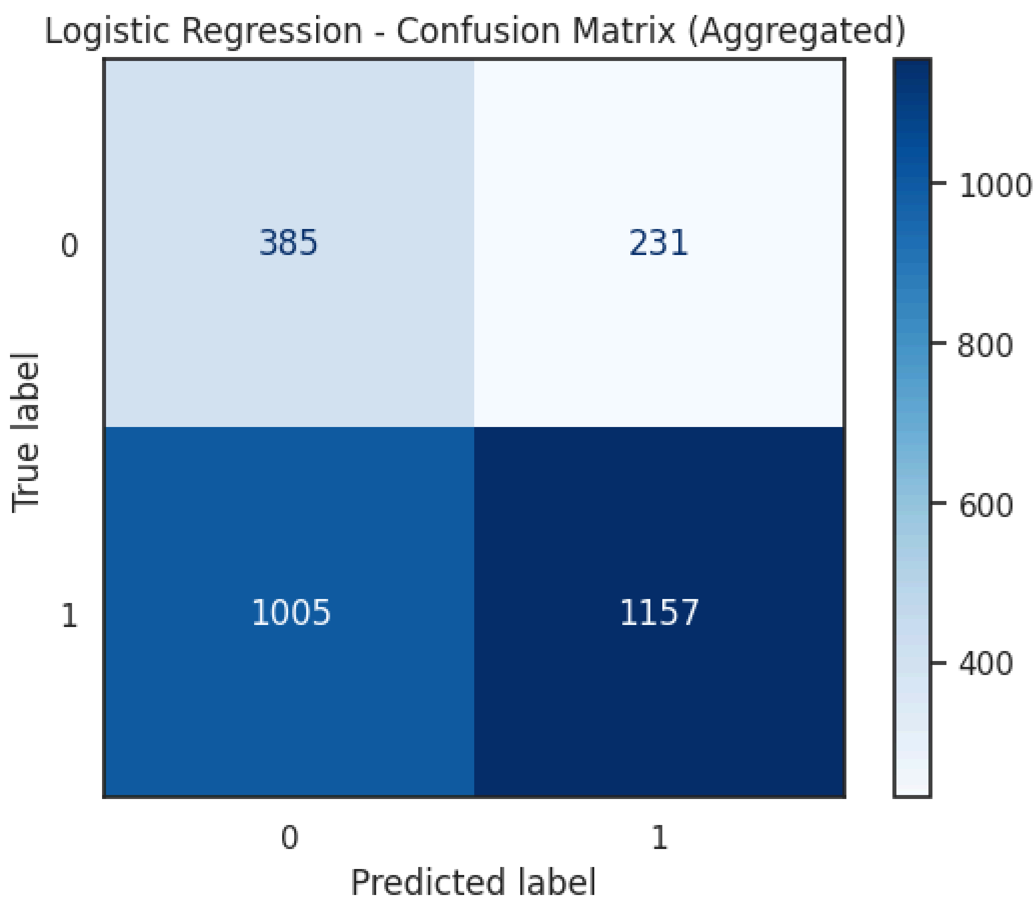


In [ ]:
```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import ConfusionMatrixDisplay

results = {}

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

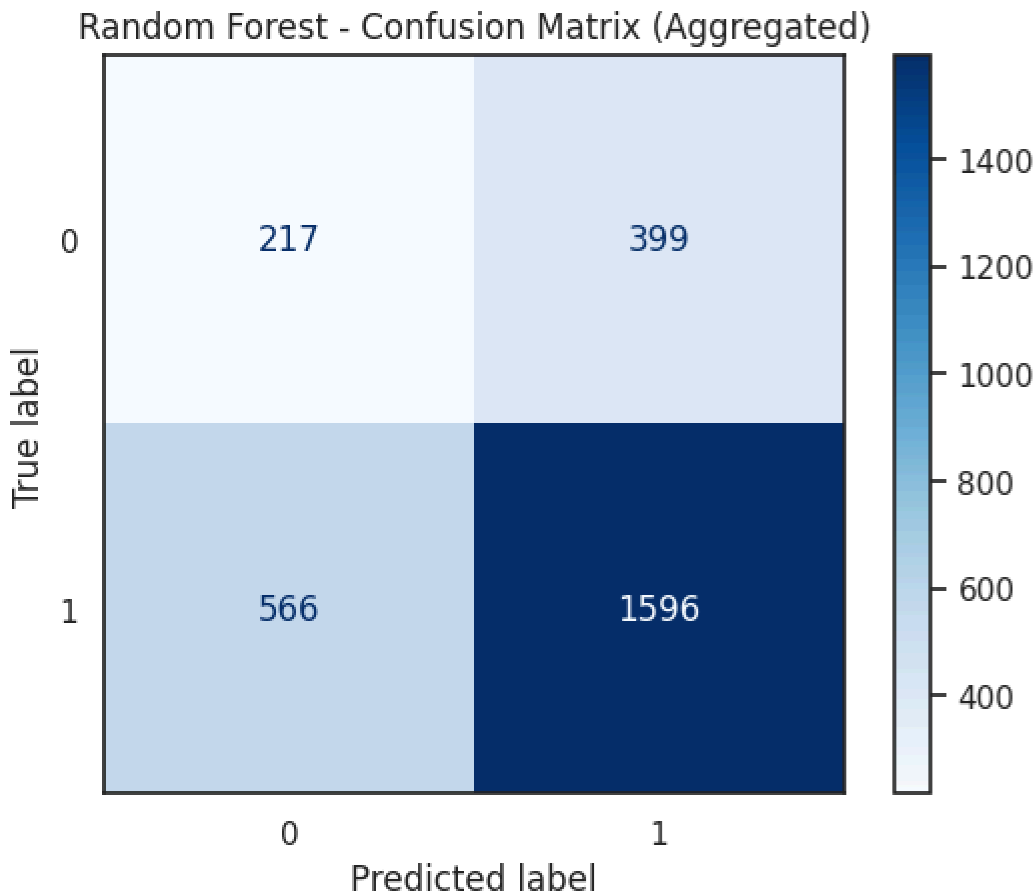
```
for name, model in models.items():
    fold_metrics = {
        "Train Accuracy": [],
        "Test Accuracy": [],
        "Recall": [],
        "Precision": [],
        "F1 Score": [],
        "ROC AUC": []
    }

    # Store aggregate predictions for classification report
    all_y_true, all_y_pred = [], []

    # Loop through folds
    for train_index, test_index in skf.split(X_train, y_train):
        X_tr, X_val = X_train.iloc[train_index], X_train.iloc[test_index]
        y_tr, y_val = y_train.iloc[train_index], y_train.iloc[test_index]

        pipeline = ImbPipeline(steps=[
            ('preprocessor', preprocessor),
            ('smote', SMOTE(random_state=42)),
            ('model', model)
        ])

        pipeline.fit(X_tr, y_tr)
        y_train_pred = pipeline.predict(X_tr)
        y_val_pred = pipeline.predict(X_val)
        y_val_proba = pipeline.predict_proba(X_val)[:, 1] if hasattr(pipeline, "pre

        # Store metrics per fold
        fold_metrics["Train Accuracy"].append(accuracy_score(y_tr, y_train_pred))
        fold_metrics["Test Accuracy"].append(accuracy_score(y_val, y_val_pred))
        fold_metrics["Recall"].append(recall_score(y_val, y_val_pred))
        fold_metrics["Precision"].append(precision_score(y_val, y_val_pred))
        fold_metrics["F1 Score"].append(f1_score(y_val, y_val_pred))
        if y_val_proba is not None:
            fold_metrics["ROC AUC"].append(roc_auc_score(y_val, y_val_proba))

        # Collect predictions for classification report
        all_y_true.extend(y_val)
        all_y_pred.extend(y_val_pred)

    # Average metrics across folds
    results[name] = {metric: np.mean(values) for metric, values in fold_metrics.ite

    # Classification report (aggregate across all folds)
    print(f"\n{name} Classification Report:\n")
    print(classification_report(all_y_true, all_y_pred))

    #Confusion matrix (aggregate)
    cm = confusion_matrix(all_y_true, all_y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot(cmap="Blues", values_format="d")
    plt.title(f"{name} - Confusion Matrix (Aggregated)")
    plt.show()
```

```python
# Convert to DataFrame (metrics summary)
metrics = pd.DataFrame(results).T
```

```
Logistic Regression Classification Report:

              precision    recall  f1-score   support

           0       0.28      0.62      0.38       616
           1       0.83      0.54      0.65      2162

    accuracy                           0.56      2778
   macro avg       0.56      0.58      0.52      2778
weighted avg       0.71      0.56      0.59      2778
```



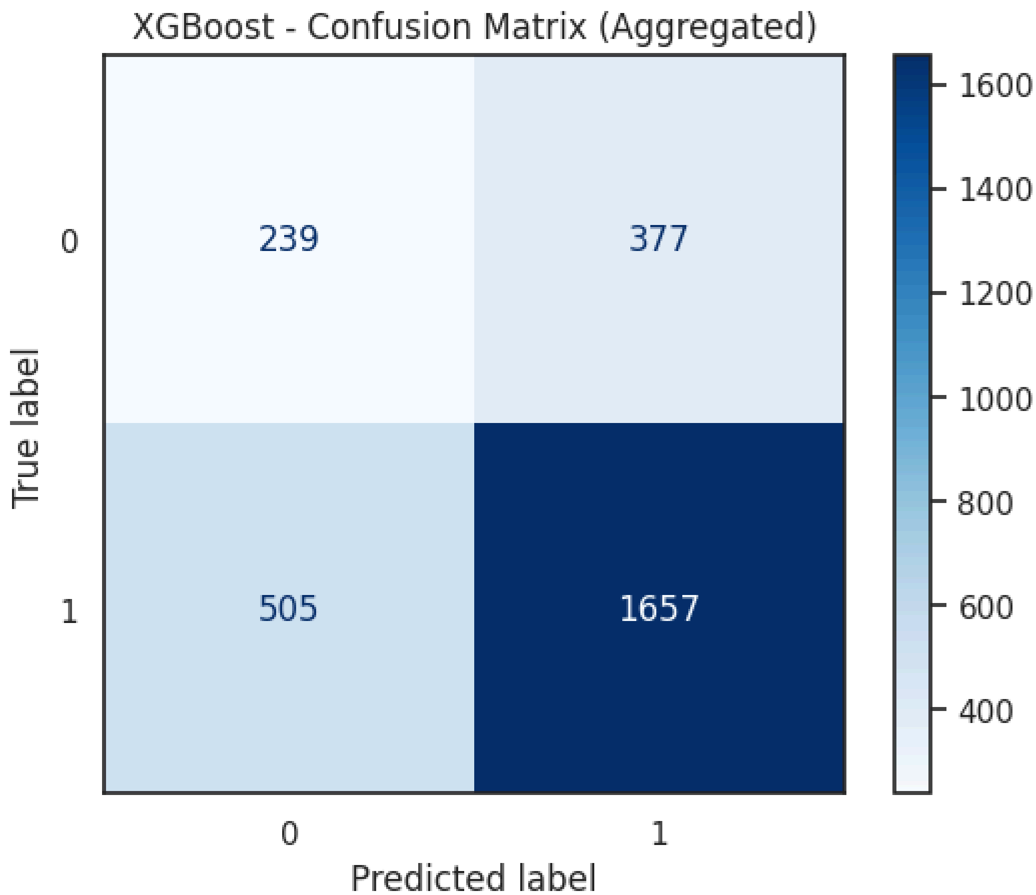

```
Random Forest Classification Report:

              precision    recall  f1-score   support

           0       0.28      0.35      0.31       616
           1       0.80      0.74      0.77      2162

    accuracy                           0.65      2778
   macro avg       0.54      0.55      0.54      2778
weighted avg       0.68      0.65      0.67      2778
```




```
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [23:0
9:35] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [23:0
9:40] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [23:0
9:45] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [23:0
9:49] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [23:0
9:50] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

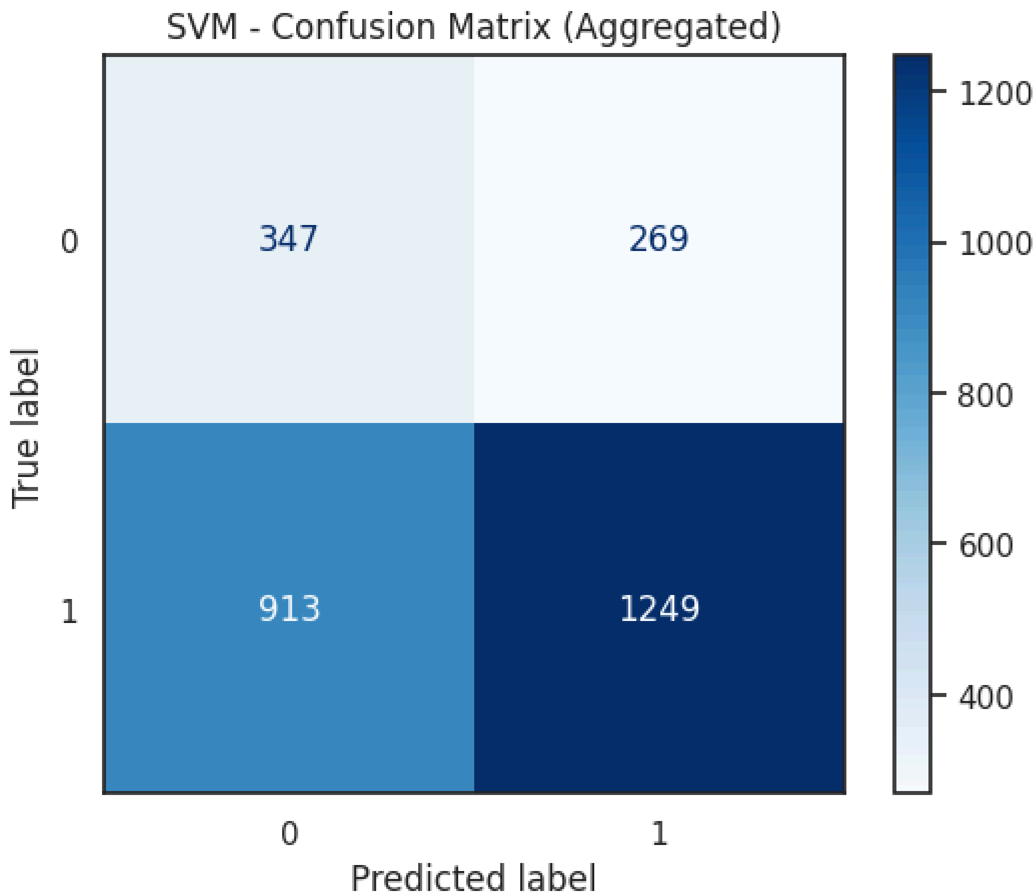
XGBoost Classification Report:

	precision	recall	f1-score	support
0	0.32	0.39	0.35	616
1	0.81	0.77	0.79	2162
accuracy			0.68	2778
macro avg	0.57	0.58	0.57	2778
weighted avg	0.71	0.68	0.69	2778



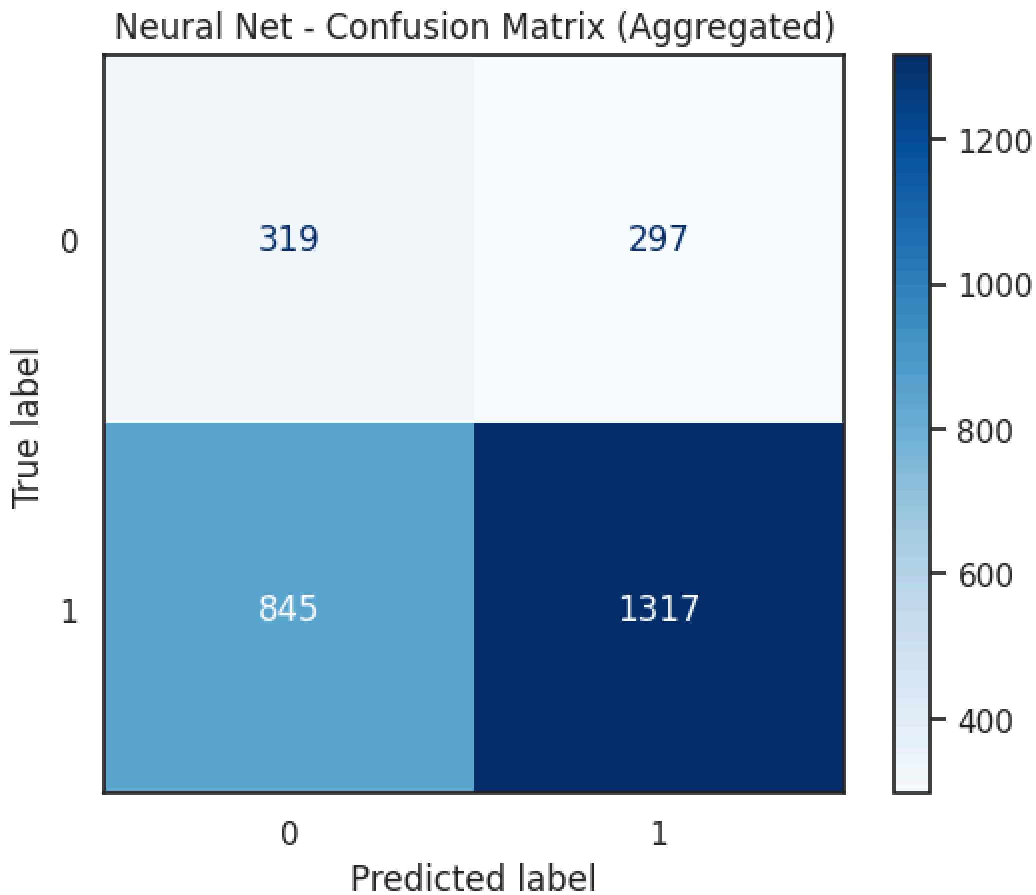
SVM Classification Report:

	precision	recall	f1-score	support
0	0.28	0.56	0.37	616
1	0.82	0.58	0.68	2162
accuracy			0.57	2778
macro avg	0.55	0.57	0.52	2778
weighted avg	0.70	0.57	0.61	2778



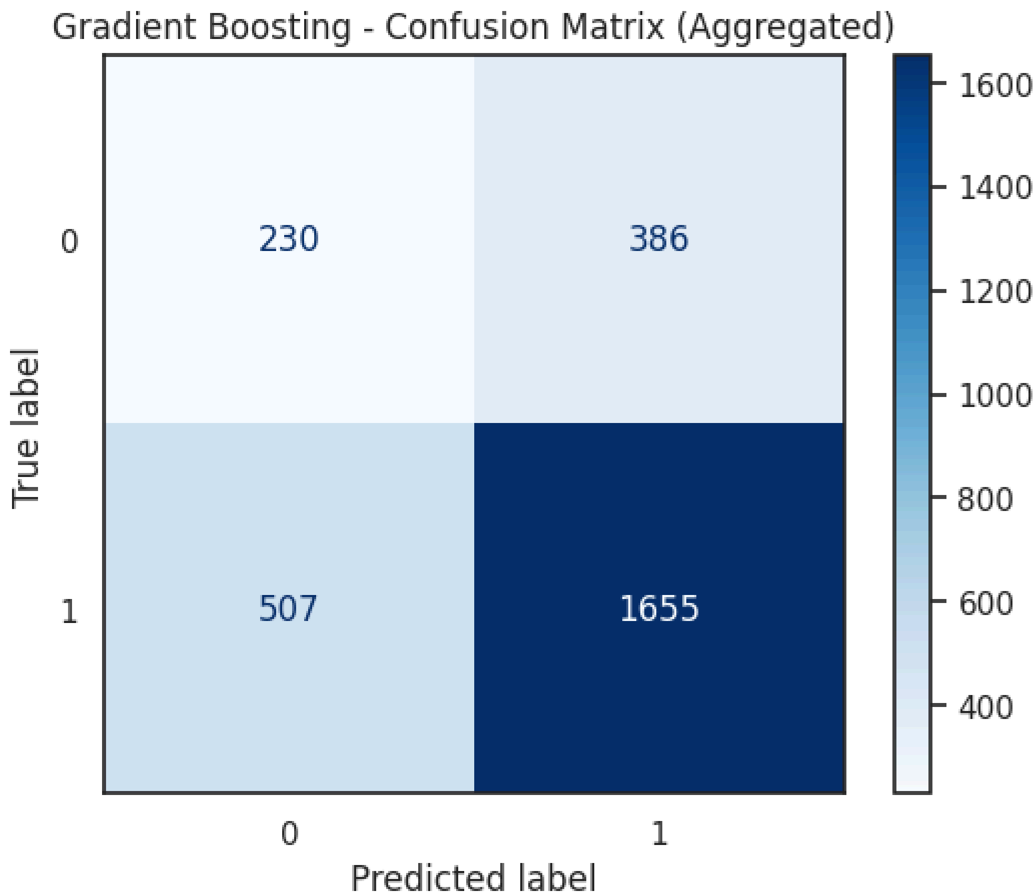
Neural Net Classification Report:

	precision	recall	f1-score	support
0	0.27	0.52	0.36	616
1	0.82	0.61	0.70	2162
accuracy			0.59	2778
macro avg	0.55	0.56	0.53	2778
weighted avg	0.70	0.59	0.62	2778



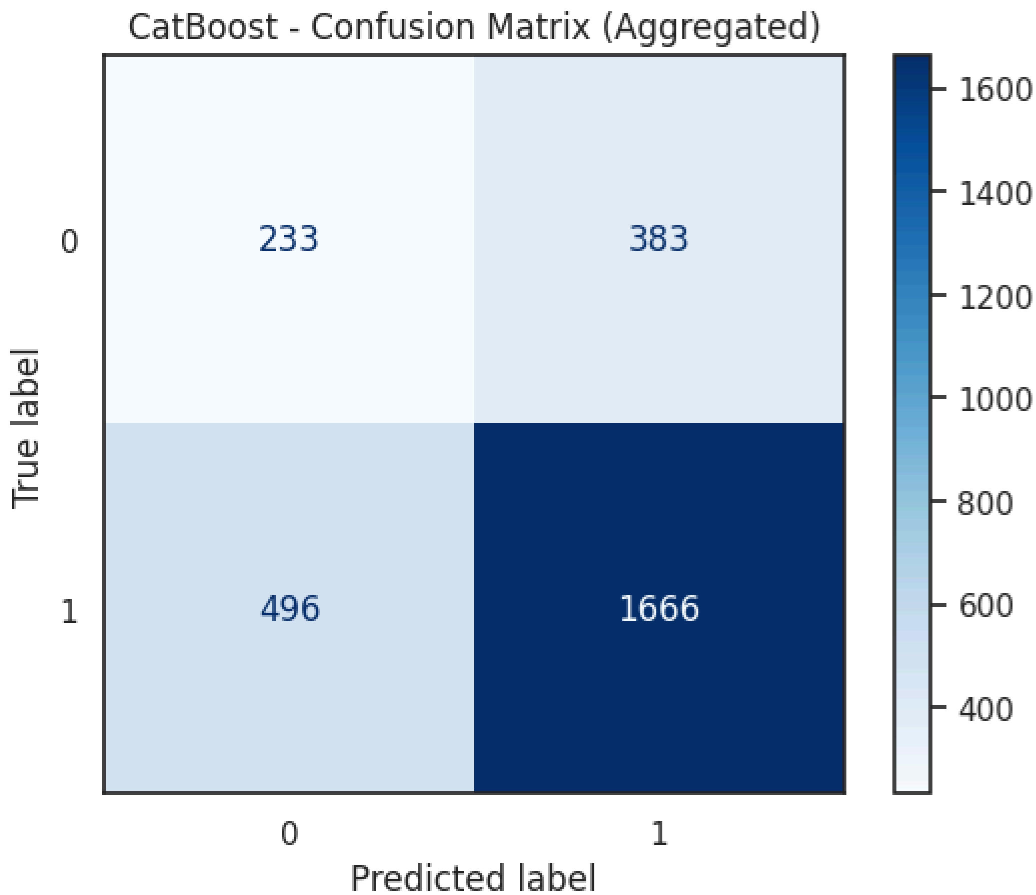
Gradient Boosting Classification Report:

	precision	recall	f1-score	support
0	0.31	0.37	0.34	616
1	0.81	0.77	0.79	2162
accuracy			0.68	2778
macro avg	0.56	0.57	0.56	2778
weighted avg	0.70	0.68	0.69	2778



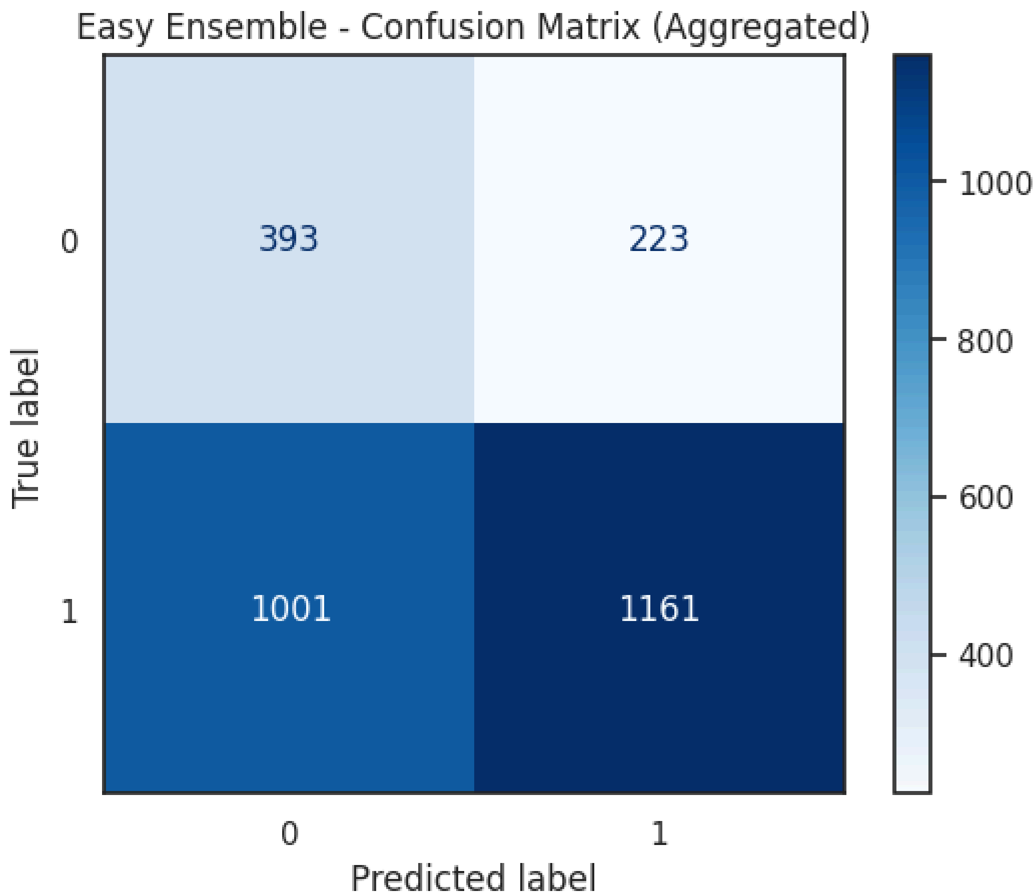
CatBoost Classification Report:

	precision	recall	f1-score	support
0	0.32	0.38	0.35	616
1	0.81	0.77	0.79	2162
accuracy			0.68	2778
macro avg	0.57	0.57	0.57	2778
weighted avg	0.70	0.68	0.69	2778

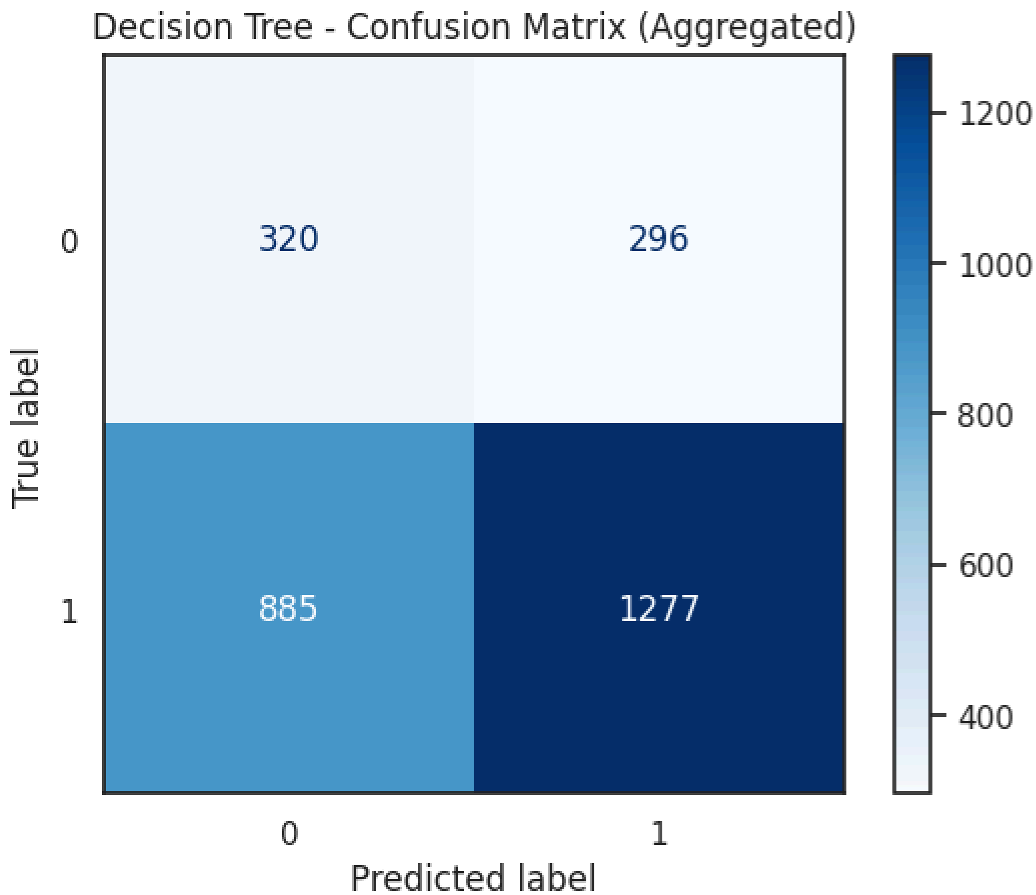


Easy Ensemble Classification Report:

	precision	recall	f1-score	support
0	0.28	0.64	0.39	616
1	0.84	0.54	0.65	2162
accuracy			0.56	2778
macro avg	0.56	0.59	0.52	2778
weighted avg	0.72	0.56	0.60	2778




```
Decision Tree Classification Report:

              precision    recall  f1-score   support

           0       0.27      0.52      0.35       616
           1       0.81      0.59      0.68      2162

    accuracy                           0.57      2778
   macro avg       0.54      0.56      0.52      2778
weighted avg       0.69      0.57      0.61      2778
```



In [ ]:
```
metrics
```

Out[ ]:

	Train Accuracy	Test Accuracy	Recall	Precision	F1 Score	ROC AUC
Logistic Regression	0.565606	0.555085	0.535152	0.833975	0.651585	0.613496
Random Forest	0.795627	0.652635	0.738205	0.800012	0.767775	0.565007
XGBoost	0.759629	0.682521	0.766435	0.814713	0.789698	0.609710
SVM	0.617531	0.574522	0.577707	0.823172	0.678794	0.599056
Neural Net	0.678278	0.588904	0.609167	0.815958	0.696577	0.583616
Gradient Boosting	0.723003	0.678556	0.765502	0.810956	0.787533	0.610013
CatBoost	0.739923	0.683587	0.770581	0.813208	0.791268	0.608802
Easy Ensemble	0.567677	0.559397	0.536969	0.840897	0.654127	0.613625
Decision Tree	0.601609	0.574860	0.590719	0.812126	0.674081	0.585806

With cross validation SVM, Ensemble and decision tree still remain top three

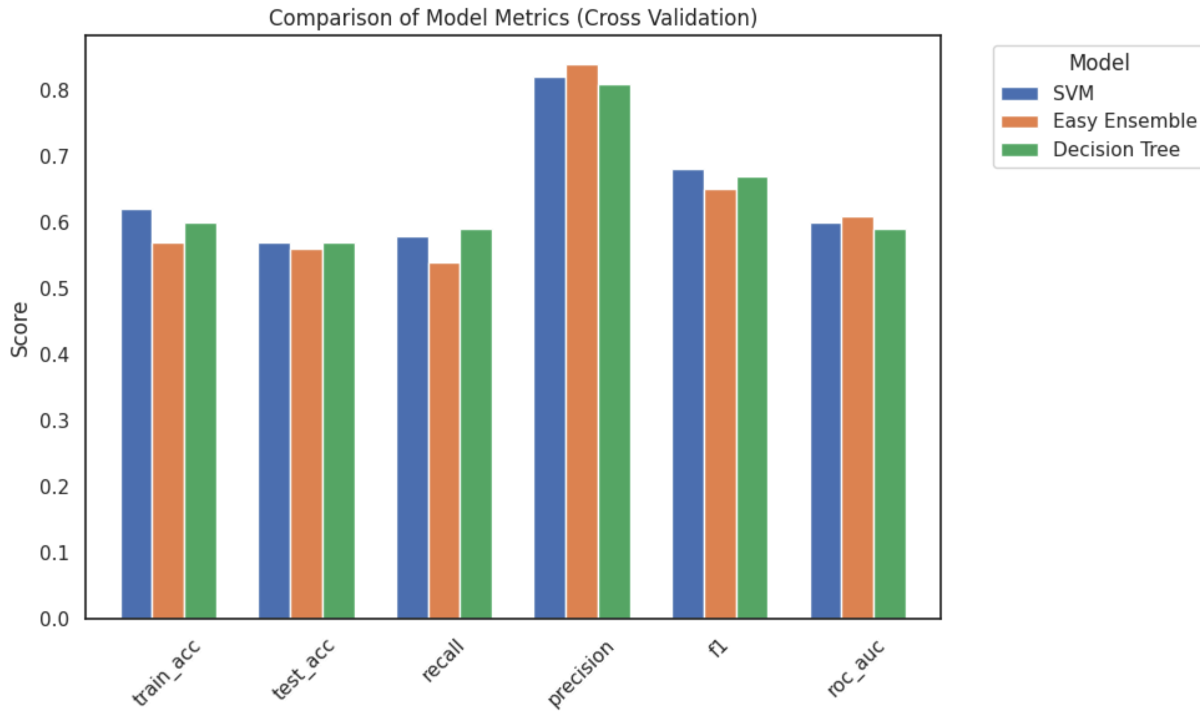
In [ ]:

```python
# cross val result comparison
#Top model Result comparison
results = {
    "SVM": {
        "train_acc": 0.62,
        "test_acc": 0.57,
        "recall": 0.58,
        "precision": 0.82,
        "f1": 0.68,
        "roc_auc": 0.60
    },
    "Easy Ensemble": {
        "train_acc": 0.57,
        "test_acc": 0.56,
        "recall": 0.54,
        "precision": 0.84,
        "f1": 0.65,
        "roc_auc": 0.61
    },
    "Decision Tree":{
        'train_acc': 0.60,
        'test_acc': 0.57,
        'recall': 0.59,
        'precision': 0.81,
        'f1': 0.67,
        'roc_auc': 0.59
    }
}

df_results2 = pd.DataFrame(results)
print(df_results2)
```

```
            SVM  Easy Ensemble  Decision Tree
train_acc  0.62           0.57           0.60
test_acc   0.57           0.56           0.57
recall     0.58           0.54           0.59
precision  0.82           0.84           0.81
f1         0.68           0.65           0.67
roc_auc    0.60           0.61           0.59
```

In [ ]:

```python
df_results2.plot(kind="bar", figsize=(10,6), width=0.7)
plt.title("Comparison of Model Metrics (Cross Validation)")
plt.ylabel("Score")
plt.xticks(rotation=45)
plt.legend(title="Model", bbox_to_anchor=(1.05,1), loc="upper left")
plt.tight_layout()
plt.show()
```



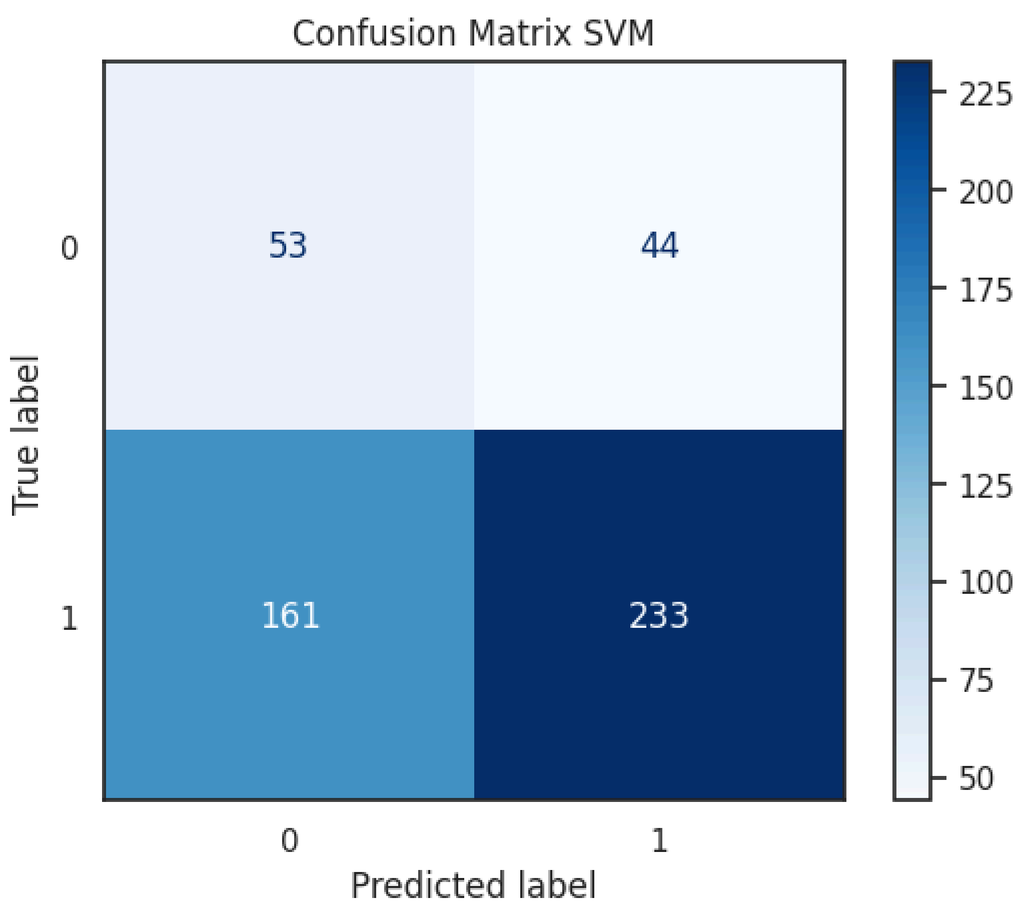
From cross-validation, SVM consistently outperformed the other models, showing stronger average performance across the folds

In [ ]:

```
# SVM pipeline (tuned)
pipeline = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', SMOTE(random_state=42)),
    ('model', SVC(
        C=0.08,
        class_weight='balanced',
        kernel='rbf',
        probability=True,
        random_state=42
    ))
])

pipeline.fit(X_train, y_train)

y_pred = pipeline.predict(X_test)
y_proba = pipeline.predict_proba(X_test)[:, 1]


# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall:", recall_score(y_test, y_pred))
print("F1-score:", f1_score(y_test, y_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_proba))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

#Confusion matrix
cm = confusion_matrix(y_test, y_pred)
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap="Blues", values_format="d")
plt.title("Confusion Matrix SVM")
plt.show()
```

```
Accuracy: 0.5824847250509165
Precision: 0.8411552346570397
Recall: 0.5913705583756346
F1-score: 0.6944858420268256
ROC-AUC: 0.5996519964414674

Classification Report:
              precision    recall  f1-score   support

           0       0.25      0.55      0.34        97
           1       0.84      0.59      0.69       394

    accuracy                           0.58       491
   macro avg       0.54      0.57      0.52       491
weighted avg       0.72      0.58      0.62       491
```



After tuning, SVM achieved better result with roc (+0.01)

In [ ]:
```
from sklearn.model_selection import cross_validate, StratifiedKFold

# Define cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

```python
# Cross-validation with multiple metrics
scoring = {
    'accuracy': 'accuracy',
    'precision': 'precision',
    'recall': 'recall',
    'f1': 'f1',
    'roc_auc': 'roc_auc'
}

cv_results = cross_validate(
    pipeline,
    X_train,
    y_train,
    cv=cv,
    scoring=scoring,
    return_train_score=False
)

# Show average performance across folds
print("Tuned SVM Cross-Validation Results (mean across folds):")
for metric in scoring.keys():
    print(f"{metric}: {cv_results['test_' + metric].mean():.4f}")
```

```
Tuned SVM Cross-Validation Results (mean across folds):
accuracy: 0.5680
precision: 0.8358
recall: 0.5550
f1: 0.6654
roc_auc: 0.6085
```

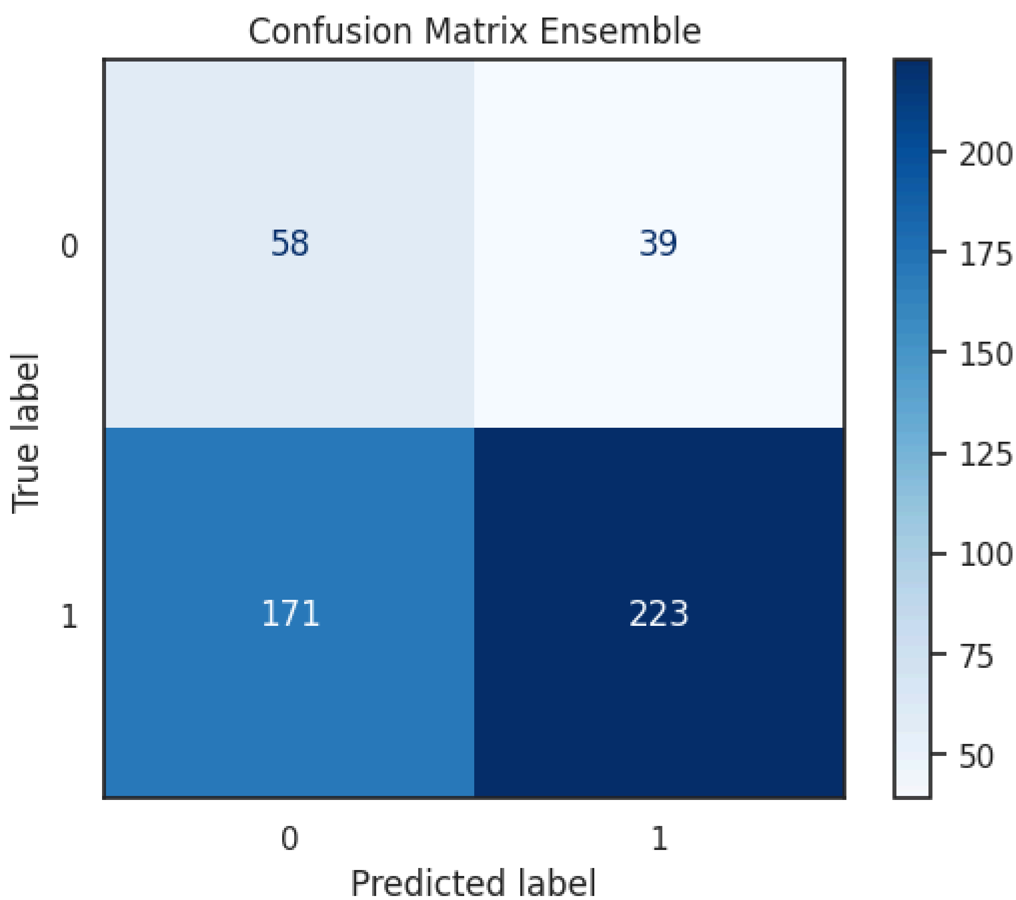
After tuning, cross-validation results for SVM declined — accuracy decreased and recall dropped by 0.02. This indicates that the tuned model underperforms, so we will proceed with the untuned version.

In [ ]:

```python
#ensemble
pipeline = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', SMOTE(random_state=42)),
    ('model', EasyEnsembleClassifier(
    n_estimators=100,
    sampling_strategy="auto",
    random_state=42))
])

pipeline.fit(X_train, y_train)

y_pred = pipeline.predict(X_test)
y_proba = pipeline.predict_proba(X_test)[:, 1]


# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall:", recall_score(y_test, y_pred))
print("F1-score:", f1_score(y_test, y_pred))
```

```
print("ROC-AUC:", roc_auc_score(y_test, y_proba))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

#Confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap="Blues", values_format="d")
plt.title("Confusion Matrix Ensemble")
plt.show()
```

```
Accuracy: 0.5723014256619144
Precision: 0.851145038167939
Recall: 0.565989847715736
F1-score: 0.6798780487804879
ROC-AUC: 0.6031581977078864

Classification Report:
               precision    recall  f1-score   support

           0       0.25      0.60      0.36        97
           1       0.85      0.57      0.68       394

    accuracy                           0.57       491
   macro avg       0.55      0.58      0.52       491
weighted avg       0.73      0.57      0.62       491
```



In [ ]:
```
from sklearn.model_selection import cross_validate, StratifiedKFold

# Define cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Cross-validation with multiple metrics
scoring = {
    'accuracy': 'accuracy',
    'precision': 'precision',
    'recall': 'recall',
    'f1': 'f1',
    'roc_auc': 'roc_auc'
}

cv_results = cross_validate(
    pipeline,
    X_train,
    y_train,
    cv=cv,
    scoring=scoring,
    return_train_score=False
)

# Show average performance across folds
print("Ensemble Cross-Validation Results (mean across folds):")
for metric in scoring.keys():
    print(f"{metric}: {cv_results['test_' + metric].mean():.4f}")
```

```
Ensemble Cross-Validation Results (mean across folds):
accuracy: 0.5594
precision: 0.8409
recall: 0.5370
f1: 0.6541
roc_auc: 0.6136
```

After tuning ensemble, results stayed the same as before

In [ ]:

Conclusion:

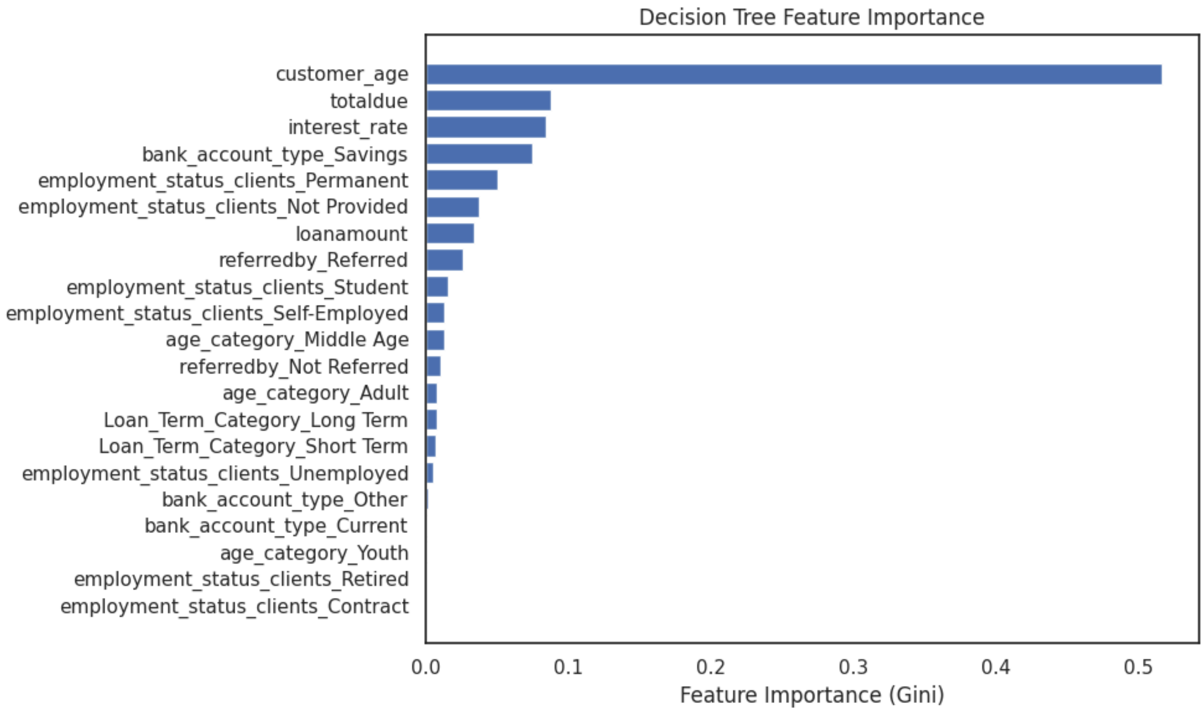
Model performance was generally poor due to feature limitations. Although SVM achieved the best results among the models tested, its performance remains satisfactory. The Stratified k fold validation result shows SVM (untuned) does a better job across folds.

Unless underlying data quality issues are resolved, deploying this model for real-world predictions would not be advisable.

Feature Importance

Decision Tree was also evaluated and performed well on the dataset. Its interpretability makes it suitable for extracting feature importance, highlighting the most influential predictors in loan default classification.

In [ ]:
```
pipeline = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', SMOTE(random_state=42)),
    ('model', DecisionTreeClassifier(class_weight='balanced', random_state=42))
])

# Fit
pipeline.fit(X_train, y_train)

# Get feature names (same logic as your code)
if isinstance(pipeline.named_steps['preprocessor'], ColumnTransformer):
    feature_names = []
    for name, transformer, columns in pipeline.named_steps['preprocessor'].transfor
        if hasattr(transformer, 'get_feature_names_out'):
            feature_names.extend(transformer.get_feature_names_out(columns))
        else:
            feature_names.extend(columns)
else:
    feature_names = X_train.columns.tolist()

# Extract feature importance
dt_importance = pipeline.named_steps['model'].feature_importances_
dt_importance_df = pd.DataFrame({
    'feature': feature_names,
    'importance': dt_importance
}).sort_values(by='importance', ascending=False)

# Plot
plt.figure(figsize=(10, 6))
plt.barh(dt_importance_df['feature'], dt_importance_df['importance'])
plt.xlabel('Feature Importance (Gini)')
plt.title('Decision Tree Feature Importance')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



Final Note:

It is highly imperative that future studies make use of datasets enriched with detailed customer information to enable more accurate predictions of loan default. Additionally, employing larger datasets will further enhance model robustness and reliability.

Data Preprocessing

Note: Application of Feature Selection

In [ ]:
```
#defining x and y
x= new[['totaldue', 'interest_rate', 'customer_age', 'employment_status_clients']]
y= new['target']
```

In [ ]:
```
#splitting data into train and test
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.15, random_st
```

In [ ]:
```
#Importing libraries foe encoding and scaling categorical and numerical columns rep
from sklearn.preprocessing import StandardScaler,OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

In [ ]:
```
num_cols = ['totaldue', 'interest_rate', 'customer_age']
cat_cols = ['employment_status_clients']
```

```
In [ ]: #create a pipeline for preprocessing
num_pipeline = Pipeline(steps=[
    ('scaler', StandardScaler())
])

cat_pipeline = Pipeline(steps=[
    ('encoder', OneHotEncoder(sparse_output= False, handle_unknown ='ignore'))
])
```

```
In [ ]: #apply preprocessing
preprocessor = ColumnTransformer(transformers=[
    ('num', num_pipeline, num_cols),
    ('cat', cat_pipeline, cat_cols)
])
```

```
In [ ]: !pip install catboost
```

```
In [ ]: #importing models and evaluation metrics required for prediction
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from catboost import CatBoostClassifier
from imblearn.ensemble import BalancedRandomForestClassifier, EasyEnsembleClassifie
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000, class_weight="balanced
    "Random Forest": RandomForestClassifier(n_estimators=200, random_state=42, clas
    "XGBoost": XGBClassifier(n_estimators=300, learning_rate=0.1, max_depth=5, rand
    "SVM": SVC(probability=True, class_weight="balanced", random_state=42),
    "Neural Net": MLPClassifier(hidden_layer_sizes=(64,32), max_iter=500, random_st
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=200, random_state=
    "CatBoost": CatBoostClassifier(iterations=200, verbose=0, random_state=42),
    "Easy Ensemble": EasyEnsembleClassifier(n_estimators=50, random_state=42),
    "Decision Tree": DecisionTreeClassifier(criterion="gini", max_depth=5, random_s
}
```

```
In [ ]: from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE

results = {}

# loop through models
for name, model in models.items():
    pipeline = ImbPipeline(steps=[
        ('preprocessor', preprocessor),
        ('smote', SMOTE(random_state=42)),
        ('model', model)
    ])

    # fit model
```

```python
    pipeline.fit(x_train, y_train)

    # predictions
    train_pred = pipeline.predict(x_train)
    test_pred = pipeline.predict(x_test)

    # probabilities (for ROC AUC)
    test_proba = pipeline.predict_proba(x_test)[:, 1]

    # metrics
    results[name] = {
        "Train Accuracy": accuracy_score(y_train, train_pred),
        "Test Accuracy": accuracy_score(y_test, test_pred),
        "Recall": recall_score(y_test, test_pred),
        "Precision": precision_score(y_test, test_pred),
        "F1 Score": f1_score(y_test, test_pred),
        "ROC AUC": roc_auc_score(y_test, test_proba),
        "Confusion Matrix": confusion_matrix(y_test, test_pred).tolist()  # stored
    }

    # Plot confusion matrix
    plt.figure(figsize=(5,4))
    sb.heatmap(results[name]["Confusion Matrix"], annot=True, fmt='d', cmap='Blues'
    plt.title(f'{name} Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    # Print classification report
    print(f"\n{name} Classification Report:\n")
    print(classification_report(y_test, test_pred))

# Convert to DataFrame (without confusion matrix column)
metrics1 = pd.DataFrame(results).T.drop(columns=["Confusion Matrix"])
```

In [ ]:

```python
metrics1
```

Summary

While boosting models like CatBoost and XGBoost show higher overall performance, they are biased toward the majority class (good loans). This makes them appear strong but weak at identifying defaulters — the class that truly matters in loan prediction. In contrast, SVM, Easy Ensemble, and Decision Tree maintain a better balance between predicting good and bad loans. Their lower scores reflect the real challenge of detecting defaulters, giving a more honest view of model performance. For credit risk, these balanced models are more reliable because they reduce the risk of approving bad loans.

In [ ]:

```python
#Top model Result comparison
results = {
    "SVM": {
        "train_acc": 0.60,
        "test_acc": 0.57,
```

```
        "recall": 0.57,
        "precision": 0.84,
        "f1": 0.68,
        "roc_auc": 0.55
    },
    "Easy Ensemble": {
        "train_acc": 0.56,
        "test_acc": 0.57,
        "recall": 0.56,
        "precision": 0.86,
        "f1": 0.68,
        "roc_auc": 0.60
    },
    "Decision Tree":{
        'train_acc': 0.62,
        'test_acc': 0.60,
        'recall': 0.63,
        'precision': 0.83,
        'f1': 0.72,
        'roc_auc': 0.56
    }
}

df_results = pd.DataFrame(results)
print(df_results)
```

In [ ]:

```
df_results.plot(kind="bar", figsize=(10,6), width=0.7)
plt.title("Comparison of Model Metrics")
plt.ylabel("Score")
plt.xticks(rotation=45)
plt.legend(title="Metrics", bbox_to_anchor=(1.05,1), loc="upper left")
plt.tight_layout()
plt.show()
```

In [ ]:

```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import ConfusionMatrixDisplay

results = {}

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

for name, model in models.items():
    fold_metrics = {
        "Train Accuracy": [],
        "Test Accuracy": [],
        "Recall": [],
        "Precision": [],
        "F1 Score": [],
        "ROC AUC": []
    }

    # Store aggregate predictions for classification report
    all_y_true, all_y_pred = [], []

    # Loop through folds
```

```python
    for train_index, test_index in skf.split(x_train, y_train):
        x_tr, x_val = x_train.iloc[train_index], x_train.iloc[test_index]
        y_tr, y_val = y_train.iloc[train_index], y_train.iloc[test_index]

        pipeline = ImbPipeline(steps=[
            ('preprocessor', preprocessor),
            ('smote', SMOTE(random_state=42)),
            ('model', model)
        ])

        pipeline.fit(x_tr, y_tr)
        y_train_pred = pipeline.predict(x_tr)
        y_val_pred = pipeline.predict(x_val)
        y_val_proba = pipeline.predict_proba(x_val)[:, 1] if hasattr(pipeline, "pre

        # Store metrics per fold
        fold_metrics["Train Accuracy"].append(accuracy_score(y_tr, y_train_pred))
        fold_metrics["Test Accuracy"].append(accuracy_score(y_val, y_val_pred))
        fold_metrics["Recall"].append(recall_score(y_val, y_val_pred))
        fold_metrics["Precision"].append(precision_score(y_val, y_val_pred))
        fold_metrics["F1 Score"].append(f1_score(y_val, y_val_pred))
        if y_val_proba is not None:
            fold_metrics["ROC AUC"].append(roc_auc_score(y_val, y_val_proba))

        # Collect predictions for classification report
        all_y_true.extend(y_val)
        all_y_pred.extend(y_val_pred)

    # Average metrics across folds
    results[name] = {metric: np.mean(values) for metric, values in fold_metrics.ite

    # Classification report (aggregate across all folds)
    print(f"\n{name} Classification Report:\n")
    print(classification_report(all_y_true, all_y_pred))

    #Confusion matrix (aggregate)
    cm = confusion_matrix(all_y_true, all_y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot(cmap="Blues", values_format="d")
    plt.title(f"{name} - Confusion Matrix (Aggregated)")
    plt.show()

# Convert to DataFrame (metrics summary)
metrics = pd.DataFrame(results).T
```

In [ ]:
```python
metrics
```

In [ ]:
```python
# cross val result comparison
#Top model Result comparison
results = {
    "SVM": {
        "train_acc": 0.59,
        "test_acc": 0.57,
        "recall": 0.56,
        "precision": 0.83,
```

```
        "f1": 0.67,
        "roc_auc": 0.60
    },
    "Easy Ensemble": {
        "train_acc": 0.58,
        "test_acc": 0.57,
        "recall": 0.56,
        "precision": 0.83,
        "f1": 0.67,
        "roc_auc": 0.60
    },
    "Decision Tree":{
        'train_acc': 0.57,
        'test_acc': 0.54,
        'recall': 0.53,
        'precision': 0.81,
        'f1': 0.64,
        'roc_auc': 0.59
    }
}

df_results2 = pd.DataFrame(results)
```

In [ ]:
```
df_results2.plot(kind="bar", figsize=(10,6), width=0.7)
plt.title("Comparison of Model Metrics (Cross Validation)")
plt.ylabel("Score")
plt.xticks(rotation=45)
plt.legend(title="Model", bbox_to_anchor=(1.05,1), loc="upper left")
plt.tight_layout()
plt.show()
```

From cross-validation, SVM and Ensemble had very close result but SVM outperformed Ensemble on Training Accuracy,showing stronger average performance across the folds

Conclusion:

Model performance was generally poor due to feature limitations. Although SVM achieved the best results among the models tested, its performance remains satisfactory. The Stratified k fold validation result shows SVM (untuned) does a better job across folds.

Unless underlying data quality issues are resolved, deploying this model for real-world predictions would not be advisable.

Feature Importance

Decision Tree was also evaluated and performed well on the dataset. Its interpretability makes it suitable for extracting feature importance, highlighting the most influential predictors in loan default classification.

In [ ]:
```
pipeline = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', SMOTE(random_state=42)),
```

```
    ('model', DecisionTreeClassifier(class_weight='balanced', random_state=42))
])

# Fit
pipeline.fit(x_train, y_train)

# Get feature names (same logic as your code)
if isinstance(pipeline.named_steps['preprocessor'], ColumnTransformer):
    feature_names = []
    for name, transformer, columns in pipeline.named_steps['preprocessor'].transfor
        if hasattr(transformer, 'get_feature_names_out'):
            feature_names.extend(transformer.get_feature_names_out(columns))
        else:
            feature_names.extend(columns)
else:
    feature_names = X_train.columns.tolist()

# Extract feature importance
dt_importance = pipeline.named_steps['model'].feature_importances_
dt_importance_df = pd.DataFrame({
    'feature': feature_names,
    'importance': dt_importance
}).sort_values(by='importance', ascending=False)

# Plot
plt.figure(figsize=(10, 6))
plt.barh(dt_importance_df['feature'], dt_importance_df['importance'])
plt.xlabel('Feature Importance (Gini)')
plt.title('Decision Tree Feature Importance')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

Overall Conclusion

The similarity in model performance before and after feature selection suggests that the initial features were generally informative, with no strong noise inflating the results. The slight performance drop after feature selection indicates that while the removed variables carried some predictive signal, the selected subset still captures the majority of the explanatory power. Thus, feature selection enhances interpretability and reduces dimensionality with only a minimal sacrifice in accuracy.

Deployment

We decided to proceed with the full feature set (before feature selection) for deployment because the models performed slightly better with all features compared to the reduced set (a drop of about –0.02 after feature selection). Since tree-based models naturally handle irrelevant variables by focusing on informative splits, removing features provided no significant performance gain. Retaining all features ensures maximum predictive power, stability with new incoming data, and avoids the risk of discarding variables that may hold hidden value in future scenarios.

Saving Pipeline for deployment

In [ ]:
```
Perf_model2= ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', SVC(
        class_weight='balanced',
        probability=True,
        random_state=42))
])
```

In [ ]:
```
#fit_model on dataset
Perf_model2.fit(X,y)
```

In [ ]:
```
#save model
import joblib
joblib.dump(Perf_model2, 'Loan_defaulter_predictor.pkl')
```