Loan Classification based on the likelihood of loan repayment using Logistic Regression

In [2]:
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import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve, roc_auc_score
from sklearn.impute import SimpleImputer

df = pd.read_csv('loan_data.csv')

print(df.head())

df.drop('Loan_ID', axis=1, inplace=True)

imputer = SimpleImputer(strategy='mean')
df[['LoanAmount', 'Loan_Amount_Term', 'Credit_History']] = imputer.fit_transform(df[['LoanAmount', 'Loan_Amount_Term', 'Credit_History']])

categorical_columns = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'Property_Area']
df = pd.get_dummies(df, columns=categorical_columns, drop_first=True)

# Convert Loan_Status to numerical values
df['Loan_Status'] = df['Loan_Status'].map({'N': 0, 'Y': 1})

X = df.drop('Loan_Status', axis=1)
y = df['Loan_Status']

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)

model = LogisticRegression(random_state=42)
model.fit(X_train, y_train)
```

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y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)

def predict_loan_repayment(new_data):
    new_data[['LoanAmount', 'Loan_Amount_Term', 'Credit_History']] = imputer.transform(new_data[['LoanAmount', 'Loan_Amount_Term', 'Credit_
    new_data = pd.get_dummies(new_data, columns=categorical_columns, drop_first=True)

    missing_cols = set(X.columns) - set(new_data.columns)
    for col in missing_cols:
        new_data[col] = 0
    new_data = new_data[X.columns]

    new_data = scaler.transform(new_data)
    predictions = model.predict(new_data)
    probabilities = model.predict_proba(new_data)[:, 1]
    return predictions, probabilities

new_loan_data = pd.DataFrame({
    'Gender': ['Male'],
    'Married': ['Yes'],
    'Dependents': ['1'],
    'Education': ['Graduate'],
    'Self_Employed': ['No'],
    'ApplicantIncome': [5000],
    'CoapplicantIncome': [2000],
    'LoanAmount': [150],
    'Loan_Amount_Term': [360],
    'Credit_History': [1],
    'Property_Area': ['Urban']
})

predictions, probabilities = predict_loan_repayment(new_loan_data)
print("Predictions:", predictions)
print("Probabilities:", probabilities)
```

```python
# Visualize the results

# Plot the distribution of predicted probabilities
plt.figure(figsize=(10, 6))
sns.histplot(probabilities, bins=10, kde=True)
plt.title('Distribution of Predicted Probabilities')
plt.xlabel('Probability of Loan Repayment')
plt.ylabel('Frequency')
plt.show()

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No', 'Yes'], yticklabels=['No', 'Yes'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# ROC Curve
y_pred_proba = model.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = roc_auc_score(y_test, y_pred_proba)

plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
# Print the dataset used
print(df)
```

```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

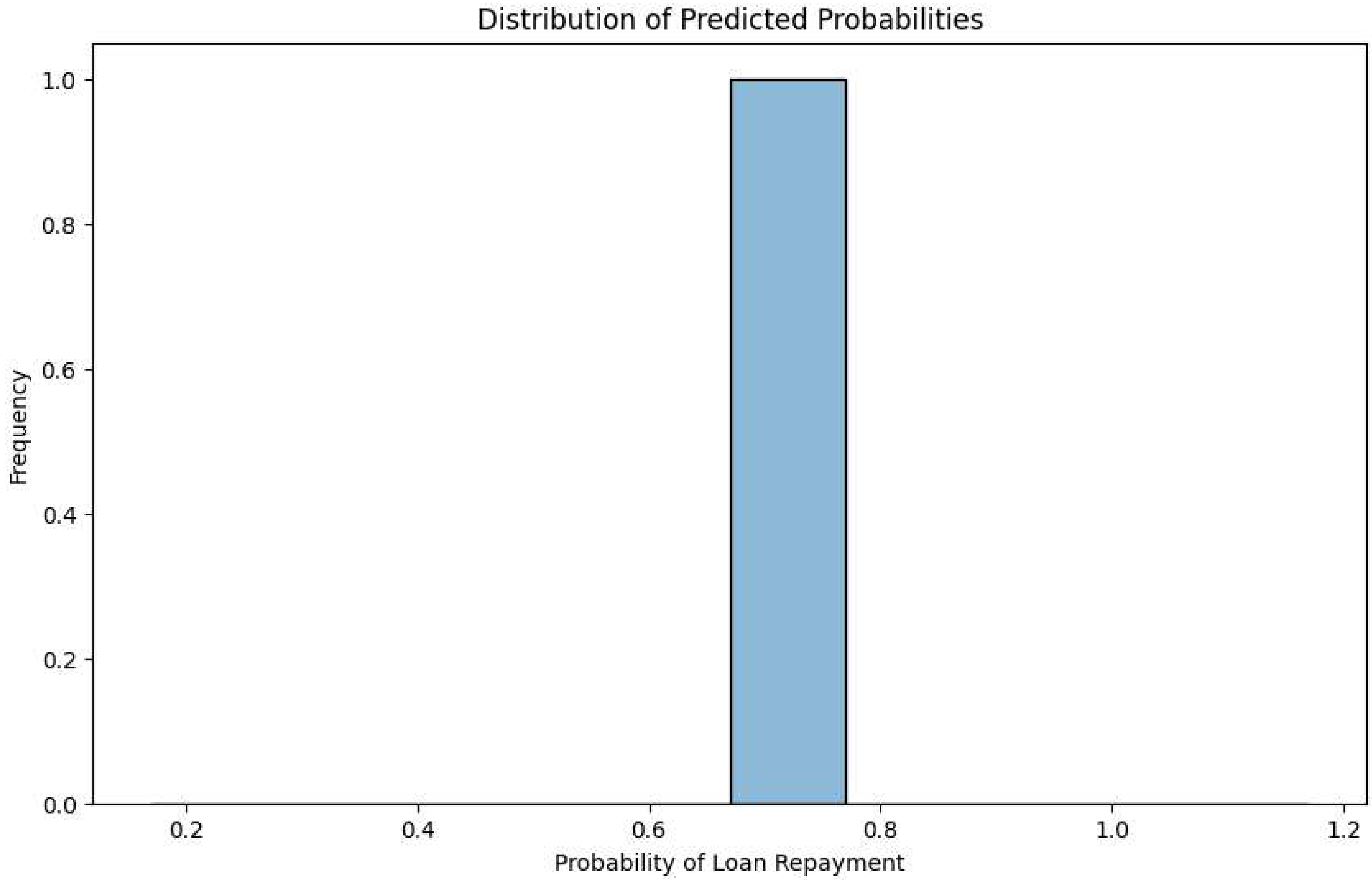
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

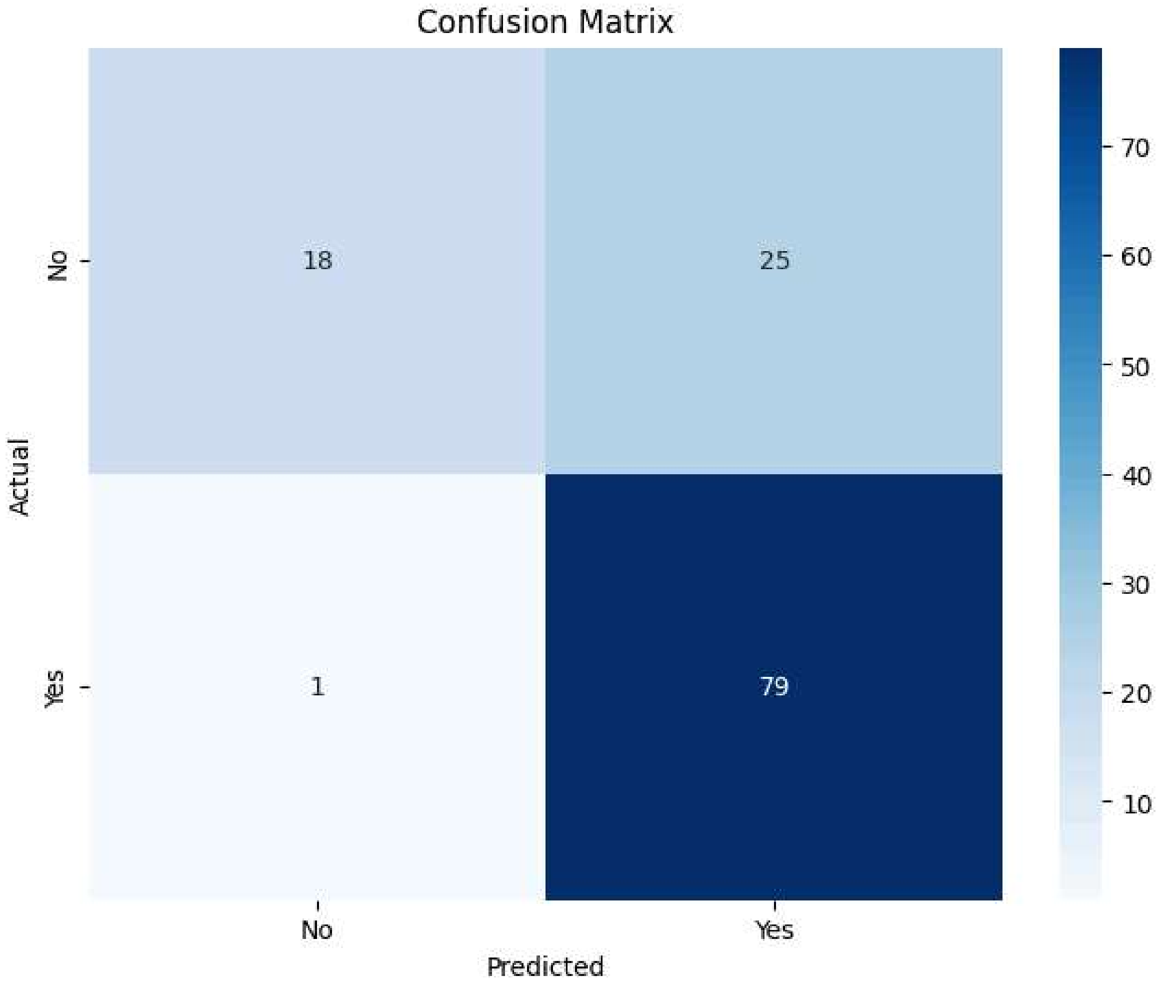
   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
Accuracy: 0.7886178861788617
Confusion Matrix:
[[18 25]
 [ 1 79]]
Classification Report:
              precision    recall  f1-score   support

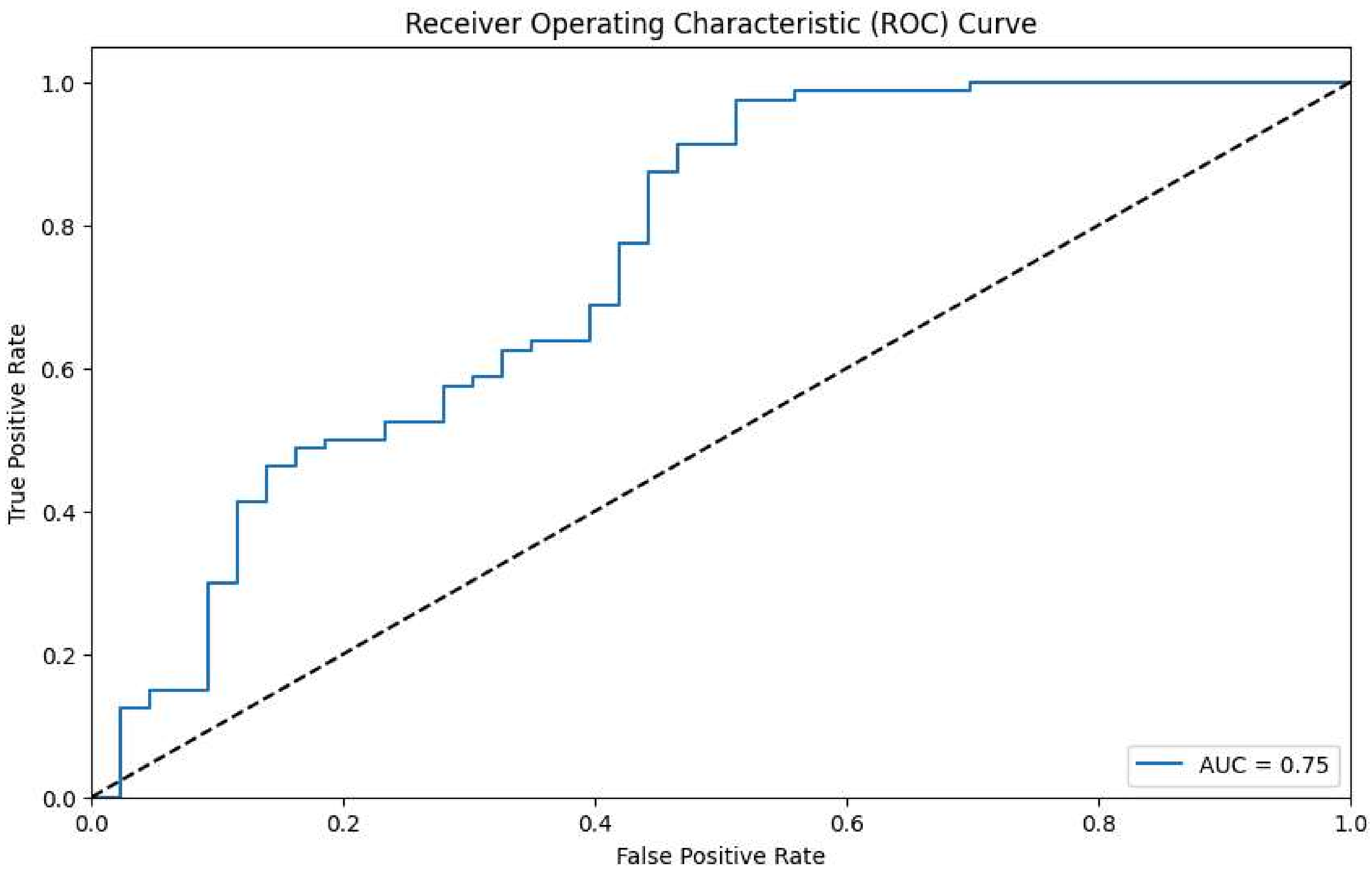
           0       0.95      0.42      0.58        43
           1       0.76      0.99      0.86        80

    accuracy                           0.79       123
   macro avg       0.85      0.70      0.72       123
weighted avg       0.83      0.79      0.76       123

Predictions: [1]
Probabilities: [0.66982468]
```


Distribution of Predicted Probabilities
Frequency
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Probability of Loan Repayment


Confusion Matrix
Actual
No
Yes
18
25
1
79
Predicted
No
Yes
70
60
50
40
30
20
10


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
AUC = 0.75

```
     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0  146.412162             360.0   
1               4583             1508.0  128.000000             360.0   
2               3000                0.0   66.000000             360.0   
3               2583             2358.0  120.000000             360.0   
4               6000                0.0  141.000000             360.0   
..               ...                ...         ...               ...   
609             2900                0.0   71.000000             360.0   
610             4106                0.0   40.000000             180.0   
611             8072              240.0  253.000000             360.0   
612             7583                0.0  187.000000             360.0   
613             4583                0.0  133.000000             360.0   

     Credit_History  Loan_Status  Gender_Male  Married_Yes  Dependents_1  \
0               1.0            1         True        False         False   
1               1.0            0         True         True          True   
2               1.0            1         True         True         False   
3               1.0            1         True         True         False   
4               1.0            1         True        False         False   
..              ...          ...          ...          ...           ...   
609             1.0            1        False        False         False   
610             1.0            1         True         True         False   
611             1.0            1         True         True          True   
612             1.0            1         True         True         False   
613             0.0            0        False        False         False   

     Dependents_2  Dependents_3+  Education_Not Graduate  Self_Employed_Yes  \
0           False          False                   False              False   
1           False          False                   False              False   
2           False          False                   False               True   
3           False          False                    True              False   
4           False          False                   False              False   
..            ...            ...                     ...                ...   
609         False          False                   False              False   
610         False           True                   False              False   
611         False          False                   False              False   
612          True          False                   False              False   
613         False          False                   False               True   

     Property_Area_Semiurban  Property_Area_Urban  
0                      False                 True  
1                      False                False  
2                      False                 True  
3                      False                 True  
```

```
4                     False               True
..                      ...                ...
609                   False              False
610                   False              False
611                   False               True
612                   False               True
613                    True              False

[614 rows x 15 columns]
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