Loan Approval Prediction Model

Introduction

As a financial institution whose core business is issuing loans, being able to approve loan applications fast will differentiate the institution from other players in the market and make the fast turn around time a competitive advantge. The project analyse the past loan datasets by looking at applicants income levels, employment status, loan amount, education and credit history to be decide whether to approve the loan. This project examines these factors and uses machine learning to be able to automate the loan approval process. We will use data from https://www.kaggle.com/datasets/altruistdelhite04/loan-prediction-problem-dataset.

Objective

A financial institution wants to automate the loan approval process by developing a machine learning model that predicts whether a loan application will be approved. By analyzing past loan application data, the model will consider attributes like income, loan amount, education, employment, and credit history to classify applications as approved or rejected

2.1 Understanding the dataset

Importing the necessary liabraries and models

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import warnings
warnings.filterwarnings('ignore')

#relevant ML libraries
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.impute import SimpleImputer

#ML models
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

In [2]:

```
# Upload train data
tr_df = pd.read_csv('train.csv')
tr_df.head()
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Lo
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Lo
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	

In [3]:

```
#Upload test data
te_df = pd.read_csv('test.csv', index_col =0)
te_df.head()
```

Out[3]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_
Loan_ID									
LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	
LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	
LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	
LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	
LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	

In [4]:

```
tr_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

In [5]:

```
# Check the numerical data
list(set(tr_df.dtypes.tolist()))
```

Out[5]:

```
[dtype('float64'), dtype('O'), dtype('int64')]
```

In [6]:

```
tr_df_numerical = tr_df.select_dtypes(include = ['float64', 'int64'])
tr_df_numerical.head()
```

Out[6]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849	0.0	NaN	360.0	1.0
1	4583	1508.0	128.0	360.0	1.0
2	3000	0.0	66.0	360.0	1.0
3	2583	2358.0	120.0	360.0	1.0
4	6000	0.0	141.0	360.0	1.0

In [7]:

```
tr_df.describe()
```

Out[7]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [8]:

```
#missing values in decsending order
tr_df.isnull().sum()
```

Out[8]:

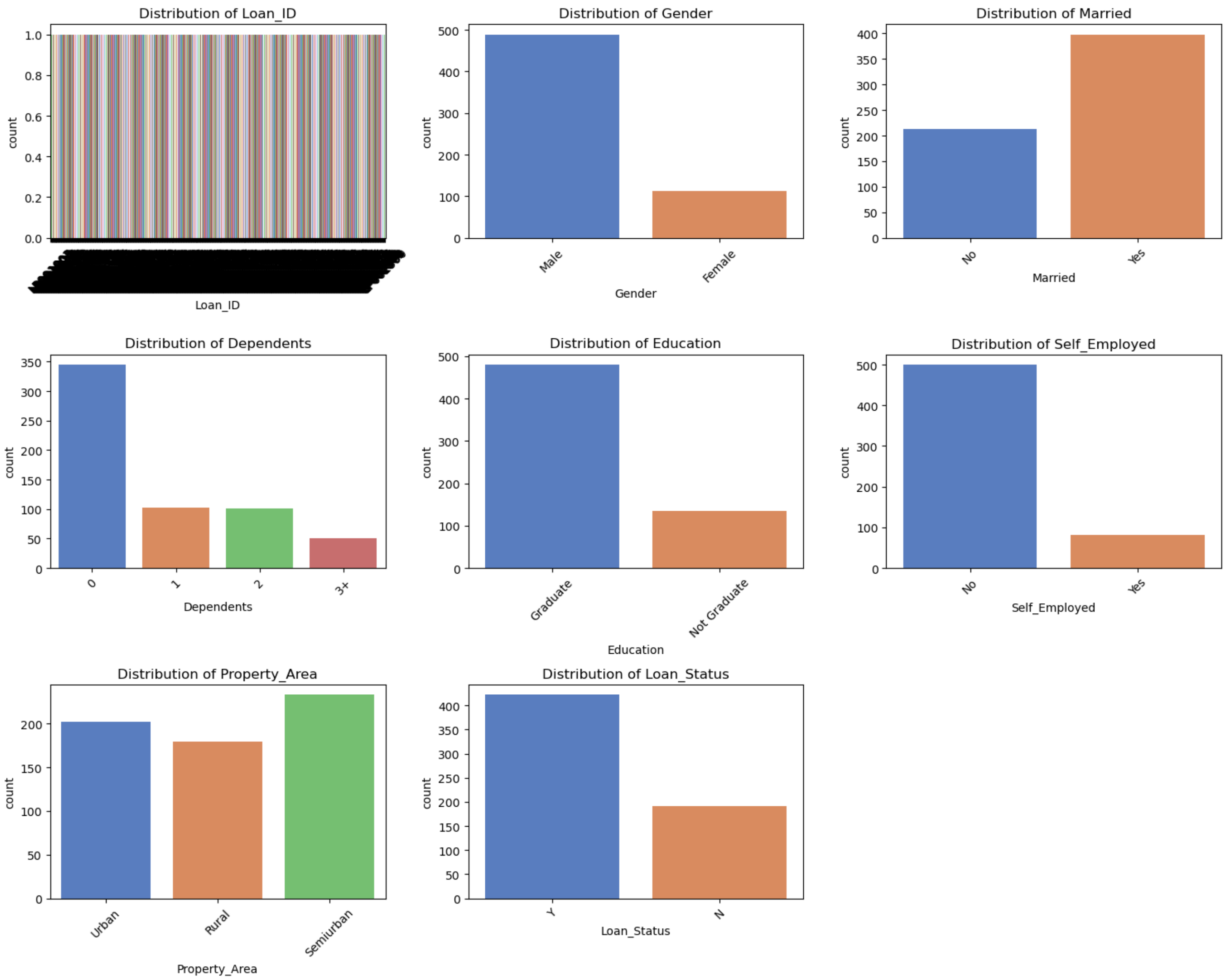
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [9]:

```
# Distribution of categorical variables
tr_df_categorical = tr_df.select_dtypes(include='object')
```

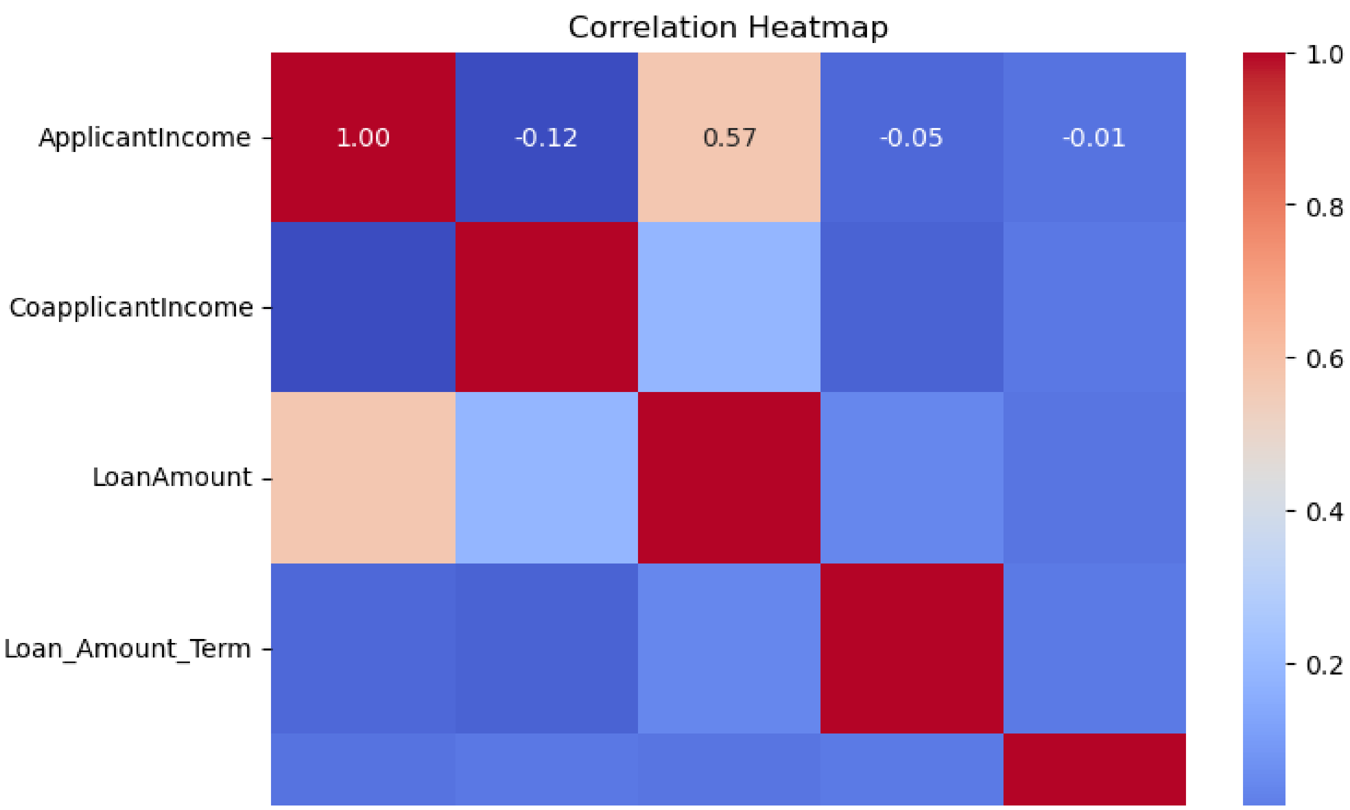
In [10]:

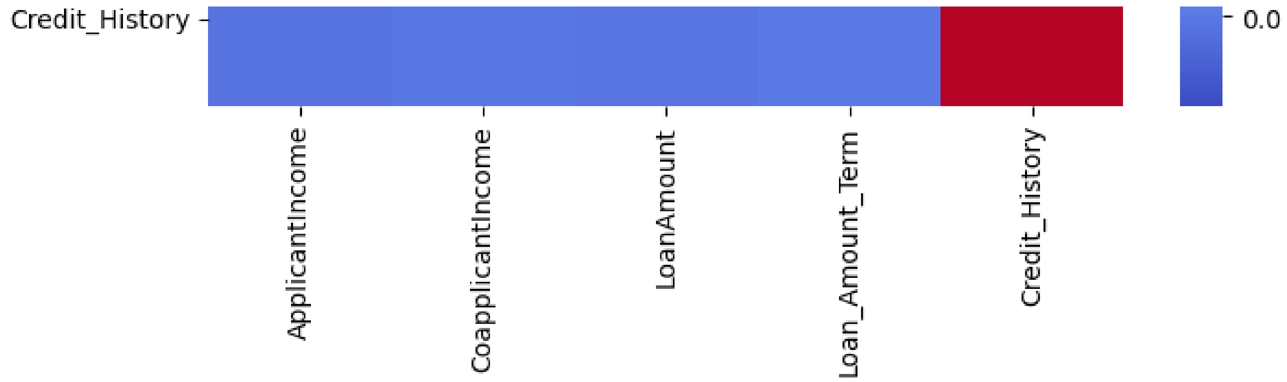
```
# Plot distribution of categorical variables
plt.figure(figsize=(15, 12))
for i, col in enumerate(tr_df_categorical, 1):
    plt.subplot(3, 3, i)
    sns.countplot(x=col, data=tr_df, palette="muted")
    plt.title(f"Distribution of {col}")
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [11]:

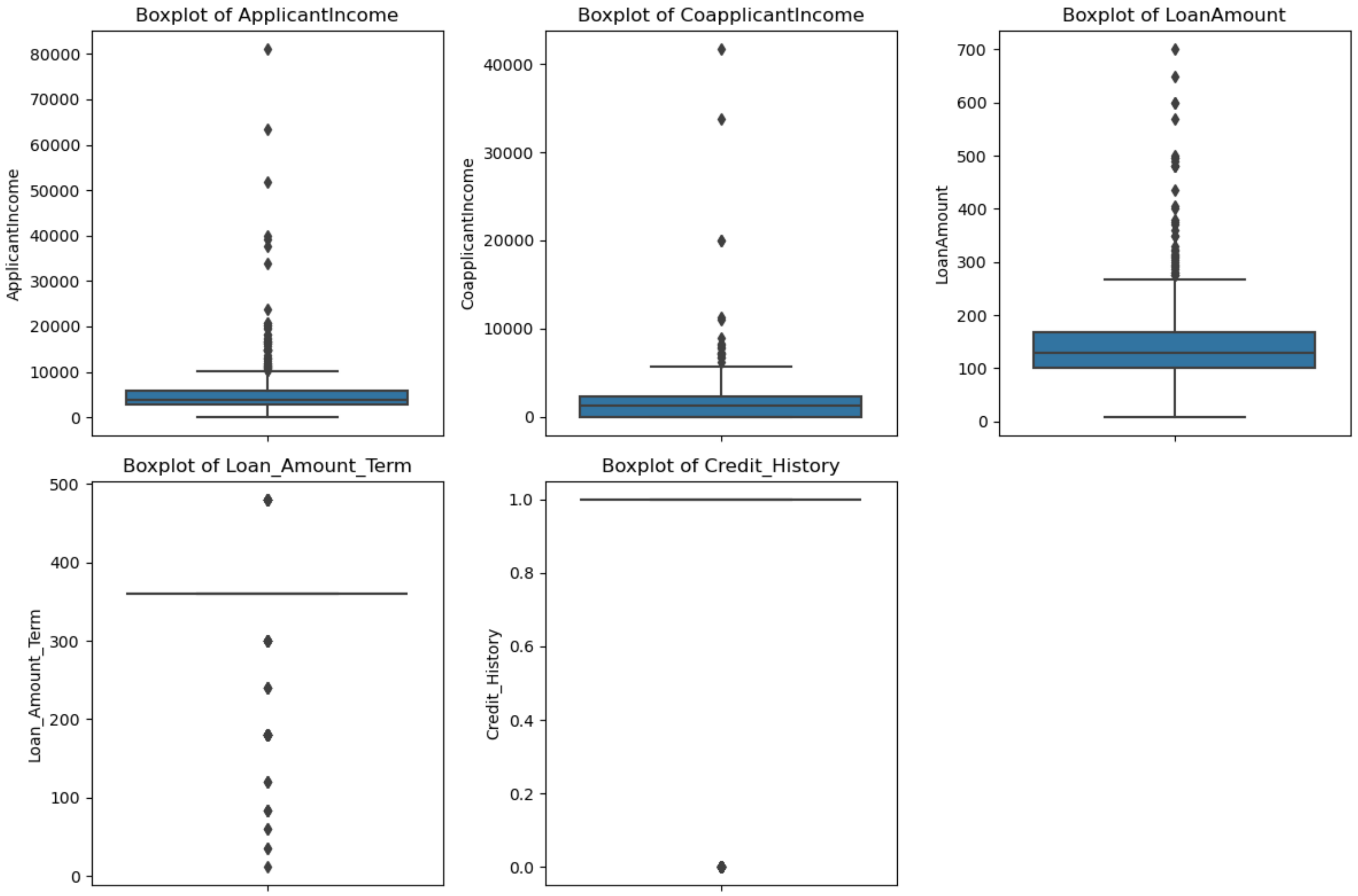
```
# Correlation Heatmap for numerical variables
plt.figure(figsize=(8, 6))
sns.heatmap(tr_df.corr(numeric_only=True), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```





In [12]:

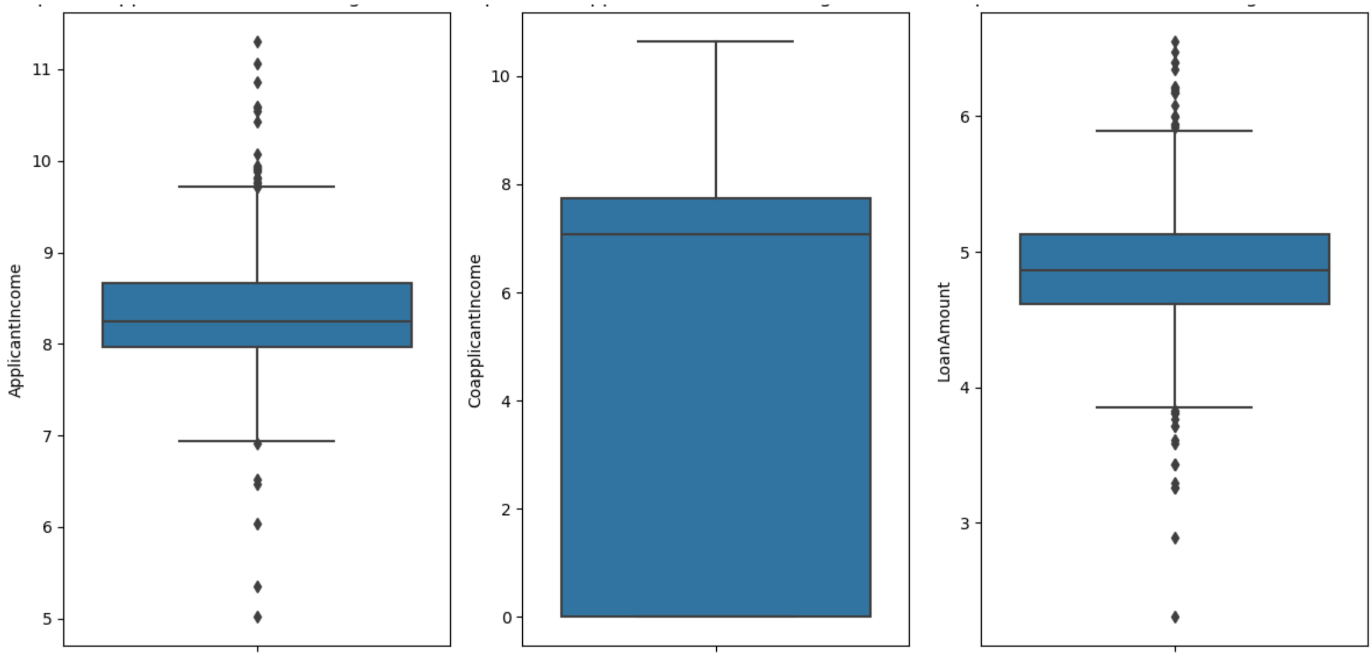
```
# Plot boxplots for all numerical columns
plt.figure(figsize=(12, 8))
for i, col in enumerate(tr_df_numerical, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(y=tr_df[col])
    plt.title(f'Boxplot of {col}')
plt.tight_layout()
plt.show()
```



In [13]:

```
#Reduce skweness for the numerical columns using Log Transformation
for col in ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount']:
    tr_df[col] = np.log1p(tr_df[col])  # log1p handles zero values

# Verify the changes using a boxplot
plt.figure(figsize=(12, 6))
for i, col in enumerate(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount'], 1):
    plt.subplot(1, 3, i)
    sns.boxplot(y=tr_df[col])
    plt.title(f'Boxplot of {col} after Log Transformation')
plt.tight_layout()
plt.show()
```

Boxplot of ApplicantIncome after Log TransforBoxplot of CoapplicantIncome after Log TransformaBoxplot of LoanAmount after Log Transformation



In [14]:

```
tr_df.isnull().sum()
```

Out[14]:

```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [15]:

```
# Handle categorical missing values with mode
for col in ['Gender', 'Married', 'Dependents', 'Self_Employed']:
    tr_df[col].fillna(tr_df[col].mode()[0], inplace=True)

# Handle numerical missing values
tr_df['LoanAmount'].fillna(tr_df['LoanAmount'].median(), inplace=True)
tr_df['Loan_Amount_Term'].fillna(tr_df['Loan_Amount_Term'].median(), inplace=True)
tr_df['Credit_History'].fillna(tr_df['Credit_History'].mode()[0], inplace=True)

# Verify no missing values remain
print(tr_df.isnull().sum())
```

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

3.1 Machine learning models

We will divide our dataset into two variables X as the features we defined earlier and y as the Loan_Status the target value we want to predict. Models we will use:

1. **Logistic Regression**
2. **Decision Tree**
3. **Random Forest**

The Process of Modeling the Data:

1. **Importing the model**
2. **Fitting the model**
3. **Predicting Loan Status**
4. **Classification report by Loan Status**
5. **Overall accuracy**

Logistic Regression

In [16]:

```
# Splitting the target variable and features
y = tr_df['Loan_Status']
X = tr_df.drop('Loan_Status', axis=1)

# 1. Handle Missing Values
num_cols = X.select_dtypes(include=['int64', 'float64']).columns
cat_cols = X.select_dtypes(include=['object']).columns.drop('Loan_ID')

num_imputer = SimpleImputer(strategy='median')
cat_imputer = SimpleImputer(strategy='most_frequent')

X[num_cols] = num_imputer.fit_transform(X[num_cols])
X[cat_cols] = cat_imputer.fit_transform(X[cat_cols])
```

In [17]:

```
# Encode Categorical Variables
label_encoder = LabelEncoder()

for col in ['Gender', 'Married', 'Education', 'Self_Employed', 'Credit_History']:
    X[col] = label_encoder.fit_transform(X[col])

X = pd.get_dummies(X, columns=['Dependents', 'Property_Area'], drop_first=True)

# Drop Loan_ID
X = X.drop('Loan_ID', axis=1)

# Encode Target Variable BEFORE train-test split
y = label_encoder.fit_transform(y)
```

In [18]:

```
# Split Data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

In [19]:

```
# Train Logistic Regression Model
LR = LogisticRegression(max_iter=200)
LR.fit(X_train, y_train)
```

Out[19]:

▾ LogisticRegression i ?

```
LogisticRegression(max_iter=200)
```

In [20]:

```python
# 5. Predictions and Evaluation
y_predict = LR.predict(X_test)

print("Accuracy Score:", accuracy_score(y_test, y_predict))
print("\nClassification Report:\n", classification_report(y_test, y_predict))
```

```
Accuracy Score: 0.8216216216216217

Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.41      0.56        51
           1       0.81      0.98      0.89       134

    accuracy                           0.82       185
   macro avg       0.84      0.69      0.72       185
weighted avg       0.83      0.82      0.80       185
```

The model performs exceptionally well for predicting "Loan Approved" (Class 1), with 98% recall and 89% F1-score.

The performance on "Loan Denied" (Class 0) is lower, particularly in recall (41%).

This suggests the model struggles to correctly identify loan denials.

The overall accuracy of 82% indicates strong predictive performance.

Decision Tree

In [21]:

```python
# Initialize the Decision Tree Classifier
dt_model = DecisionTreeClassifier(criterion='gini', max_depth=4, random_state=0)
```

In [22]:

```python
# Train the model
dt_model.fit(X_train, y_train)
```

Out[22]:

```
▼            DecisionTreeClassifier          i ?

DecisionTreeClassifier(max_depth=4, random_state=0)
```

In [23]:

```python
# Make predictions
y_pred_dt = dt_model.predict(X_test)
```

In [24]:

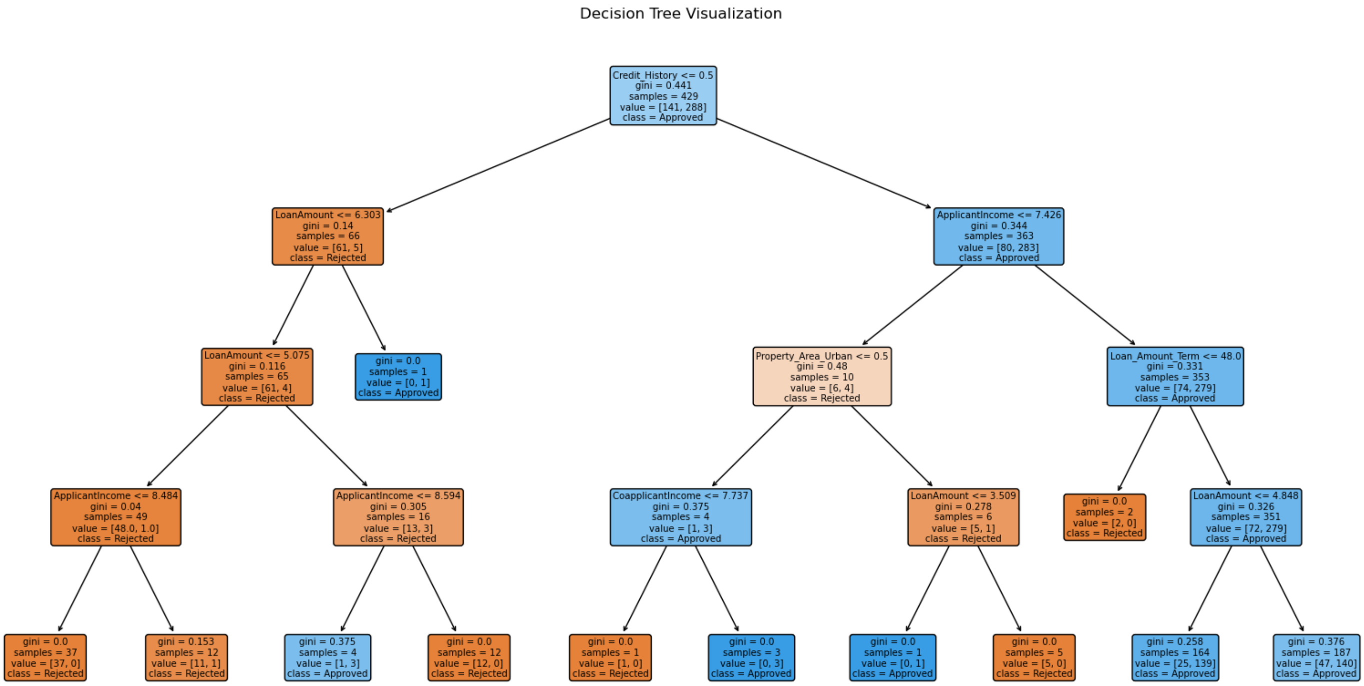
```python
# Evaluate the model
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Decision Tree Accuracy:", accuracy_dt)
print("\nClassification Report:\n", classification_report(y_test, y_pred_dt))
```

```
Decision Tree Accuracy: 0.7837837837837838

Classification Report:
               precision    recall  f1-score   support

           0       0.79      0.29      0.43        51
           1       0.78      0.97      0.87       134
```

```
    accuracy                           0.78       185
   macro avg       0.79      0.63      0.65       185
weighted avg       0.78      0.78      0.75       185
```

In [25]:

```
# Visualize the Decision Tree
plt.figure(figsize=(20, 10))
plot_tree(dt_model,
          feature_names=X_train.columns,
          class_names=['Rejected', 'Approved'],
          filled=True,
          rounded=True)
plt.title("Decision Tree Visualization")
plt.show()
```



Class 0 (Rejected Loans): Precision (0.79): 79% of the predicted rejections are correct. Recall (0.29): Only 29% of actual rejections are correctly identified. F1-Score (0.43): Indicates a low balance between precision and recall for this class.

Class 1 (Approved Loans): Precision (0.78): 78% of the predicted approvals are correct. Recall (0.97): The model captures 97% of actual approvals, which is excellent. F1-Score (0.87): A strong overall performance for this class

Random Forest

In [26]:

```
# Initialize the Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, max_depth=6, random_state=0, class_w
eight='balanced')
```

In [27]:

```
# Train the model
rf_model.fit(X_train, y_train)
```

Out[27]:

▼ RandomForestClassifier i ?

```
RandomForestClassifier(class_weight='balanced', max_depth=6, random_state=0)
```

In [28]:

```
# Make predictions
y_pred_rf = rf_model.predict(X_test)
```

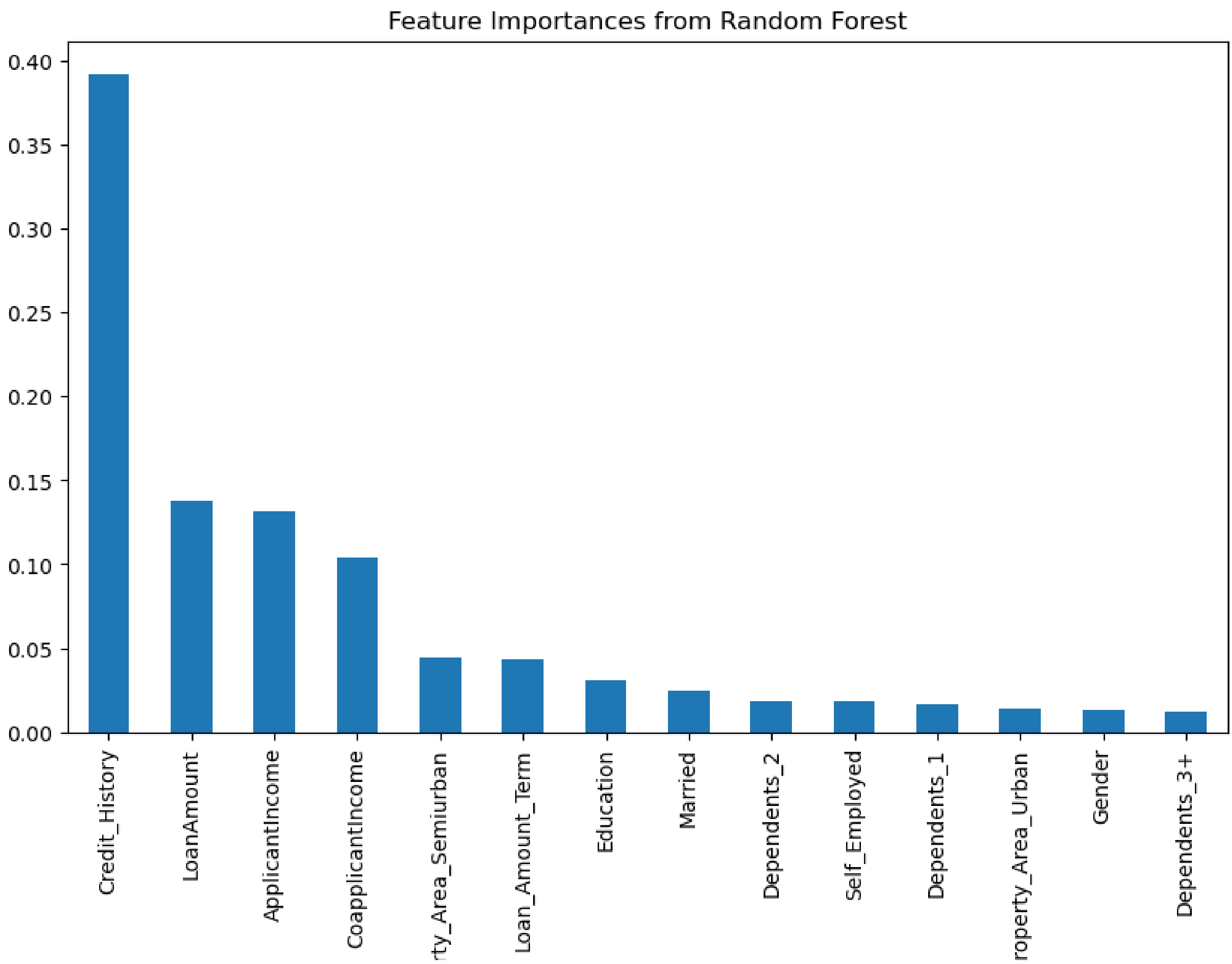
In [29]:

```
# Evaluate the model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print("Random Forest Accuracy:", accuracy_rf)
print("\nClassification Report:\n", classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.827027027027027

Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.47      0.60        51
           1       0.83      0.96      0.89       134

    accuracy                           0.83       185
   macro avg       0.83      0.72      0.74       185
weighted avg       0.83      0.83      0.81       185
```

In [30]:

```
# Feature Importance
feature_importances = pd.Series(rf_model.feature_importances_, index=X_train.columns)
feature_importances = feature_importances.sort_values(ascending=False)

plt.figure(figsize=(10, 6))
feature_importances.plot(kind='bar')
plt.title("Feature Importances from Random Forest")
plt.show()
```



Class 0 (Rejected Loans): Precision (0.83): 83% of the predicted loan rejections are correct. Recall (0.47): Only 47% of actual rejections are correctly identified. F1-Score (0.60): Reflects moderate performance, showing room for improvement in recall.

Class 1 (Approved Loans): Precision (0.83): 83% of predicted approvals are correct. Recall (0.96): The model captures 96% of actual approvals, which is excellent.

F1-Score (0.89): Demonstrates a very strong balance of precision and recall for this class.

Insights

Class 1 (Approved Loans):

The model performs exceptionally well, with high recall and F1-score. This shows the model can confidently approve loans when the status is "Approved".

Class 0 (Rejected Loans): The model struggles to identify rejected loans (low recall at 47%). While precision is good, the low recall means many actual rejections are misclassified as approvals. Improvements Over Decision Tree:

Accuracy improved from 78.3% to 82.7%. Precision, recall, and F1-score for both classes improved slightly.

Conclusion

In [31]:

```
score = [accuracy_score(y_test, y_predict),accuracy_dt,accuracy_rf]
Models = pd.DataFrame({
    'Model': ["Logistic Regression","Decision Tree","Random Forest",],
    'Score': score})
Models.sort_values(by='Score', ascending=False)
```

Out[31]:

	Model	Score
2	Random Forest	0.827027
0	Logistic Regression	0.821622
1	Decision Tree	0.783784

The best model to use is the Random Forest

Applying to the test data

In [32]:

```
# Example: Evaluate the final model on the test data
y_test_pred = rf_model.predict(X_test)

print("Final Model Performance on Test Data:")
print("Accuracy:", accuracy_score(y_test, y_test_pred))
print("\nClassification Report:\n", classification_report(y_test, y_test_pred))
```

```
Final Model Performance on Test Data:
Accuracy: 0.827027027027027

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.47      0.60        51
```

```
           0       0.83      0.47      0.60        51
           1       0.83      0.96      0.89       134

    accuracy                           0.83       185
   macro avg       0.83      0.72      0.74       185
weighted avg       0.83      0.83      0.81       185
```

This indicates the model correctly predicts the loan status (approved/rejected) for 82.70% of the test data.

Class 0 (Rejected Loans):

Precision (0.83): When the model predicts a loan as "Rejected," it is correct 83% of the time.

Recall (0.47): The model correctly identifies only 47% of actual rejected loans.

F1-Score (0.60): This is the balance between precision and recall for Class 0. The low recall indicates that many rejected loans are misclassified as approved.

Class 1 (Approved Loans):

Precision (0.83): When the model predicts a loan as "Approved," it is correct 83% of the time.

Recall (0.96): The model correctly identifies 96% of all actual approved loans.

F1-Score (0.89): Strong performance, as precision and recall are both high.

High Recall for Approved Loans (Class 1): The model is very good at capturing most of the approved loans, achieving a 96% recall.

Low Recall for Rejected Loans (Class 0): The model struggles to identify rejected loans, missing 53% of actual rejections.

Class Imbalance: The dataset has 51 rejected loans (minority) and 134 approved loans (majority). This class imbalance causes the model to favor predicting "Approved."

Overall Conclusion

The Random Forest Model can be used when automating the loan apporval process. We will however need to address the class imbalance and explore new features or interactions between existing features to help the model identify rejected loans better.