loan-approval-prediction

October 22, 2024

1 Loan Approval Prediction Using Machine Learning

2 Importing necessary libraries

[1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from xgboost import XGBClassifier
from sklearn.impute import SimpleImputer
```

3 Loading the dataset

[2]:
```
df = pd.read_csv('C:/Users/ASUS/Desktop/Power BI Practice/loan_data.csv')
df.head(10)
```

[2]:
```
    Loan_ID Gender Married  Dependents     Education Self_Employed  \
0  LP001002   Male      No         0.0      Graduate            No
1  LP001003   Male     Yes         1.0      Graduate            No
2  LP001005   Male     Yes         0.0      Graduate           Yes
3  LP001006   Male     Yes         0.0  Not Graduate            No
4  LP001008   Male      No         0.0      Graduate            No
5  LP001011   Male     Yes         2.0      Graduate           Yes
6  LP001013   Male     Yes         0.0  Not Graduate            No
7  LP001014   Male     Yes         3.0      Graduate            No
8  LP001018   Male     Yes         2.0      Graduate            No
9  LP001020   Male     Yes         1.0      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
5           5417            4196.0       267.0              360.0
6           2333            1516.0        95.0              360.0
7           3036            2504.0       158.0              360.0
8           4006            1526.0       168.0              360.0
9          12841           10968.0       349.0              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
5             1.0         Urban           Y
6             1.0         Urban           Y
7             0.0     Semiurban           N
8             1.0         Urban           Y
9             1.0     Semiurban           N
```

4 Basic data exploration

[3]:
```python
print(df.info())    # Display the data types and missing values
print(df.describe())    # Show basic statistics of numerical columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 598 entries, 0 to 597
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            598 non-null    object
 1   Gender             598 non-null    object
 2   Married            598 non-null    object
 3   Dependents         586 non-null    float64
 4   Education          598 non-null    object
 5   Self_Employed      598 non-null    object
 6   ApplicantIncome    598 non-null    int64
 7   CoapplicantIncome  598 non-null    float64
 8   LoanAmount         577 non-null    float64
 9   Loan_Amount_Term   584 non-null    float64
 10  Credit_History     549 non-null    float64
 11  Property_Area      598 non-null    object
 12  Loan_Status        598 non-null    object
dtypes: float64(5), int64(1), object(7)
```

```
memory usage: 60.9+ KB
None
       Dependents  ApplicantIncome  CoapplicantIncome  LoanAmount  \
count  586.000000       598.000000         598.000000  577.000000
mean     0.755973      5292.252508        1631.499866  144.968804
std      1.007751      5807.265364        2953.315785   82.704182
min      0.000000       150.000000           0.000000    9.000000
25%      0.000000      2877.500000           0.000000  100.000000
50%      0.000000      3806.000000        1211.500000  127.000000
75%      1.750000      5746.000000        2324.000000  167.000000
max      3.000000     81000.000000       41667.000000  650.000000

       Loan_Amount_Term  Credit_History
count        584.000000      549.000000
mean         341.917808        0.843352
std           65.205994        0.363800
min           12.000000        0.000000
25%          360.000000        1.000000
50%          360.000000        1.000000
75%          360.000000        1.000000
max          480.000000        1.000000
```

5 Handle missing values (if any)

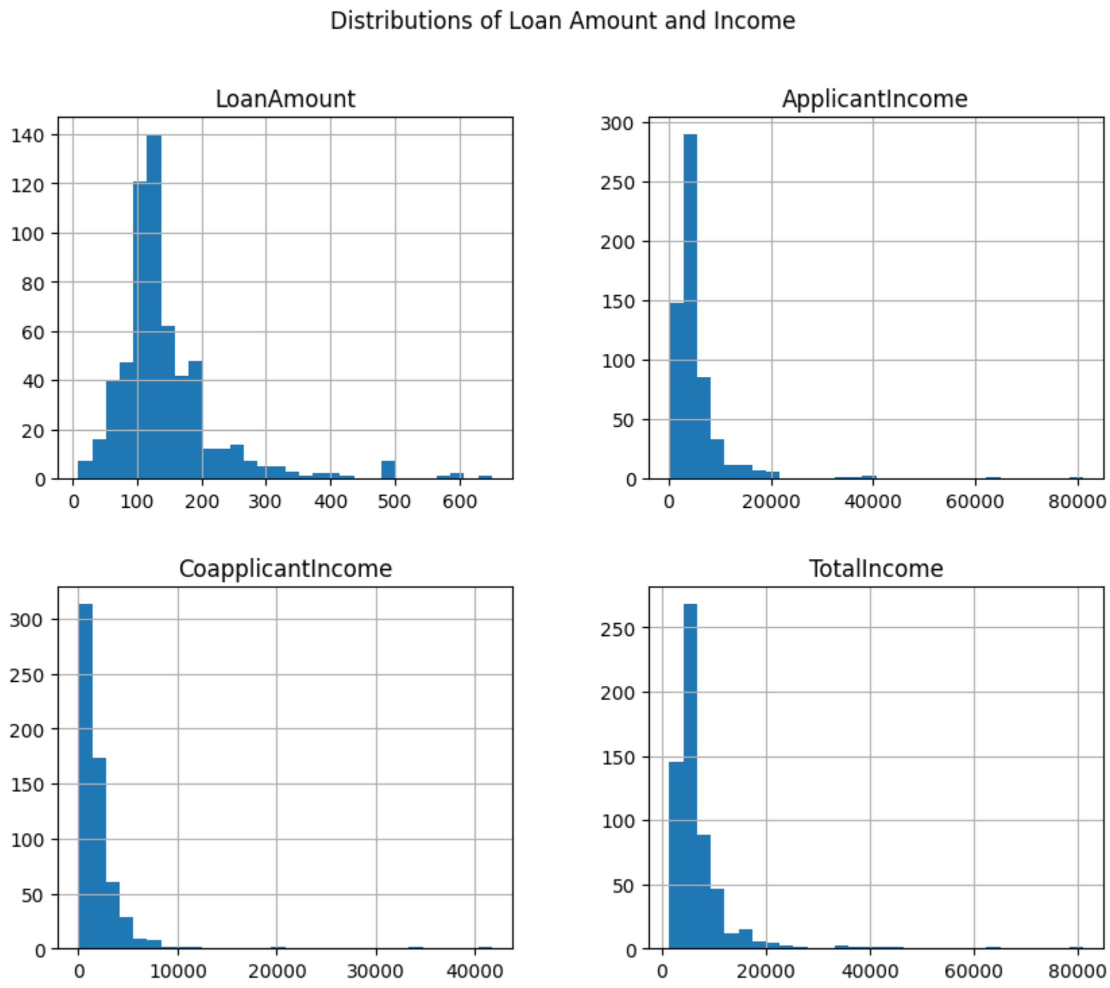
[4]:
```
# Fill missing values with median or mode depending on the column type
df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].median())
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].
↪median())
df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].
↪mode()[0])

df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0])
df['Married'] = df['Married'].fillna(df['Married'].mode()[0])
df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])
df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])
```

6 Feature engineering - Adding log-transformed values for skewed numerical columns

[5]:
```
# Log-transform skewed numerical columns to normalize them
df['LoanAmount_log'] = np.log(df['LoanAmount'] + 1)  # Adding 1 to avoid log(0)
df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df['TotalIncome_log'] = np.log(df['TotalIncome'] + 1)
```

7 Visualizing distributions of numerical features

[6]:
```
df[['LoanAmount', 'ApplicantIncome', 'CoapplicantIncome', 'TotalIncome']].
↪hist(bins=30, figsize=(10, 8))
plt.suptitle('Distributions of Loan Amount and Income')
plt.show()
```

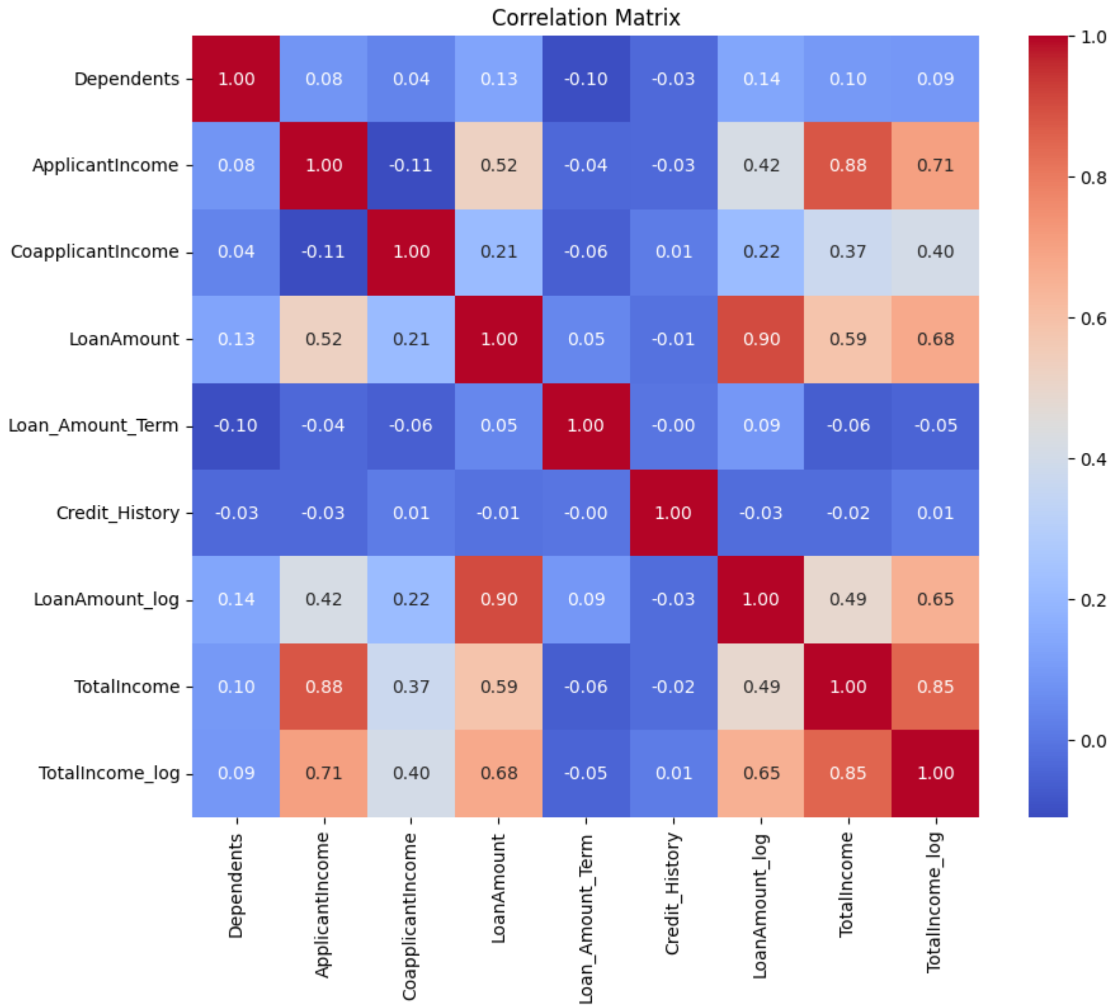


8 Bar plot of Loan_Status counts to visualize class distribution

[7]:
```
plt.figure(figsize=(6, 4))
sns.countplot(x='Loan_Status', data=df)
plt.title('Loan Approval Distribution')
plt.show()
```

9 Correlation heatmap - only for numerical columns

[8]:
```
# Correlation analysis of numerical features to identify relationships
plt.figure(figsize=(10, 8))
numerical_df = df.select_dtypes(include=[np.number])   # Select only numerical␣
 ↪columns
corr_matrix = numerical_df.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



10 Encode categorical variables

[9]:

```
# Label encode categorical columns
encoder = LabelEncoder()
df['Gender'] = encoder.fit_transform(df['Gender'])
df['Married'] = encoder.fit_transform(df['Married'])
df['Education'] = encoder.fit_transform(df['Education'])
df['Self_Employed'] = encoder.fit_transform(df['Self_Employed'])
df['Property_Area'] = encoder.fit_transform(df['Property_Area'])
df['Loan_Status'] = encoder.fit_transform(df['Loan_Status'])  # Target variable

# Replace '3+' in Dependents with 3 and convert to integer type
df['Dependents'] = df['Dependents'].replace('3+', 3).astype(int)
```

11 Prepare the data for modeling

[10]:
```
# Select features and target variable for modeling
X = df[['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',␣
 ↪'LoanAmount_log',
        'Loan_Amount_Term', 'Credit_History', 'Property_Area',␣
 ↪'TotalIncome_log']]
y = df['Loan_Status']
```

12 Split the data into training and testing sets

[11]:
```
# Use train_test_split to create training and testing datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)
```

13 Model training - RandomForestClassifier

[12]:
```
# Train a Random Forest classifier on the training data
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
```

[12]:
```
RandomForestClassifier(random_state=42)
```

14 Make predictions and evaluate the model

[13]:
```
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')   # Printing accuracy of the model
```

```
Accuracy: 77.22%
```

15 Display the confusion matrix and classification report

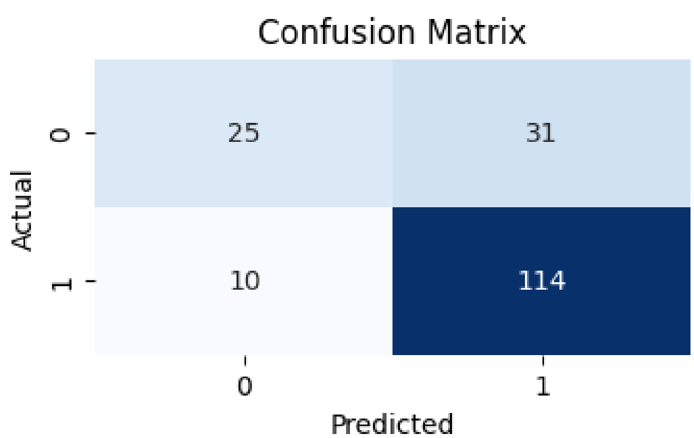
[14]:
```
conf_matrix = confusion_matrix(y_test, y_pred)
print('Confusion Matrix:\n', conf_matrix)
print('Classification Report:\n', classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[ 25  31]
 [ 10 114]]
Classification Report:
               precision    recall  f1-score   support
```

```
              0       0.71      0.45      0.55        56
              1       0.79      0.92      0.85       124

       accuracy                           0.77       180
      macro avg       0.75      0.68      0.70       180
   weighted avg       0.76      0.77      0.75       180
```

16 Visualize the confusion matrix

[15]:
```
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



17 Handle class imbalance using SMOTE

[16]:
```
smote = SMOTE(random_state=42)
X_res, y_res = smote.fit_resample(X, y)
```

18 Train an XGBoost model for comparison

[17]:
```
model_xgb = XGBClassifier(random_state=42)  # Removed use_label_encoder
model_xgb.fit(X_res, y_res)
y_pred_xgb = model_xgb.predict(X_test)

xgb_accuracy = accuracy_score(y_test, y_pred_xgb)
```

```
print(f'XGBoost Accuracy: {xgb_accuracy * 100:.2f}%')
```

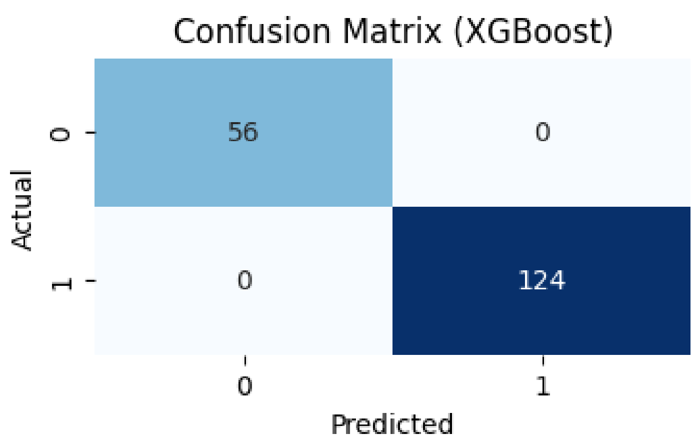
```
XGBoost Accuracy: 100.00%
```

[18]:
```
# Display confusion matrix and classification report for XGBoost
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
print('Confusion Matrix (XGBoost):\n', conf_matrix_xgb)
print('Classification Report (XGBoost):\n', classification_report(y_test,␣
↪y_pred_xgb))
```

```
Confusion Matrix (XGBoost):
 [[ 56   0]
 [  0 124]]
Classification Report (XGBoost):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        56
           1       1.00      1.00      1.00       124

    accuracy                           1.00       180
   macro avg       1.00      1.00      1.00       180
weighted avg       1.00      1.00      1.00       180
```

19 Visualize the confusion matrix for XGBoost

[19]:
```
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix_xgb, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix (XGBoost)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



20 Feature Importance

[20]:
```
# Visualize the importance of different features used in the Random Forest model
feature_importances = model.feature_importances_
features = X.columns
importance_df = pd.DataFrame({'Feature': features, 'Importance':␣
↪feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df, hue='Feature',␣
↪palette='coolwarm', dodge=False, legend=False)
plt.title('Feature Importances')
plt.show()
```