Loan Approval Prediction using Machine Learning

Developed by: Nimisha Davis

Linkedin : https://www.linkedin.com/in/nimishadavis/

Introduction:

Loans are a crucial financial service, enabling individuals to manage education, living expenses, and acquire assets like houses and cars. However, banks must carefully evaluate loan applications based on several factors to mitigate risk and maximize profitability. This project utilizes machine learning to predict the likelihood of loan approval based on applicant profiles, easing decision-making processes for financial institutions.

Objective:

The primary goal of this project is to predict whether a loan application will be approved or rejected. Key features considered include marital status, education, income, credit history, and other demographic and financial details.

Dataset Description:

The dataset used for predicting loan approval contains 13 features that provide critical information about the applicant's profile and financial status. Here's a detailed description of each feature:

1.Loan: A unique identifier for each loan application.

2.Gender: The gender of the applicant (Male/Female).

3.Married: The marital status of the applicant (Yes/No).

4.Dependents: Indicates whether the applicant has any dependents (Yes/No).

5.Education: Whether the applicant is a graduate or not (Graduate/Not Graduate).

6.Self_Employed: Whether the applicant is self-employed (Yes/No).

7.ApplicantIncome: The income of the applicant.

8.CoapplicantIncome: The income of the co-applicant (if applicable).

9.LoanAmount: The amount of the loan applied for (in thousands).

10.Loan_Amount_Term: The duration of the loan (in months).

11.Credit_History: The applicant's credit history, indicating the individual's ability to repay their debts (1 for a positive credit history, 0 for a negative one).

12.Property_Area: The location of the property for which the loan is requested (Rural/Semi-Urban/Urban).

13.Loan_Status: The target variable, which indicates whether the loan was approved (Y for Yes, N for No).

Using this dataset, machine learning models can be trained to predict whether a loan application is likely to be approved or not based on these features, enabling banks to make more efficient and accurate decisions.

Importing Libraries and Dataset

In [5]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [6]:
```
data = pd.read_csv("data/LoanApprovalPrediction.csv")
data.head()
```

Out[6]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
0	LP001002	Male	No	0.0	Graduate	No	5849	0.0	NaN	360.0
1	LP001003	Male	Yes	1.0	Graduate	No	4583	1508.0	128.0	360.0
2	LP001005	Male	Yes	0.0	Graduate	Yes	3000	0.0	66.0	360.0
3	LP001006	Male	Yes	0.0	Not Graduate	No	2583	2358.0	120.0	360.0
4	LP001008	Male	No	0.0	Graduate	No	6000	0.0	141.0	360.0

Data Preprocessing and visualization

In [8]:
```
data.dtypes
```

Out[8]:
```
Loan_ID               object
Gender                object
Married               object
Dependents           float64
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

In [9]:
```python
data.describe()
```

Out[9]:

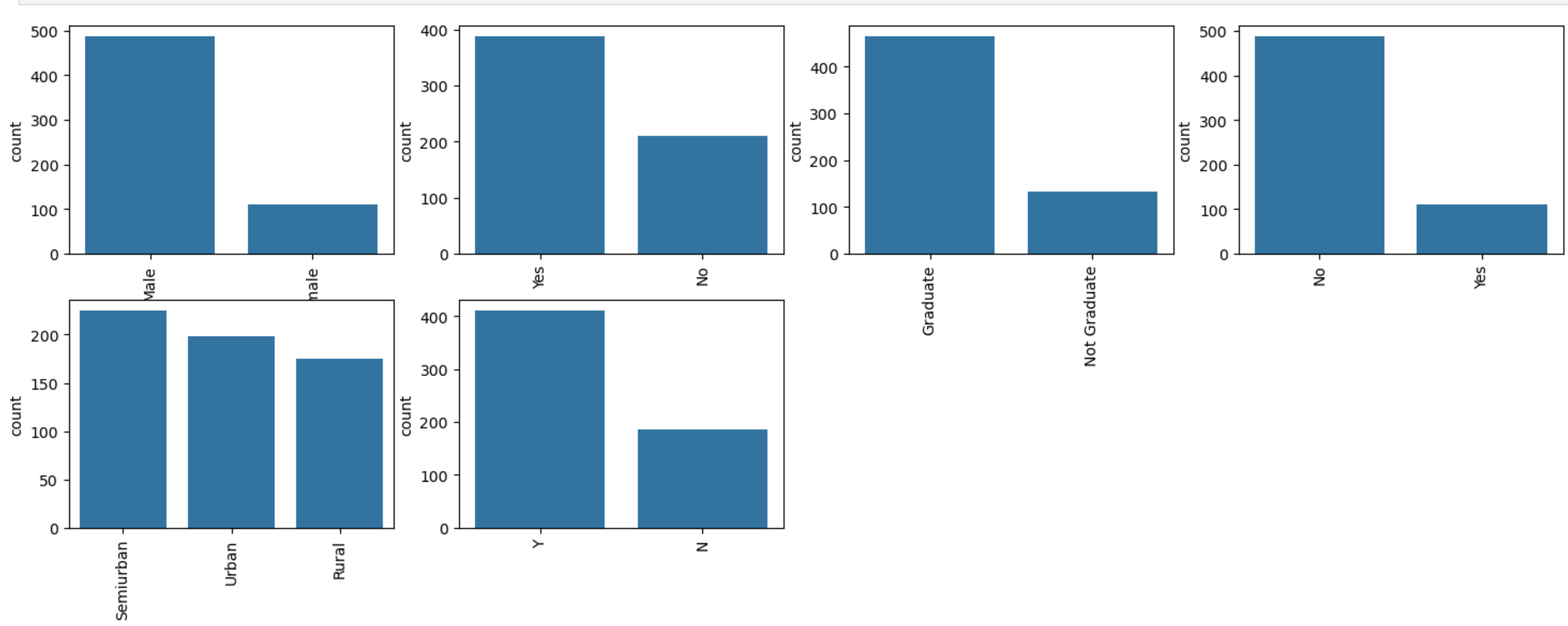
	Dependents	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	586.000000	598.000000	598.000000	577.000000	584.000000	549.000000
mean	0.755973	5292.252508	1631.499866	144.968804	341.917808	0.843352
std	1.007751	5807.265364	2953.315785	82.704182	65.205994	0.363800
min	0.000000	150.000000	0.000000	9.000000	12.000000	0.000000
25%	0.000000	2877.500000	0.000000	100.000000	360.000000	1.000000
50%	0.000000	3806.000000	1211.500000	127.000000	360.000000	1.000000
75%	1.750000	5746.000000	2324.000000	167.000000	360.000000	1.000000
max	3.000000	81000.000000	41667.000000	650.000000	480.000000	1.000000

In [10]:
```python
obj = (data.dtypes == 'object')
print("Categorical variables:",len(list(obj[obj].index)))
```

```
Categorical variables: 7
```

In [11]:
```python
# Dropping Loan_ID column
data.drop(['Loan_ID'],axis=1,inplace=True)
```

In [12]:
```python
obj = (data.dtypes == 'object')
object_cols = list(obj[obj].index)
plt.figure(figsize=(18,36))
index = 1

for col in object_cols:
  y = data[col].value_counts()
  plt.subplot(11,4,index)
  plt.xticks(rotation=90)
  sns.barplot(x=list(y.index), y=y)
  index +=1
```



In [13]:
```python
# Label encoding
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
obj = (data.dtypes == 'object')
for col in list(obj[obj].index):
    data[col] = label_encoder.fit_transform(data[col])
```

In [14]:
```python
# To find the number of columns with
# datatype==object
obj = (data.dtypes == 'object')
print("Categorical variables:",len(list(obj[obj].index)))
```

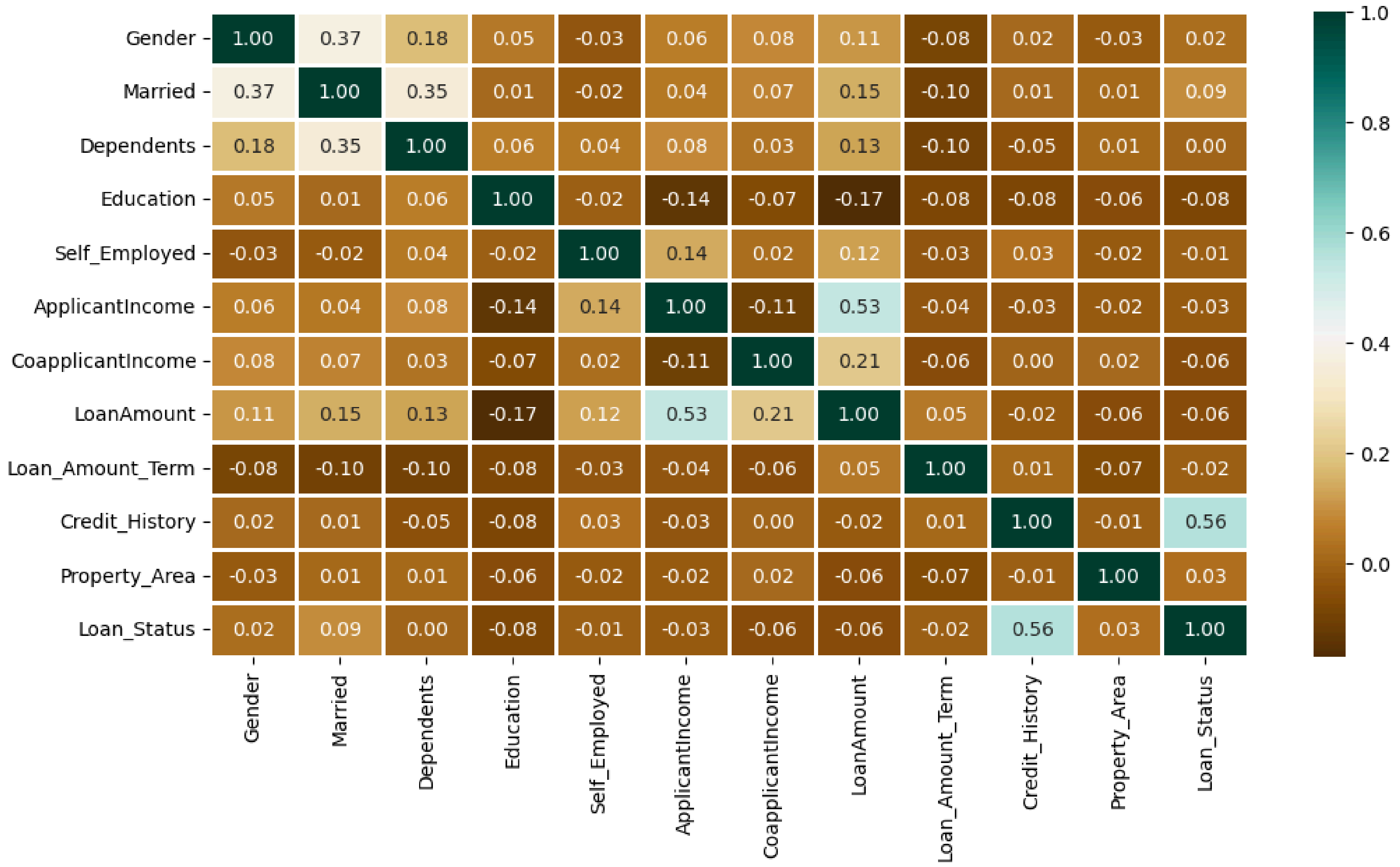
```
Categorical variables: 0
```

In [15]:
```python
data.duplicated().sum()
```

Out[15]: 0

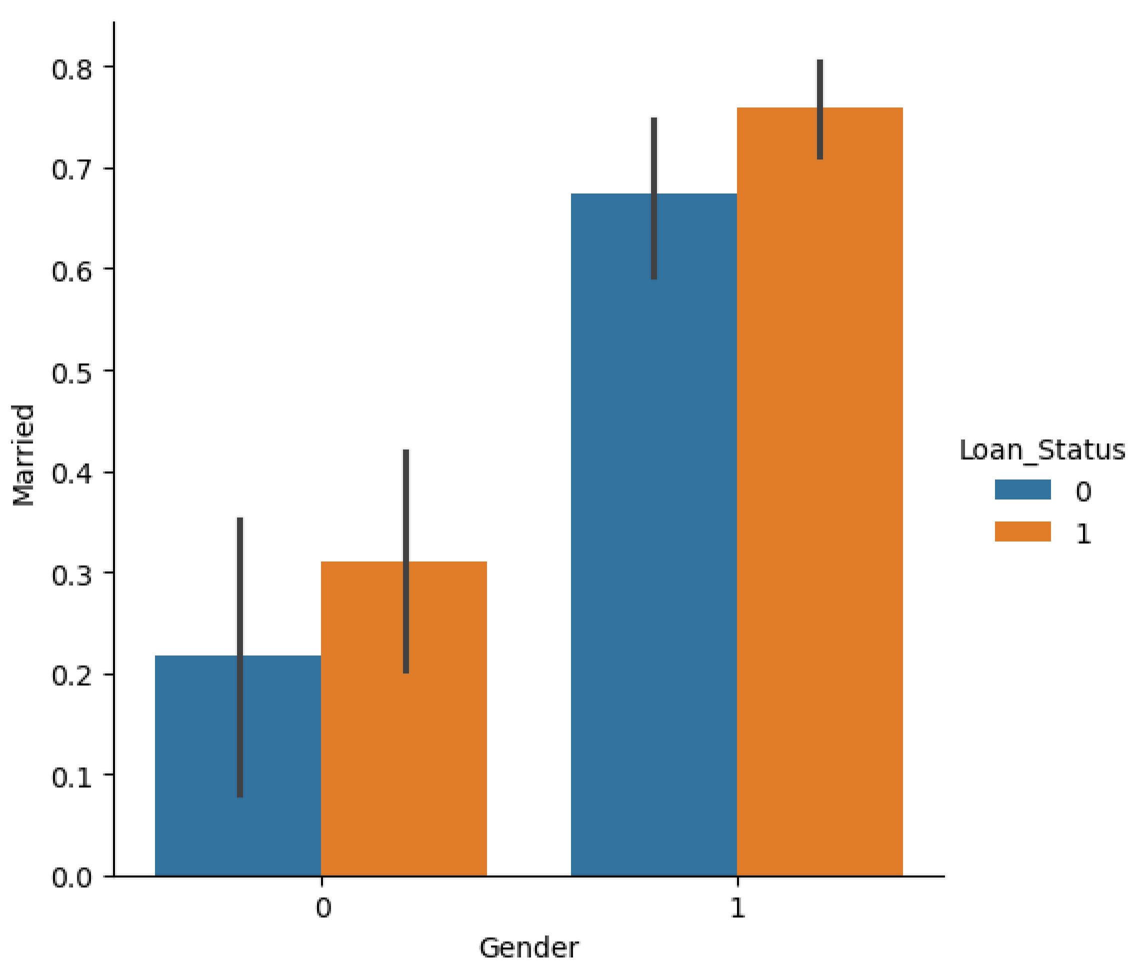
In [16]:
```python
# correlation between Loan Amount and ApplicantIncome.
# It also shows that Credit_History has a high impact on Loan_Status
plt.figure(figsize=(12,6))
sns.heatmap(data.corr(),cmap='BrBG',fmt='.2f',linewidths=2,annot=True)
```

Out[16]: <Axes: >



In [17]:
```python
sns.catplot(x="Gender", y="Married",
                       hue="Loan_Status",
                       kind="bar",
                       data=data)
```

Out[17]: <seaborn.axisgrid.FacetGrid at 0x148f5381f40>



In [18]:
```python
data.isna().sum()
```

Out[18]:
```
Gender                0
Married               0
Dependents           12
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           21
Loan_Amount_Term     14
Credit_History       49
Property_Area         0
Loan_Status           0
dtype: int64
```

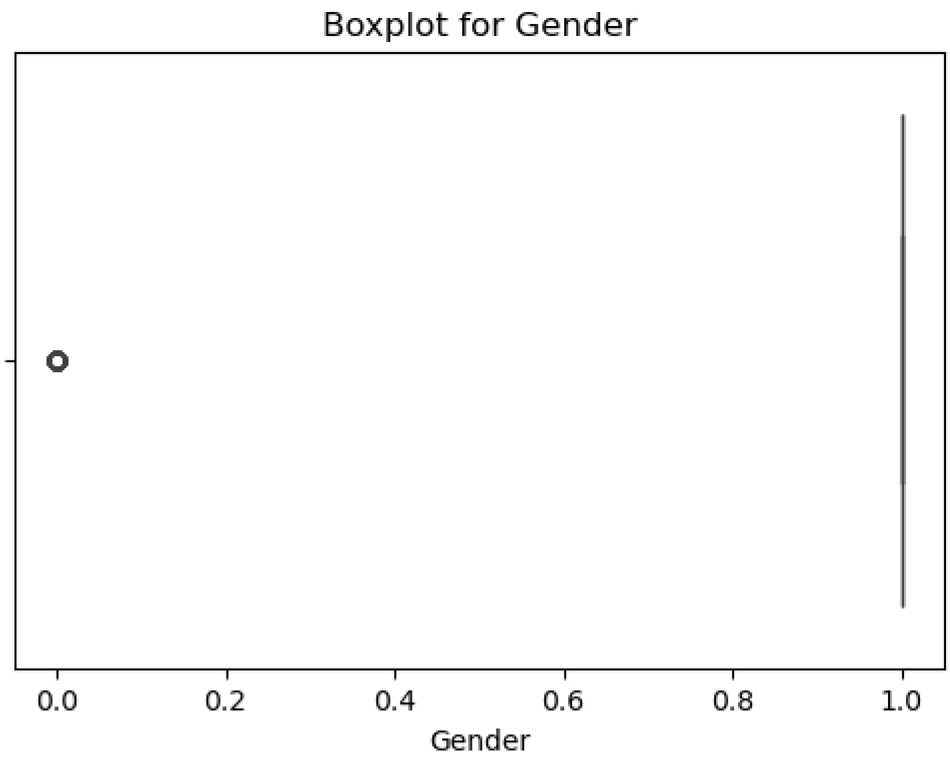
In [19]:
```python
# missing values handling
for col in data.columns:
    data[col] = data[col].fillna(data[col].mean())
```

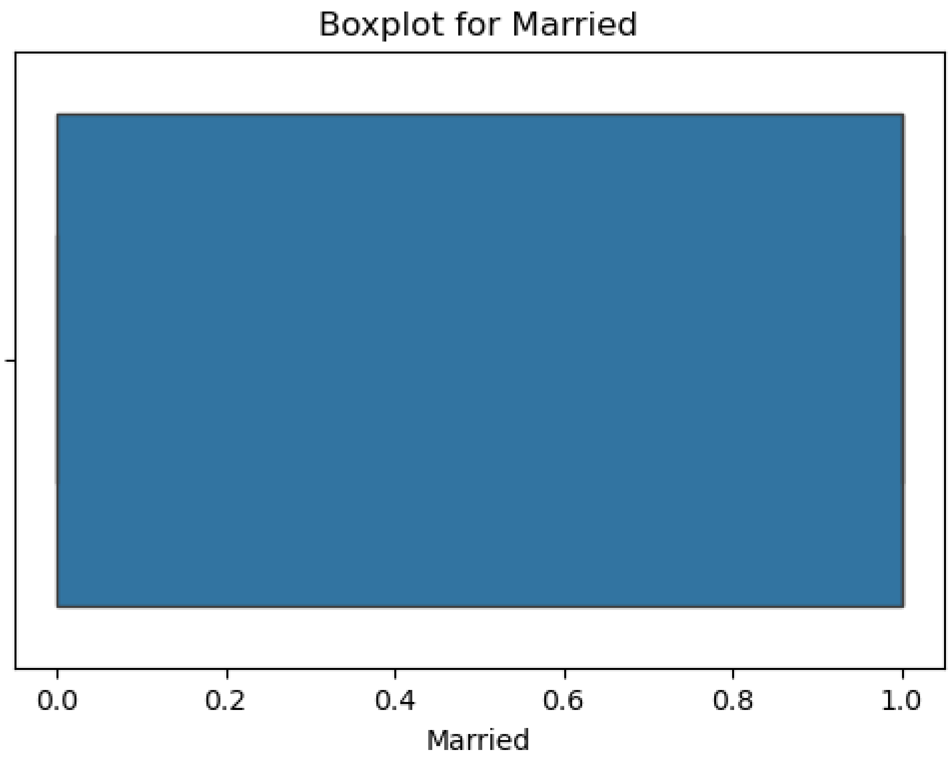
In [20]:
```python
data.isna().sum()
```

Out[20]:
```
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
```

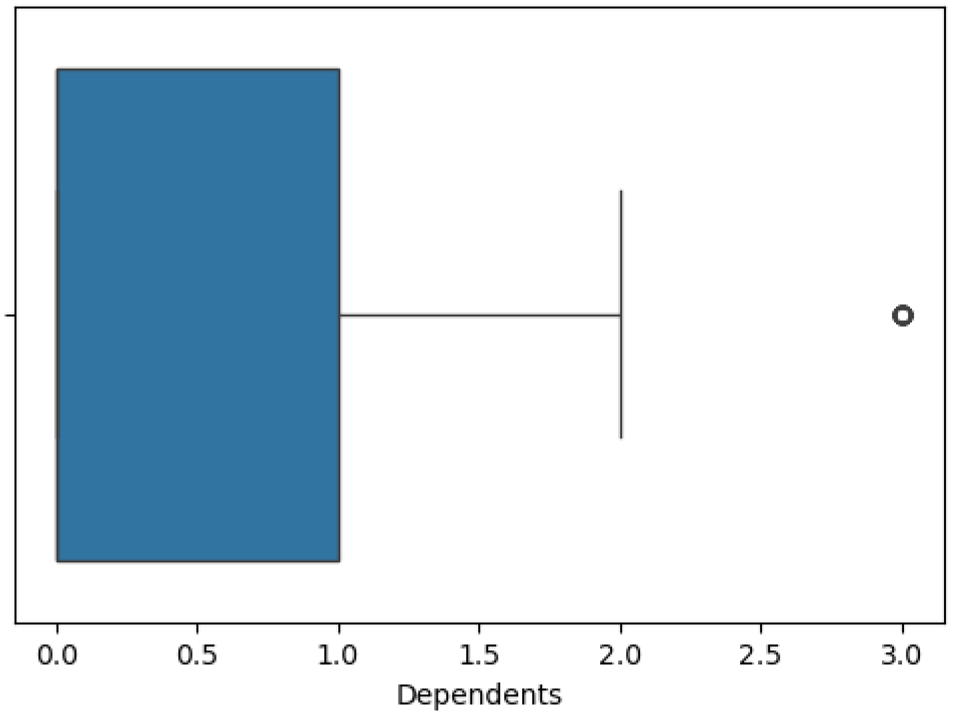
Outlier detection and handling

In [22]:
```python
data.columns = data.columns.str.strip()
numeric_columns = data.select_dtypes(include=[np.number]).columns
for col in numeric_columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=data[col])
    plt.title(f"Boxplot for {col}")
    plt.show()
```

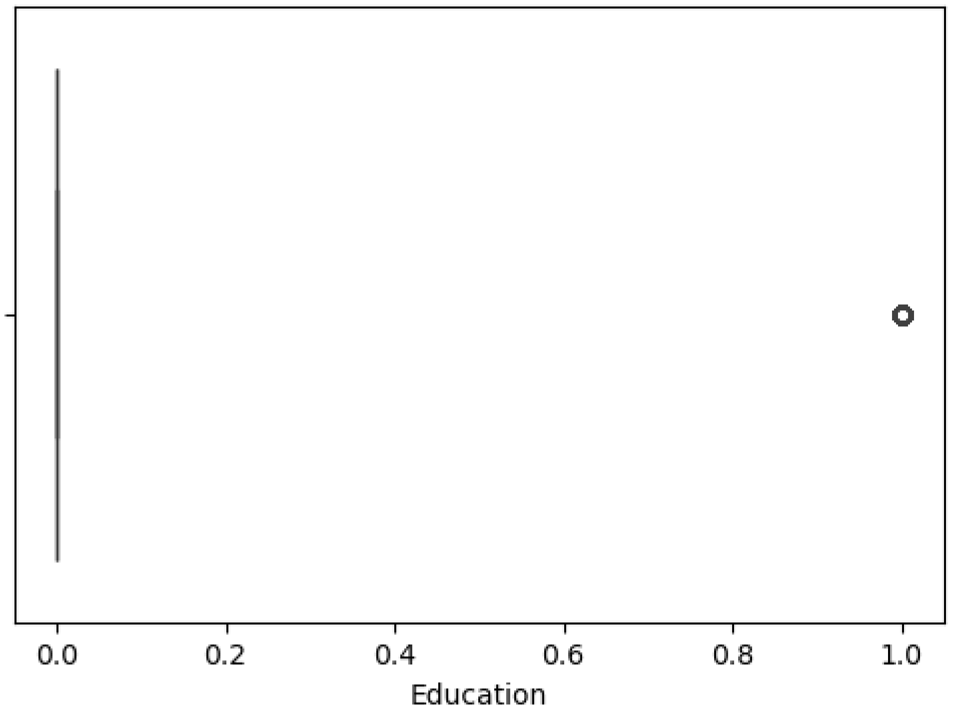




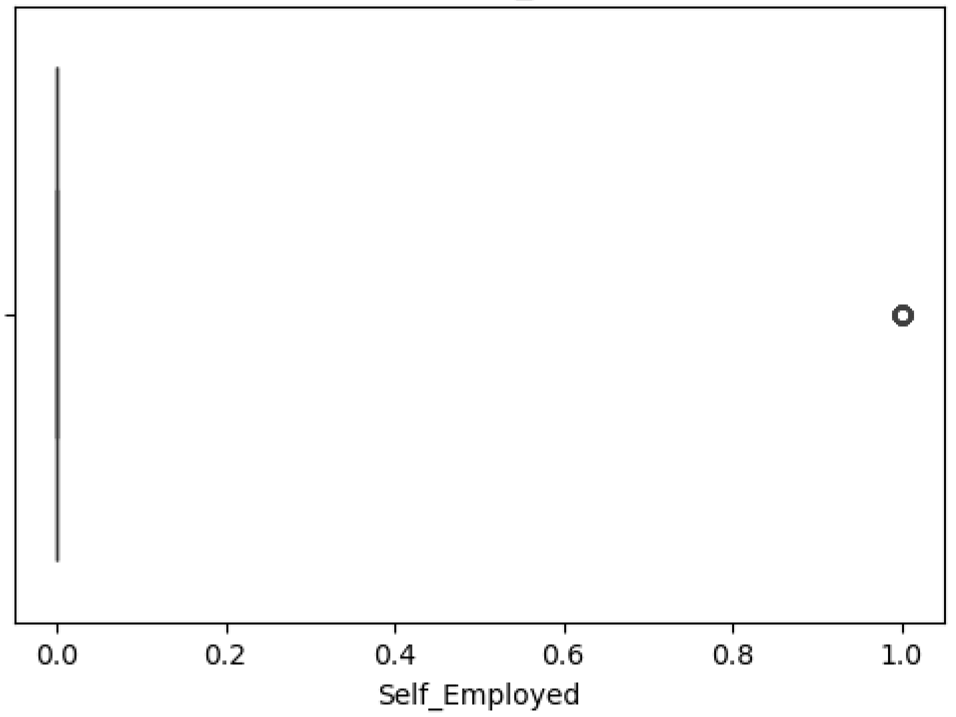
Boxplot for Dependents



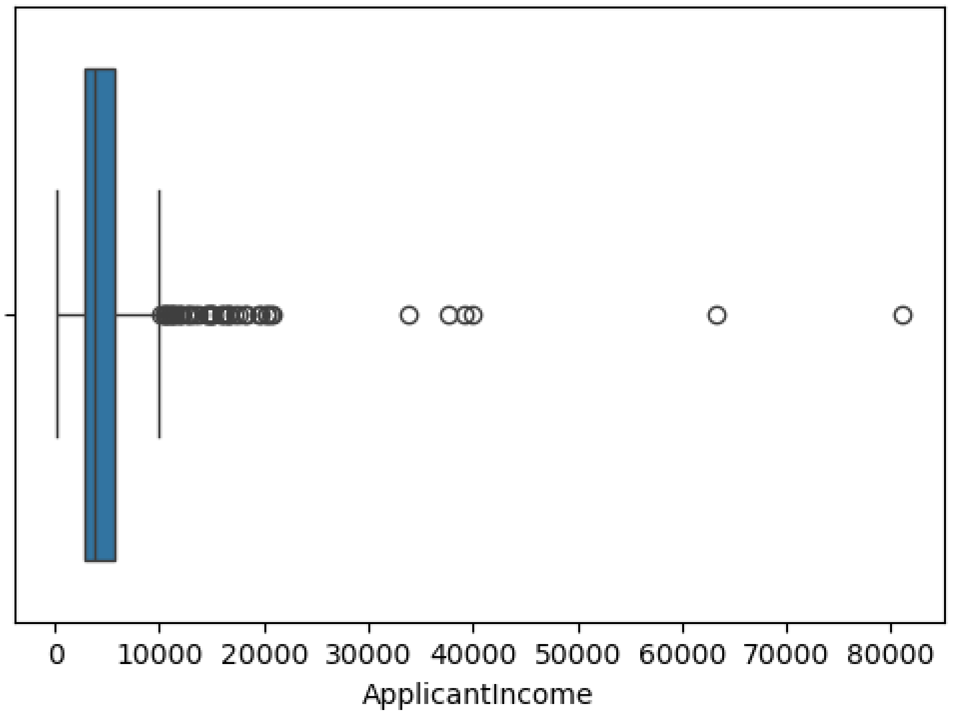
Boxplot for Education



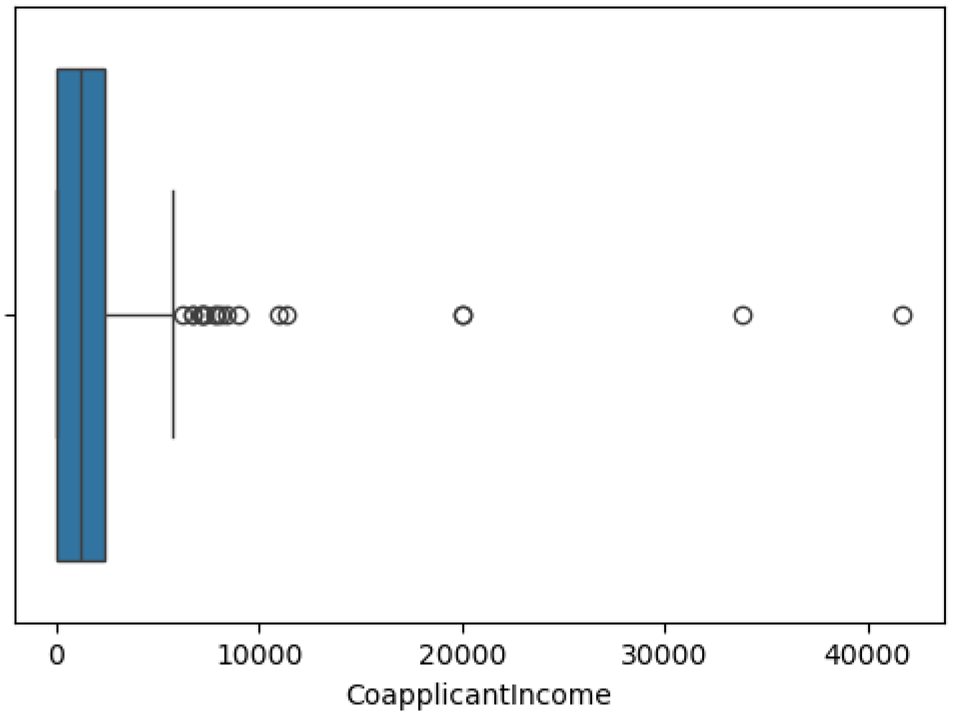
Boxplot for Self_Employed



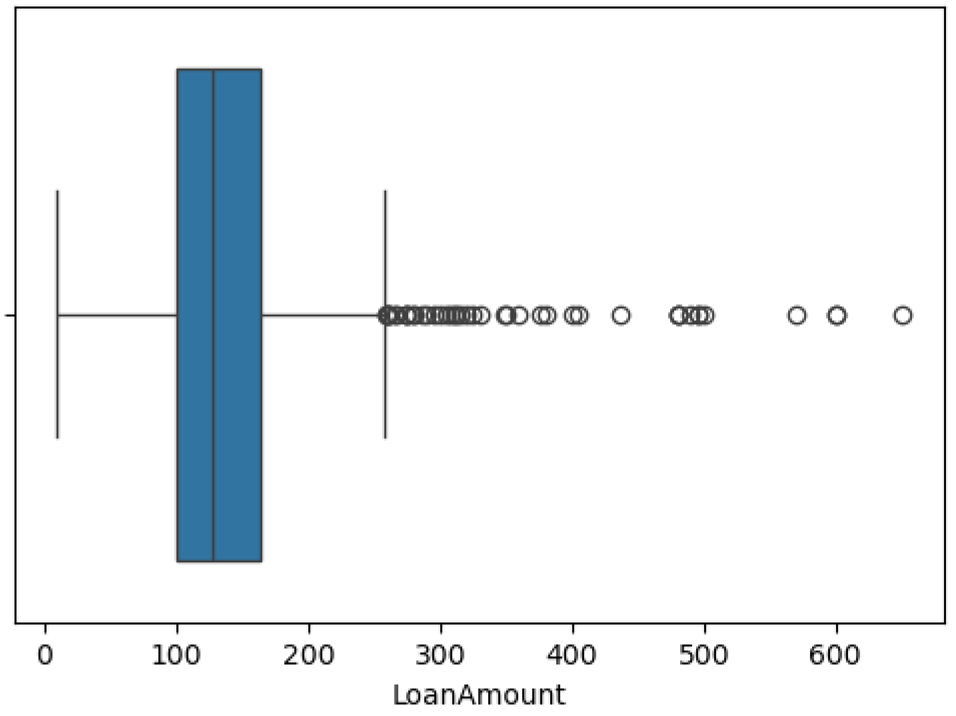
Boxplot for ApplicantIncome



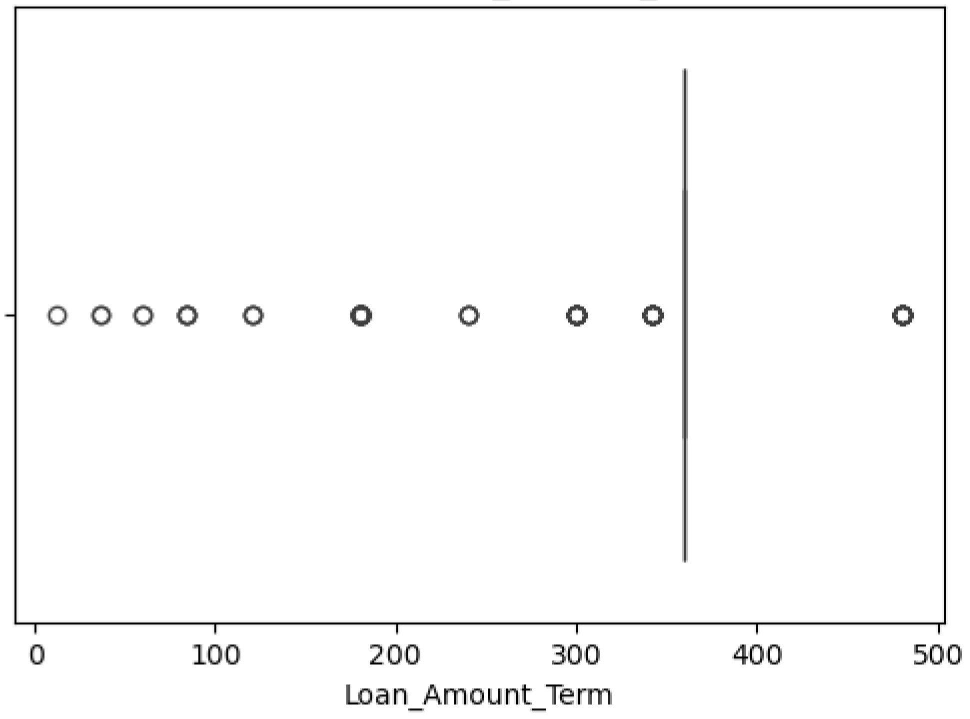
Boxplot for CoapplicantIncome



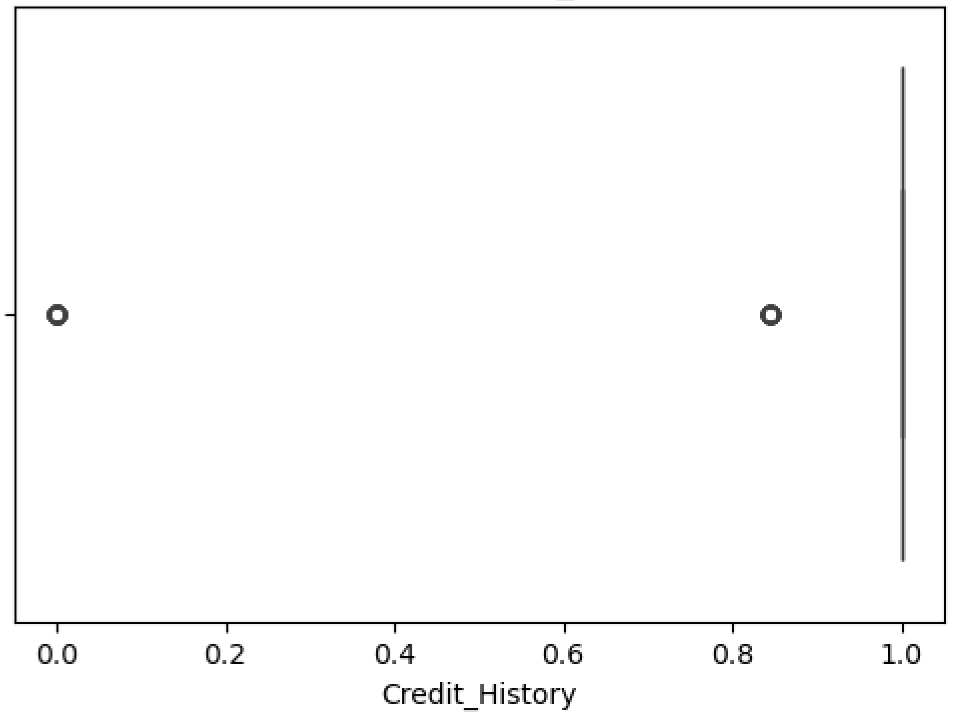
Boxplot for LoanAmount

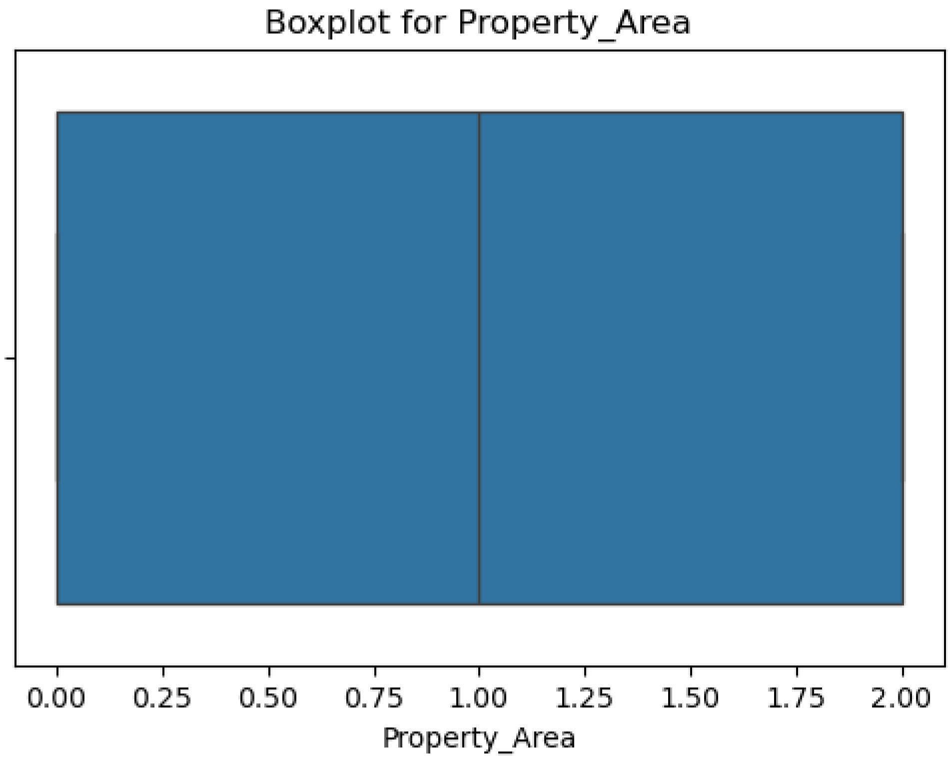


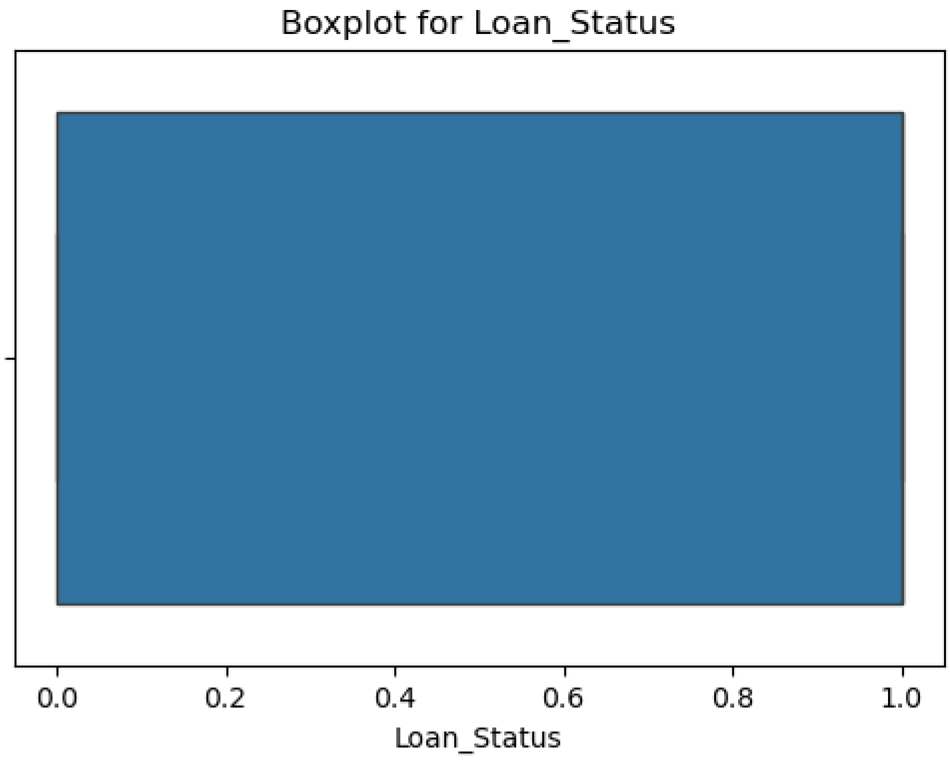
Boxplot for Loan_Amount_Term



Boxplot for Credit_History



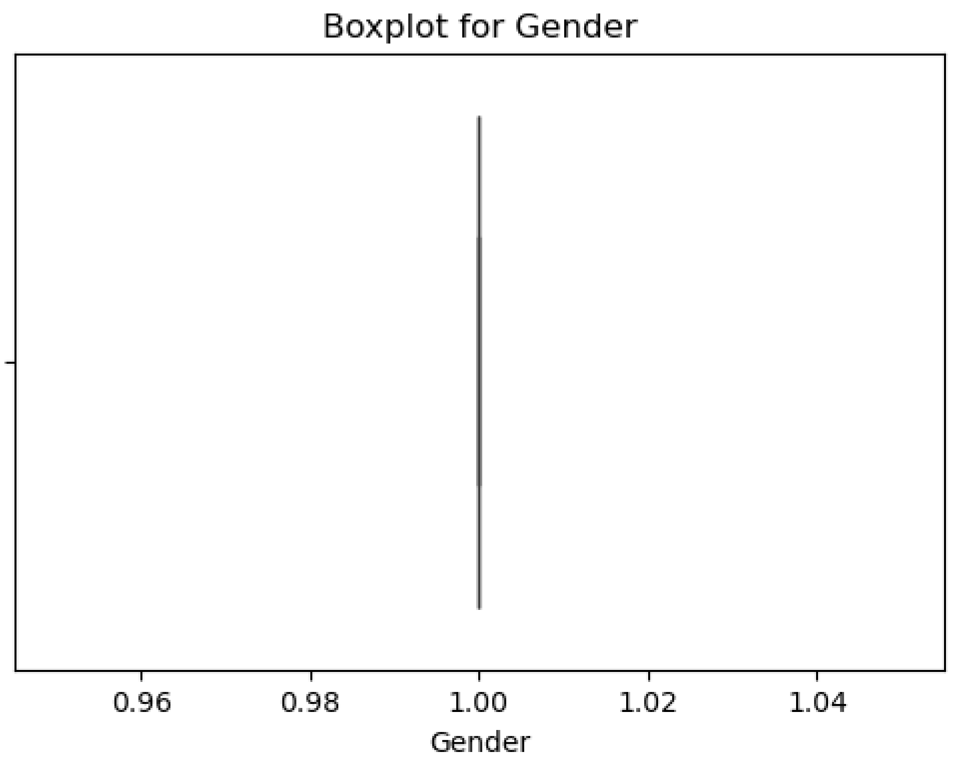


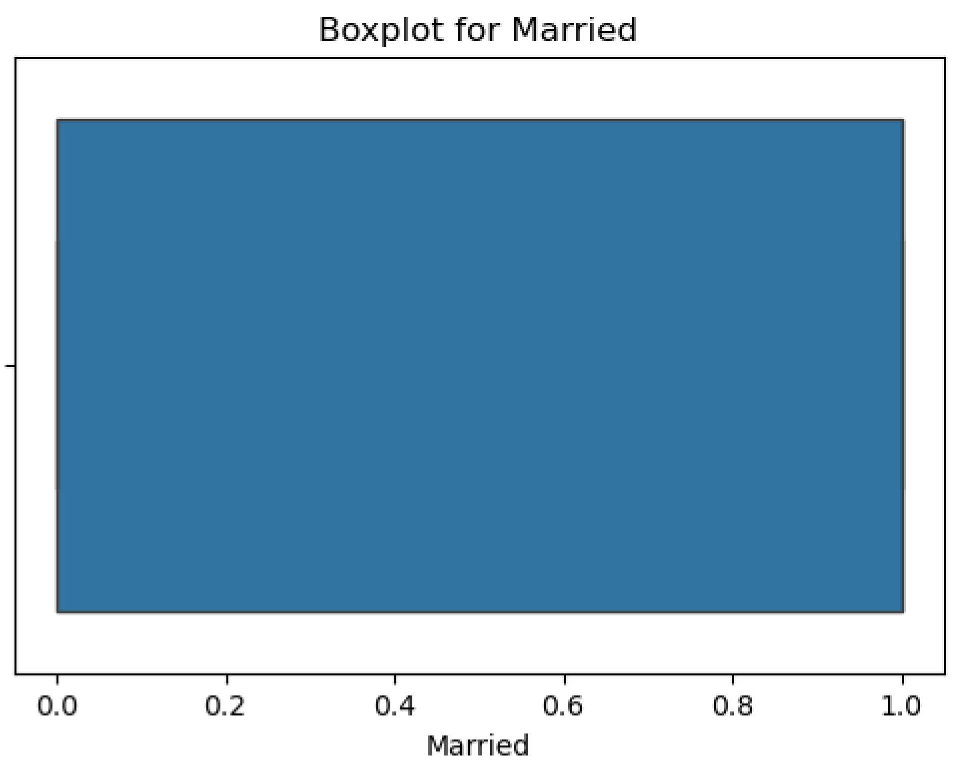


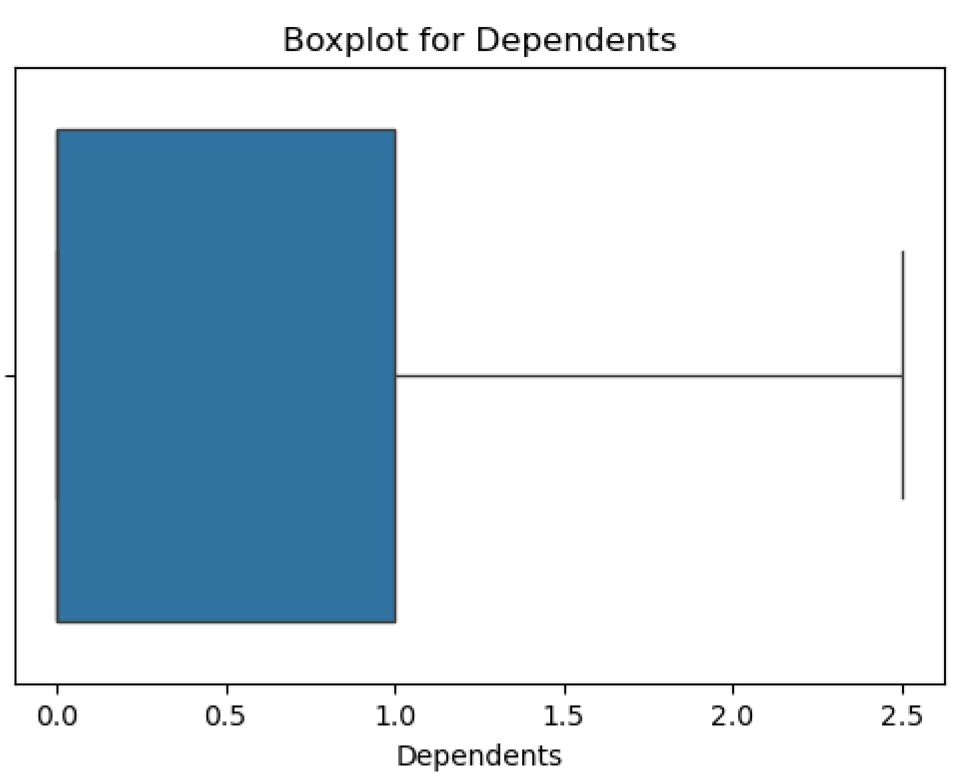
In [23]:
```
def handle_outliers_clip(df):
    for col in df.select_dtypes(include=[np.number]).columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df[col] = df[col].clip(lower=lower_bound, upper=upper_bound)
    return df

data_no_outliers_clip = handle_outliers_clip(data)
print(data_no_outliers_clip.head())
```

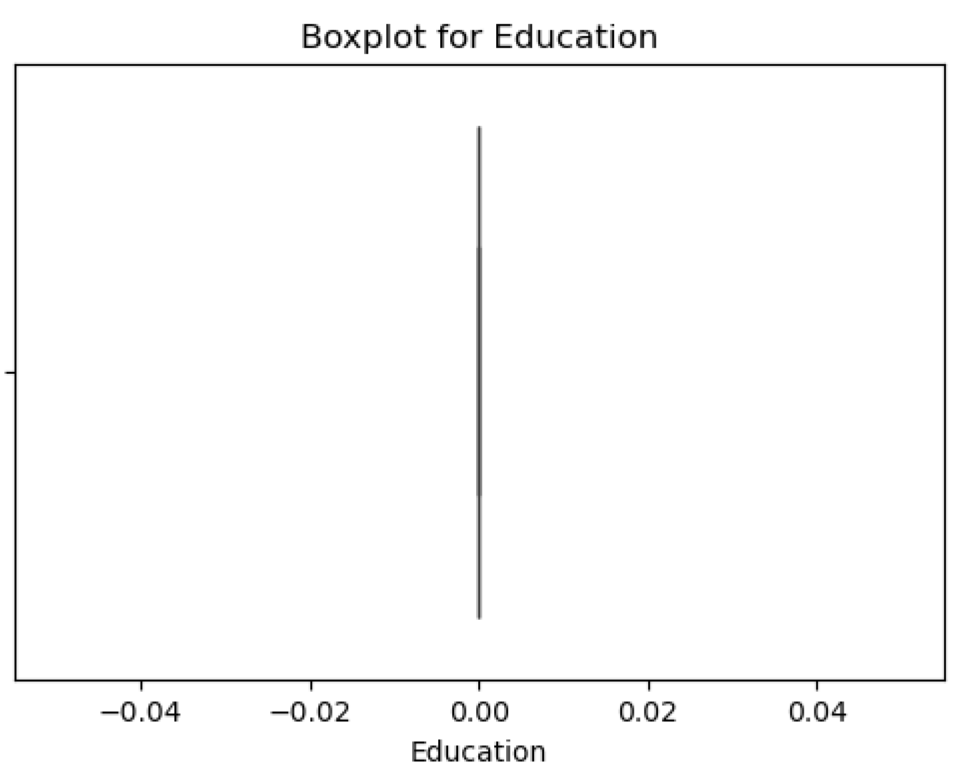
```
   Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
0       1        0         0.0          0              0           5849.0   
1       1        1         1.0          0              0           4583.0   
2       1        1         0.0          0              0           3000.0   
3       1        1         0.0          0              0           2583.0   
4       1        0         0.0          0              0           6000.0   

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  144.968804             360.0             1.0   
1             1508.0  128.000000             360.0             1.0   
2                0.0   66.000000             360.0             1.0   
3             2358.0  120.000000             360.0             1.0   
4                0.0  141.000000             360.0             1.0   

   Property_Area  Loan_Status  
0              2            1  
1              0            0  
2              2            1  
3              2            1  
4              2            1  
```

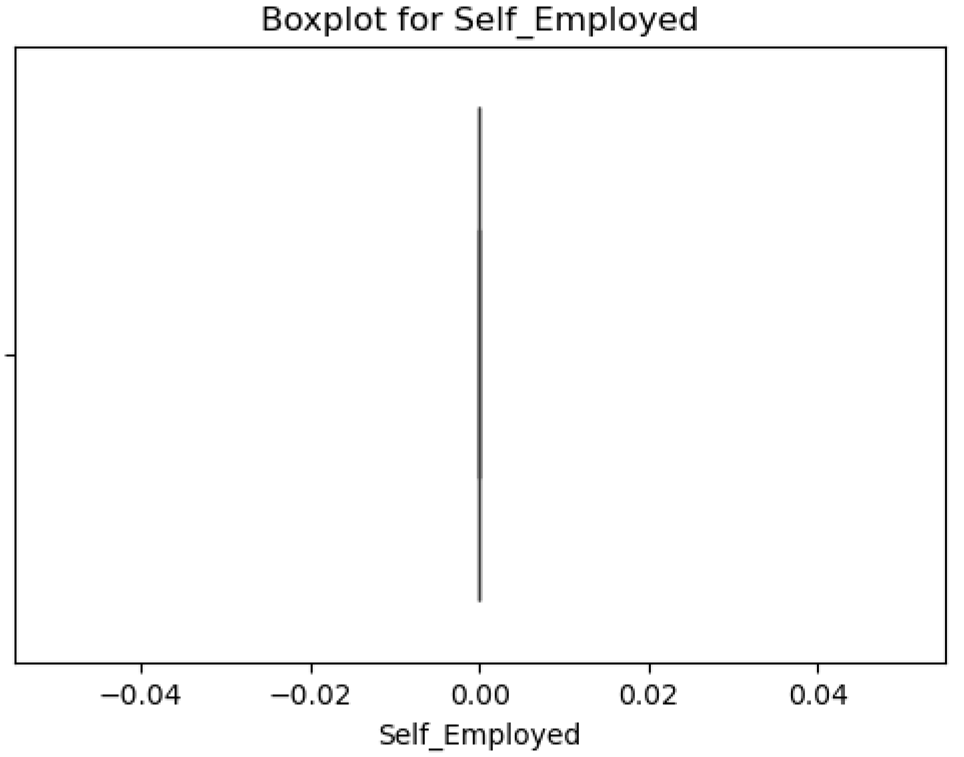
In [24]:
```
# checking if outliers still exist
data.columns = data.columns.str.strip()
numeric_columns = data.select_dtypes(include=[np.number]).columns
for col in numeric_columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=data[col])
    plt.title(f"Boxplot for {col}")
    plt.show()
```

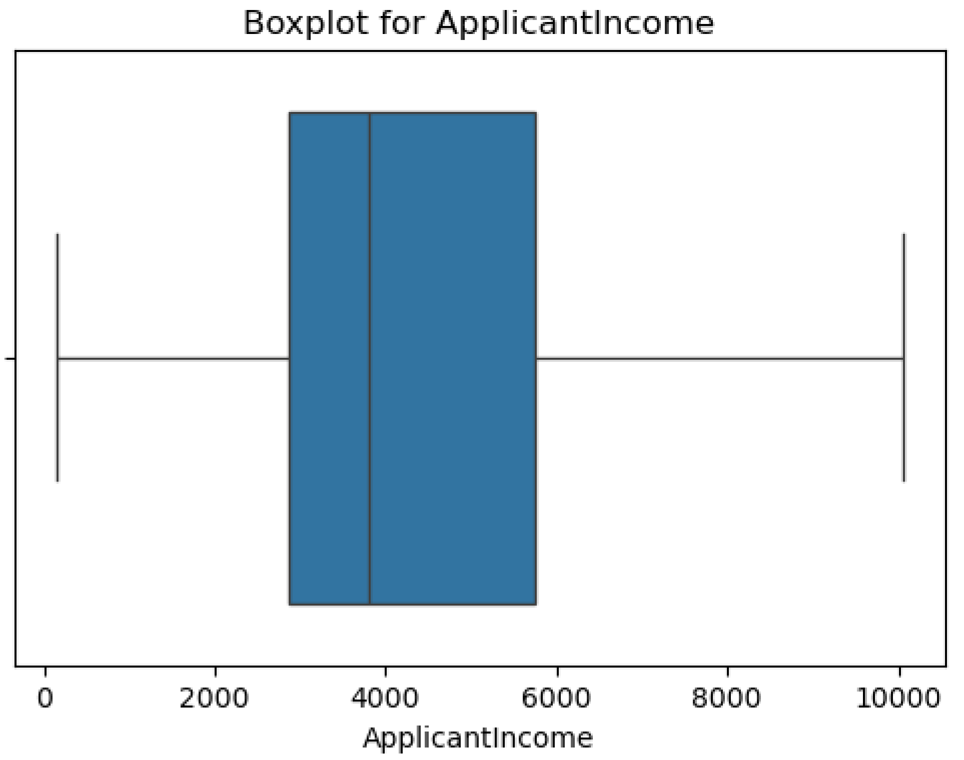

Boxplot for Gender
0.96
0.98
1.00
1.02
1.04
Gender

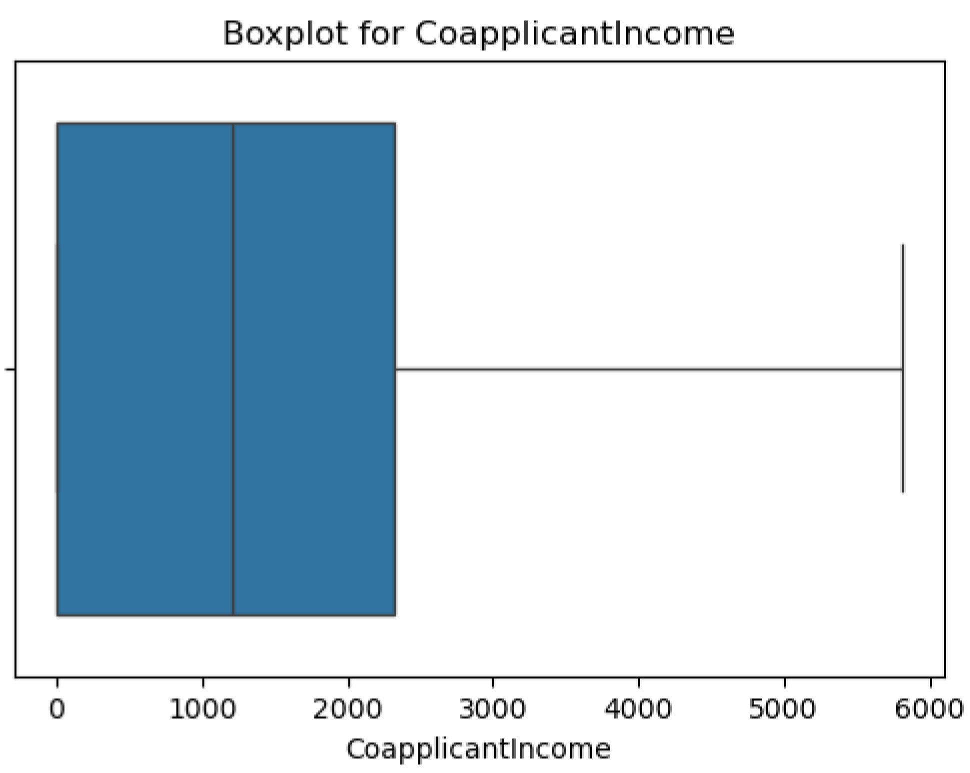

Boxplot for Married
0.0
0.2
0.4
0.6
0.8
1.0
Married

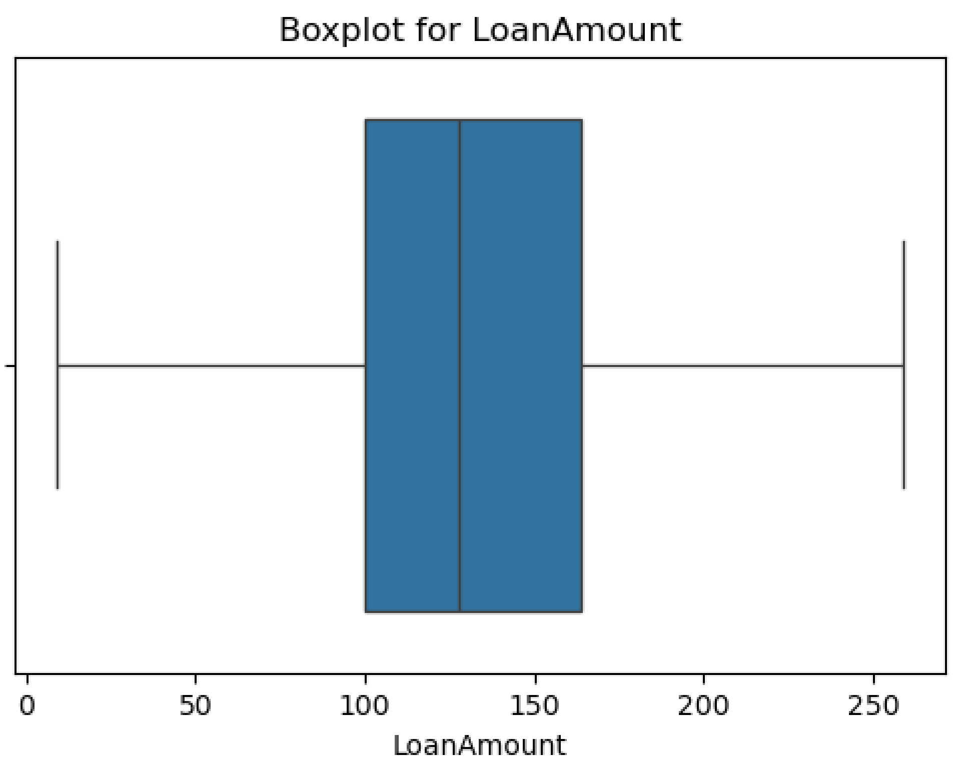

Boxplot for Dependents
0.0
0.5
1.0
1.5
2.0
2.5
Dependents

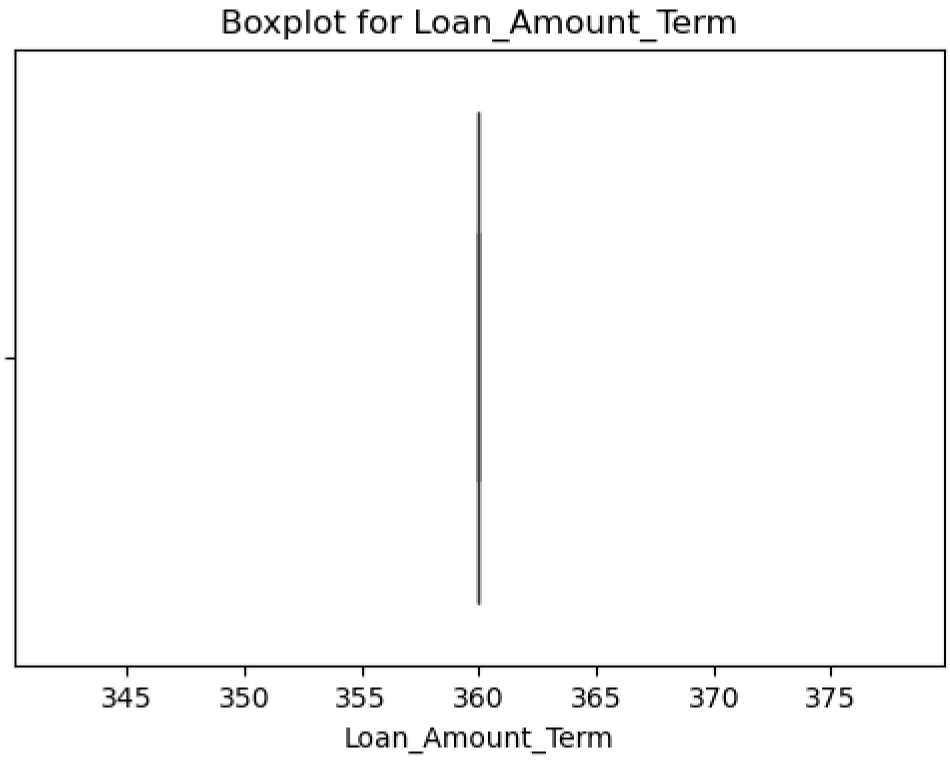

Boxplot for Education
−0.04
−0.02
0.00
0.02
0.04
Education

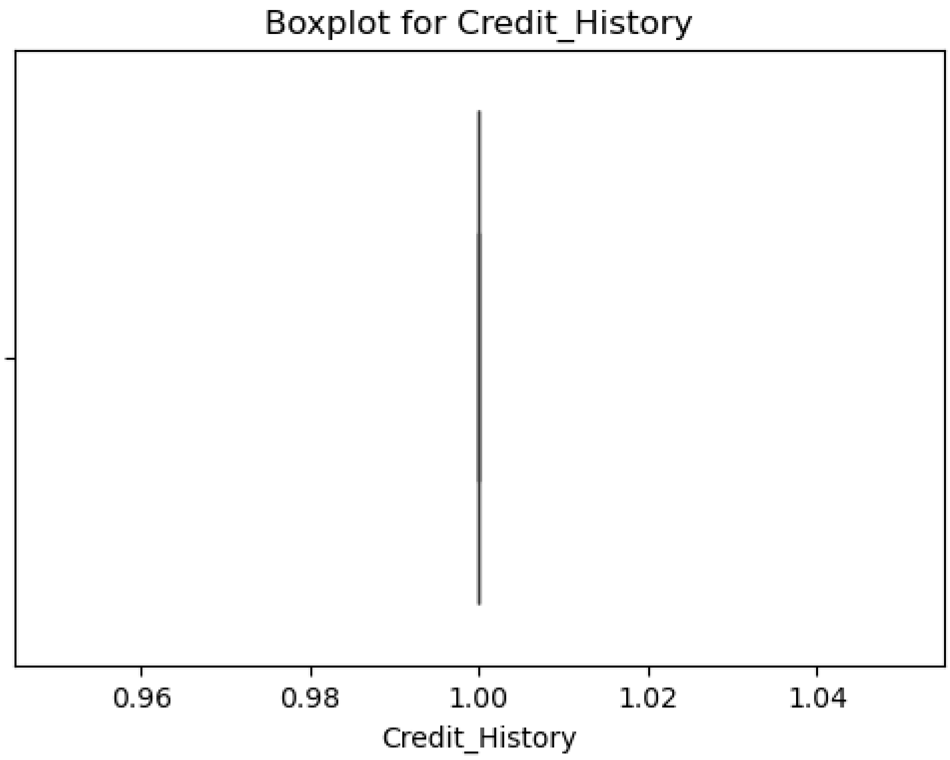

Boxplot for Self_Employed
−0.04
−0.02
0.00
0.02
0.04
Self_Employed

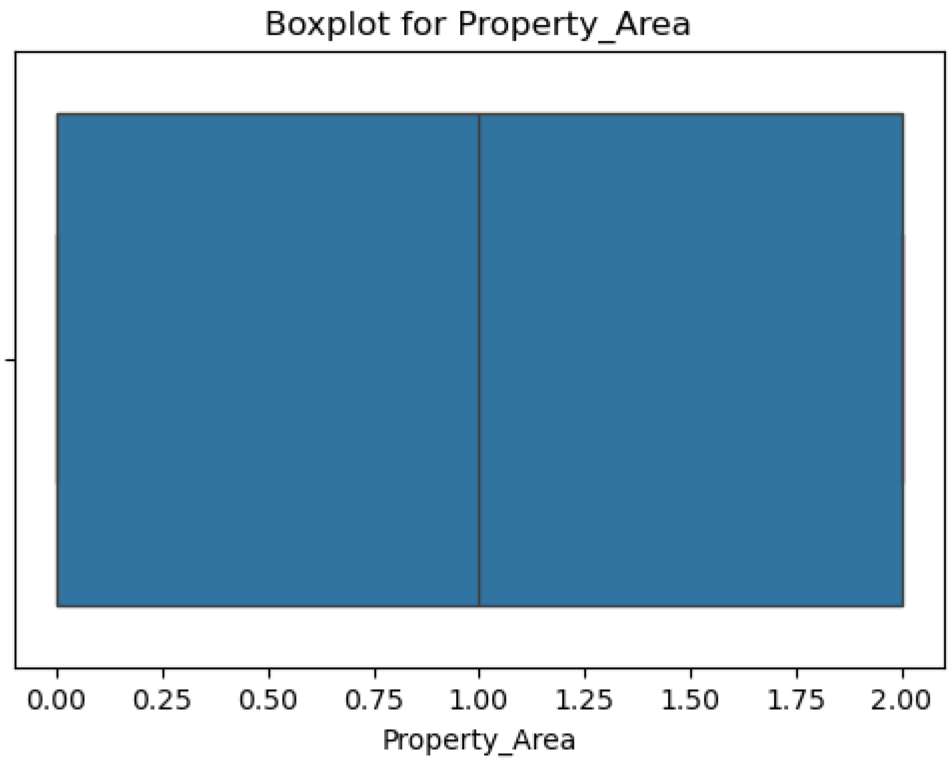

Boxplot for ApplicantIncome
0
2000
4000
6000
8000
10000
ApplicantIncome

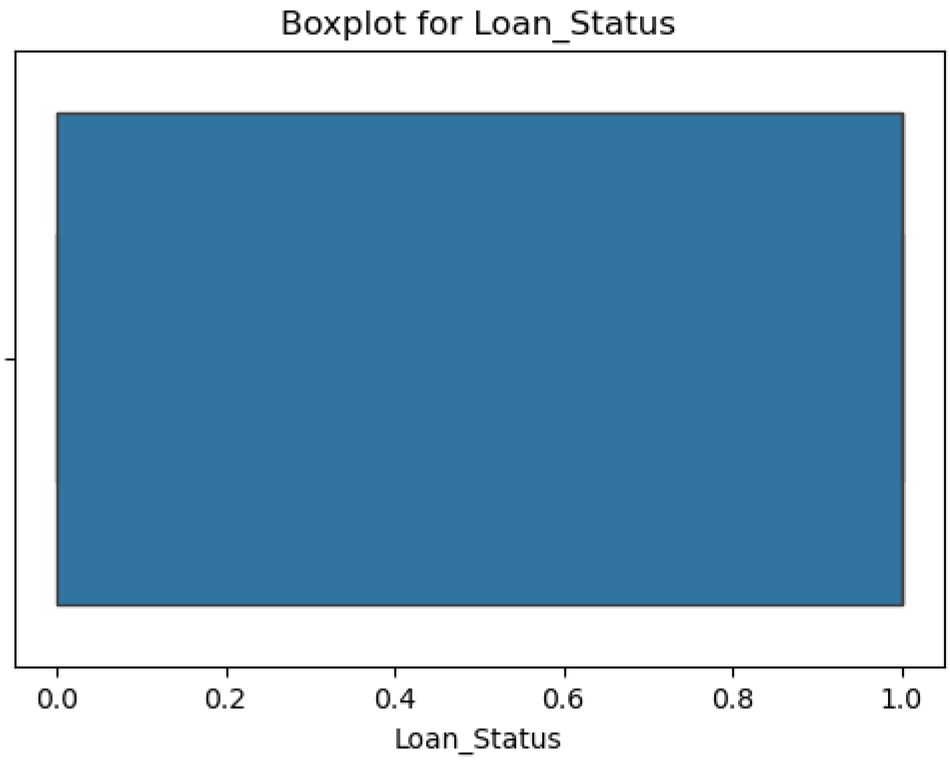

Boxplot for CoapplicantIncome
0
1000
2000
3000
4000
5000
6000
CoapplicantIncome


Boxplot for LoanAmount
0
50
100
150
200
250
LoanAmount









In [25]:
```
# Feature Engineering
```

```
data['Total_Income'] = data['ApplicantIncome'] + data['CoapplicantIncome']
```

In [26]:
```
# Scale Numeric Features

from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
data[['Total_Income', 'LoanAmount', 'Loan_Amount_Term']] = scaler.fit_transform(data[['Total_Income', 'LoanAmount', 'Loan_Amount_T
```

Splitting Dataset

In [28]:
```
X = data.drop(['Loan_Status'],axis=1)
Y = data['Loan_Status']
X.shape,Y.shape
```

Out[28]:
```
((598, 12), (598,))
```

In [29]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2, random_state=42)
X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
```

Out[29]:
```
((478, 12), (120, 12), (478,), (120,))
```

In [30]:
```
print(data['Loan_Status'].value_counts(normalize=True) * 100)
```

```
Loan_Status
1    68.729097
0    31.270903
Name: proportion, dtype: float64
```

In [31]:
```
from imblearn.over_sampling import SMOTE


smote = SMOTE(random_state=42)
X_train, Y_train = smote.fit_resample(X_train, Y_train)

print("Class distribution after SMOTE:")
print(Y_train.value_counts())
```

```
Class distribution after SMOTE:
Loan_Status
0    326
1    326
Name: count, dtype: int64
```

Model training and evaluation

In [33]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBoostClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report

classifiers = {
    'Random Forest Classifier' : RandomForestClassifier(n_estimators = 7, criterion = 'entropy', random_state =7),
    'Logistic Regression': LogisticRegression(random_state=42),
    'Logistic Regression (ElasticNet)': LogisticRegression(penalty='elasticnet', solver='saga', l1_ratio=0.5, random_state=42),
    # 'SVM': SVC(kernel='linear', random_state=42),
    'KNN': KNeighborsClassifier(n_neighbors=3),
    'Naive Bayes': GaussianNB(),
    'Decision Tree': DecisionTreeClassifier(random_state=42, max_depth=5),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42, learning_rate=0.2, max_depth=7,min_samples_split=10, n_estima
    'AdaBoost': AdaBoostClassifier(random_state=42),
    'XGBoost': XGBClassifier(random_state=42),
}

for name, clf in classifiers.items():
    clf.fit(X_train, Y_train)
    Y_pred = clf.predict(X_test)
    accuracy = accuracy_score(Y_test, Y_pred)
    print(f'{name} Accuracy: {accuracy * 100:.2f}%')
    print("\nClassification Report:")
    print(classification_report(Y_test, Y_pred))
    print("*" * 30)
```

```
Random Forest Classifier Accuracy: 65.00%

Classification Report:
              precision    recall  f1-score   support

           0       0.41      0.49      0.45        35
           1       0.77      0.72      0.74        85

    accuracy                           0.65       120
   macro avg       0.59      0.60      0.60       120
weighted avg       0.67      0.65      0.66       120

******************************
Logistic Regression Accuracy: 58.33%

Classification Report:
              precision    recall  f1-score   support

           0       0.33      0.43      0.38        35
           1       0.73      0.65      0.69        85

    accuracy                           0.58       120
   macro avg       0.53      0.54      0.53       120
weighted avg       0.62      0.58      0.60       120

******************************
Logistic Regression (ElasticNet) Accuracy: 46.67%

Classification Report:
              precision    recall  f1-score   support

           0       0.29      0.57      0.38        35
           1       0.71      0.42      0.53        85

    accuracy                           0.47       120
   macro avg       0.50      0.50      0.46       120
weighted avg       0.58      0.47      0.49       120

******************************
KNN Accuracy: 55.00%

Classification Report:
              precision    recall  f1-score   support

           0       0.31      0.46      0.37        35
           1       0.72      0.59      0.65        85

    accuracy                           0.55       120
   macro avg       0.52      0.52      0.51       120
weighted avg       0.60      0.55      0.57       120

******************************
Naive Bayes Accuracy: 58.33%

Classification Report:
              precision    recall  f1-score   support

           0       0.33      0.40      0.36        35
           1       0.73      0.66      0.69        85

    accuracy                           0.58       120
   macro avg       0.53      0.53      0.53       120
weighted avg       0.61      0.58      0.59       120

******************************
Decision Tree Accuracy: 54.17%

Classification Report:
              precision    recall  f1-score   support

           0       0.22      0.23      0.23        35
           1       0.68      0.67      0.67        85

    accuracy                           0.54       120
   macro avg       0.45      0.45      0.45       120
weighted avg       0.55      0.54      0.54       120

******************************
Gradient Boosting Accuracy: 62.50%

Classification Report:
              precision    recall  f1-score   support

           0       0.36      0.37      0.37        35
           1       0.74      0.73      0.73        85

    accuracy                           0.62       120
   macro avg       0.55      0.55      0.55       120
weighted avg       0.63      0.62      0.63       120

******************************
AdaBoost Accuracy: 58.33%

Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.34      0.46      0.39        35
           1       0.74      0.64      0.68        85

    accuracy                           0.58       120
   macro avg       0.54      0.55      0.54       120
weighted avg       0.62      0.58      0.60       120

******************************
XGBoost Accuracy: 65.00%

Classification Report:
               precision    recall  f1-score   support

           0       0.39      0.37      0.38        35
           1       0.75      0.76      0.76        85

    accuracy                           0.65       120
   macro avg       0.57      0.57      0.57       120
weighted avg       0.64      0.65      0.65       120

******************************
```

Based on the results of various models, XGBoost and Random Forest demonstrate the highest accuracy (65%) in this case, while other models such as Gradient Boosting (62.5%) and AdaBoost (58.33%) also perform moderately well.

In [35]:

```
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [50, 100, 150],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

xgb = XGBClassifier(random_state=42, use_label_encoder=False, eval_metric='logloss')
grid_search = GridSearchCV(estimator=xgb, param_grid=param_grid, scoring='accuracy', cv=5, verbose=1)
grid_search.fit(X_train, Y_train)
print("Best Parameters:", grid_search.best_params_)
best_xgb_model = grid_search.best_estimator_
Y_pred_xgb = best_xgb_model.predict(X_test)
print(f"Optimized XGBoost Accuracy: {accuracy_score(Y_test, Y_pred_xgb) * 100:.2f}%")
print("\nClassification Report:\n", classification_report(Y_test, Y_pred_xgb))
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
Best Parameters: {'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 150, 'subsample': 0.8}
Optimized XGBoost Accuracy: 66.67%

Classification Report:
               precision    recall  f1-score   support

           0       0.42      0.40      0.41        35
           1       0.76      0.78      0.77        85

    accuracy                           0.67       120
   macro avg       0.59      0.59      0.59       120
weighted avg       0.66      0.67      0.66       120
```

Save the Model:

In [37]:

```
import joblib

joblib.dump(grid_search.best_estimator_, "optimized_xgboost_model.pkl")
```

Out[37]: ['optimized_xgboost_model.pkl']

XGBoost Model Evaluation Report :

The project successfully demonstrates the utility of machine learning in loan approval prediction. By leveraging features like credit history, marital status, and income, the XGBoost emerged as the most effective model.

Model: XGBoost Classifier Optimization Method: GridSearchCV Accuracy: 66.67%

Macro Average:

Precision: 0.59 Recall: 0.59 F1-Score: 0.59

Weighted Average:

Precision: 0.66 Recall: 0.67 F1-Score: 0.66

Analysis:

The optimized XGBoost model achieves a good accuracy of 66.67%, with particularly strong performance in predicting class 1 (with a recall of 0.78 and F1-score of 0.77). However, there is a noticeable drop in performance for class 0, where the model struggles with precision and recall, indicating that the model has room for improvement, particularly in distinguishing the minority class (class 0).

In [57]:

```
#END
```