Loan Approval Prediction Model

Problem Statement:

Develop a machine learning model to predict **loan approval status** based on applicant features. The model will be trained on a dataset containing loan applications and their outcomes. It will help financial institutions automate and improve the accuracy of loan approval decisions.

Objective:

To predict **Loan Approval Status** using a Machine Learning Model.

Benefits:

The benefits of this solution include:

- **Lenders** can make **faster and more accurate loan approval decisions**, reducing manual effort.
- **Applicants** will get **quicker responses** and **fairer evaluations** based on objective data.
- **Financial institutions** can **minimize default risks** by identifying high-risk applicants more effectively.

```
#Importing Required Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_curve, roc_auc_score

# Load the Dataset

df = pd.read_csv('loan_approval_dataset.csv')
df.head()

   loan_id   no_of_dependents      education  self_employed
income_annum  \
0        1                  2       Graduate             No
9600000
1        2                  0   Not Graduate            Yes
4100000
2        3                  3       Graduate             No
9100000
```

```
3        4                  3       Graduate             No
8200000
4        5                  5   Not Graduate            Yes
9800000

    loan_amount   loan_term   cibil_score
residential_assets_value  \
0      29900000          12           778                     2400000

1      12200000           8           417                     2700000

2      29700000          20           506                     7100000

3      30700000           8           467                    18200000

4      24200000          20           382                    12400000


    commercial_assets_value   luxury_assets_value
bank_asset_value  \
0                  17600000              22700000              8000000

1                   2200000               8800000              3300000

2                   4500000              33300000             12800000

3                   3300000              23300000              7900000

4                   8200000              29400000              5000000


   loan_status
0     Approved
1     Rejected
2     Rejected
3     Rejected
4     Rejected
```

```
# Getting shape of dataset
df.shape
```

```
(4269, 13)
```

```
df.head()
```

```
   loan_id   no_of_dependents      education  self_employed
income_annum  \
0        1                  2       Graduate             No
9600000
1        2                  0   Not Graduate            Yes
4100000
```

```
2        3                  3       Graduate            No
9100000
3        4                  3       Graduate            No
8200000
4        5                  5   Not Graduate           Yes
9800000

    loan_amount   loan_term   cibil_score
residential_assets_value  \
0      29900000          12           778                        2400000

1      12200000           8           417                        2700000

2      29700000          20           506                        7100000

3      30700000           8           467                       18200000

4      24200000          20           382                       12400000


    commercial_assets_value   luxury_assets_value
bank_asset_value  \
0                  17600000              22700000                8000000

1                   2200000               8800000                3300000

2                   4500000              33300000               12800000

3                   3300000              23300000                7900000

4                   8200000              29400000                5000000


   loan_status
0     Approved
1     Rejected
2     Rejected
3     Rejected
4     Rejected
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4269 entries, 0 to 4268
Data columns (total 13 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   loan_id                    4269 non-null   int64
 1    no_of_dependents          4269 non-null   int64
 2    education                 4269 non-null   object
 3    self_employed             4269 non-null   object
```

```
 4    income_annum              4269 non-null   int64
 5    loan_amount               4269 non-null   int64
 6    loan_term                 4269 non-null   int64
 7    cibil_score               4269 non-null   int64
 8    residential_assets_value  4269 non-null   int64
 9    commercial_assets_value   4269 non-null   int64
 10   luxury_assets_value       4269 non-null   int64
 11   bank_asset_value          4269 non-null   int64
 12   loan_status               4269 non-null   object
dtypes: int64(10), object(3)
memory usage: 433.7+ KB
None
```

```
# Statistical summary of numerical columns
df.describe()
```

```
           loan_id   no_of_dependents   income_annum   loan_amount  \
count  4269.000000        4269.000000   4.269000e+03  4.269000e+03
mean   2135.000000           2.498712   5.059124e+06  1.513345e+07
std    1232.498479           1.695910   2.806840e+06  9.043363e+06
min       1.000000           0.000000   2.000000e+05  3.000000e+05
25%    1068.000000           1.000000   2.700000e+06  7.700000e+06
50%    2135.000000           3.000000   5.100000e+06  1.450000e+07
75%    3202.000000           4.000000   7.500000e+06  2.150000e+07
max    4269.000000           5.000000   9.900000e+06  3.950000e+07

         loan_term   cibil_score   residential_assets_value  \
count  4269.000000   4269.000000               4.269000e+03
mean     10.900445    599.936051               7.472617e+06
std       5.709187    172.430401               6.503637e+06
min       2.000000    300.000000              -1.000000e+05
25%       6.000000    453.000000               2.200000e+06
50%      10.000000    600.000000               5.600000e+06
75%      16.000000    748.000000               1.130000e+07
max      20.000000    900.000000               2.910000e+07

        commercial_assets_value   luxury_assets_value
bank_asset_value
count              4.269000e+03          4.269000e+03
4.269000e+03
mean               4.973155e+06          1.512631e+07
4.976692e+06
std                4.388966e+06          9.103754e+06
3.250185e+06
min                0.000000e+00          3.000000e+05
0.000000e+00
25%                1.300000e+06          7.500000e+06
2.300000e+06
50%                3.700000e+06          1.460000e+07
4.600000e+06
```

```
75%                   7.600000e+06          2.170000e+07
7.100000e+06
max                   1.940000e+07          3.920000e+07
1.470000e+07

# Checking for Duplicate values
df.duplicated().sum()

np.int64(0)

# Dropping rows with null values
df.dropna(inplace=True)

#Removing Blank spaces from column names and values

df.columns = df.columns.str.strip()

df['loan_status'] = df['loan_status'].str.strip()  # Remove spaces

df = df.apply(lambda x: x.str.strip() if x.dtype == 'object' else x)

# Data Transformation on Education, Self Employed Coloumns

df['education'] = df['education'].replace({'Not Graduate': 0,
'Graduate': 1})

df['self_employed'] = df['self_employed'].replace({'No': 0, 'Yes': 1})

df.head()

   loan_id  no_of_dependents  education  self_employed
income_annum  \
0        1                 2          1              0       9600000

1        2                 0          0              1       4100000

2        3                 3          1              0       9100000

3        4                 3          1              0       8200000

4        5                 5          0              1       9800000


   loan_amount  loan_term  cibil_score  residential_assets_value  \
0     29900000         12          778                   2400000
1     12200000          8          417                   2700000
2     29700000         20          506                   7100000
3     30700000          8          467                  18200000
4     24200000         20          382                  12400000

   commercial_assets_value  luxury_assets_value  bank_asset_value
loan_status
```

```
0                 17600000                22700000              8000000
Approved
1                  2200000                 8800000              3300000
Rejected
2                  4500000                33300000             12800000
Rejected
3                  3300000                23300000              7900000
Rejected
4                  8200000                29400000              5000000
Rejected
```

```
# Data Transformation on Loan Status Coloumns

df['loan_status'] = df['loan_status'].map({'Approved': 1, 'Rejected':
0})

df.head()
```

```
   loan_id  no_of_dependents  education  self_employed
income_annum  \
0        1                 2          1              0       9600000

1        2                 0          0              1       4100000

2        3                 3          1              0       9100000

3        4                 3          1              0       8200000

4        5                 5          0              1       9800000


   loan_amount  loan_term  cibil_score  residential_assets_value  \
0     29900000         12          778                   2400000
1     12200000          8          417                   2700000
2     29700000         20          506                   7100000
3     30700000          8          467                  18200000
4     24200000         20          382                  12400000

   commercial_assets_value  luxury_assets_value  bank_asset_value
loan_status
0                 17600000             22700000           8000000
1
1                  2200000              8800000           3300000
0
2                  4500000             33300000          12800000
0
3                  3300000             23300000           7900000
0
4                  8200000             29400000           5000000
0
```

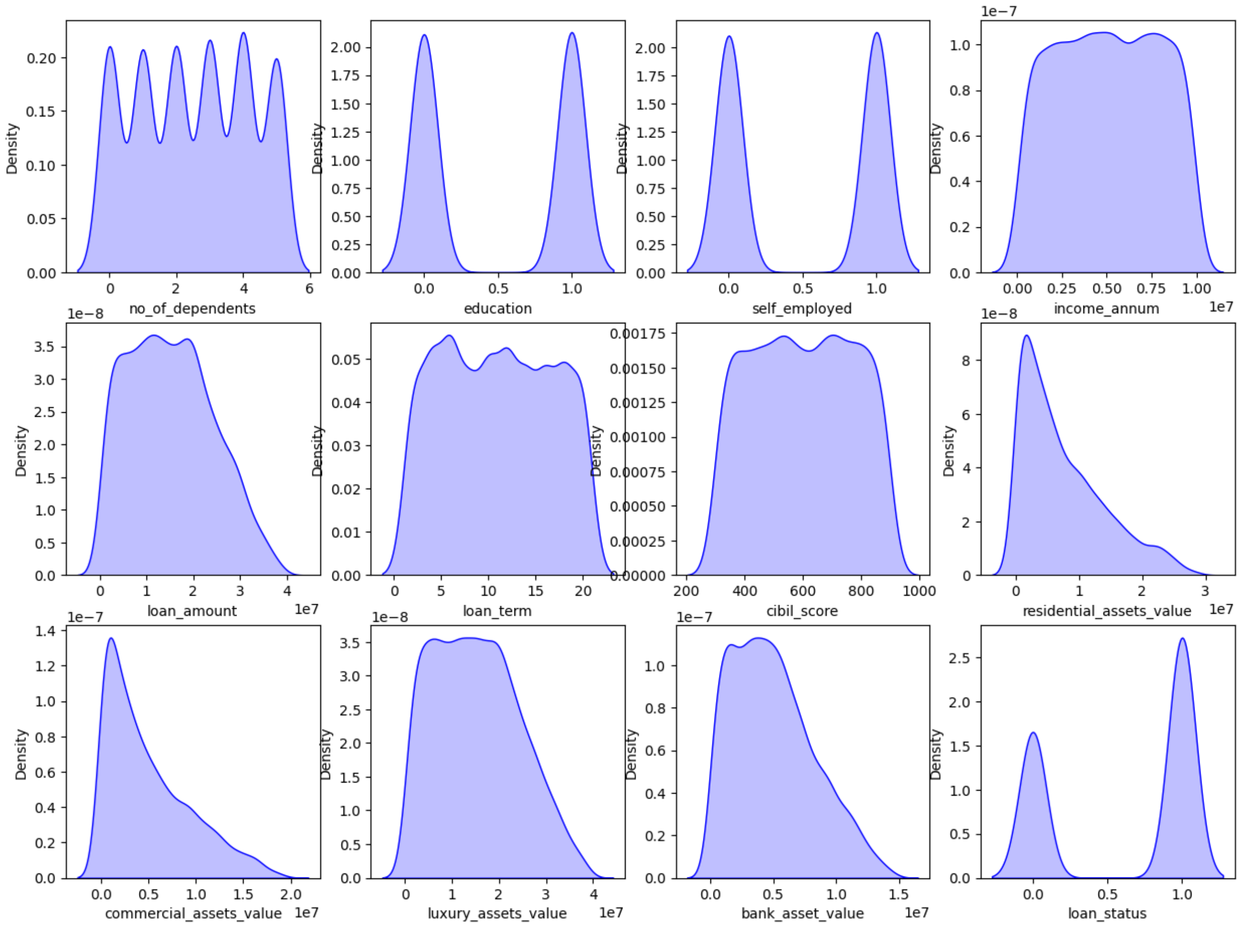
Exploratory Data Analysis (EDA)

- Visualize relationships between features.
- Identify trends and patterns.

1.Univariate Analysis

It focuses on examining a single variable at a time. It helps in understanding the distribution of the data.

```
# Univariate analysis
plt.figure(figsize=(15, 15))

numerical_columns = ['no_of_dependents', 'education', 'self_employed',

    'income_annum', 'loan_amount', 'loan_term', 'cibil_score',
    'residential_assets_value', 'commercial_assets_value',
    'luxury_assets_value', 'bank_asset_value', 'loan_status']

for i in range(len(numerical_columns)):
    plt.subplot(4, 4, i + 1)
    sns.kdeplot(x=df[numerical_columns[i]], fill=True, color='b')  #
Replaced shade with fill
    plt.xlabel(numerical_columns[i])

plt.show()
```



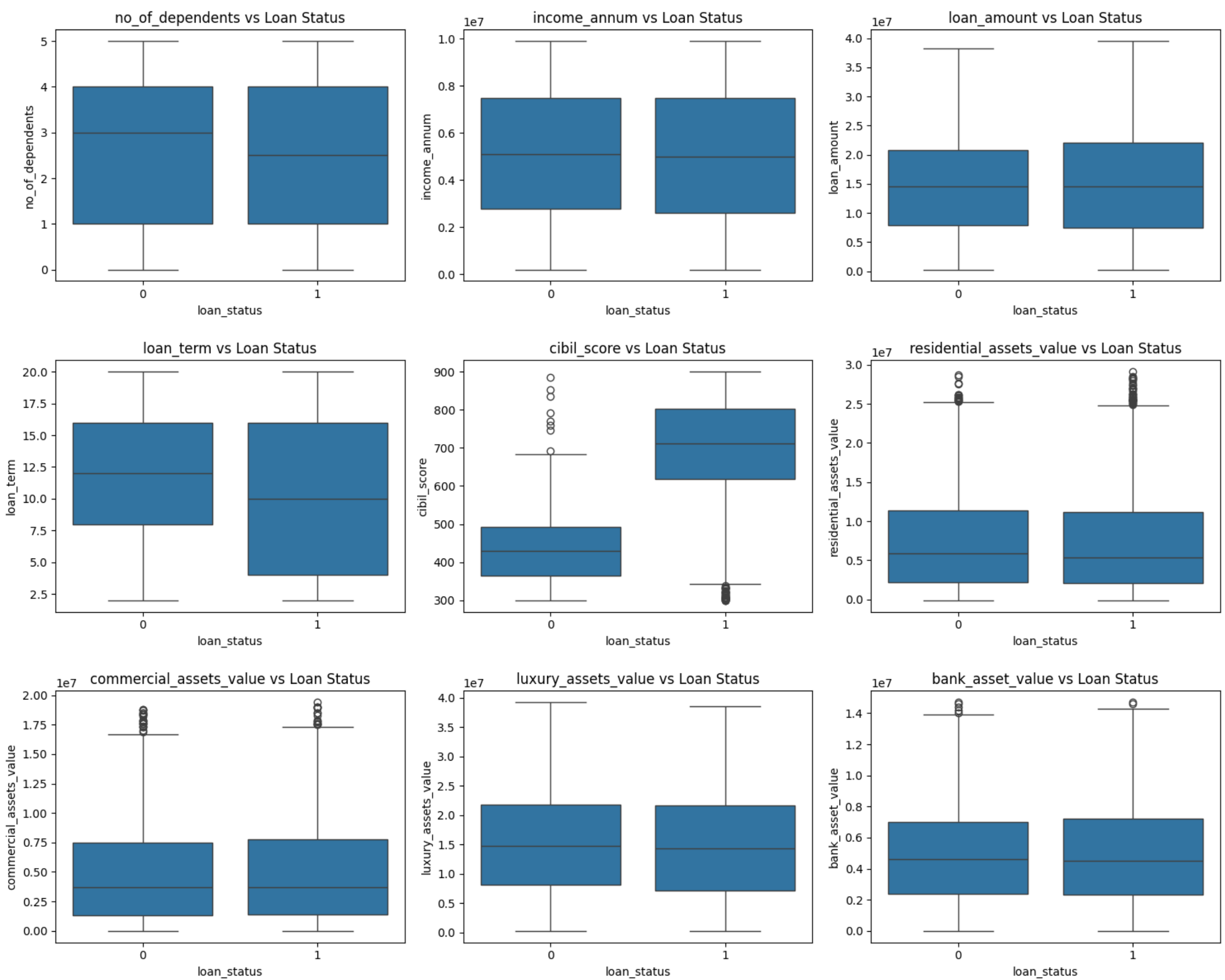

```
print(df.columns)  # List all column names

Index(['loan_id', 'no_of_dependents', 'education', 'self_employed',
       'income_annum', 'loan_amount', 'loan_term', 'cibil_score',
       'residential_assets_value', 'commercial_assets_value',
       'luxury_assets_value', 'bank_asset_value', 'loan_status'],
      dtype='object')
```

2.Bivariate Analysis

It helps in understanding the relationship between two variables, and alows us to know how they are related with each other negatively or postively.

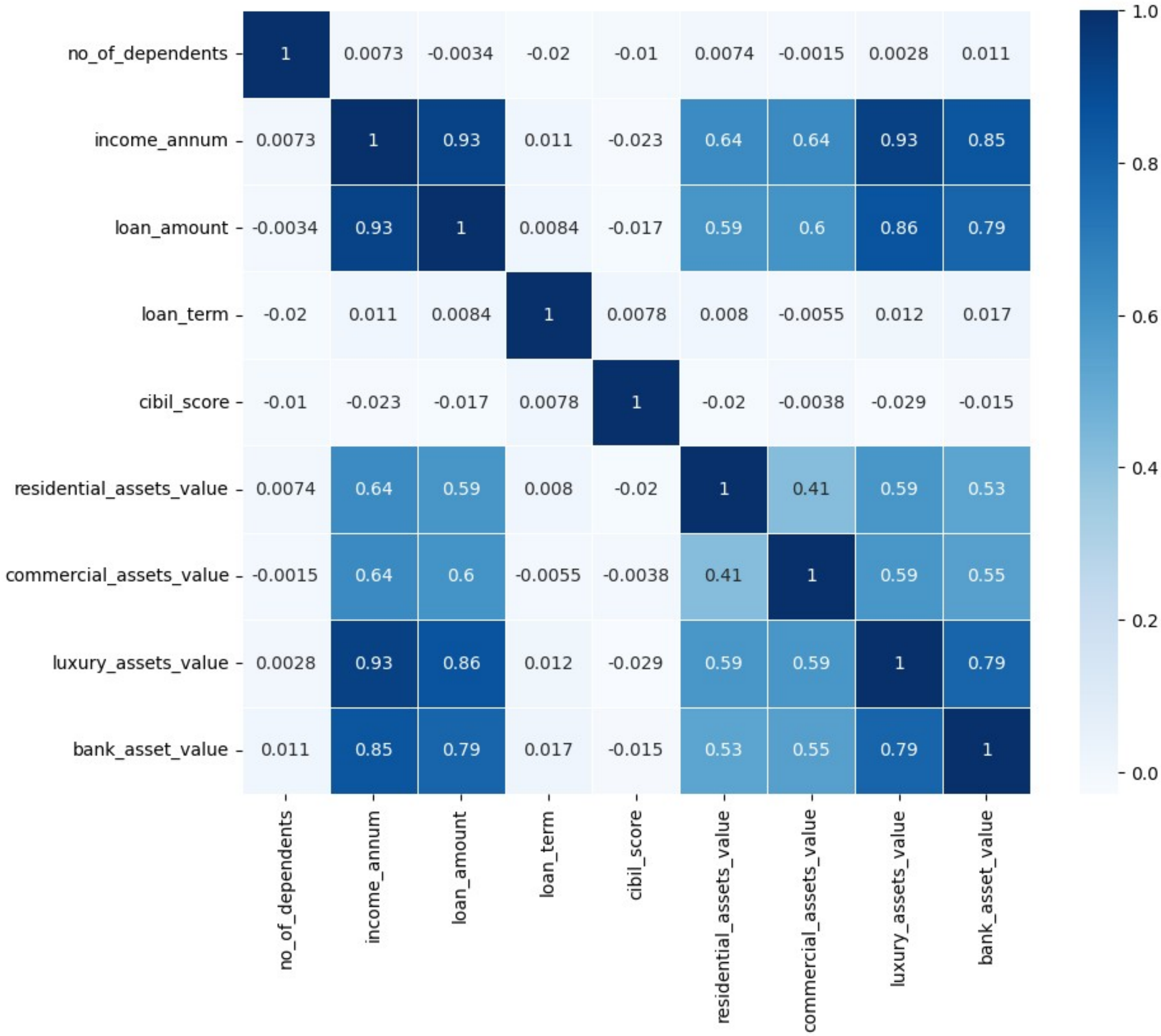
```
#Bivariate Analysis

numerical_columns = ['no_of_dependents', 'income_annum',
'loan_amount', 'loan_term',
                     'cibil_score', 'residential_assets_value',
'commercial_assets_value',
                     'luxury_assets_value', 'bank_asset_value']
plt.figure(figsize=(15, 12))
```

```
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(3, 3, i)
    sns.boxplot(data=df, x='loan_status', y=col)
    plt.title(f"{col} vs Loan Status")

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



3.Multivariate Analysis (Relation between multiple variables)

```
#MultiVariate Analysis

# Plot the heatmap of the correlation between each of the numerical
features

plt.figure(figsize=(10, 8))  # Increase figure size
sns.heatmap(df[numerical_columns].corr(), annot=True, cmap='Blues',
linewidths=0.5)

plt.show()
```



Model Selection & Training:

```
#Adding all asset cols into one col.

df['total_assets'] = df['residential_assets_value'] +
df['commercial_assets_value'] + df['luxury_assets_value'] +
df['bank_asset_value']

#Dropping non required columns

df.drop(columns=['residential_assets_value',
'commercial_assets_value', 'luxury_assets_value', 'bank_asset_value'],
inplace=True)

df.head()
```

```
   loan_id  no_of_dependents  education  self_employed
income_annum  \
0        1                 2          1              0       9600000

1        2                 0          0              1       4100000

2        3                 3          1              0       9100000

3        4                 3          1              0       8200000

4        5                 5          0              1       9800000


   loan_amount  loan_term  cibil_score  loan_status  total_assets
0     29900000         12          778            1      50700000
1     12200000          8          417            0      17000000
2     29700000         20          506            0      57700000
3     30700000          8          467            0      52700000
4     24200000         20          382            0      55000000

# Dropping the unwanted columns(Less Required Cols)
df.drop(columns=['loan_id', 'no_of_dependents', 'education',
'self_employed'], inplace=True)

#Removing Target Variable and creating the feature matrix `x`, which
will be used for training the model.
x = df.drop(columns=['loan_status'])

# Creating the Target matrix `y`, which contains target variable
y = df['loan_status']
```

Features (X) and Target (y) in Supervised Learning

- **Features (X):** Input variables used to predict the target. Examples:
  - **CIBIL Score**
  - **Loan Amount**
  - **Total Assets**
  - **Loan Term**
  - **Income Annum**
- **Target (y):** The output variable we want to predict, i.e., **Loan Approval Status (Approved/Not Approved)**.

Why Split the Dataset?

- **X (Features):** Helps the model learn patterns influencing loan approval.

- **y (Target):** The value the model aims to predict.
- Separating features and target allows the model to understand relationships and make accurate predictions.

Split data into training and testing sets.

```
# Divide the dataset into training (80%) and testing (20%) subsets
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

Train the Regression Model

```
# Instantiate the Logistic Regression model
model = LogisticRegression()

# Fit the model using the training dataset
model.fit(x_train, y_train)

# Generate predictions on the test dataset
y_pred = model.predict(x_test)

# Display the first 10 predicted values
print('Predictions',y_pred[:10])

Predictions [0 1 0 1 1 1 1 0 1 0]

#Getting Model Accuracy

print('Accuracy',accuracy_score(y_test,y_pred))

print('Accuracy',classification_report(y_test,y_pred))

Accuracy 0.9063231850117096
Accuracy               precision    recall  f1-score   support

           0       0.88      0.87      0.87       318
           1       0.92      0.93      0.93       536

    accuracy                           0.91       854
   macro avg       0.90      0.90      0.90       854
weighted avg       0.91      0.91      0.91       854
```

Model Evaluation

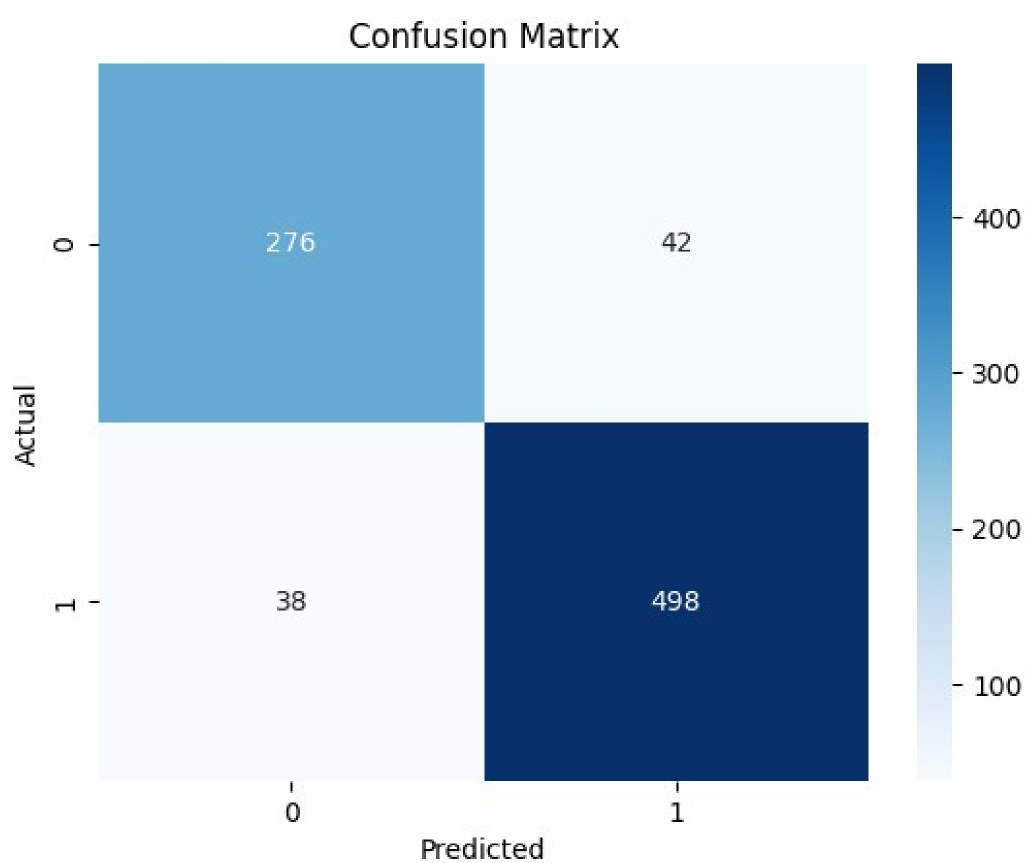
Evaluating Model Using

- **Confusion Matrix**: Displays the true positive, false positive, true negative, and false negative values to assess classification performance.

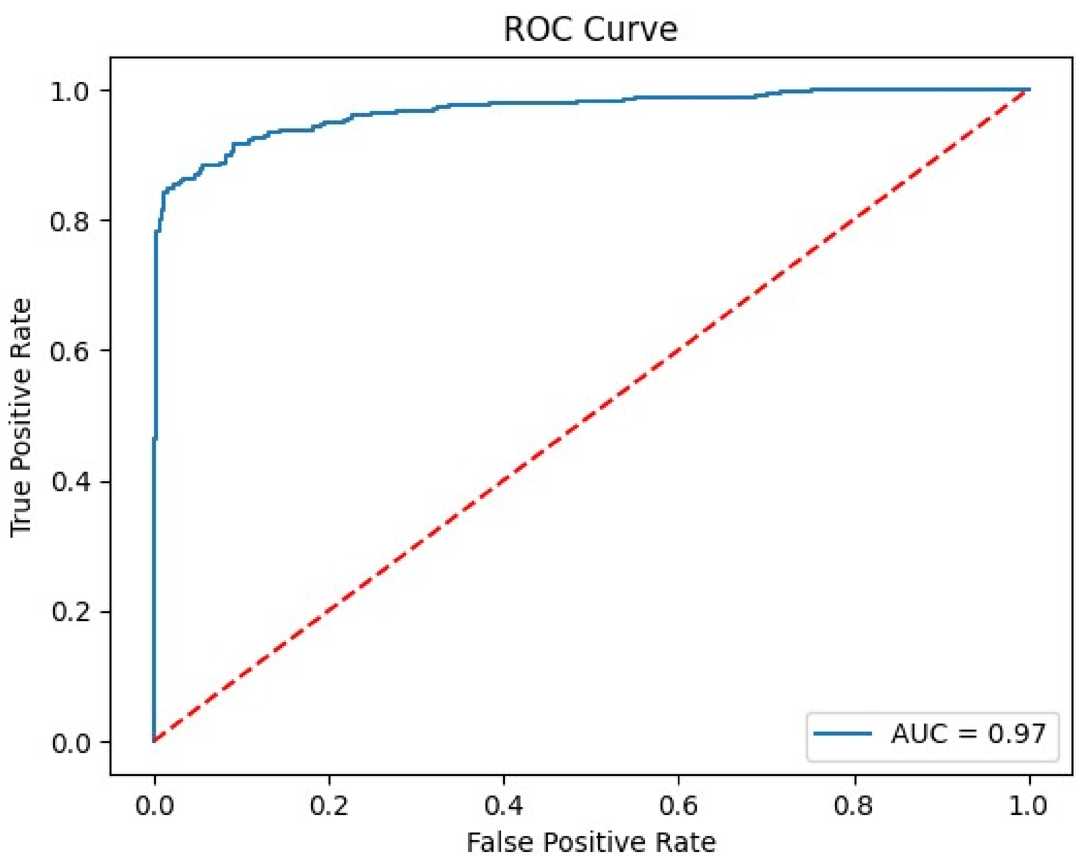
- **ROC Curve & AUC (Area Under Curve)**: Shows the trade-off between true positive rate and false positive rate, with AUC values closer to 1 indicating better performance.

- **Feature Importance (Logistic Regression Coefficients)**: Highlights the most influential features in model predictions, helping in feature selection and interpretability.

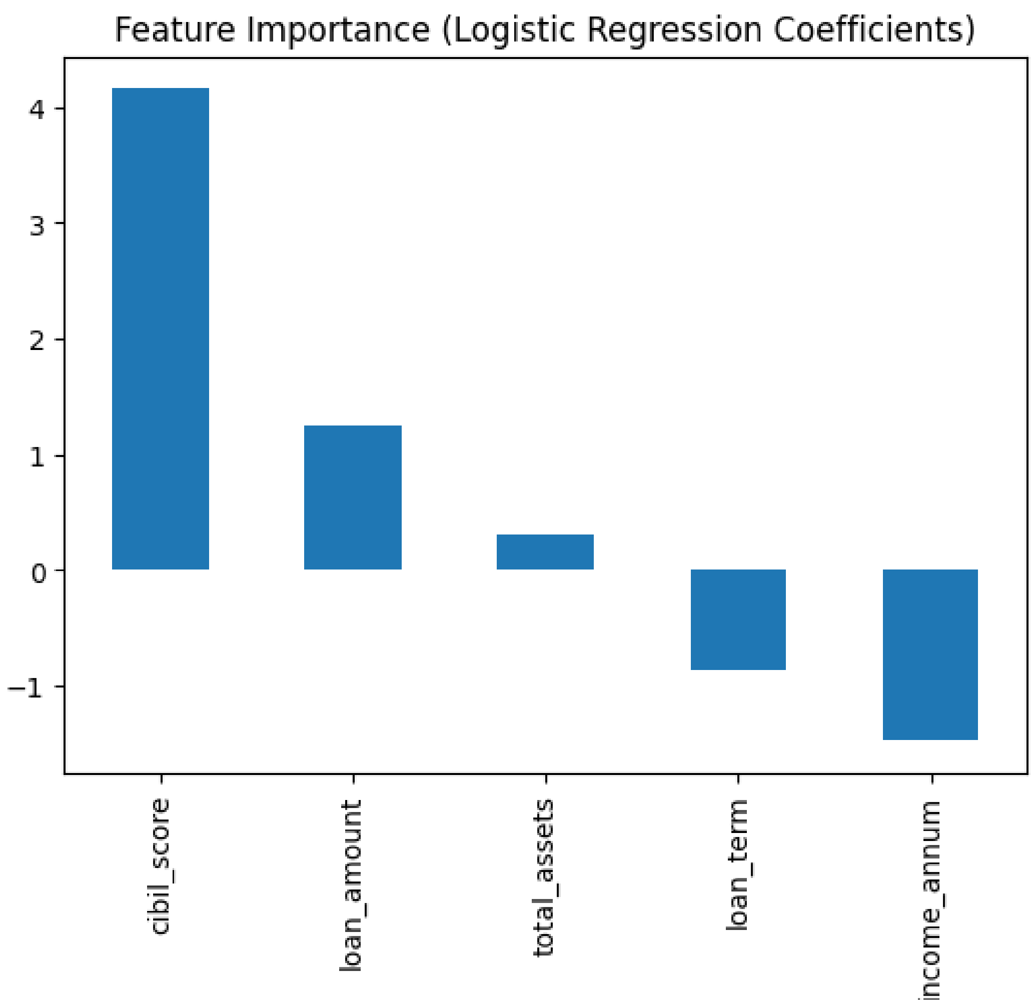
```
#Confusion Matrix

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=[0,1],
yticklabels=[0,1])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



```
# ROC Curve & AUC (Area Under Curve)

y_pred_prob = model.predict_proba(x_test)[:,1]  # Probabilities for class 1
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
auc_score = roc_auc_score(y_test, y_pred_prob)

plt.plot(fpr, tpr, label=f"AUC = {auc_score:.2f}")
plt.plot([0,1], [0,1], 'r--')  # Random guess line
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```




```
#Feature Importance (Logistic Regression Coefficients)

importance = pd.Series(model.coef_[0], index=x.columns)  # Use original x DataFrame
importance.sort_values(ascending=False).plot(kind='bar')
plt.title("Feature Importance (Logistic Regression Coefficients)")
plt.show()
```



Model Evaluation Result

Confusion Matrix

- **True Positives (498)** and **True Negatives (276)** indicate good classification.
- **False Positives (42)** and **False Negatives (38)** should be analyzed for potential improvements.

ROC Curve (AUC = 0.97)

- A high AUC value suggests excellent model performance and strong discriminatory power.

Feature Importance

- **CIBIL Score** has the highest impact on predictions.
- **Loan Amount** also plays a significant role.
- **Income Annum** negatively influences predictions, indicating an inverse relationship.