```python
#Importing the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
import warnings
warnings.filterwarnings('ignore')
```

```python
#loading 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
```

Some Numerical Information about the Data

```
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
```

```
df.nunique()
```

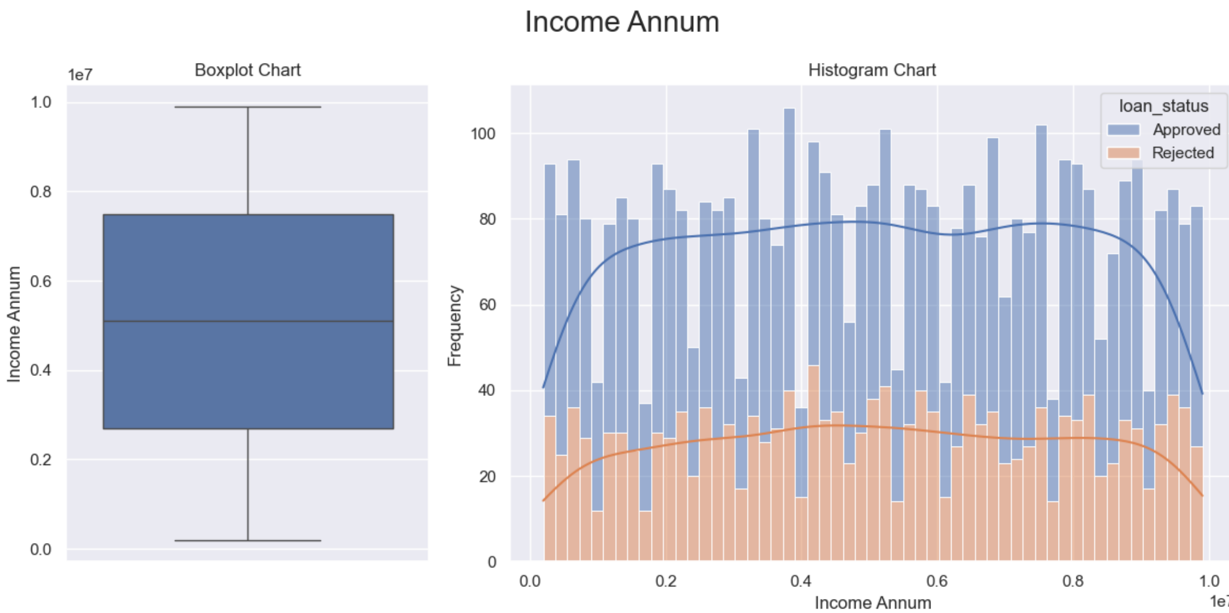
```
loan_id                      4269
 no_of_dependents               6
 education                      2
 self_employed                  2
 income_annum                  98
 loan_amount                  378
 loan_term                     10
 cibil_score                  601
 residential_assets_value     278
 commercial_assets_value      188
 luxury_assets_value          379
 bank_asset_value             146
 loan_status                    2
dtype: int64
```

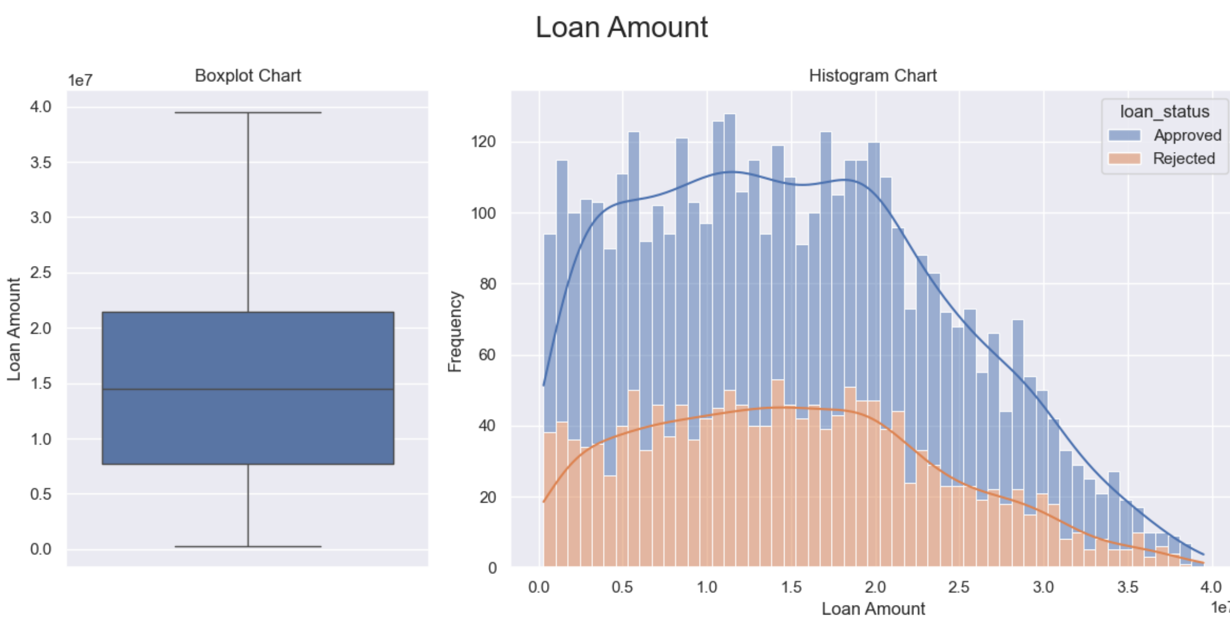
Data Cleaning

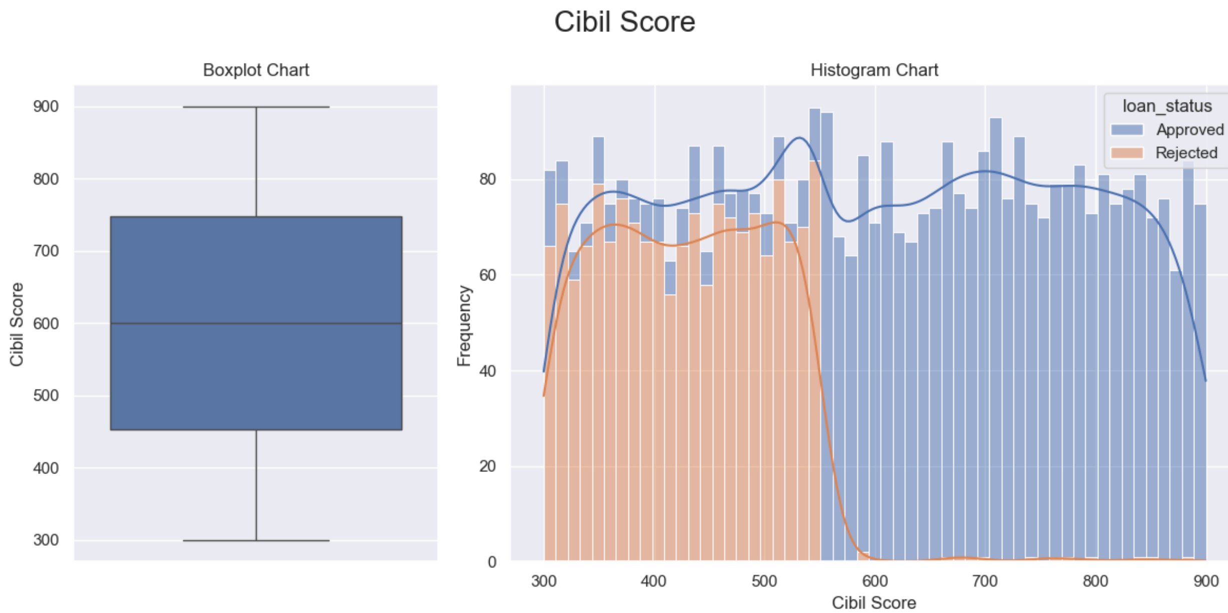
```
# we have a space in first of coulmns and some column values, now drop
that
df = df.rename(columns=lambda x : x.strip())
cols = ['education', 'self_employed', 'loan_status']
df[cols] = df[cols].applymap(lambda x : x.strip())
```

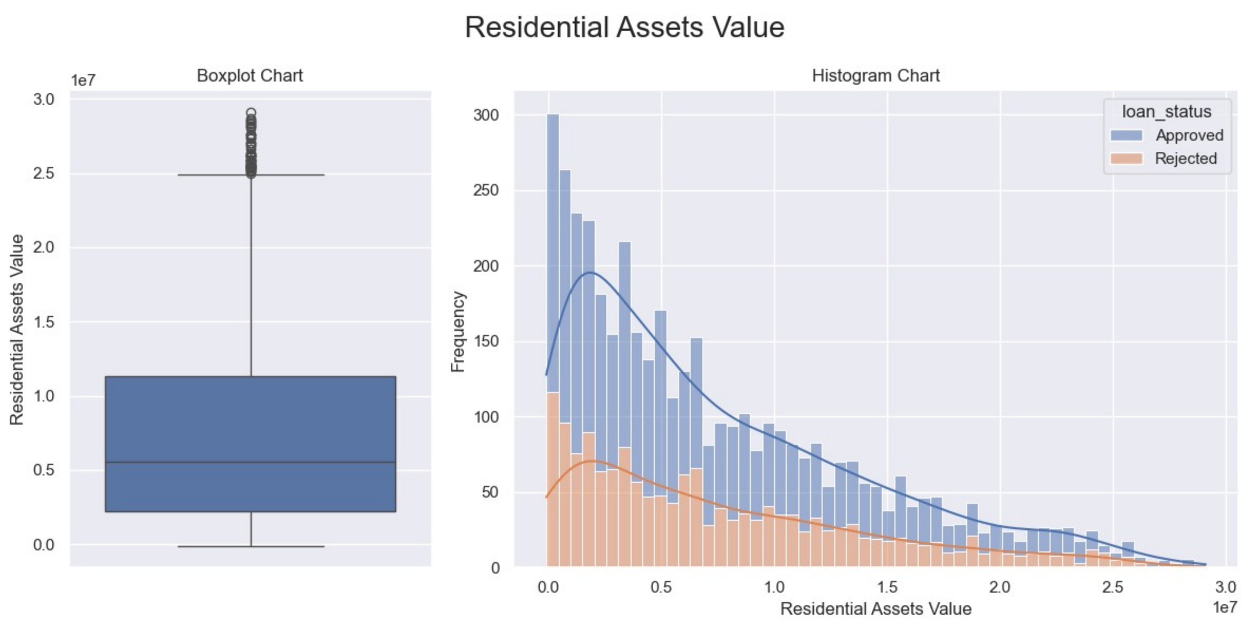
Data Visualization

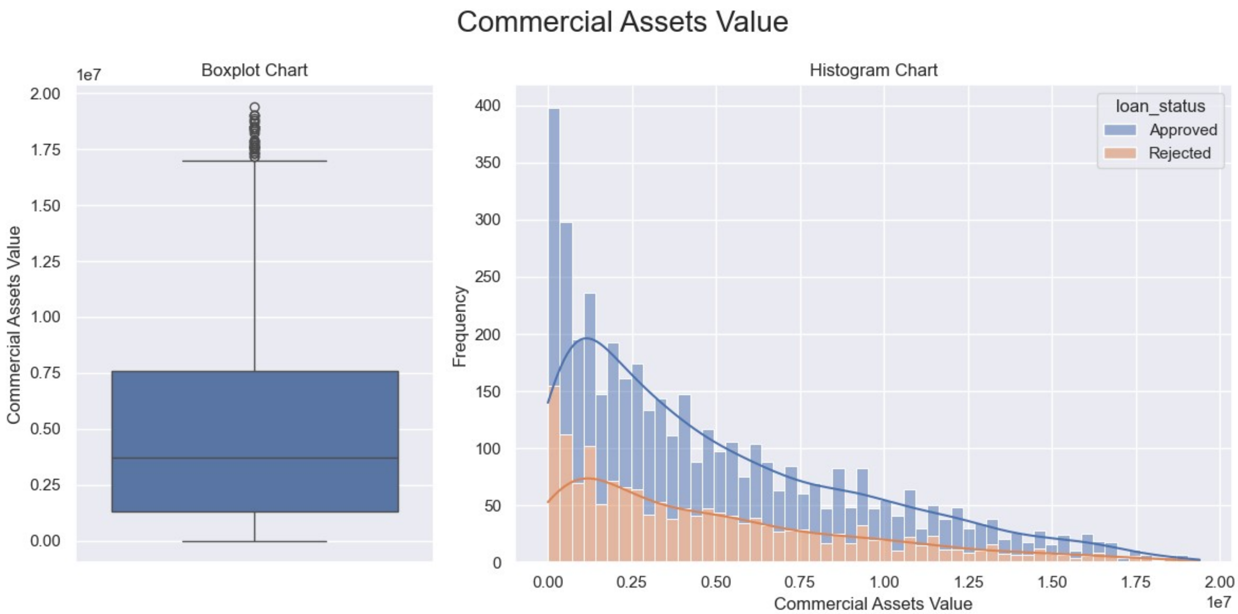
```
# Define list of Continuous columns Names
continuous = ['income_annum', 'loan_amount', 'cibil_score',
'residential_assets_value', 'commercial_assets_value',
'luxury_assets_value', 'bank_asset_value']

# Define a function to Capitalize the first element of string and
remove '_' character
def title(name):
    return (' '.join(word.capitalize()for word in name.split('_')))


# Distribution of Categorical Features
def plot_continious_distribution(df, column, hue):

    width_ratios = [2, 4]
    gridspec_kw = {'width_ratios':width_ratios}
    fig, ax = plt.subplots(1, 2, figsize=(12, 6), gridspec_kw =
gridspec_kw)
    fig.suptitle(f' {title(column)} ', fontsize=20)

    sns.boxplot(df[column], ax=ax[0])
    ax[0].set_title('Boxplot Chart')
    ax[0].set_ylabel(title(column))

    sns.histplot(x = df[column], kde=True, ax=ax[1], hue=df[hue],
multiple = 'stack', bins=55)
    ax[1].set_title('Histogram Chart')
    ax[1].set_ylabel('Frequency')
    ax[1].set_xlabel(title(column))

    plt.tight_layout()
    plt.show()
for conti in continuous :
    plot_continious_distribution(df, conti, 'loan_status')
```

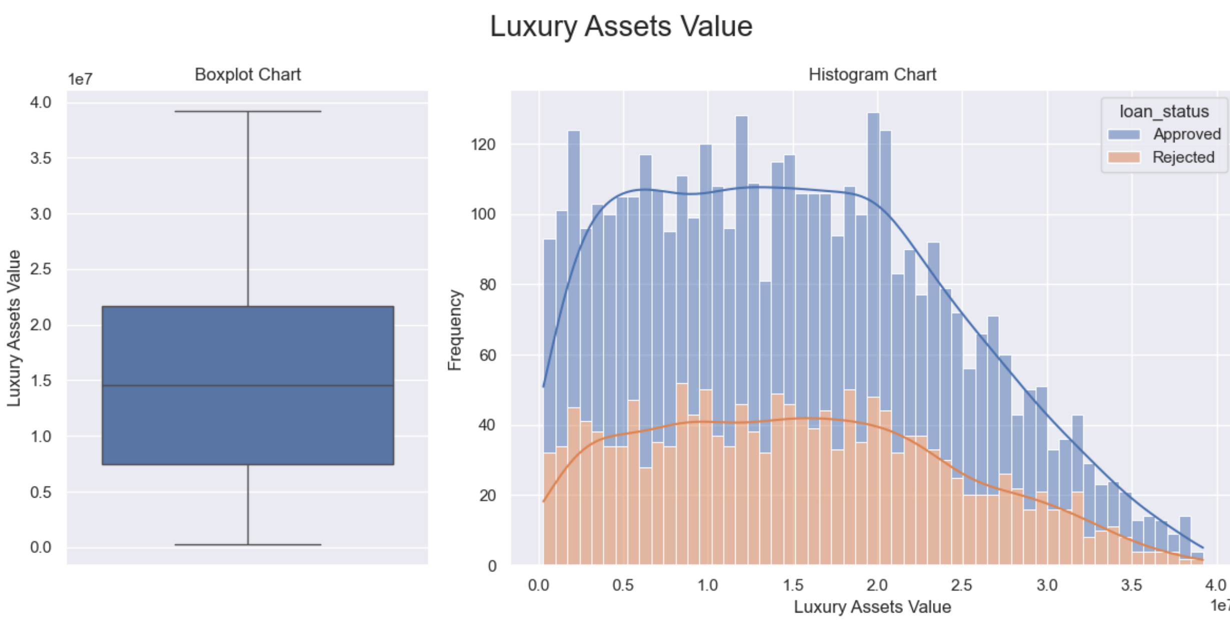

Income Annum
Boxplot Chart
1e7
1.0
0.8
0.6
0.4
0.2
0.0
Income Annum
Histogram Chart
loan_status
Approved
Rejected
Frequency
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0
Income Annum
1e7

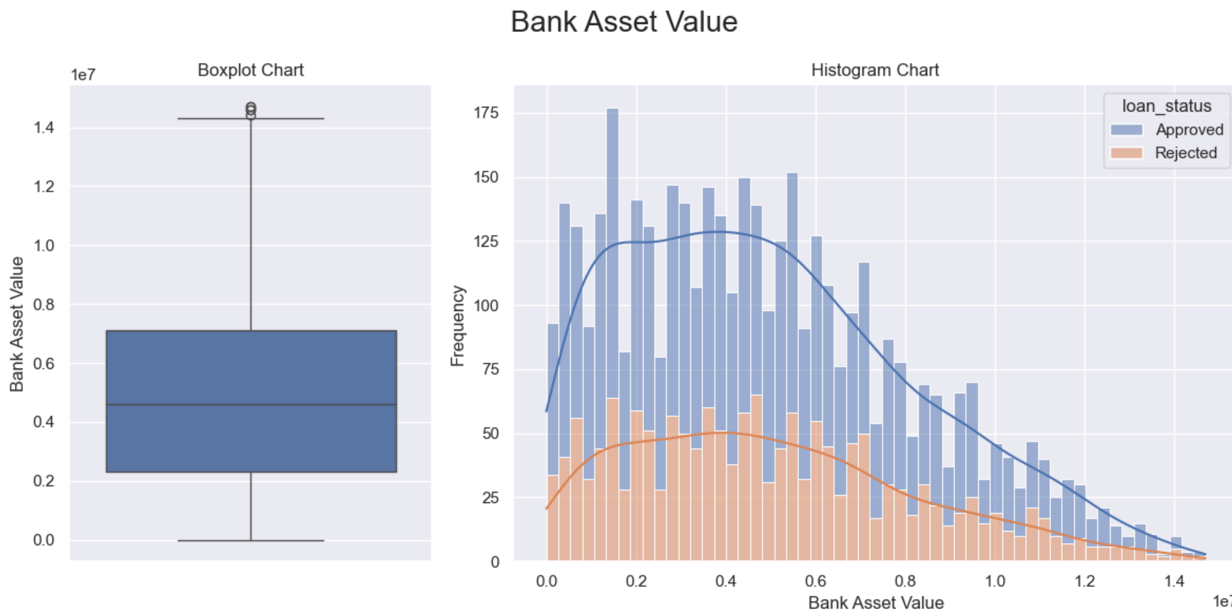

Loan Amount
Boxplot Chart
1e7
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Loan Amount
Histogram Chart
loan_status
Approved
Rejected
Frequency
120
100
80
60
40
20
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Loan Amount
1e7


Cibil Score
Boxplot Chart
Cibil Score
Histogram Chart
Frequency
loan_status
Approved
Rejected
Cibil Score

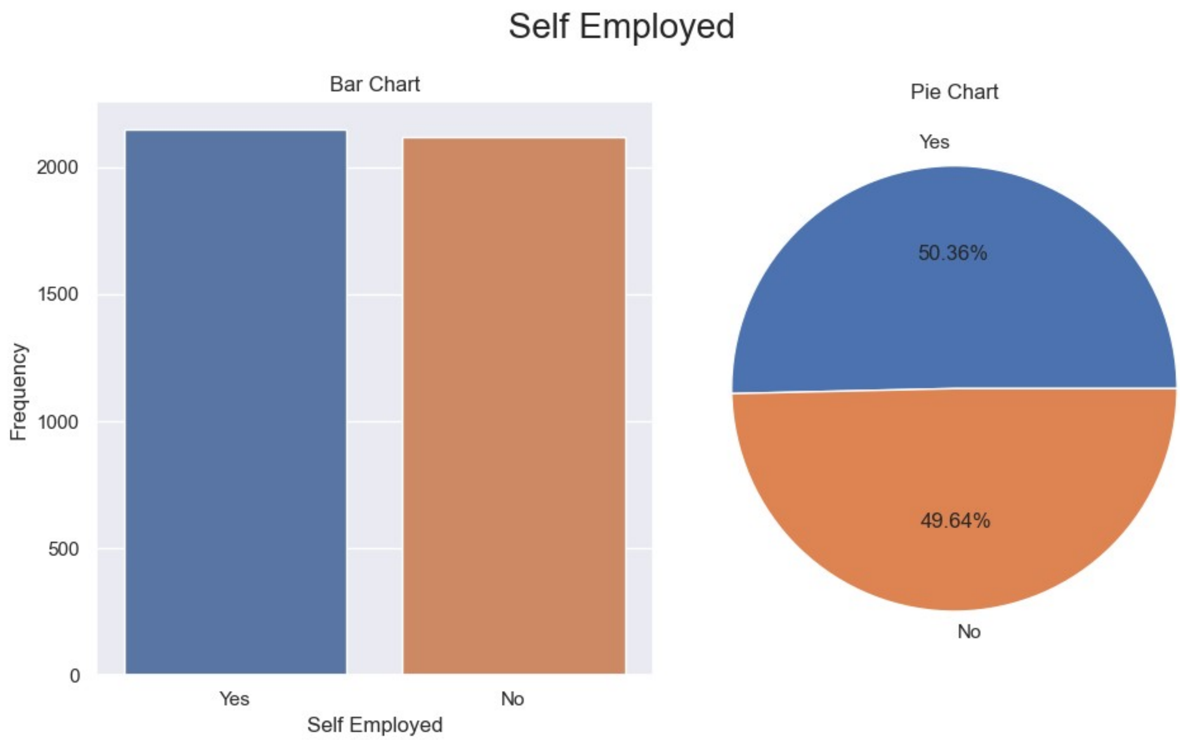

Residential Assets Value
Boxplot Chart
1e7
Residential Assets Value
Histogram Chart
Frequency
loan_status
Approved
Rejected
Residential Assets Value
1e7

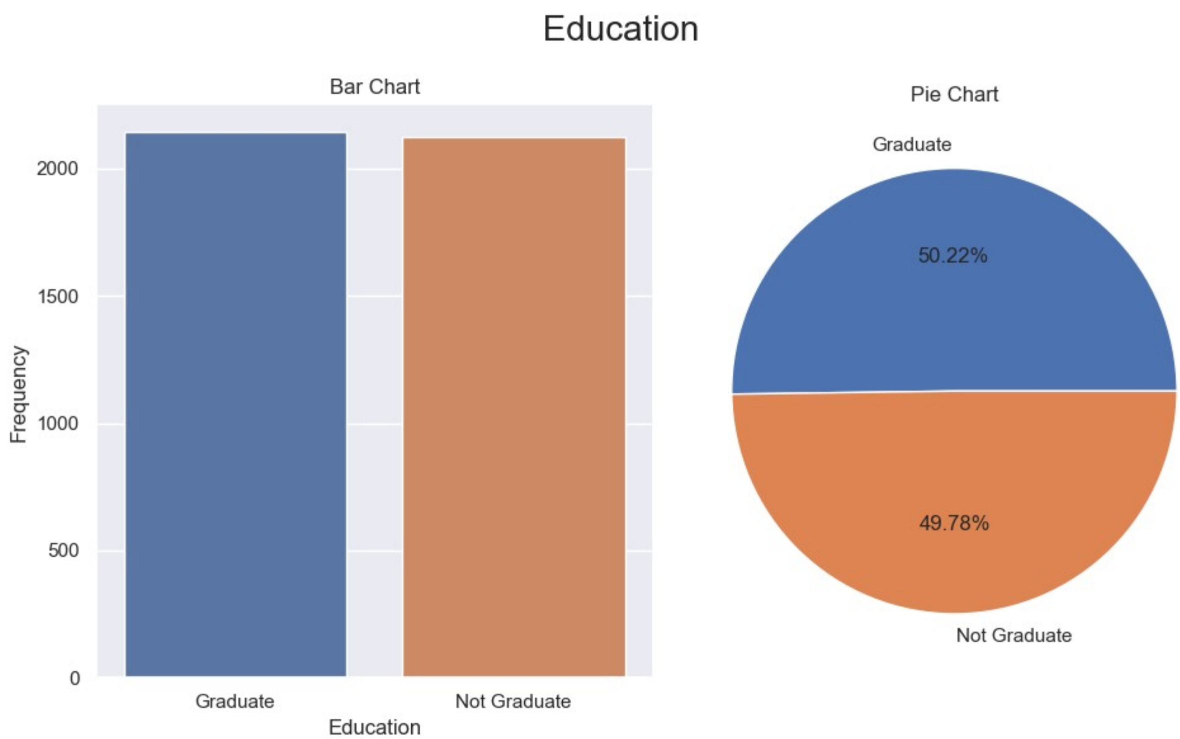

Commercial Assets Value
Boxplot Chart
1e7
Commercial Assets Value
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Histogram Chart
loan_status
Approved
Rejected
Frequency
0
50
100
150
200
250
300
350
400
Commercial Assets Value
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
1e7


Luxury Assets Value
Boxplot Chart
1e7
Luxury Assets Value
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Histogram Chart
loan_status
Approved
Rejected
Frequency
0
20
40
60
80
100
120
Luxury Assets Value
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
1e7



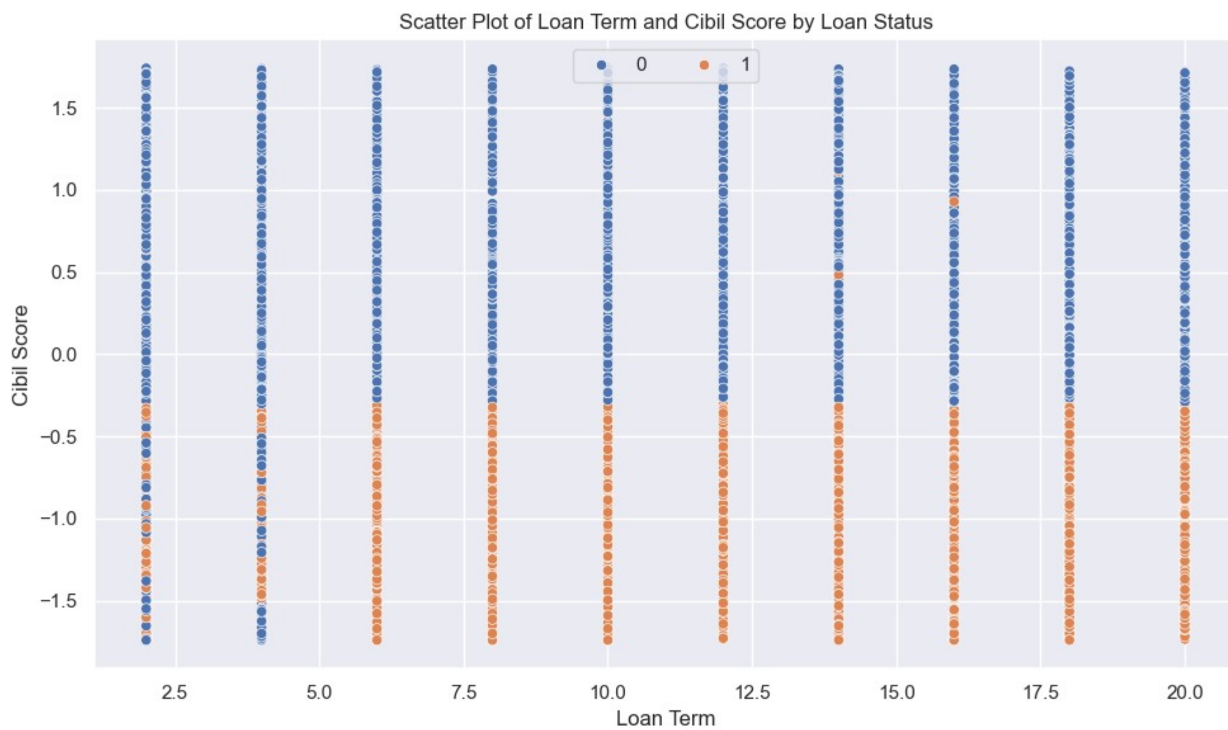

```python
# Define list of Categorical columns Names
categorical = ['self_employed', 'education']

# distribution of categorical features

def plot_categorical_distribution(df, column):
    fig, ax = plt.subplots(1, 2, figsize=(10, 6))
    fig.suptitle(f' {title(column)} ', fontsize=20)

    sns.barplot(df[column].value_counts(), ax=ax[0], palette='deep')
    ax[0].set_title('Bar Chart')
    ax[0].set_xlabel(title(column))
    ax[0].set_ylabel('Frequency')


    df[column].value_counts().plot(kind='pie', autopct="%.2f%%",
ax=ax[1])
    ax[1].set_title('Pie Chart')
    ax[1].set_ylabel(None)

    plt.tight_layout()
    plt.show()

for cat in categorical:
    plot_categorical_distribution(df, cat)
```

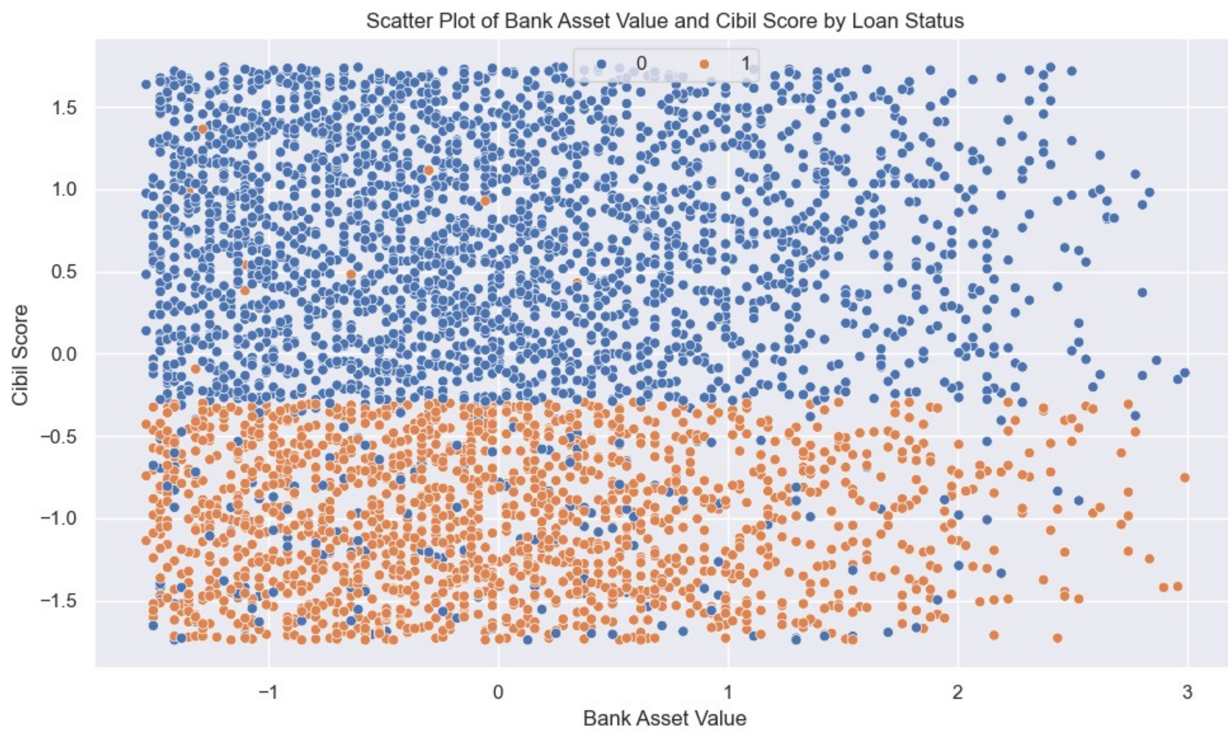




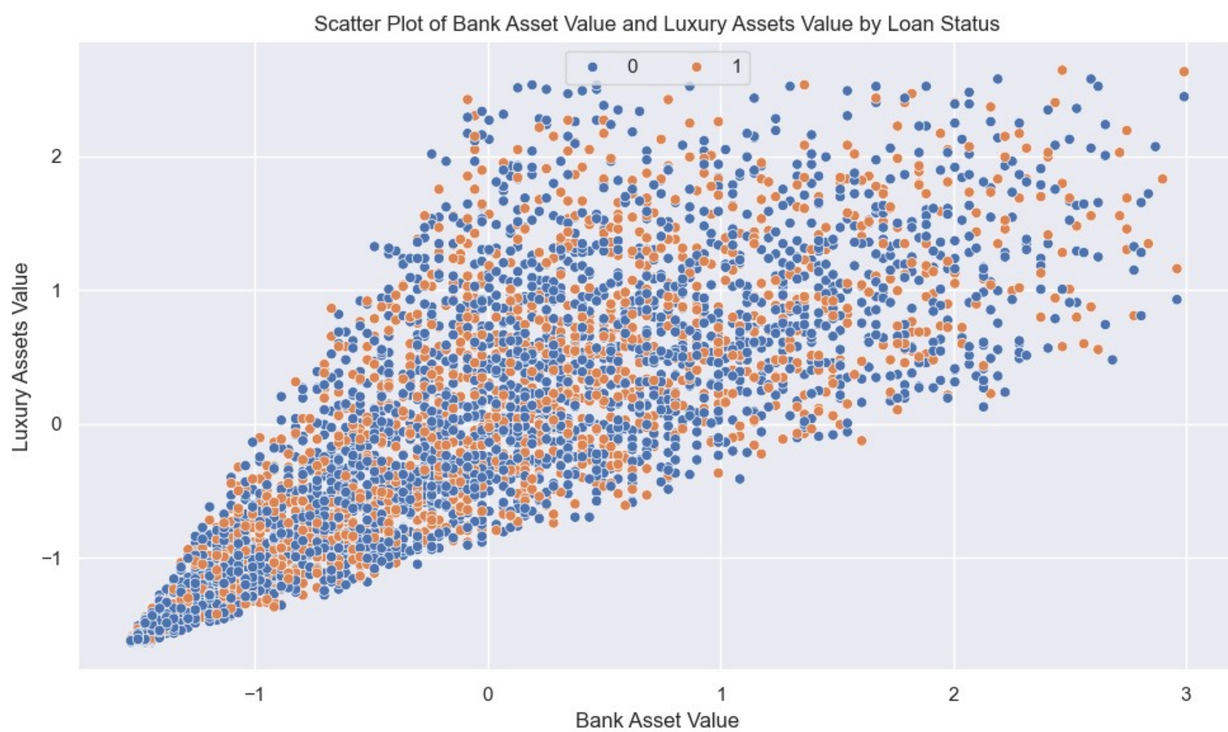

```
# Define a Function for Scatter Plot
def scatter_plot(data, x, y, hue):
    plt.figure(figsize=(10,6))
    sns.scatterplot(data=data, x=x, y=y, hue=hue)
```

```
    plt.title(f'Scatter Plot of {title(x)} and {title(y)} by
{title(hue)}')
    plt.legend(title=None, ncol=2, loc='upper center')
    plt.xlabel(title(x))
    plt.ylabel(title(y))

    plt.tight_layout()
    plt.show()

scatter_plot(data=df, x="loan_term", y="cibil_score",
hue="loan_status")
scatter_plot(data=df, x="bank_asset_value", y="cibil_score",
hue="loan_status")
scatter_plot(data=df, x="bank_asset_value", y="luxury_assets_value",
hue="loan_status")
scatter_plot(data=df, x="income_annum", y="loan_amount",
hue="loan_status")
```



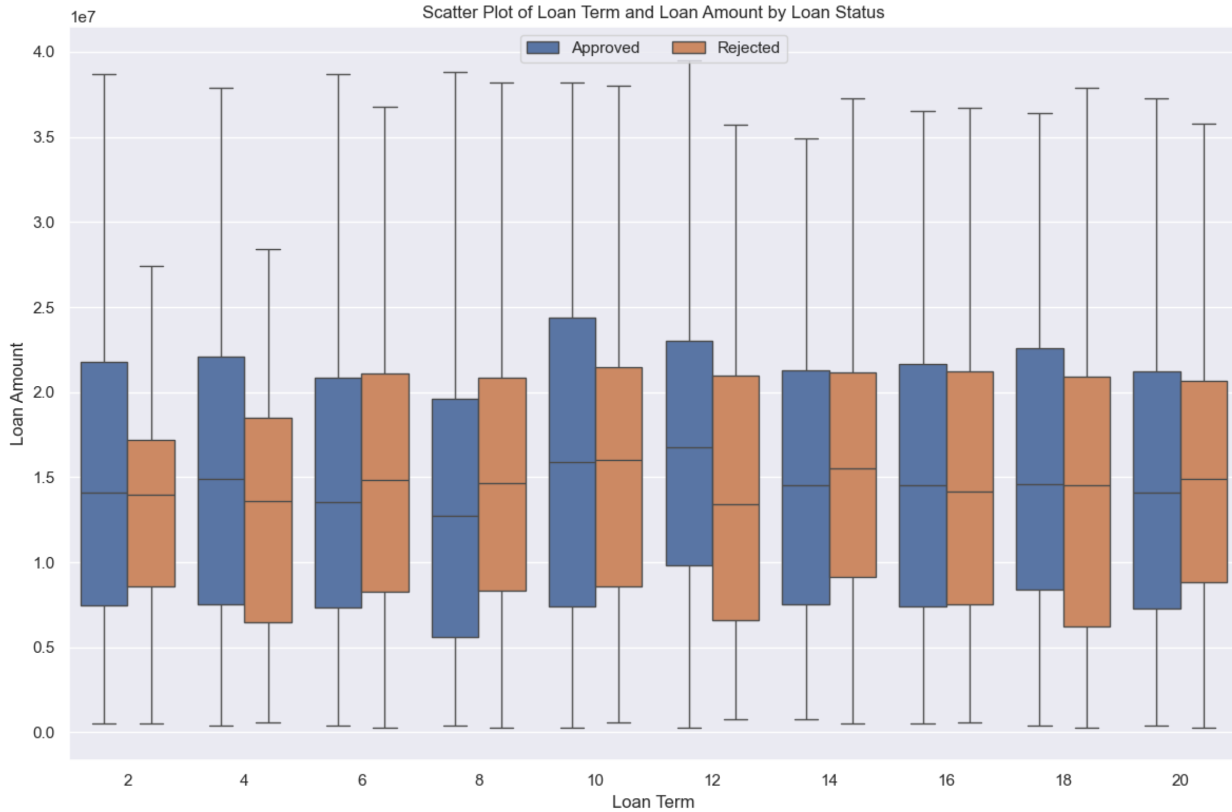


Scatter Plot of Bank Asset Value and Cibil Score by Loan Status
0
1
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
Cibil Score
−1
0
1
2
3
Bank Asset Value

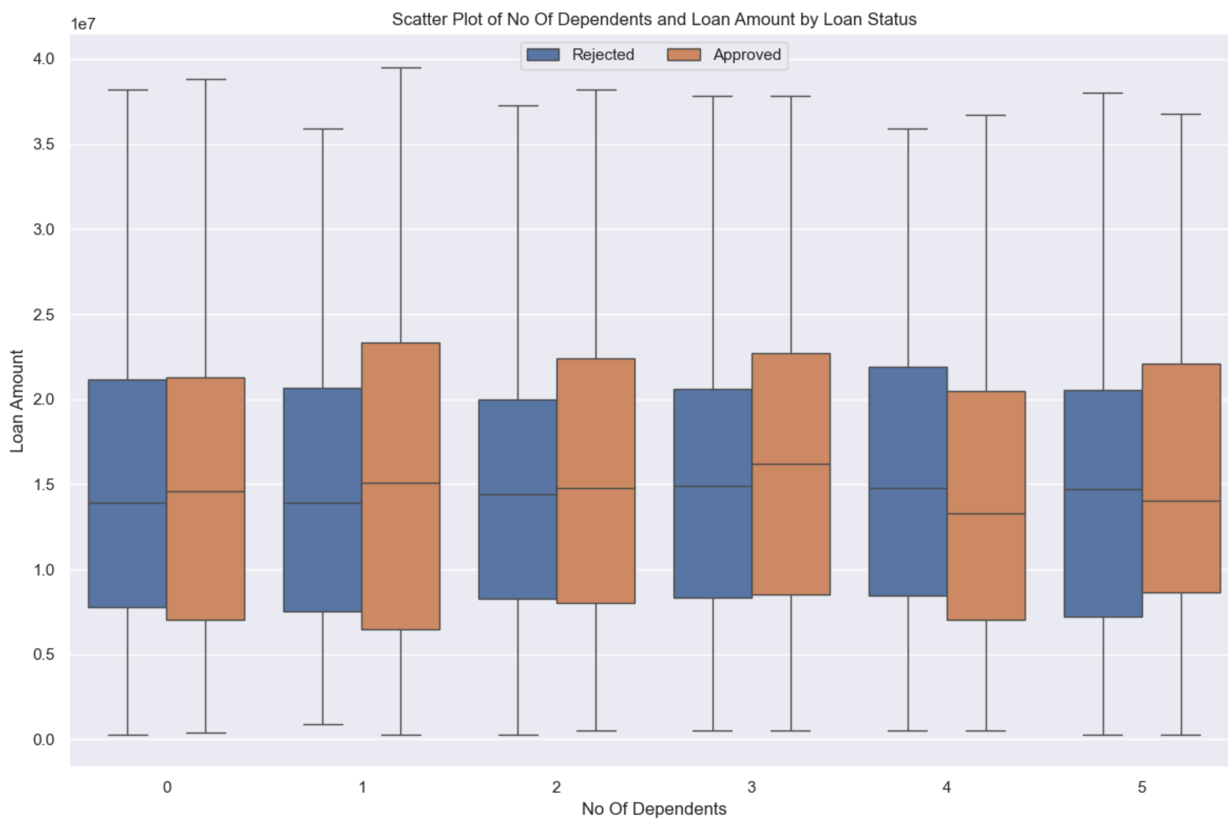


Scatter Plot of Bank Asset Value and Luxury Assets Value by Loan Status
0
1
2
1
0
−1
Luxury Assets Value
−1
0
1
2
3
Bank Asset Value


```
# Define a Function for Scatter Plot
def box_plot(data, x, y, hue):
    plt.figure(figsize=(12,8))
    sns.boxplot(data=data, x=x, y=y, hue=hue)
    plt.title(f'Scatter Plot of {title(x)} and {title(y)} by
{title(hue)}')
    plt.legend(title=None, ncol=2, loc='upper center')
    plt.xlabel(title(x))
    plt.ylabel(title(y))

    plt.tight_layout()
    plt.show()

box_plot(data=df, x="loan_term", y="loan_amount", hue="loan_status")
box_plot(data=df, x="no_of_dependents", y="loan_amount",
hue="loan_status")
```



Scatter Plot of Loan Term and Loan Amount by Loan Status
1e7
Approved
Rejected
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Loan Amount
2
4
6
8
10
12
14
16
18
20
Loan Term



Scatter Plot of No Of Dependents and Loan Amount by Loan Status
1e7
Rejected
Approved
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Loan Amount
0
1
2
3
4
5
No Of Dependents

Data Preprocessing

```
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Initialize StandardScaler
stc = StandardScaler()
# Initialize LabelEncoder
le = LabelEncoder()

stc_cols = ['bank_asset_value', 'luxury_assets_value',
'commercial_assets_value', 'residential_assets_value',
'cibil_score','loan_amount','income_annum']
le_cols = ['loan_status', 'education', 'self_employed']

# Apply Standard Scaler to the selected columns
df[stc_cols] = stc.fit_transform(df[stc_cols])

# Apply Label Encoder to the selected column
for col in le_cols :
    df[col] = le.fit_transform(df[col])
```

Training and Evaluating Different Models

```
from sklearn.model_selection import train_test_split

x = df.drop(['loan_status', 'loan_id'], axis=1)
y = df['loan_status']  # Target Variable

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

#Importing the Libraries
from sklearn.ensemble import  GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier

# List of Models to Try
models = [
    ('Gradient Boosting', GradientBoostingClassifier()),
    ('K-Nearest Neighbors', KNeighborsClassifier()),
    ('Random Forest', RandomForestClassifier()),
    ('Decision Tree', DecisionTreeClassifier()),
    ('XGB Classifier', XGBClassifier())
```

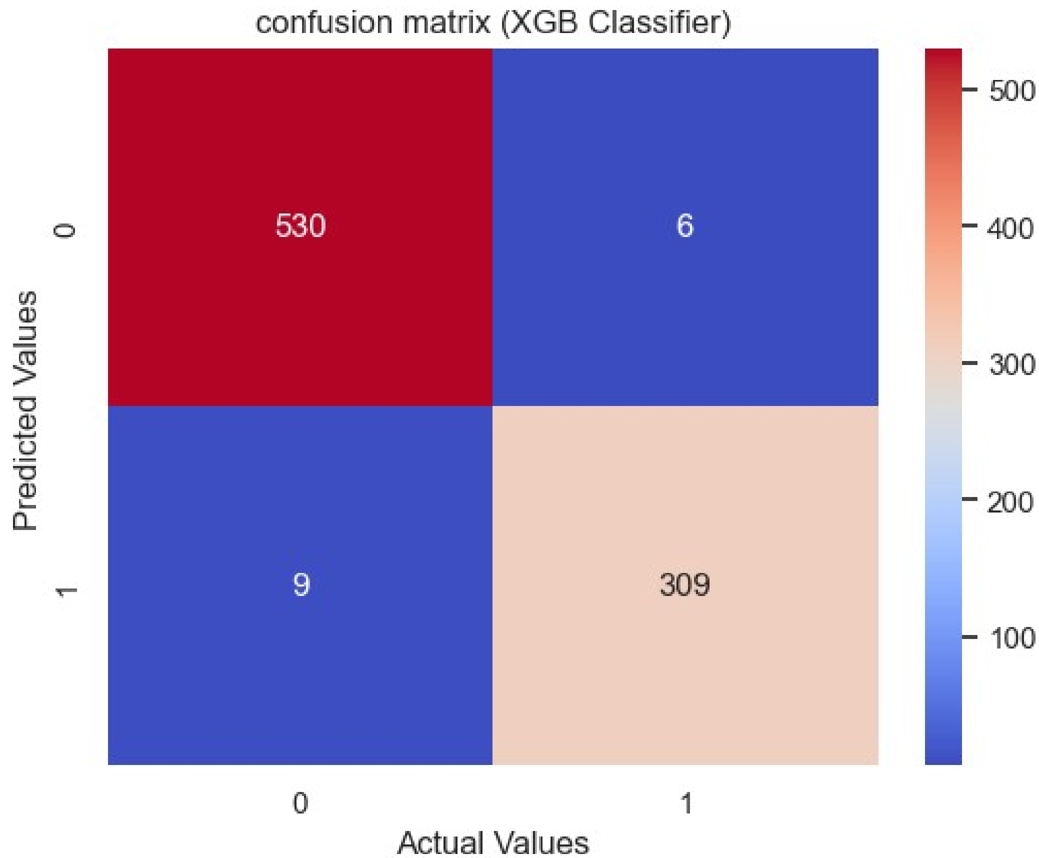
```
]

# Train and evaluate each model
for name, model in models:
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    print(f'Training accuracy: {name}', model.score(x_train, y_train))
    print(f'Test accuracy: {name}', accuracy_score(y_test, y_pred))
    print()
```

```
Training accuracy: Gradient Boosting 0.99502196193265
Test accuracy: Gradient Boosting 0.977751756440281

Training accuracy: K-Nearest Neighbors 0.9376281112737921
Test accuracy: K-Nearest Neighbors 0.8981264637002342

Training accuracy: Random Forest 1.0
Test accuracy: Random Forest 0.9754098360655737

Training accuracy: Decision Tree 1.0
Test accuracy: Decision Tree 0.9765807962529274

Training accuracy: XGB Classifier 1.0
Test accuracy: XGB Classifier 0.9824355971896955
```

```
xgb = XGBClassifier()
xgb.fit(x_train, y_train)
xgb_pred = xgb.predict(x_test)

accuracy = accuracy_score(y_test, xgb_pred)
print(f'R-squared (XGB Classifier): {round(accuracy, 3)}')
```

```
R-squared (XGB Classifier): 0.982
```

```
from sklearn.metrics import confusion_matrix, classification_report
sns.heatmap(confusion_matrix(y_test,xgb_pred),annot= True, cmap =
'coolwarm', fmt='.0f')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('confusion matrix (XGB Classifier)')
plt.show()
```




```
# Visualize Classification report for XGB Classifier
print(classification_report(y_test,xgb_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       536
           1       0.98      0.97      0.98       318

    accuracy                           0.98       854
   macro avg       0.98      0.98      0.98       854
weighted avg       0.98      0.98      0.98       854
```

Summary and Conclusion

In this project, I focused on predicting loan approval using various data preprocessing techniques and a machine learning model. The steps and methodologies employed are as follows:

1. Data Cleaning:
    - Column and Value Cleanup: Removed spaces from column names and values to ensure consistency and avoid errors during data processing.
2. Data Visualization:

   - Created appropriate visualizations to explore and understand the data patterns and relationships, providing valuable insights into the dataset.
3. Data Standardization and Label Encoding:
   - Performed data standardization to normalize the features.
   - Applied label encoding to convert categorical variables into numerical format.
4. Model Training and Evaluation:
   - Trained an XGBoost (XGB) model on the processed dataset.
   - The model achieved a high accuracy of 98.2%.

These steps ensured a comprehensive analysis and model training process, leading to a highly accurate prediction model for loan approval.

Developed by Hosein Mohammadi

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