```
#1. Introduction
#The Smart Loan Recovery Model is designed to predict the likelihood
of loan recovery by analyzing borrower attributes and loan details.
The project leverages machine learning techniques, data preprocessing,
and feature engineering to improve prediction accuracy and aid
financial institutions in minimizing loan default risks.


# Data Collection & Preprocessing

import pandas as pd

df = pd.read_csv(r"C:\Users\HP\Downloads\loan-recovery (1).csv")
df
```

```
    Borrower_ID  Age  Gender Employment_Type  Monthly_Income
Num_Dependents  \
0         BRW_1   59    Male        Salaried          215422
0
1         BRW_2   49  Female        Salaried           60893
0
2         BRW_3   35    Male        Salaried          116520
1
3         BRW_4   63  Female        Salaried          140818
2
4         BRW_5   28    Male        Salaried           76272
1
..          ...  ...     ...             ...             ...
...
495     BRW_496   46  Female        Salaried          248483
1
496     BRW_497   30  Female        Salaried          243590
3
497     BRW_498   46  Female        Salaried          113864
2
498     BRW_499   54    Male        Salaried          158401
2
499     BRW_500   61    Male   Self-Employed           40169
1

    Loan_ID  Loan_Amount  Loan_Tenure  Interest_Rate  ...
Collateral_Value  \
0      LN_1      1445796           60          12.39  ...
1.727997e+06
1      LN_2      1044620           12          13.47  ...
1.180032e+06
2      LN_3      1923410           72           7.74  ...
2.622540e+06
3      LN_4      1811663           36          12.23  ...
1.145493e+06
```

```
4      LN_5        88578            48          16.13  ...
0.000000e+00
..      ...          ...           ...            ...  ...
...
495  LN_496       740796            72          16.59  ...
0.000000e+00
496  LN_497      1408126            60          11.03  ...
0.000000e+00
497  LN_498       375203            48           9.16  ...
0.000000e+00
498  LN_499      1769890            24          11.19  ...
1.272774e+06
499  LN_500       394866            12           9.14  ...
0.000000e+00

     Outstanding_Loan_Amount  Monthly_EMI  Payment_History  \
0               2.914130e+05      4856.88          On-Time
1               6.652042e+05     55433.68          On-Time
2               1.031372e+06     14324.61          Delayed
3               2.249739e+05      6249.28          On-Time
4               3.918989e+04       816.46          On-Time
..                       ...          ...              ...
495             4.135285e+05      5743.45          Delayed
496             3.173740e+05      5289.57          Delayed
497             3.300302e+05      6875.63          Delayed
498             1.565339e+06     65222.46          On-Time
499             1.881581e+05     15679.84          On-Time

    Num_Missed_Payments  Days_Past_Due      Recovery_Status  \
0                     0              0  Partially Recovered
1                     0              0      Fully Recovered
2                     2            124      Fully Recovered
3                     1             56      Fully Recovered
4                     1             69      Fully Recovered
..                  ...            ...                  ...
495                   2            169      Fully Recovered
496                   2            102  Partially Recovered
497                   3            140      Fully Recovered
498                   3              9  Partially Recovered
499                   1            116          Written Off

    Collection_Attempts  Collection_Method Legal_Action_Taken
0                     1   Settlement Offer                 No
1                     2   Settlement Offer                 No
2                     2       Legal Notice                 No
3                     2              Calls                 No
4                     0    Debt Collectors                 No
..                  ...                ...                ...
495                   2   Settlement Offer                 No
496                   9   Settlement Offer                 No
```

```
497                   3   Settlement Offer                 No
498                   9              Calls                 No
499                   6   Settlement Offer                Yes

[500 rows x 21 columns]
```

```python
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Borrower_ID               500 non-null    object
 1   Age                       500 non-null    int64
 2   Gender                    500 non-null    object
 3   Employment_Type           500 non-null    object
 4   Monthly_Income            500 non-null    int64
 5   Num_Dependents            500 non-null    int64
 6   Loan_ID                   500 non-null    object
 7   Loan_Amount               500 non-null    int64
 8   Loan_Tenure               500 non-null    int64
 9   Interest_Rate             500 non-null    float64
 10  Loan_Type                 500 non-null    object
 11  Collateral_Value          500 non-null    float64
 12  Outstanding_Loan_Amount  500 non-null    float64
 13  Monthly_EMI               500 non-null    float64
 14  Payment_History           500 non-null    object
 15  Num_Missed_Payments       500 non-null    int64
 16  Days_Past_Due             500 non-null    int64
 17  Recovery_Status           500 non-null    object
 18  Collection_Attempts       500 non-null    int64
 19  Collection_Method         500 non-null    object
 20  Legal_Action_Taken        500 non-null    object
dtypes: float64(4), int64(8), object(9)
memory usage: 82.2+ KB
None
```

```python
# Handling Missing Values

print(df.isnull().sum())
```

```
Borrower_ID                0
Age                        0
Gender                     0
Employment_Type            0
Monthly_Income             0
Num_Dependents             0
Loan_ID                    0
Loan_Amount                0
```

```
Loan_Tenure                   0
Interest_Rate                 0
Loan_Type                     0
Collateral_Value              0
Outstanding_Loan_Amount       0
Monthly_EMI                   0
Payment_History               0
Num_Missed_Payments           0
Days_Past_Due                 0
Recovery_Status               0
Collection_Attempts           0
Collection_Method             0
Legal_Action_Taken            0
dtype: int64
```

```
print(df.head())
```

```
  Borrower_ID  Age  Gender Employment_Type  Monthly_Income
Num_Dependents  \
0       BRW_1   59    Male        Salaried          215422
0
1       BRW_2   49  Female        Salaried           60893
0
2       BRW_3   35    Male        Salaried          116520
1
3       BRW_4   63  Female        Salaried          140818
2
4       BRW_5   28    Male        Salaried           76272
1

  Loan_ID  Loan_Amount  Loan_Tenure  Interest_Rate  ...
Collateral_Value  \
0    LN_1      1445796           60          12.39  ...
1.727997e+06
1    LN_2      1044620           12          13.47  ...
1.180032e+06
2    LN_3      1923410           72           7.74  ...
2.622540e+06
3    LN_4      1811663           36          12.23  ...
1.145493e+06
4    LN_5        88578           48          16.13  ...
0.000000e+00

   Outstanding_Loan_Amount  Monthly_EMI  Payment_History
Num_Missed_Payments  \
0             2.914130e+05      4856.88          On-Time
0
1             6.652042e+05     55433.68          On-Time
0
2             1.031372e+06     14324.61          Delayed
```

```
2
3           2.249739e+05      6249.28          On-Time
1
4           3.918989e+04       816.46          On-Time
1

   Days_Past_Due      Recovery_Status Collection_Attempts
Collection_Method  \
0              0  Partially Recovered                   1   Settlement
Offer
1              0      Fully Recovered                   2   Settlement
Offer
2            124      Fully Recovered                   2        Legal
Notice
3             56      Fully Recovered                   2
Calls
4             69      Fully Recovered                   0    Debt
Collectors

  Legal_Action_Taken
0                 No
1                 No
2                 No
3                 No
4                 No

[5 rows x 21 columns]
```

```python
df.drop(columns=["Borrower_ID", "Loan_ID"], inplace=True)

df
```

```
     Age  Gender Employment_Type  Monthly_Income  Num_Dependents
Loan_Amount  \
0     59    Male        Salaried          215422               0
1445796
1     49  Female        Salaried           60893               0
1044620
2     35    Male        Salaried          116520               1
1923410
3     63  Female        Salaried          140818               2
1811663
4     28    Male        Salaried           76272               1
88578
..   ...     ...             ...             ...             ...
...
495   46  Female        Salaried          248483               1
740796
496   30  Female        Salaried          243590               3
1408126
```

```
497   46  Female        Salaried          113864                2
375203
498   54    Male        Salaried          158401                2
1769890
499   61    Male   Self-Employed           40169                1
394866

     Loan_Tenure  Interest_Rate Loan_Type  Collateral_Value  \
0             60          12.39      Home      1.727997e+06
1             12          13.47      Auto      1.180032e+06
2             72           7.74      Home      2.622540e+06
3             36          12.23      Home      1.145493e+06
4             48          16.13  Personal      0.000000e+00
..           ...            ...       ...               ...
495           72          16.59  Personal      0.000000e+00
496           60          11.03  Personal      0.000000e+00
497           48           9.16  Personal      0.000000e+00
498           24          11.19      Auto      1.272774e+06
499           12           9.14  Personal      0.000000e+00

     Outstanding_Loan_Amount  Monthly_EMI Payment_History  \
0               2.914130e+05      4856.88         On-Time
1               6.652042e+05     55433.68         On-Time
2               1.031372e+06     14324.61         Delayed
3               2.249739e+05      6249.28         On-Time
4               3.918989e+04       816.46         On-Time
..                       ...          ...             ...
495             4.135285e+05      5743.45         Delayed
496             3.173740e+05      5289.57         Delayed
497             3.300302e+05      6875.63         Delayed
498             1.565339e+06     65222.46         On-Time
499             1.881581e+05     15679.84         On-Time

     Num_Missed_Payments  Days_Past_Due      Recovery_Status  \
0                      0              0  Partially Recovered
1                      0              0      Fully Recovered
2                      2            124      Fully Recovered
3                      1             56      Fully Recovered
4                      1             69      Fully Recovered
..                   ...            ...                  ...
495                    2            169      Fully Recovered
496                    2            102  Partially Recovered
497                    3            140      Fully Recovered
498                    3              9  Partially Recovered
499                    1            116          Written Off

     Collection_Attempts Collection_Method Legal_Action_Taken
0                      1  Settlement Offer                 No
1                      2  Settlement Offer                 No
2                      2      Legal Notice                 No
```

```
3                       2             Calls                   No
4                       0   Debt Collectors                   No
..                    ...               ...                  ...
495                     2  Settlement Offer                   No
496                     9  Settlement Offer                   No
497                     3  Settlement Offer                   No
498                     9             Calls                   No
499                     6  Settlement Offer                  Yes

[500 rows x 19 columns]
```

```python
# Encoding Categorical Variables

pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\hp\appdata\local\programs\python\python313\lib\site-packages (1.6.1)
Requirement already satisfied: numpy>=1.19.5 in c:\users\hp\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn) (2.2.3)
Requirement already satisfied: scipy>=1.6.0 in c:\users\hp\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn) (1.15.2)
Requirement already satisfied: joblib>=1.2.0 in c:\users\hp\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\hp\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn) (3.6.0)
Note: you may need to restart the kernel to use updated packages.
```

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

categorical_cols = ["Gender", "Employment_Type", "Loan_Type",
"Payment_History", "Recovery_Status", "Collection_Method",
"Legal_Action_Taken"]
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

df
```

```
     Age  Gender  Employment_Type  Monthly_Income  Num_Dependents  \
0     59       1                1          215422               0
1     49       0                1           60893               0
2     35       1                1          116520               1
3     63       0                1          140818               2
4     28       1                1           76272               1
```

```
..   ...     ...              ...            ...            ...
495   46       0                1         248483              1
496   30       0                1         243590              3
497   46       0                1         113864              2
498   54       1                1         158401              2
499   61       1                2          40169              1

     Loan_Amount  Loan_Tenure  Interest_Rate  Loan_Type
Collateral_Value  \
0        1445796           60          12.39          2
1.727997e+06
1        1044620           12          13.47          0
1.180032e+06
2        1923410           72           7.74          2
2.622540e+06
3        1811663           36          12.23          2
1.145493e+06
4          88578           48          16.13          3
0.000000e+00
..           ...          ...            ...        ...
...
495       740796           72          16.59          3
0.000000e+00
496      1408126           60          11.03          3
0.000000e+00
497       375203           48           9.16          3
0.000000e+00
498      1769890           24          11.19          0
1.272774e+06
499       394866           12           9.14          3
0.000000e+00

     Outstanding_Loan_Amount  Monthly_EMI  Payment_History  \
0               2.914130e+05      4856.88                2
1               6.652042e+05     55433.68                2
2               1.031372e+06     14324.61                0
3               2.249739e+05      6249.28                2
4               3.918989e+04       816.46                2
..                       ...          ...              ...
495             4.135285e+05      5743.45                0
496             3.173740e+05      5289.57                0
497             3.300302e+05      6875.63                0
498             1.565339e+06     65222.46                2
499             1.881581e+05     15679.84                2

     Num_Missed_Payments  Days_Past_Due  Recovery_Status
Collection_Attempts  \
0                      0              0                1
1
1                      0              0                0
```

```
2
2                      2           124                0
2
3                      1            56                0
2
4                      1            69                0
0
..                   ...           ...              ...
...
495                    2           169                0
2
496                    2           102                1
9
497                    3           140                0
3
498                    3             9                1
9
499                    1           116                2
6

     Collection_Method  Legal_Action_Taken
0                    3                   0
1                    3                   0
2                    2                   0
3                    0                   0
4                    1                   0
..                 ...                 ...
495                  3                   0
496                  3                   0
497                  3                   0
498                  0                   0
499                  3                   1

[500 rows x 19 columns]
```

```
# Feature Engineering

df['Debt_to_Income'] = df['Loan_Amount'] / (df['Monthly_Income'] + 1)
# Avoid division by zero
df['Risk_Score'] = (df['Interest_Rate'] * df['Num_Missed_Payments']) /
10

df
```

```
     Age  Gender  Employment_Type  Monthly_Income  Num_Dependents  \
0     59       1                1          215422               0
1     49       0                1           60893               0
2     35       1                1          116520               1
3     63       0                1          140818               2
4     28       1                1           76272               1
```

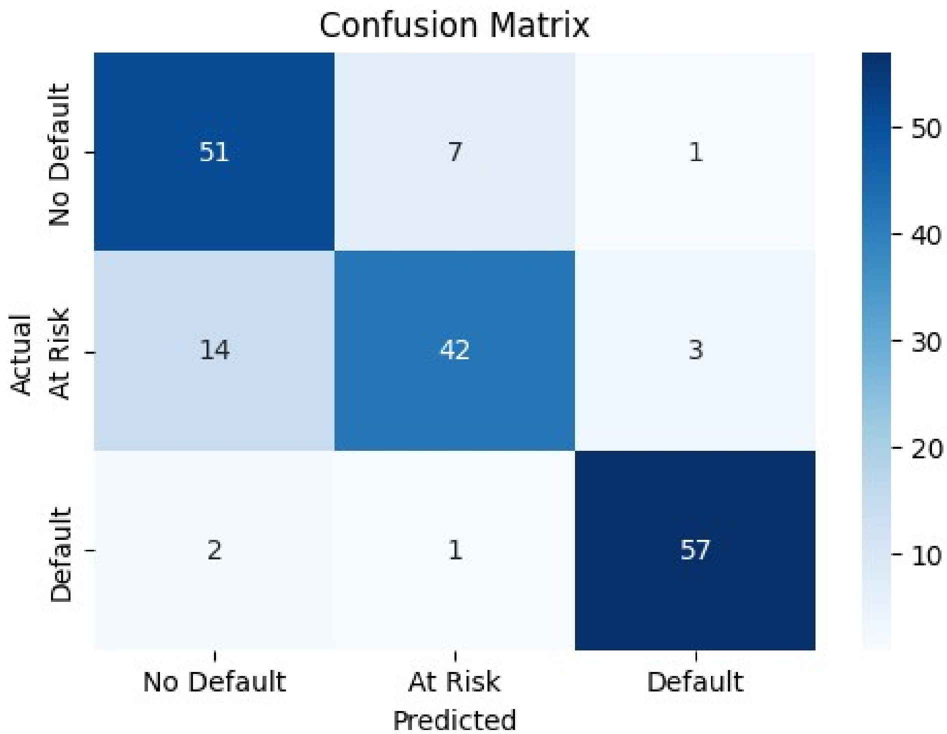
```
..   ...     ...                ...             ...              ...
495   46       0                  1          248483                1
496   30       0                  1          243590                3
497   46       0                  1          113864                2
498   54       1                  1          158401                2
499   61       1                  2           40169                1

     Loan_Amount  Loan_Tenure  Interest_Rate  Loan_Type
Collateral_Value  \
0        1445796           60          12.39          2
1.727997e+06
1        1044620           12          13.47          0
1.180032e+06
2        1923410           72           7.74          2
2.622540e+06
3        1811663           36          12.23          2
1.145493e+06
4          88578           48          16.13          3
0.000000e+00
..           ...          ...            ...        ...
...
495       740796           72          16.59          3
0.000000e+00
496      1408126           60          11.03          3
0.000000e+00
497       375203           48           9.16          3
0.000000e+00
498      1769890           24          11.19          0
1.272774e+06
499       394866           12           9.14          3
0.000000e+00

     ...  Monthly_EMI  Payment_History  Num_Missed_Payments
Days_Past_Due  \
0    ...      4856.88                2                    0
0
1    ...     55433.68                2                    0
0
2    ...     14324.61                0                    2
124
3    ...      6249.28                2                    1
56
4    ...       816.46                2                    1
69
..   ...          ...              ...                  ...
...
495  ...      5743.45                0                    2
169
496  ...      5289.57                0                    2
```

```
102
497  ...      6875.63               0                    3
140
498  ...     65222.46               2                    3
9
499  ...     15679.84               2                    1
116

     Recovery_Status  Collection_Attempts  Collection_Method  \
0                  1                    1                  3
1                  0                    2                  3
2                  0                    2                  2
3                  0                    2                  0
4                  0                    0                  1
..               ...                  ...                ...
495                0                    2                  3
496                1                    9                  3
497                0                    3                  3
498                1                    9                  0
499                2                    6                  3

     Legal_Action_Taken  Debt_to_Income  Risk_Score
0                     0        6.711428       0.000
1                     0       17.154728       0.000
2                     0       16.506982       1.548
3                     0       12.865189       1.223
4                     0        1.161328       1.613
..                  ...             ...         ...
495                   0        2.981262       3.318
496                   0        5.780698       2.206
497                   0        3.295157       2.748
498                   0       11.173407       3.357
499                   1        9.829873       0.914

[500 rows x 21 columns]

# Handling Class Imbalance

X = df.drop(columns=["Recovery_Status"])  # Features
y = df["Recovery_Status"]

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn.model_selection import GridSearchCV

!pip install imbalanced-learn
from imblearn.over_sampling import SMOTE
!pip install xgboost
from xgboost import XGBClassifier
```

```
Requirement already satisfied: imbalanced-learn in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (0.13.0)
Requirement already satisfied: numpy<3,>=1.24.3 in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (from
imbalanced-learn) (2.2.3)
Requirement already satisfied: scipy<2,>=1.10.1 in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (from
imbalanced-learn) (1.15.2)
Requirement already satisfied: scikit-learn<2,>=1.3.2 in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (from
imbalanced-learn) (1.6.1)
Requirement already satisfied: sklearn-compat<1,>=0.1 in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (from
imbalanced-learn) (0.1.3)
Requirement already satisfied: joblib<2,>=1.1.1 in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (from
imbalanced-learn) (1.4.2)
Requirement already satisfied: threadpoolctl<4,>=2.0.0 in c:\users\hp\
appdata\local\programs\python\python313\lib\site-packages (from
imbalanced-learn) (3.6.0)
Requirement already satisfied: xgboost in c:\users\hp\appdata\local\
programs\python\python313\lib\site-packages (3.0.0)
Requirement already satisfied: numpy in c:\users\hp\appdata\local\
programs\python\python313\lib\site-packages (from xgboost) (2.2.3)
Requirement already satisfied: scipy in c:\users\hp\appdata\local\
programs\python\python313\lib\site-packages (from xgboost) (1.15.2)
```

```python
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)

# Data Splitting & Scaling
# Model Selection & Training

rf = RandomForestClassifier()
xgb = XGBClassifier()

from sklearn.model_selection import RandomizedSearchCV

# Handling Class Imbalance with SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)

# Splitting Data
X_train, X_test, y_train, y_test = train_test_split(X_resampled,
y_resampled, test_size=0.2, stratify=y_resampled, random_state=42)

param_dist = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 15, 20],
    'learning_rate': [0.01, 0.1, 0.2],
    'random_state': [42]
```

```
}
grid_search = RandomizedSearchCV(xgb, param_distributions=param_dist,
cv=5, scoring='f1_weighted', n_iter=10, n_jobs=-1, random_state=42)
grid_search.fit(X_train, y_train)

best_model = grid_search.best_estimator_

best_model.fit(X_train, y_train)
y_pred = best_model.predict(X_test)

# Model Evaluation

accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print(classification_report(y_test, y_pred))

Accuracy: 0.84
              precision    recall  f1-score   support

           0       0.76      0.86      0.81        59
           1       0.84      0.71      0.77        59
           2       0.93      0.95      0.94        60

    accuracy                           0.84       178
   macro avg       0.85      0.84      0.84       178
weighted avg       0.85      0.84      0.84       178


import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d',
cmap='Blues', xticklabels=['No Default', 'At Risk', 'Default'],
yticklabels=['No Default', 'At Risk', 'Default'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```




```
# Conclusion
# The Smart Loan Recovery Model provides a data-driven approach to
predicting loan repayment likelihood.

# By leveraging SMOTE, feature engineering, and hyperparameter tuning,
the model improves classification performance.

# The insights from the model can help financial institutions make
informed lending decisions and minimize risks.
```