LOAN APPROVAL PREDICTION

MACHINE LEARNING PROJECT

PRESENTED BY

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❖ INTRODUCTION.

In today's fast-paced financial world, loan approval is a critical aspect of banking and lending institutions. Traditionally, loan approvals have been heavily dependent on manual assessments, where loan officers examine credit histories, income reports, and other personal factors to determine whether an applicant is eligible for a loan. While this approach has been effective in certain cases, it can be inefficient, prone to human error, and often results in inconsistent decision-making. This process can also be time-consuming for both the applicants and the institutions, leading to long waiting periods and sometimes missed opportunities.

With the advent of data analytics and machine learning, financial institutions have begun to explore automation for improving loan approval processes. Machine learning models can process vast amounts of data to make informed decisions, providing a more objective, faster, and consistent approach to loan approval. The integration of these advanced technologies is not only expected to streamline workflows but also to enhance the accuracy of predicting the likelihood of loan repayment.

A key challenge, however, lies in developing a predictive system that can balance the complexities of human financial behavior and existing data patterns. The objective of the Loan-Approval-Prediction system is to build such a solution—an automated, reliable, and scalable model that can predict the approval or rejection of loan applications based on several historical and real-time data points.

The ultimate aim of implementing such a system is to minimize the time spent on each loan decision while maintaining high accuracy, reducing biases, and making the process fairer for all applicants. In doing so, lending institutions can improve their operations, provide quicker responses to applicants, and increase overall customer satisfaction.

❖ OBJECTIVE : **To predict loan approval status using machine learning 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.

❖ 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
```

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

```
np.int64(0)
```

```python
# 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
```

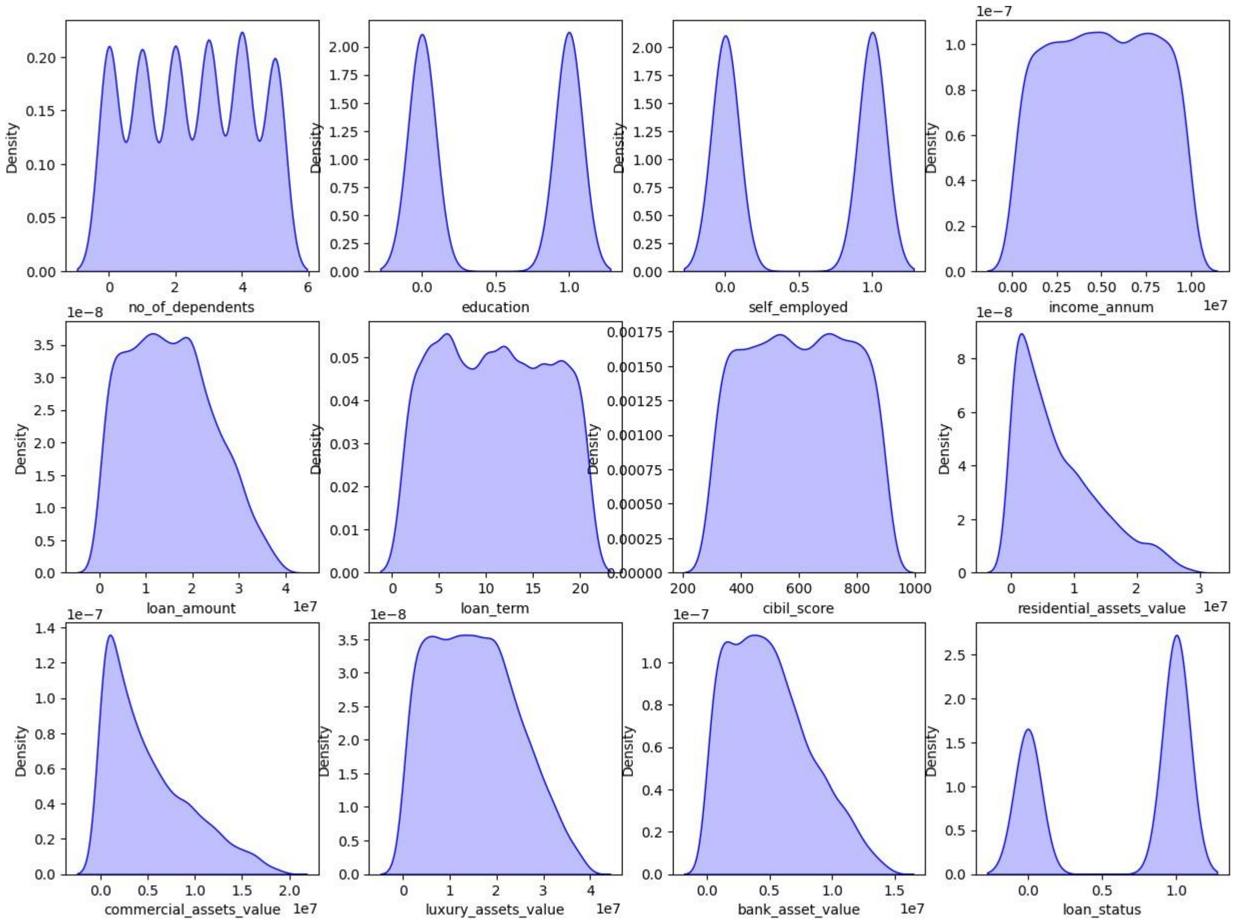
Exploratory Data Analysis (EDA)

- 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
```

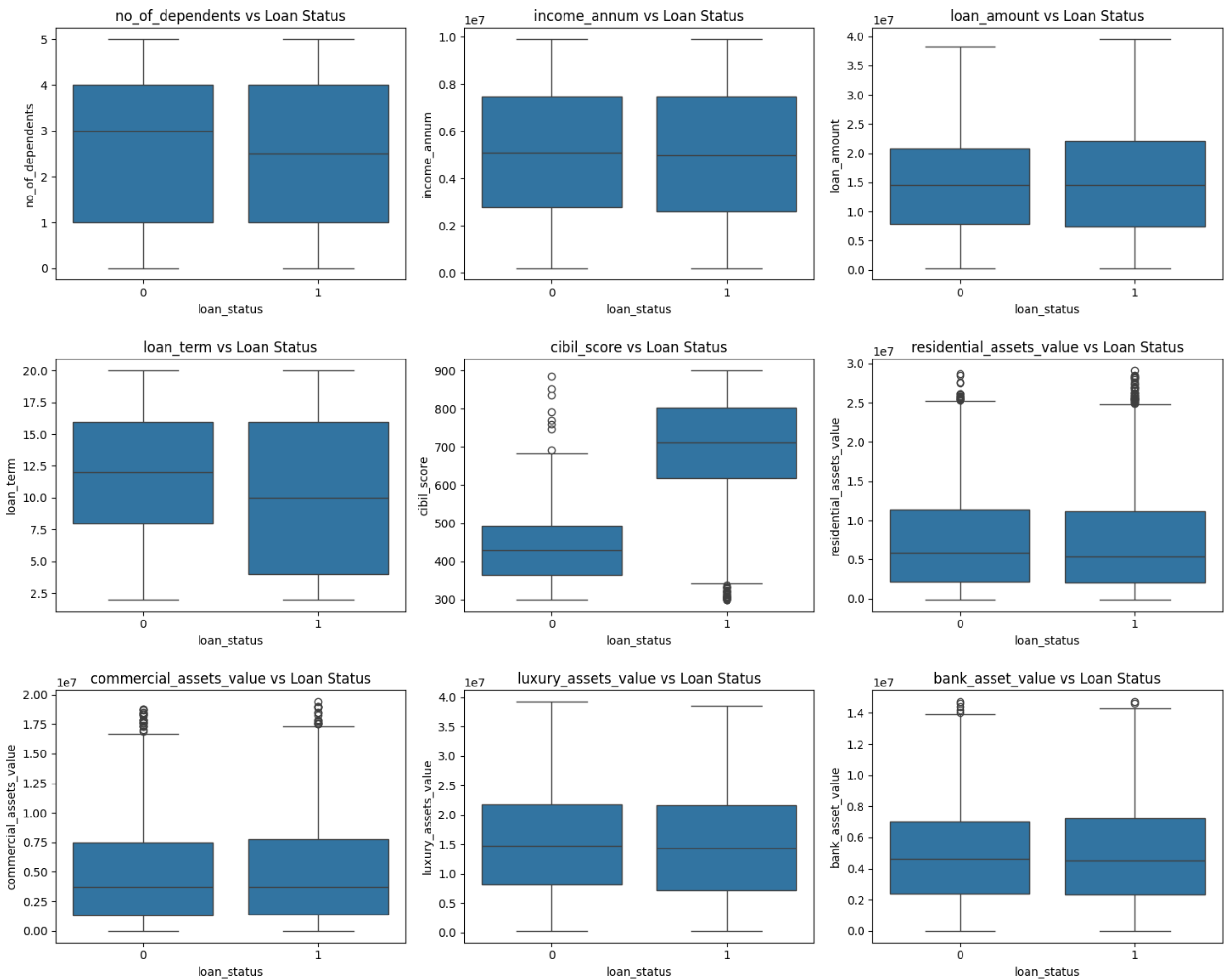
```
Index(['loan_id', 'no_of_dependents', 'education', 'self_employed',
       'income_annum', 'loan_amount', 'loan_term', 'cibil_score',
       'residential_assets_value', 'commercial_assets_value',
       'luxury_assets_value', 'bank_asset_value', 'loan_status'],
      dtype='object')
```

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.

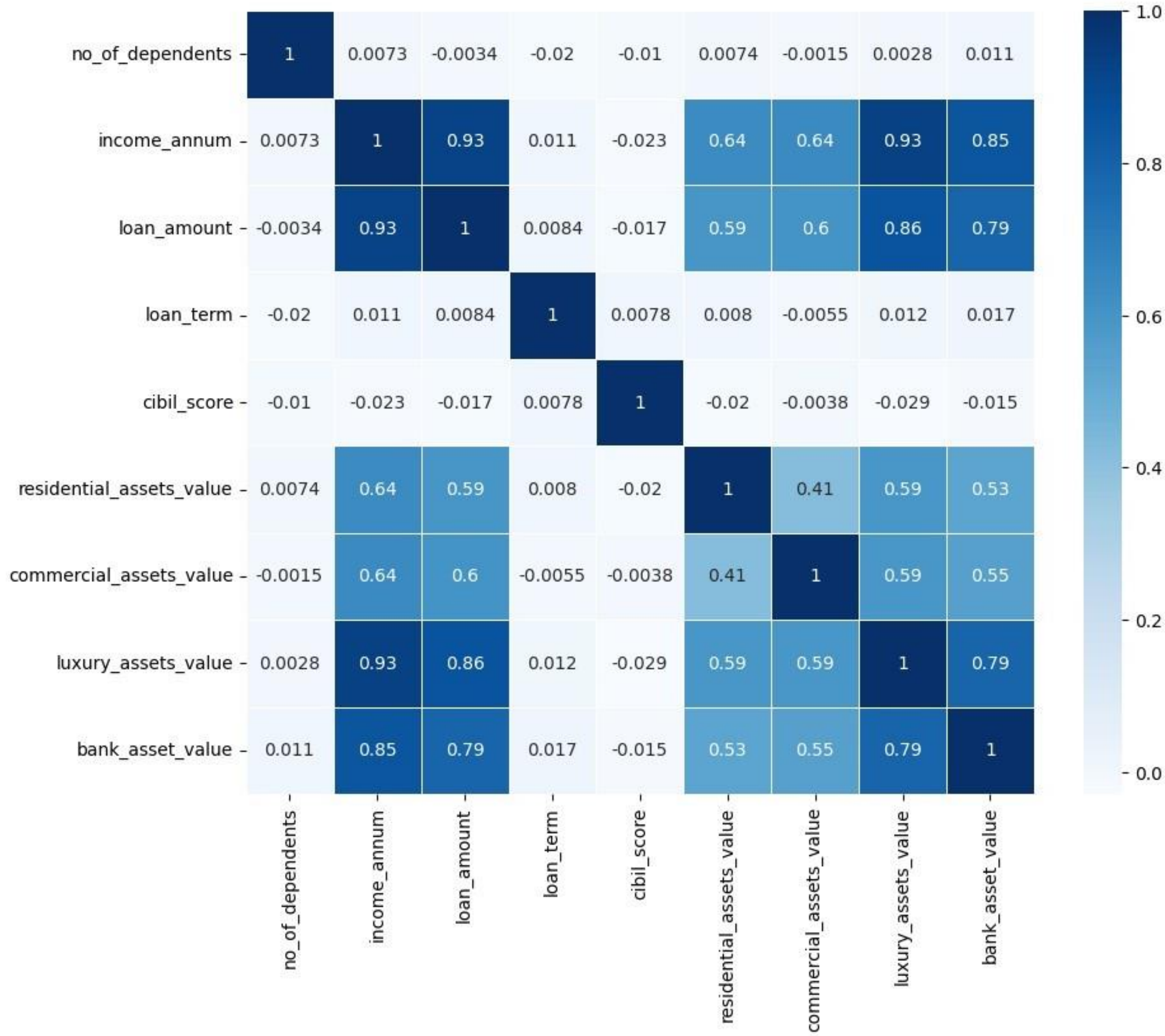
```
#Bivariate Analysis

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

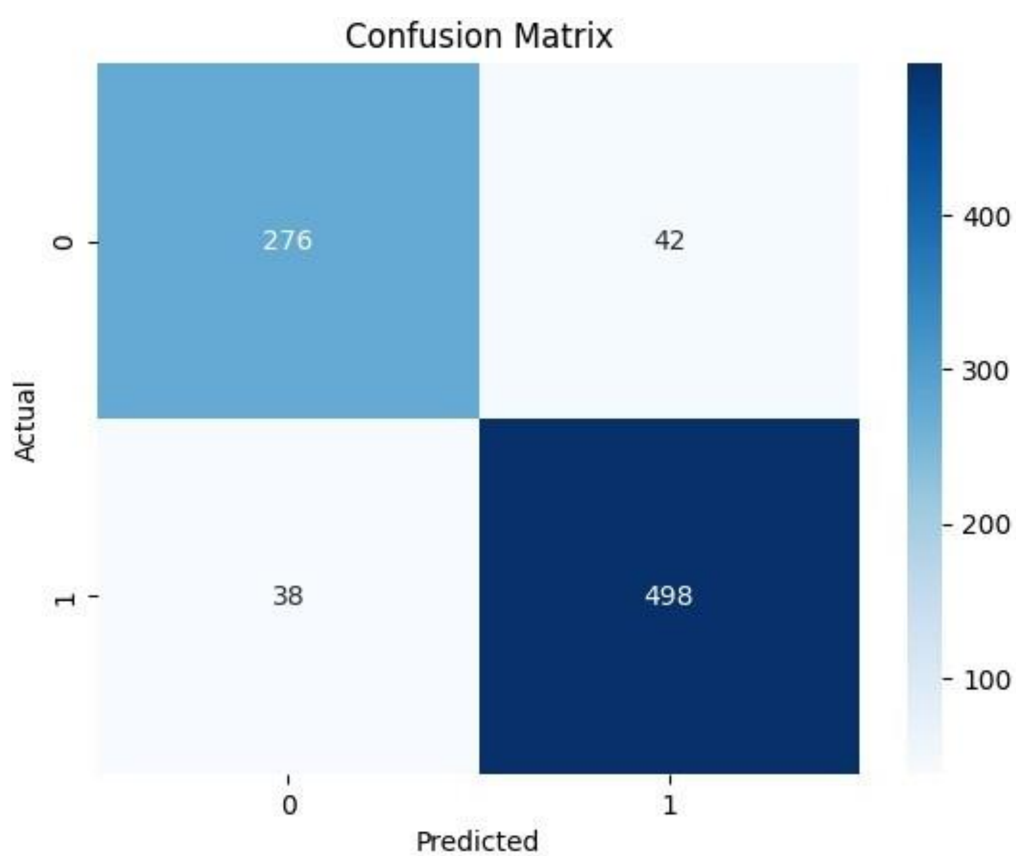
Evaluating Model Using

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

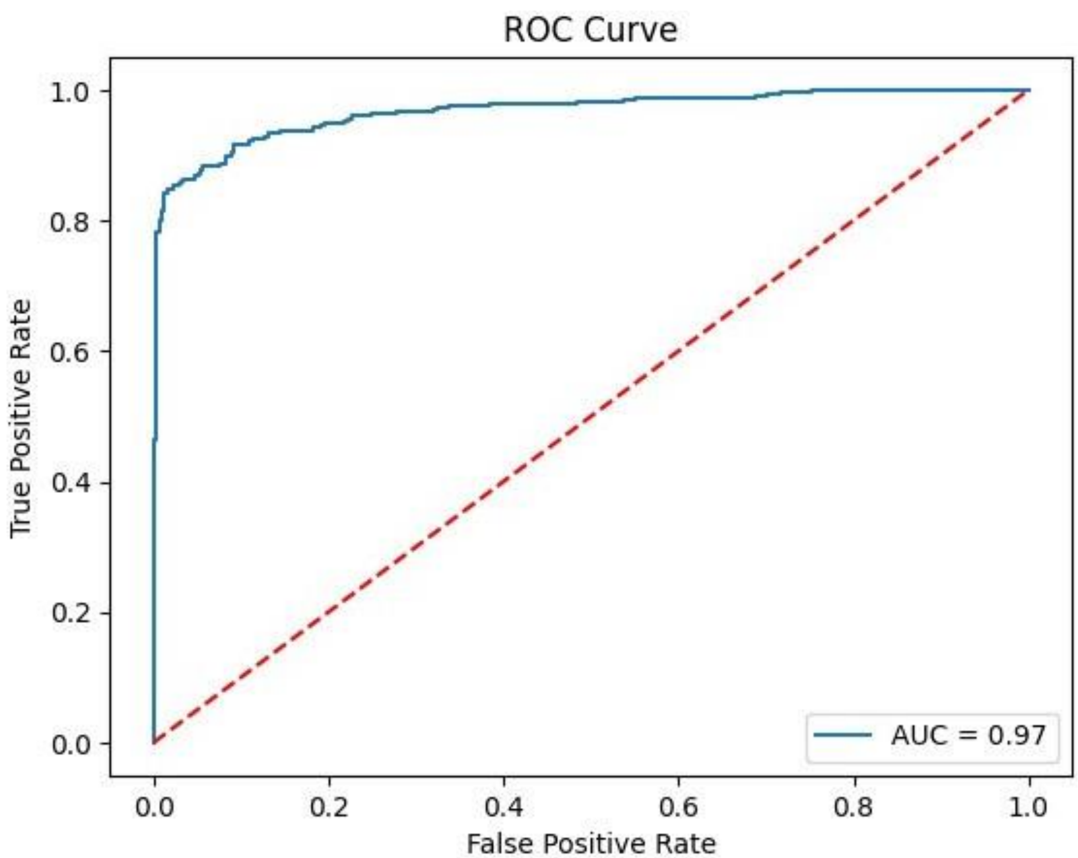
- **ROC Curve & AUC (Area Under Curve)**: Shows the trade-off between true positive rate and false positive rate, with AUC values closer to 1 indicating better performance.

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

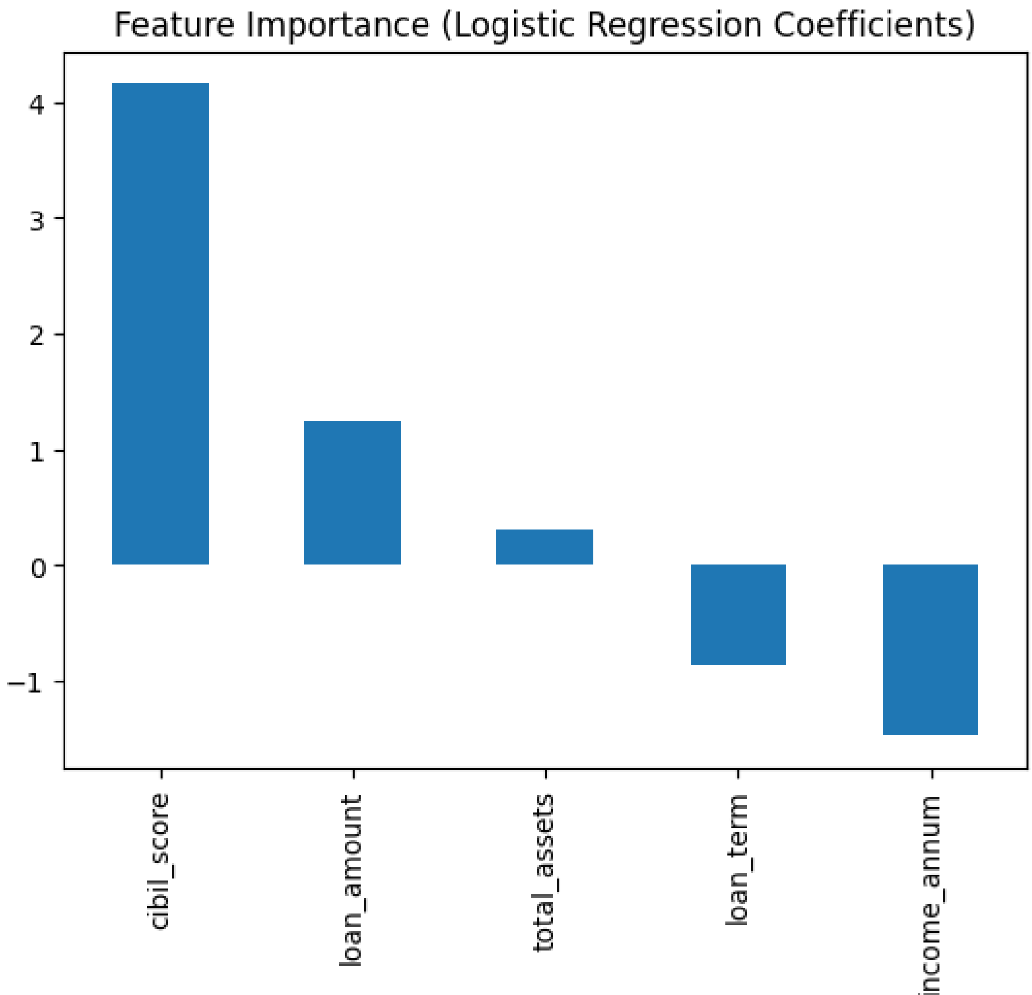
```
#Confusion Matrix

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()
```



```python
# 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()
```




```python
#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.