Loan Approval Prediction Model

About the Data Set

1. **ApplicantID**: Unique identifier for each applicant.
2. **Gender**: Applicant's gender.
3. **Married**: Applicant's marital status.
4. **Dependents**: Number of dependents.
5. **Education**: Education level (Graduate/Not Graduate).
6. **SelfEmployed**: Whether the applicant is self-employed.
7. **ApplicantIncome**: Income of the applicant.
8. **CoapplicantIncome**: Income of the co-applicant.
9. **LoanAmount**: Amount of the loan applied for.
10. **Loan_Amount_Term**: Duration of the loan in months.
11. **Credit_History**: Credit history (1 for good, 0 for bad).
12. **Loan_Status**: Whether the loan was approved (Yes/No).

Objective: Predict whether a loan will be approved or not based on the applicant's profile (e.g., income, credit history, education).

- **Approach**: Use machine learning techniques such as logistic regression, decision trees, or random forests to build a classification model. The target variable would be `Loan_Status`, and features could include `ApplicantIncome`, `CoapplicantIncome`, `Credit_History`, and more.
- **Outcome**: Develop a model to assist financial institutions in making informed decisions about loan approvals.

In [ ]:
```
import pandas as pd
df= pd.read_csv("loan_approval_prediction.csv")
```

In [ ]:
```
df.dtypes
```

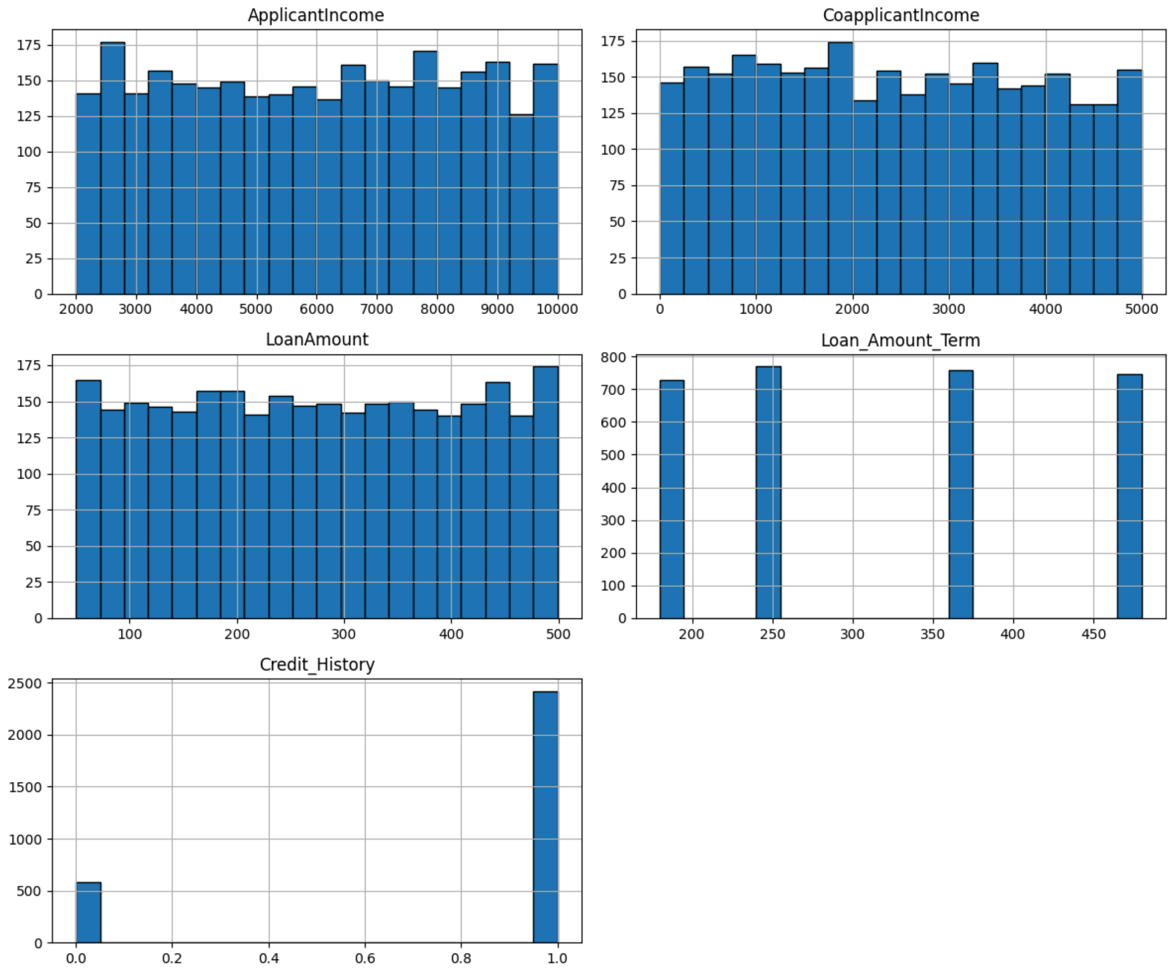
Out[ ]:
```
ApplicantID          object
Gender               object
Married              object
Dependents           object
Education            object
SelfEmployed         object
ApplicantIncome       int64
CoapplicantIncome     int64
LoanAmount            int64
Loan_Amount_Term      int64
Credit_History        int64
Loan_Status          object
dtype: object
```

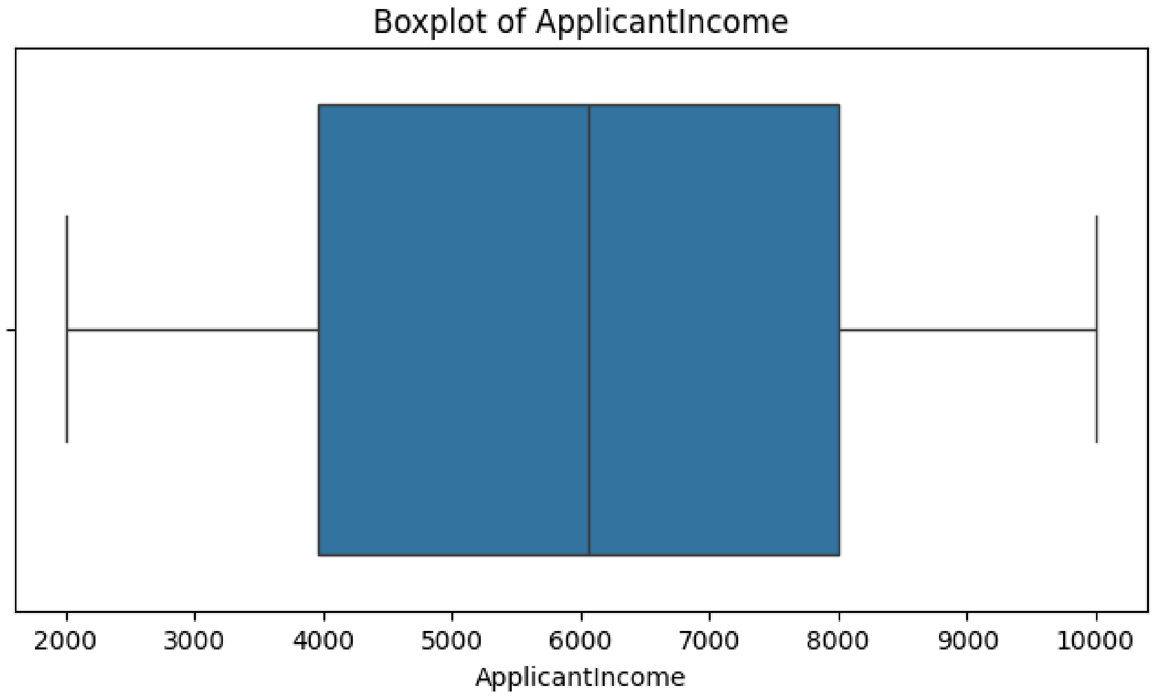
EDA

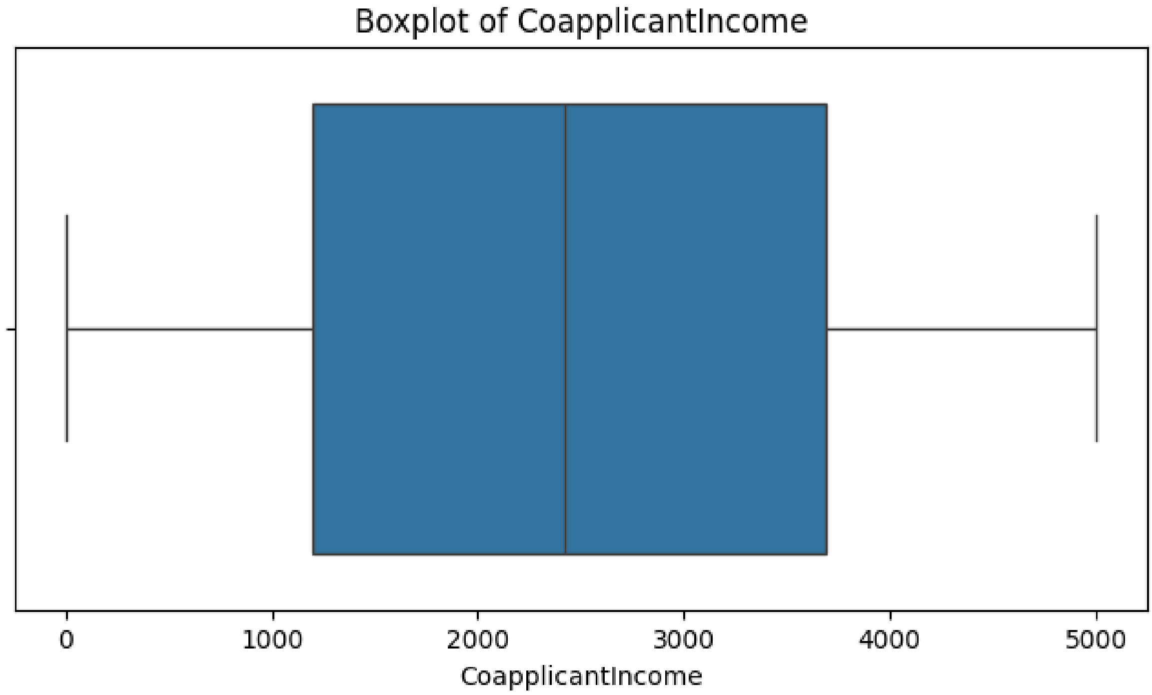
Univariate Analysis

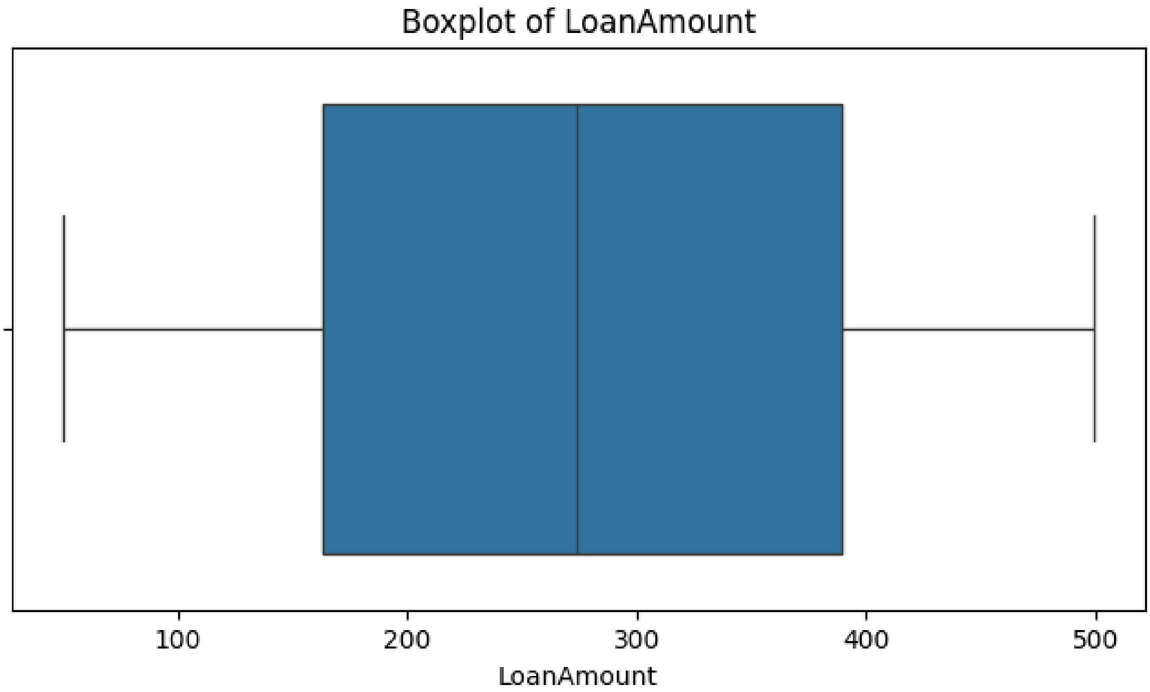
In [ ]:

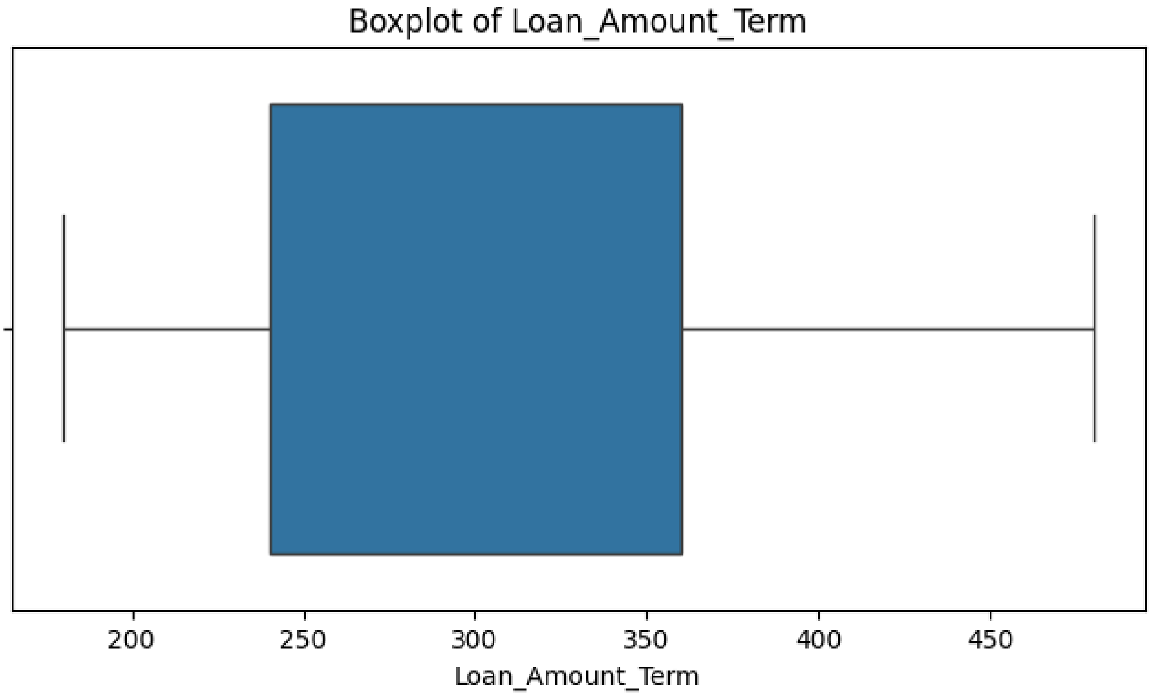
```
import matplotlib.pyplot as plt
import seaborn as sns

# Histograms for numerical features
df.hist(figsize=(12, 10), bins=20, edgecolor='black')
plt.tight_layout()
plt.show()

# Boxplots for numerical features
for column in ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amoun
    plt.figure(figsize=(8, 4))
    sns.boxplot(x=df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()
```




Boxplot of ApplicantIncome
2000
3000
4000
5000
6000
7000
8000
9000
10000
ApplicantIncome

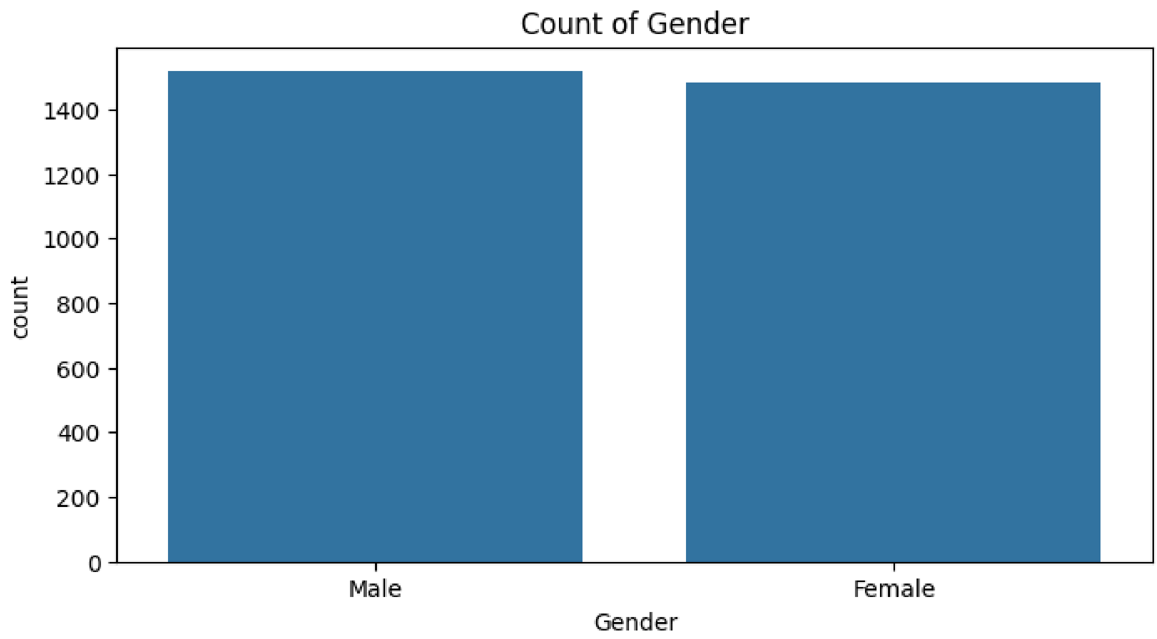

Boxplot of CoapplicantIncome
0
1000
2000
3000
4000
5000
CoapplicantIncome

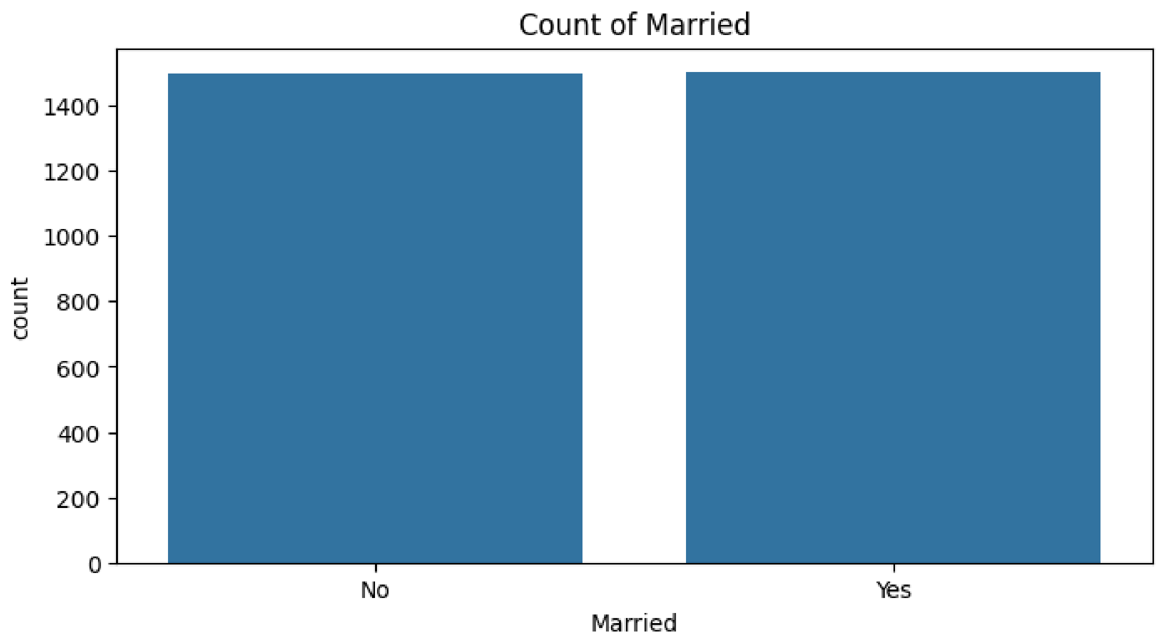


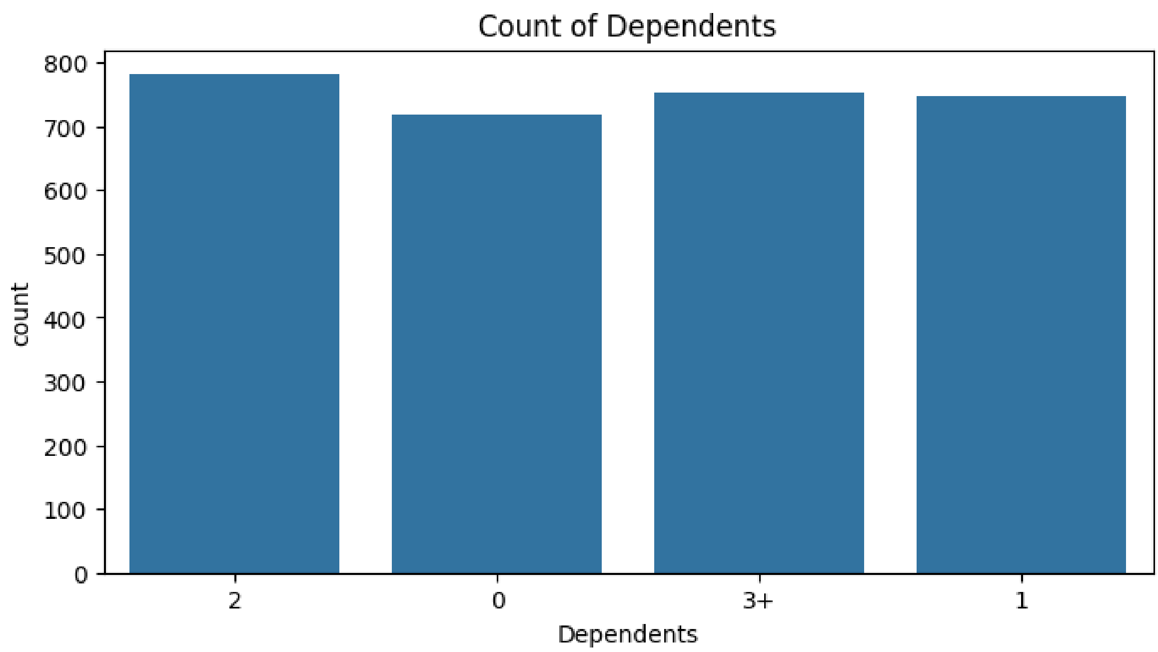


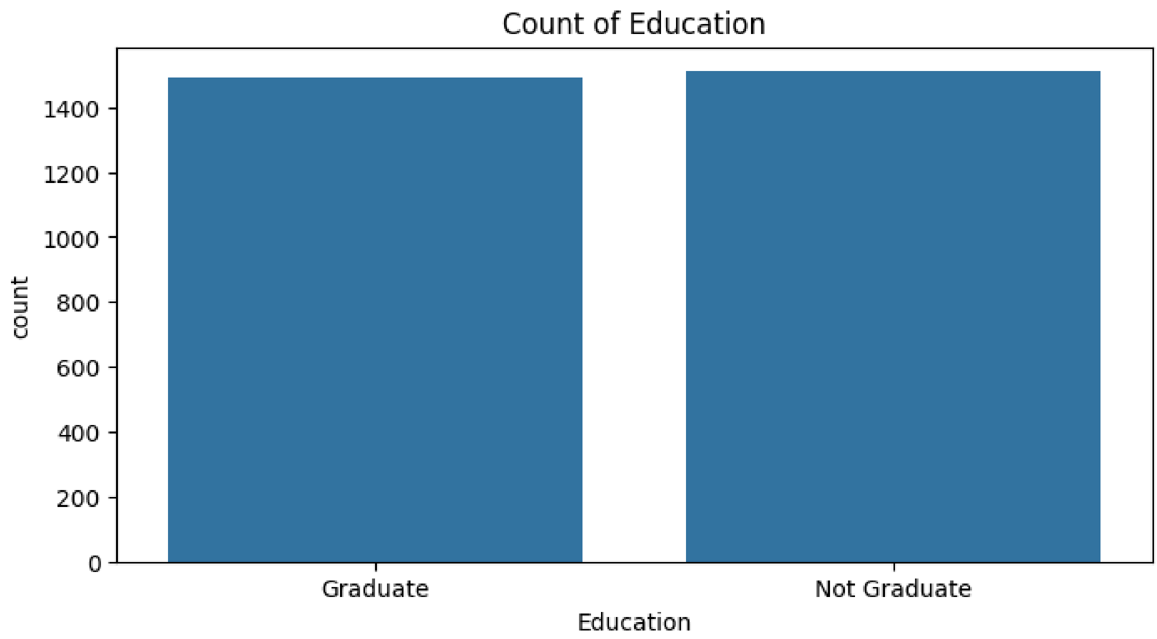
Categorical Features

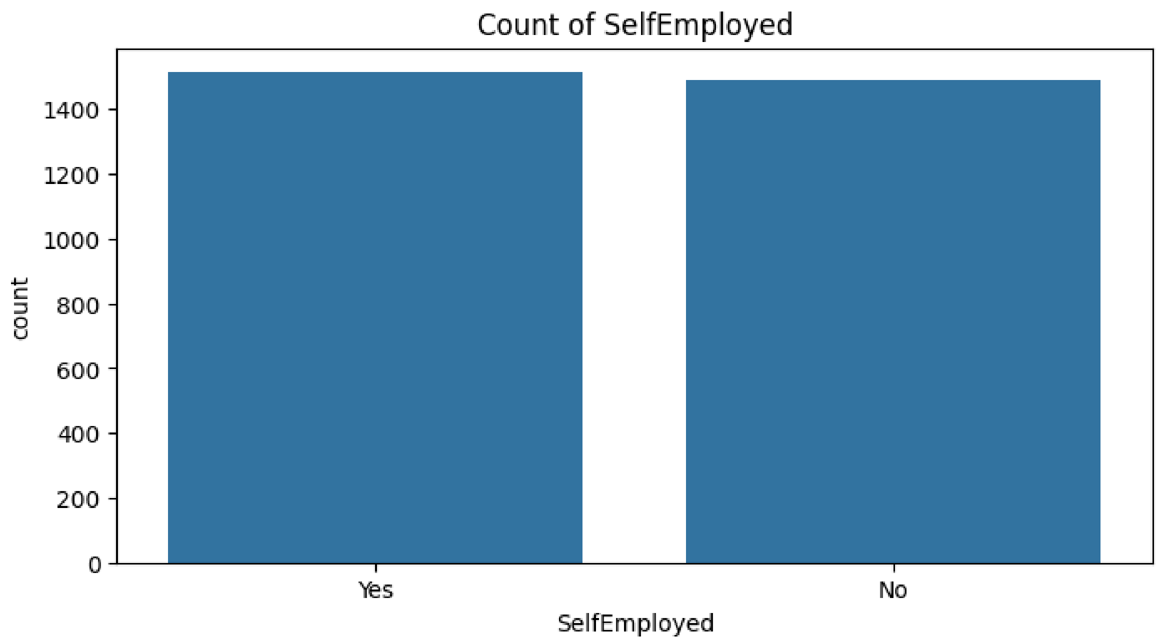
In [ ]:
```
# Count plots for categorical features
categorical_features = ['Gender', 'Married', 'Dependents', 'Education', 'SelfEmp

for feature in categorical_features:
    plt.figure(figsize=(8, 4))
    sns.countplot(data=df, x=feature)
    plt.title(f'Count of {feature}')
    plt.show()
```

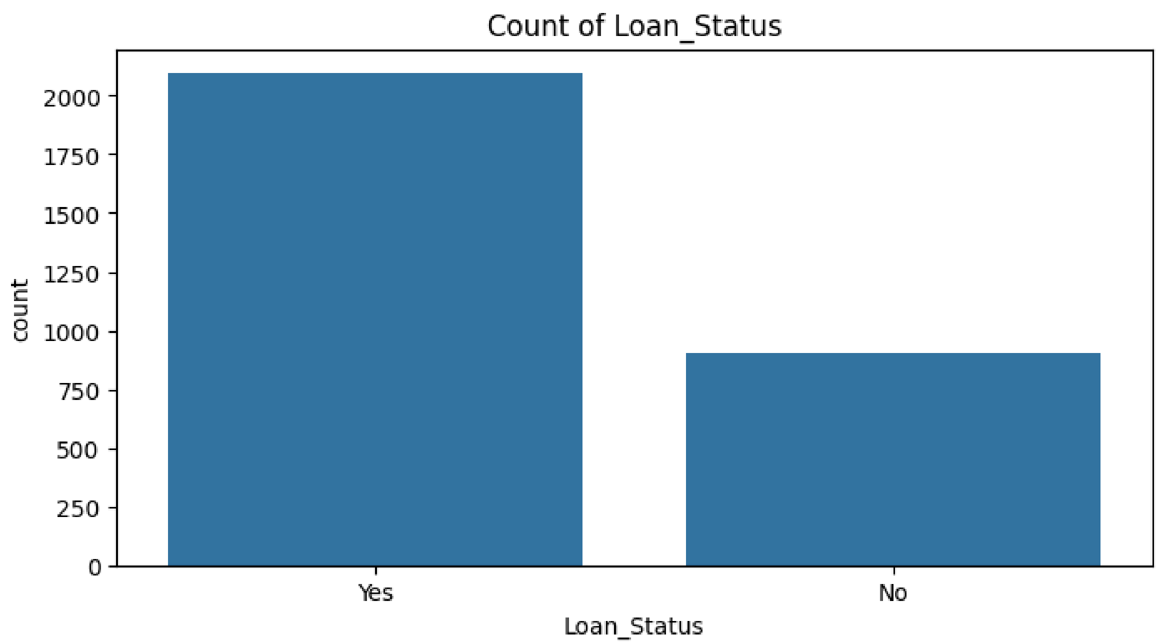

Count of Gender
count
1400
1200
1000
800
600
400
200
0
Male
Female
Gender


Count of Married
count
1400
1200
1000
800
600
400
200
0
No
Yes
Married


Count of Dependents
count
800
700
600
500
400
300
200
100
0
2
0
3+
1
Dependents

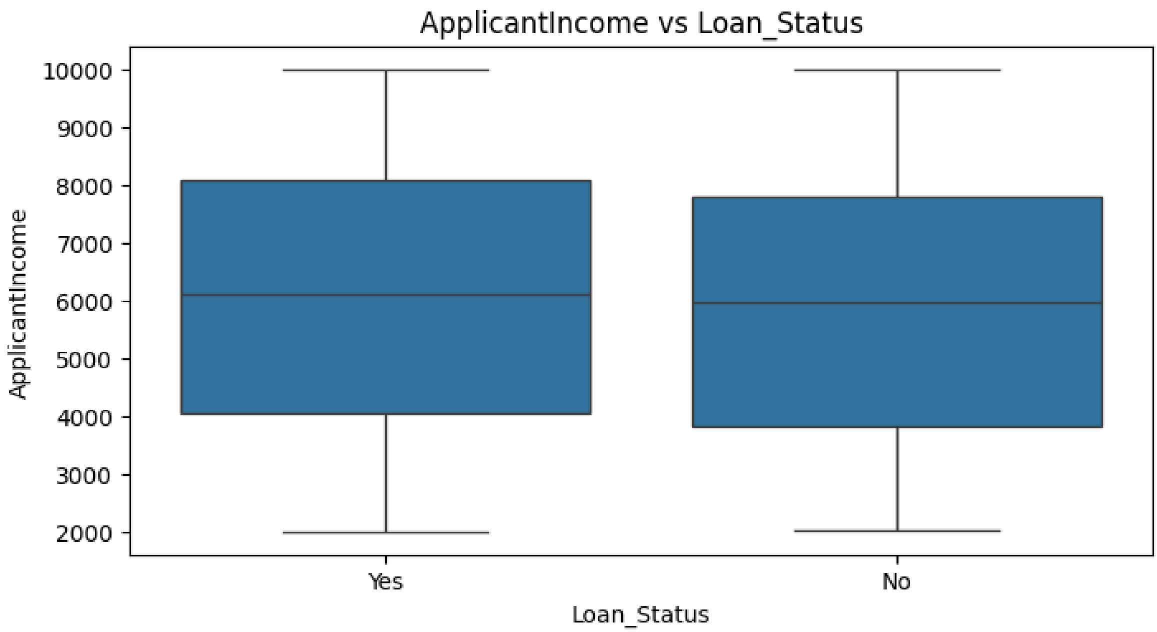

Count of Education
count
0
200
400
600
800
1000
1200
1400
Graduate
Not Graduate
Education

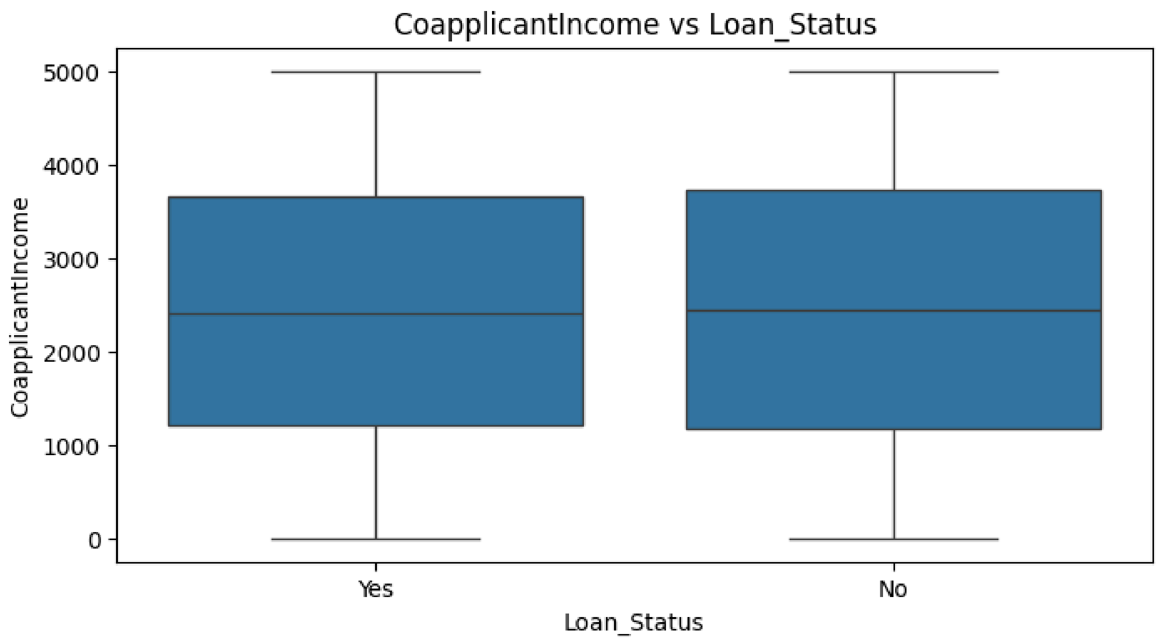

Count of SelfEmployed
count
0
200
400
600
800
1000
1200
1400
Yes
No
SelfEmployed

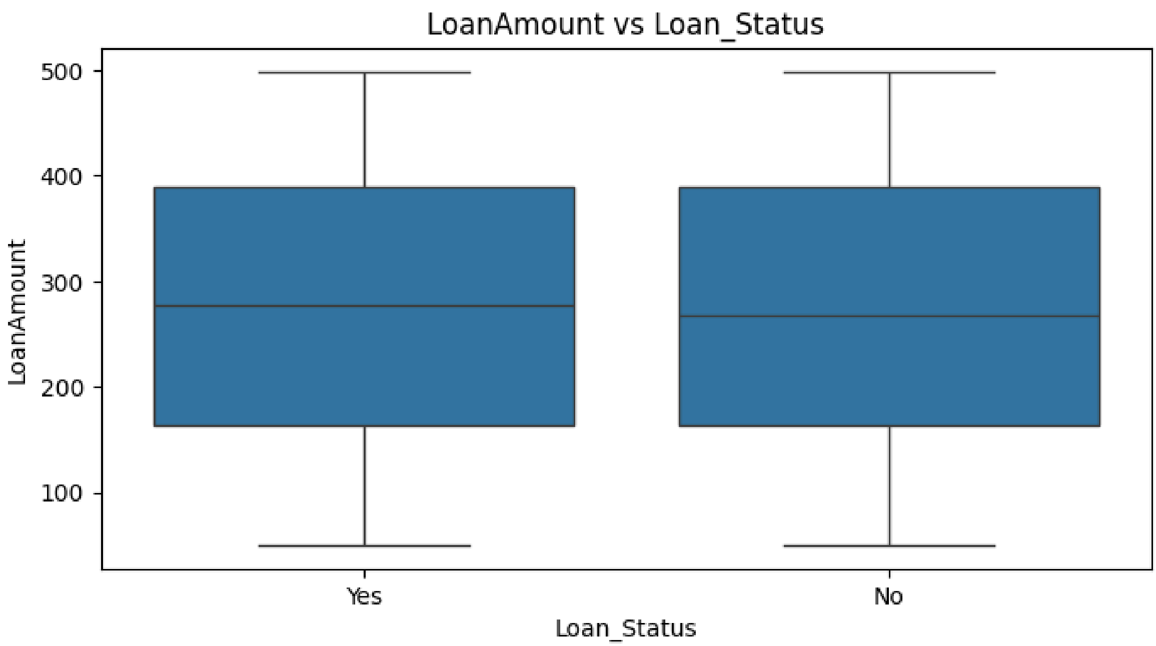

Count of Loan_Status
count
0
250
500
750
1000
1250
1500
1750
2000
Yes
No
Loan_Status

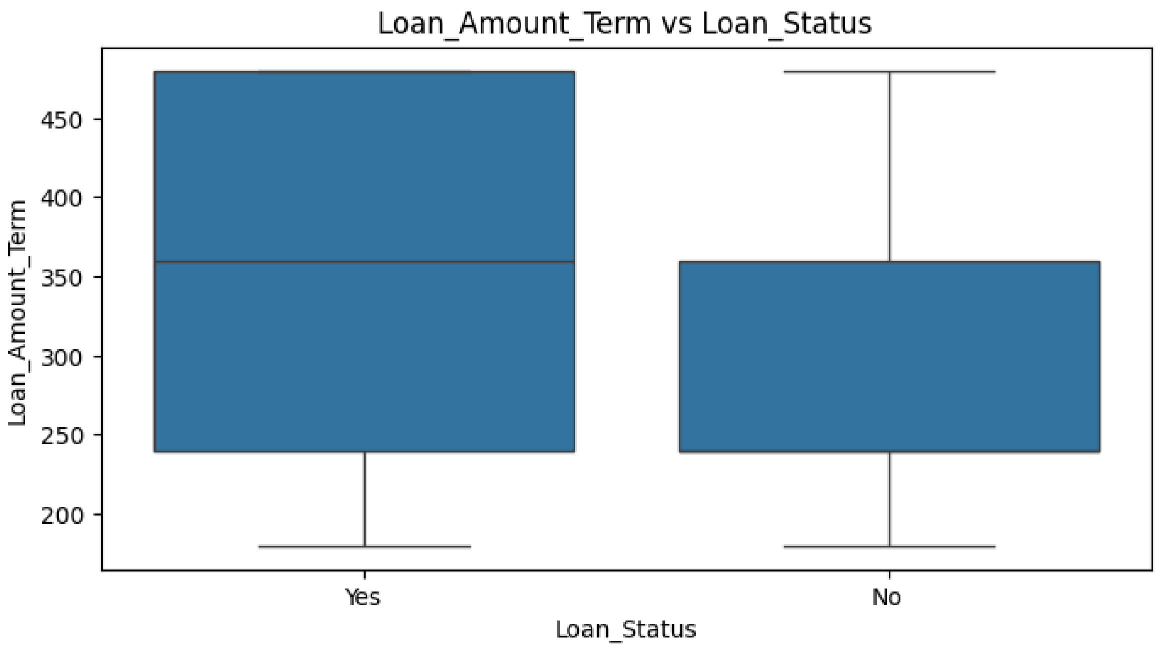
Bivariate Analysis(Num vs Loan status)

In [ ]:
```
# Boxplots for numerical features vs. Loan_Status
for column in ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amoun
    plt.figure(figsize=(8, 4))
    sns.boxplot(x=df['Loan_Status'], y=df[column])
    plt.title(f'{column} vs Loan_Status')
    plt.show()
```









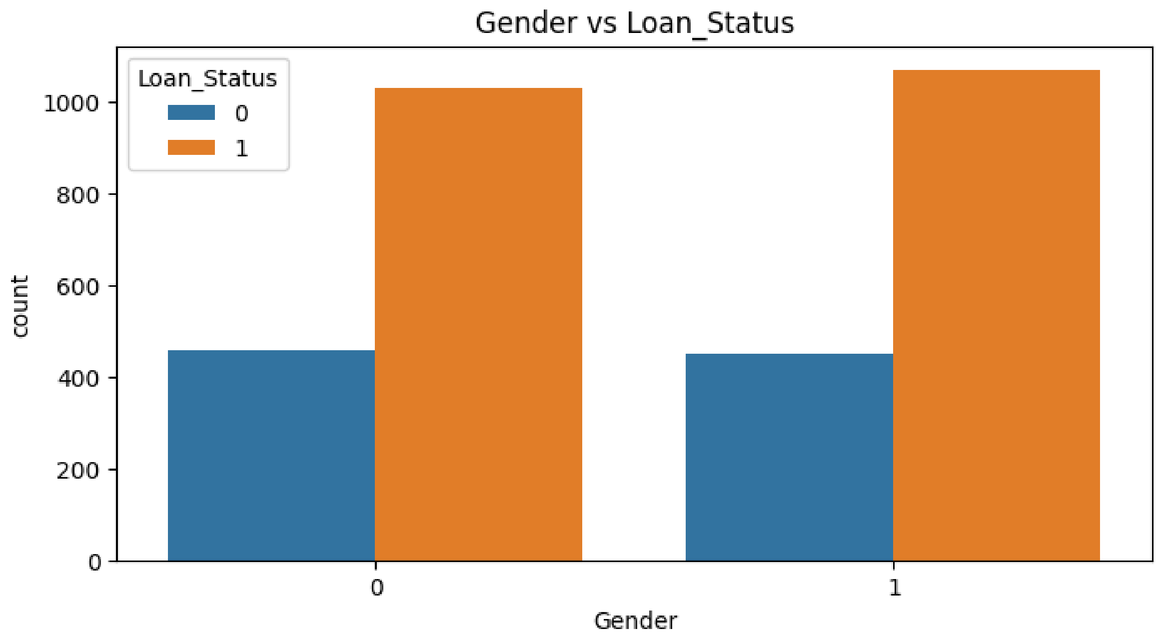
Level Encoding

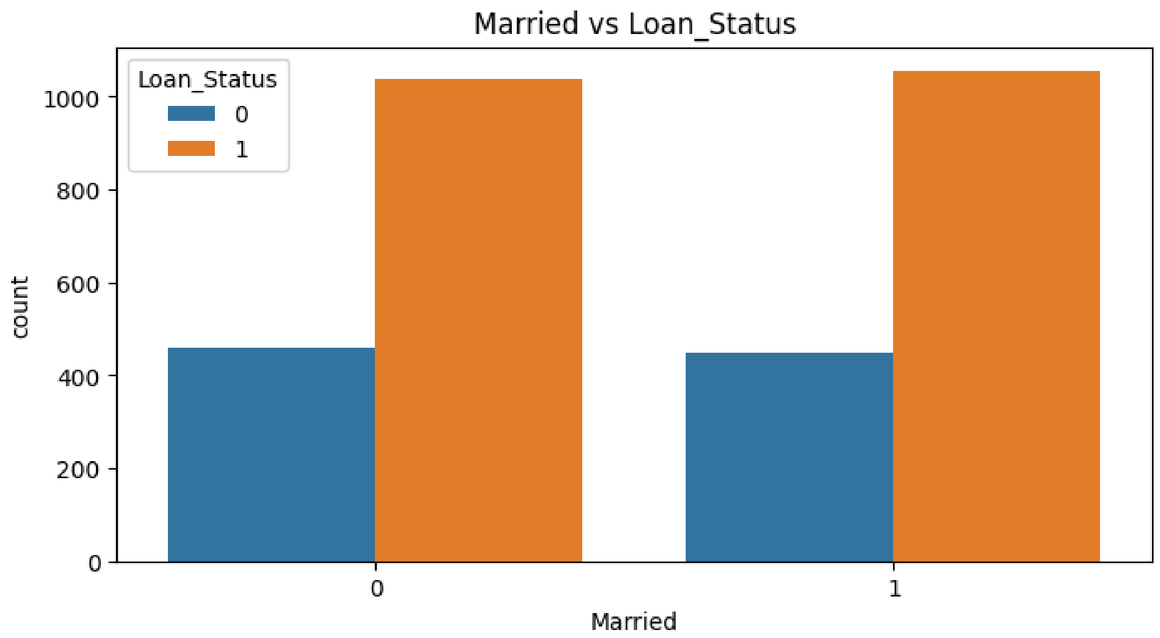
In [ ]:
```
df = df.drop(columns=['ApplicantID'])
```

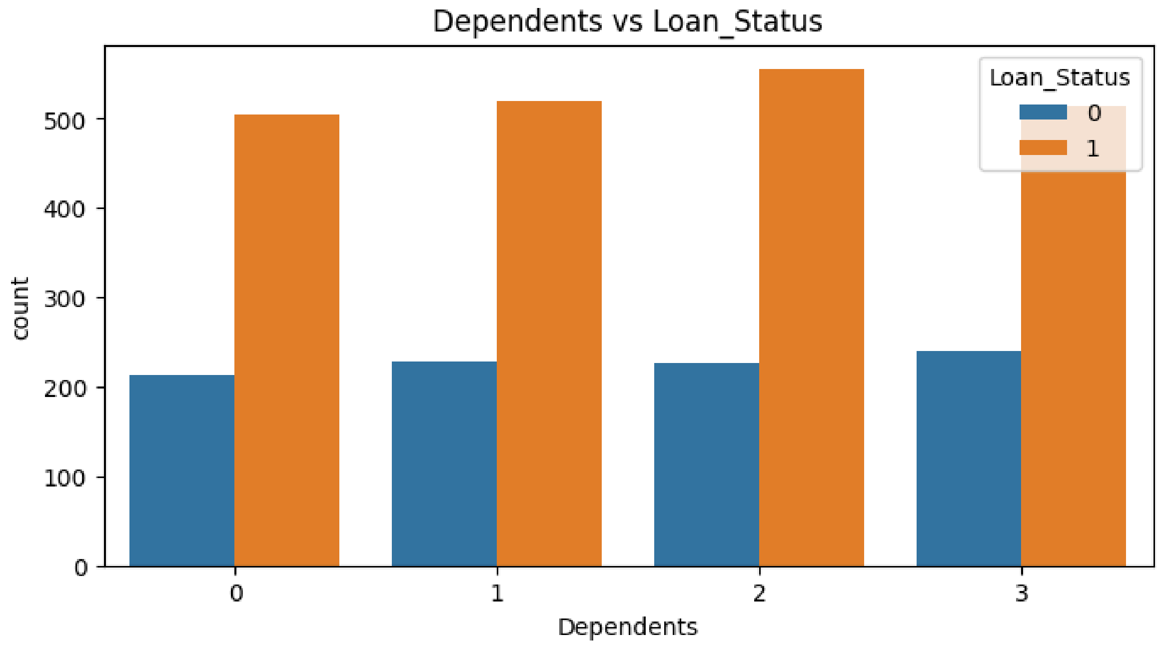
In [ ]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
df['Gender'] = le.fit_transform(df['Gender'])
df['Married'] = le.fit_transform(df['Married'])
df['Dependents'] = le.fit_transform(df['Dependents'])
df['Education'] = le.fit_transform(df['Education'])
df['SelfEmployed'] = le.fit_transform(df['SelfEmployed'])
df['Loan_Status'] = le.fit_transform(df['Loan_Status'])
```

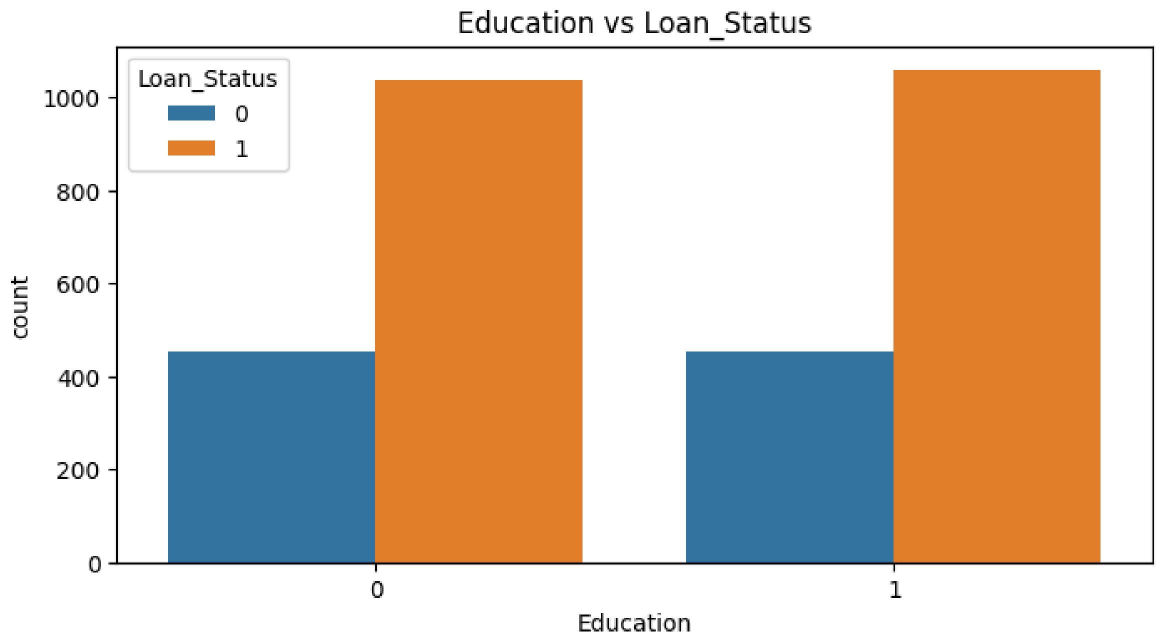
Bivariate Analysis (cat vs Loan status)

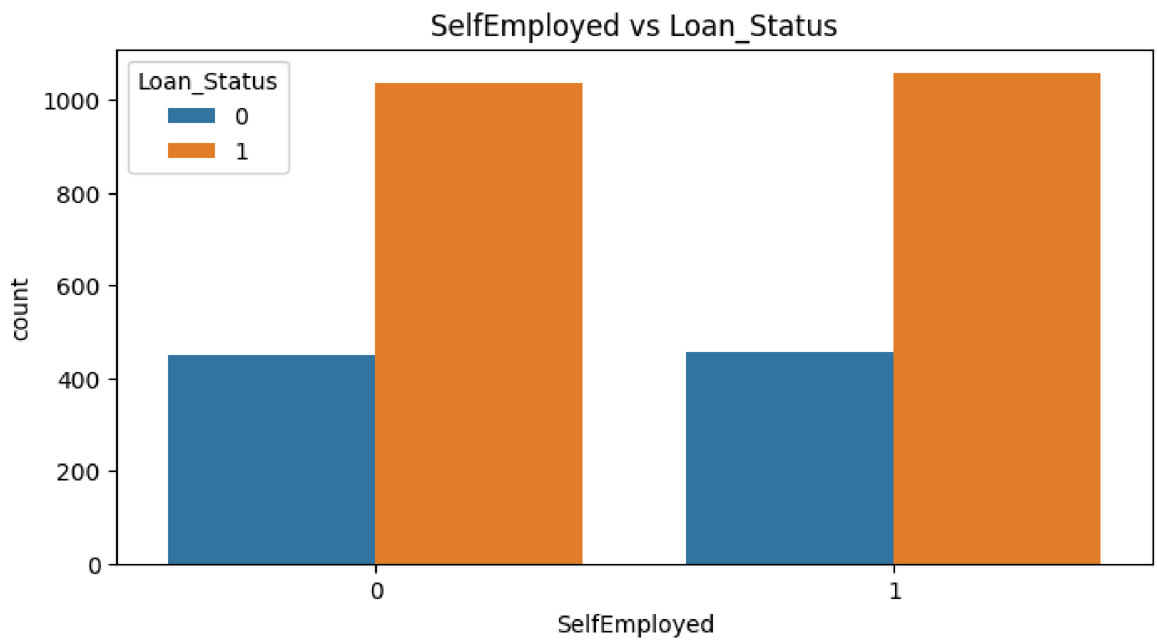
In [ ]:
```
# Count plots for categorical features vs. Loan_Status
for feature in categorical_features:
    plt.figure(figsize=(8, 4))
    sns.countplot(data=df, x=feature, hue='Loan_Status')
    plt.title(f'{feature} vs Loan_Status')
    plt.show()
```

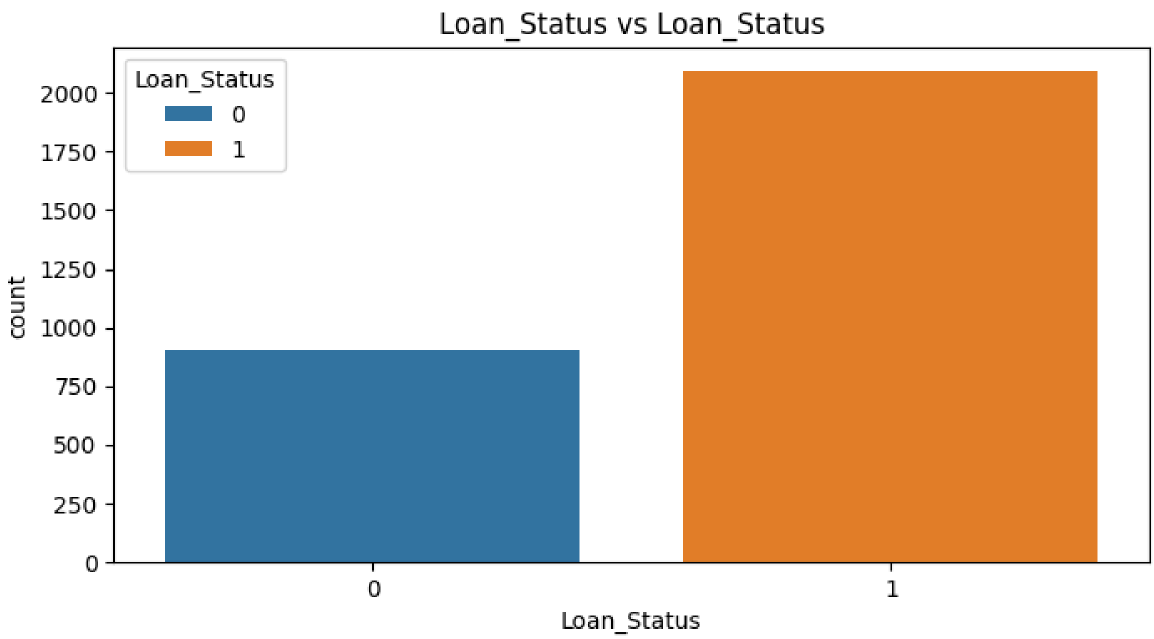





Dependents vs Loan_Status
count
0
100
200
300
400
500
0
1
2
3
Dependents
Loan_Status
0
1


Education vs Loan_Status
count
0
200
400
600
800
1000
0
1
Education
Loan_Status
0
1


SelfEmployed vs Loan_Status
count
0
200
400
600
800
1000
0
1
SelfEmployed
Loan_Status
0
1

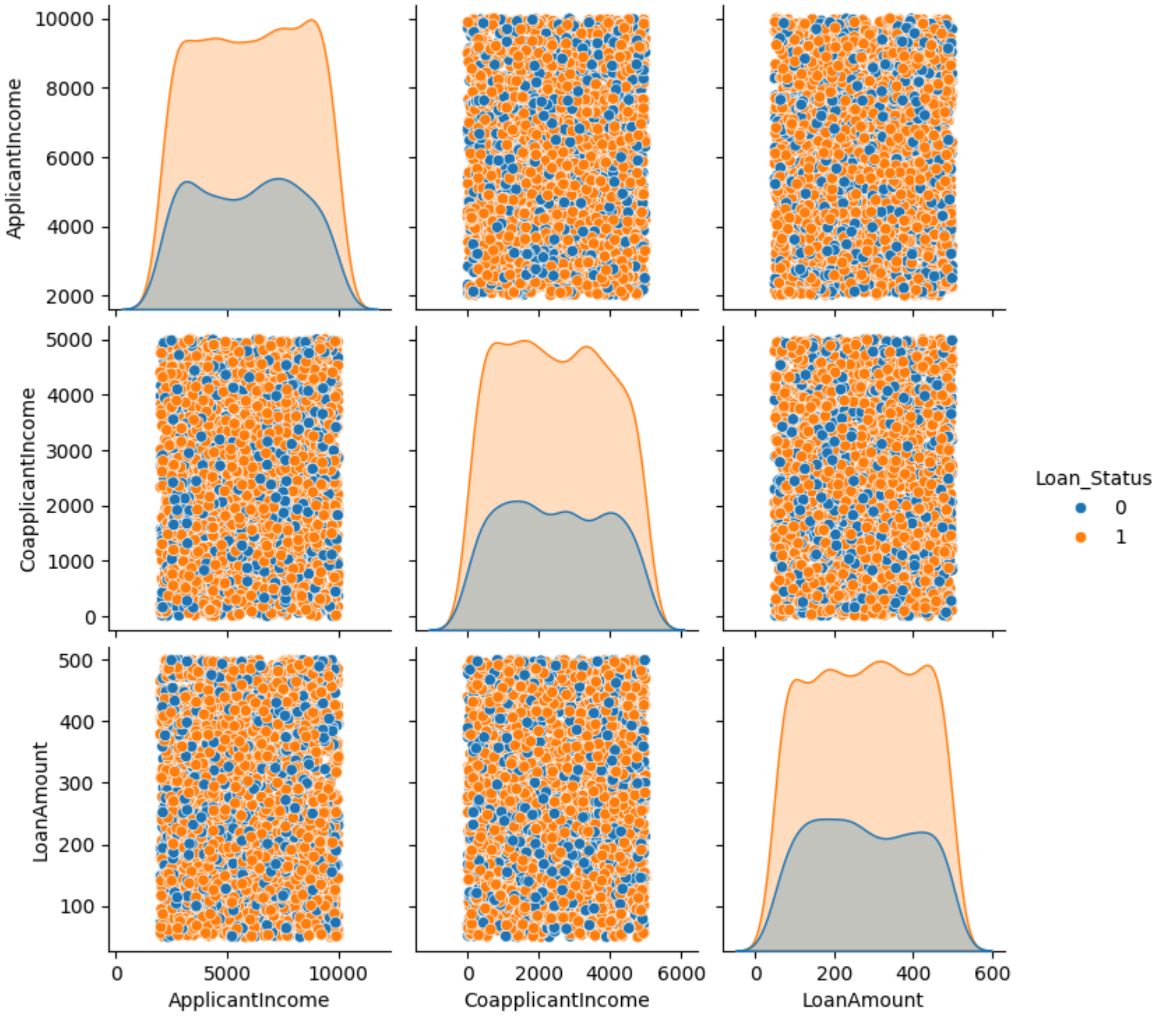


Pair Plot

In [ ]:

```
# Pairplot for some key features
sns.pairplot(df, hue='Loan_Status', vars=['ApplicantIncome', 'CoapplicantIncome'
plt.show()
```

```
c:\Users\aneek\AppData\Local\Programs\Python\Python39\lib\site-packages\seaborn\a
xisgrid.py:123: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Feature Engineering

In [ ]:
```
df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df['IncomeToLoanRatio'] = df['TotalIncome'] / df['LoanAmount']
df['LoanTermYears'] = df['Loan_Amount_Term'] / 12
df['Dependents'] = df['Dependents'].replace({'0': 0, '1': 1, '2': 2, '3+': 3})
```

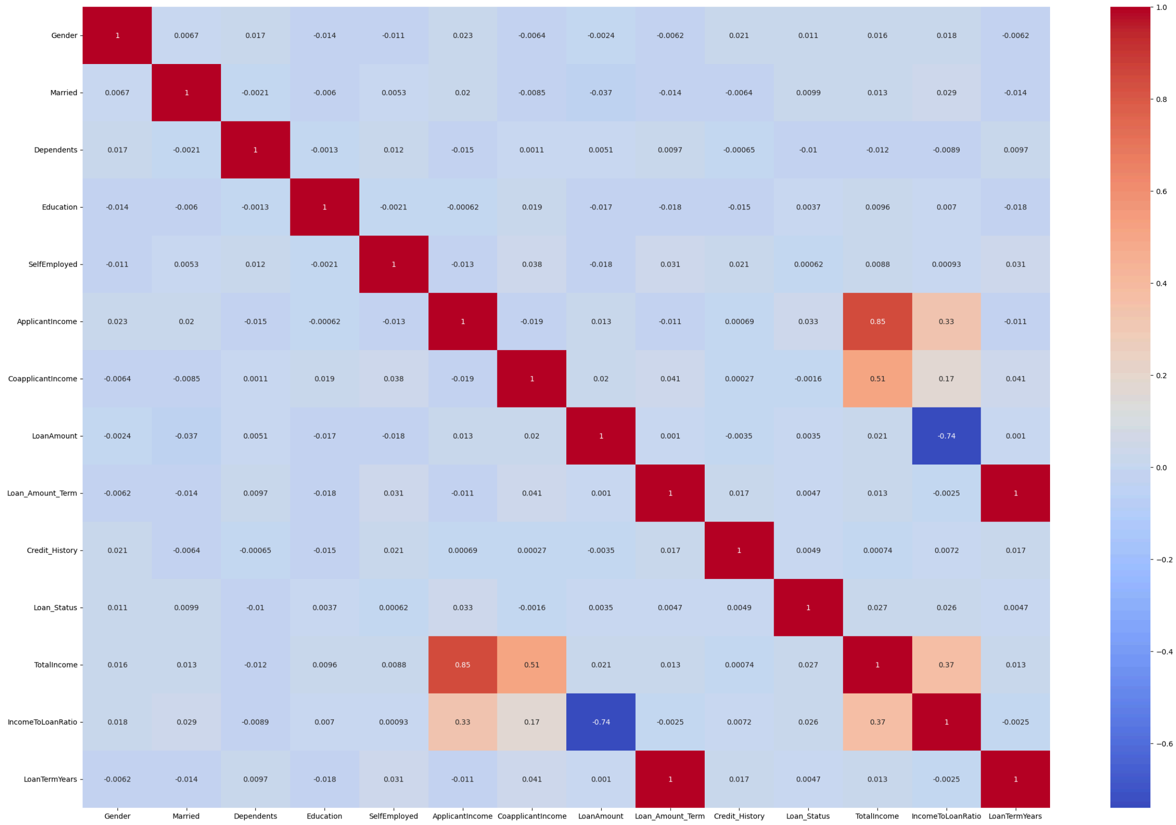
Scaling

In [ ]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
numerical_features = ['TotalIncome', 'LoanAmount', 'IncomeToLoanRatio', 'LoanTer
df[numerical_features] = scaler.fit_transform(df[numerical_features])
```

Multicolinearity Check

In [ ]:
```
correlation_matrix = df.corr()
print(correlation_matrix['Loan_Status'].sort_values(ascending=False))

import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(30, 20))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```

```
Loan_Status          1.000000
ApplicantIncome      0.032683
TotalIncome          0.027203
IncomeToLoanRatio    0.025949
Gender               0.011090
Married              0.009874
Credit_History       0.004864
LoanTermYears        0.004674
Loan_Amount_Term     0.004674
Education            0.003663
LoanAmount           0.003488
SelfEmployed         0.000625
CoapplicantIncome   -0.001550
Dependents          -0.010429
Name: Loan_Status, dtype: float64
```



In [ ]:
```
df = df.drop(columns=['ApplicantIncome', 'CoapplicantIncome', 'Loan_Amount_Term'
```

In [ ]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd

# Prepare a DataFrame for VIF calculation
X = df.drop(columns=['Loan_Status'])  # Exclude the target variable
X = pd.DataFrame(StandardScaler().fit_transform(X), columns=X.columns)  # Scale

# Calculate VIF
vif_data = pd.DataFrame()
vif_data['Feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape

print(vif_data)
```

```
            Feature       VIF
0            Gender  1.001721
1           Married  1.001929
2        Dependents  1.000730
3         Education  1.001461
4      SelfEmployed  1.002946
5        LoanAmount  2.869826
6    Credit_History  1.001488
7       TotalIncome  1.506634
8  IncomeToLoanRatio 3.329694
9     LoanTermYears  1.002171
```

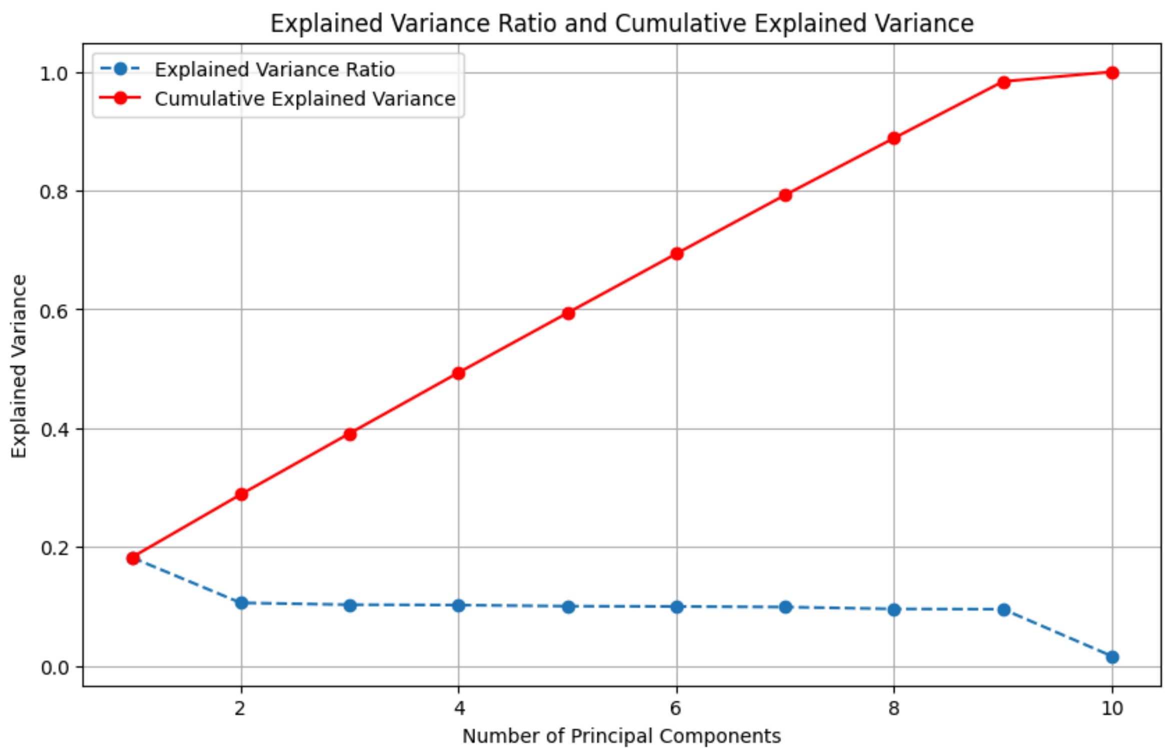
PCA

1. Prepare the Data

In [ ]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Drop the target variable for PCA
X = df.drop(columns=['Loan_Status'])

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

2. Apply PCA

In [ ]:
```
# Initialize PCA
pca = PCA()

# Fit PCA to the scaled data
X_pca = pca.fit_transform(X_scaled)

# Explained variance ratio for each principal component
explained_variance_ratio = pca.explained_variance_ratio_

# Cumulative explained variance
cumulative_explained_variance = explained_variance_ratio.cumsum()

# Plot explained variance ratio
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.plot(range(1, len(explained_variance_ratio) + 1), explained_variance_ratio,
plt.plot(range(1, len(cumulative_explained_variance) + 1), cumulative_explained_
plt.xlabel('Number of Principal Components')
plt.ylabel('Explained Variance')
plt.title('Explained Variance Ratio and Cumulative Explained Variance')
plt.legend()
plt.grid(True)
plt.show()
```



3. Determine the number of PCA

In [ ]:
```
# Determine the number of components to retain 95% variance
n_components = next(i for i, total in enumerate(cumulative_explained_variance) i
print(f'Number of components to retain 95% variance: {n_components}')
```

```
Number of components to retain 95% variance: 9
```

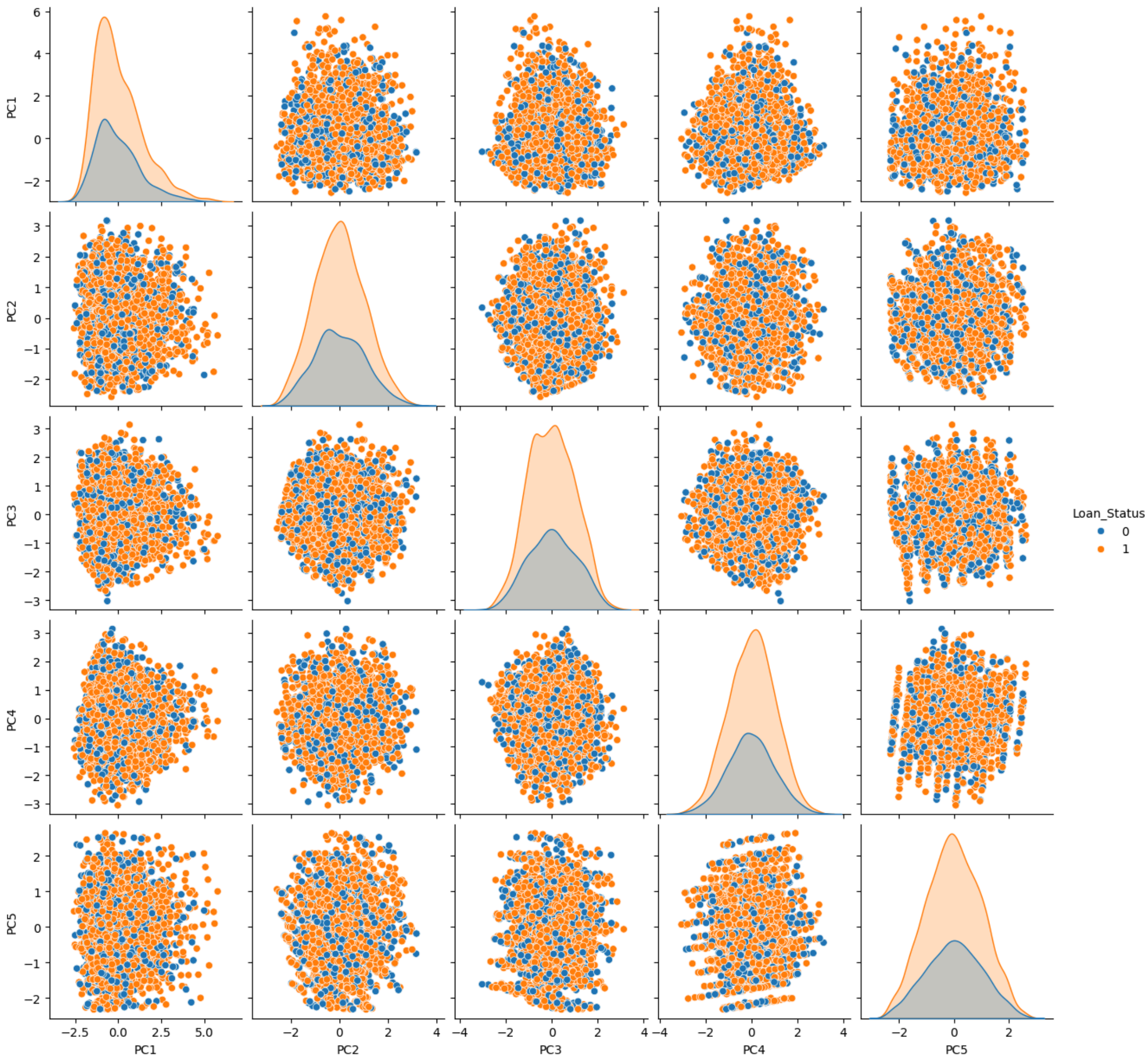
4. Transform the data as per PCA

In [ ]:
```
# Initialize PCA with the selected number of components
pca = PCA(n_components=n_components)

# Fit and transform the data
X_pca_selected = pca.fit_transform(X_scaled)

# Create a DataFrame for the principal components
pca_df = pd.DataFrame(X_pca_selected, columns=[f'PC{i+1}' for i in range(n_compo

# Append the target variable
pca_df['Loan_Status'] = df['Loan_Status'].values
```

5. Visualize Principle Component (Pair wise)

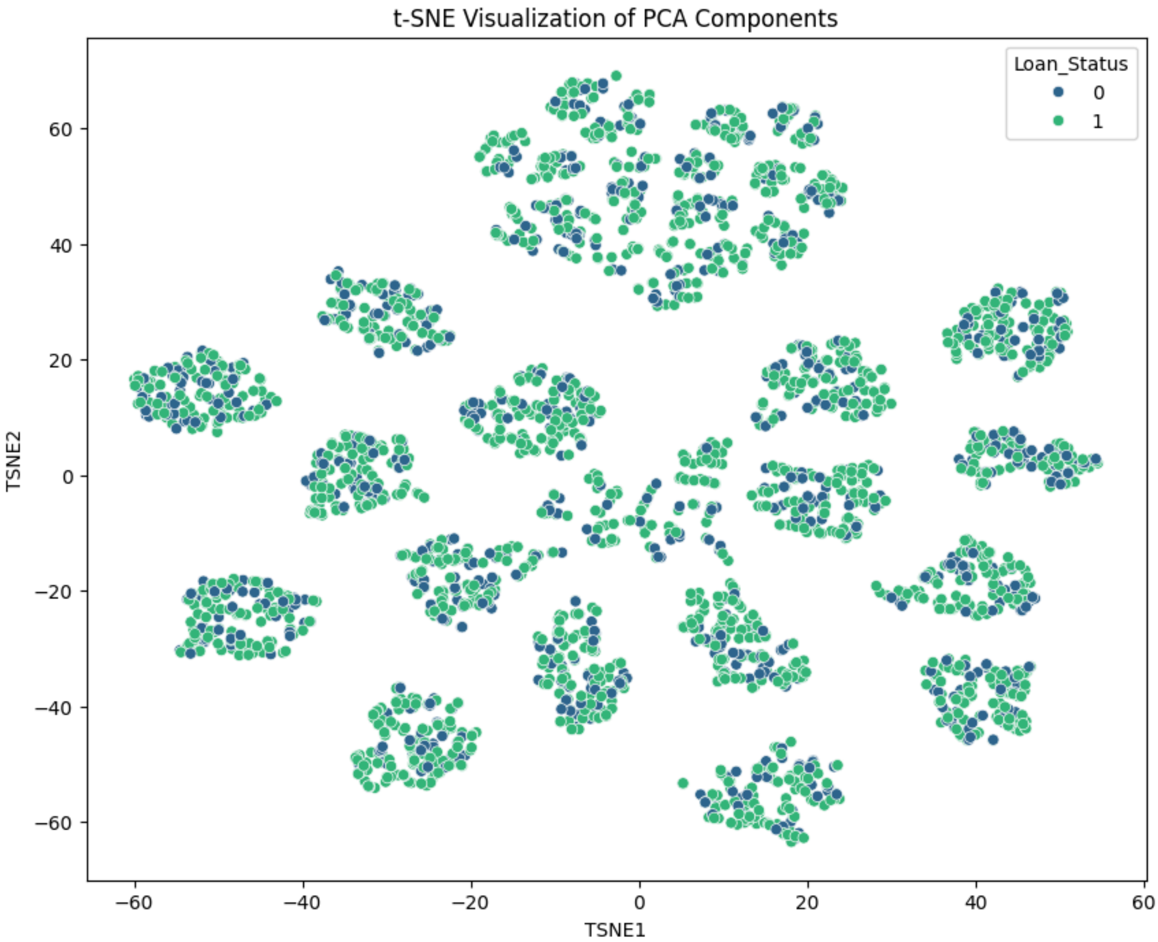
In [ ]:
```
# Pairplot for the first few principal components
import seaborn as sns

# Select the first few principal components for pairplot
pca_df_9_subset = pca_df[['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'Loan_Status']]

sns.pairplot(pca_df_9_subset, hue='Loan_Status')
plt.show()
```

```
c:\Users\aneek\AppData\Local\Programs\Python\Python39\lib\site-packages\seaborn\a
xisgrid.py:123: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



6. Visualize Principle Component (TSNE)

In [ ]:
```
from sklearn.manifold import TSNE

# Apply t-SNE to the PCA components
tsne = TSNE(n_components=2, random_state=42)
X_tsne = tsne.fit_transform(X_pca)

# Create a DataFrame for t-SNE results
tsne_df = pd.DataFrame(X_tsne, columns=['TSNE1', 'TSNE2'])
tsne_df['Loan_Status'] = df['Loan_Status'].values

# Plot t-SNE results
plt.figure(figsize=(10, 8))
sns.scatterplot(data=tsne_df, x='TSNE1', y='TSNE2', hue='Loan_Status', palette='
plt.title('t-SNE Visualization of PCA Components')
plt.show()
```



7. Analyze Component Loadings

In [ ]:
```
# Print the components to understand feature contributions
components_df = pd.DataFrame(pca.components_, columns=X.columns, index=[f'PC{i+1
print(components_df)
```

	Gender	Married	Dependents	Education	SelfEmployed	LoanAmount	\
PC1	0.022960	0.058194	-0.015487	0.021297	0.018147	-0.631594	
PC2	-0.196291	0.103568	-0.221514	0.342607	-0.468417	-0.070949	
PC3	-0.674177	-0.120211	-0.019411	0.224554	0.415660	-0.232446	
PC4	-0.264680	-0.324935	-0.370385	0.242175	0.015680	0.323596	
PC5	0.191753	-0.360162	0.745582	0.472001	0.004237	0.022234	
PC6	-0.059161	0.764809	0.211725	0.052023	0.363749	0.162205	
PC7	-0.158966	-0.135497	0.199157	-0.624297	-0.320835	-0.026557	
PC8	0.262547	0.279319	-0.186677	0.396867	-0.380513	-0.080153	
PC9	0.549422	-0.234008	-0.371344	-0.015568	0.476361	-0.080896	

	Credit_History	TotalIncome	IncomeToLoanRatio	LoanTermYears
PC1	0.009419	0.306534	0.708590	0.000840
PC2	-0.482855	-0.144204	0.000929	-0.553085
PC3	-0.113271	-0.421758	-0.009629	0.250254
PC4	-0.143626	0.671612	0.019023	0.226969
PC5	-0.218418	0.076742	0.014863	0.022533
PC6	-0.357929	0.274589	-0.036623	0.023593
PC7	-0.559832	-0.005094	0.033193	0.329819
PC8	-0.025165	-0.196243	-0.024737	0.685366
PC9	-0.493384	-0.166921	-0.011748	-0.018553

Model Building

In [ ]:
```
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

# Features and target variable
X = df.drop(columns=['Loan_Status'])
y = df['Loan_Status']
# Split the data
X_res, y_res = SMOTE(random_state=42).fit_resample(X, y)
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.2,
```

In [ ]:
```
print(f'Training data shape: X_train: {X_train.shape}, y_train: {y_train.shape}'
print(f'Testing data shape: X_test: {X_test.shape}, y_test: {y_test.shape}')
```

```
Training data shape: X_train: (3348, 10), y_train: (3348,)
Testing data shape: X_test: (838, 10), y_test: (838,)
```

1. Basic - Logistic Regression

In [ ]:
```
from sklearn.linear_model import LogisticRegression
# Initialize the Logistic Regression model
log_reg = LogisticRegression(class_weight='balanced', random_state=42)

# Fit the model
log_reg.fit(X_train, y_train)

# Predict on test data
y_pred = log_reg.predict(X_test)
```

2. Intermediate - Random Forest

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

# Initialize the Random Forest model
rf_model = RandomForestClassifier(class_weight='balanced', random_state=42)

# Fit the model
rf_model.fit(X_train, y_train)

# Predict on test data
y_pred_rf = rf_model.predict(X_test)
```

3. Advance - GBM

In [ ]:
```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import classification_report,confusion_matrix
# Initialize the Gradient Boosting model
gb_model = GradientBoostingClassifier(random_state=42)

# Fit the model
gb_model.fit(X_train, y_train)

# Predict on test data
y_pred_gb = gb_model.predict(X_test)

# Evaluate the model
```

```
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_gb))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_gb))
```

```
Confusion Matrix:
[[188 241]
 [ 72 337]]

Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.44      0.55       429
           1       0.58      0.82      0.68       409

    accuracy                           0.63       838
   macro avg       0.65      0.63      0.61       838
weighted avg       0.65      0.63      0.61       838
```

In [ ]:

```
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_sc

# Define the models
models = {
    'Decision Tree': DecisionTreeClassifier(max_depth=100,random_state=46,class_
    'Random Forest': RandomForestClassifier(max_depth=100, random_state=46, clas
    'GBM': GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, rando
    'Support Vector Classifier': SVC(probability=True, random_state=46, class_we
    'Logistic Regression': LogisticRegression(random_state=46, max_iter=10000, c
}

# Dictionary to store model performance
performance = {}

# Evaluate each model
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:, 1]  # For probability-based metrics

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='macro')
    recall = recall_score(y_test, y_pred, average='macro')
    precision = precision_score(y_test, y_pred, average='macro')
    kappa = cohen_kappa_score(y_test, y_pred)
    mcc = matthews_corrcoef(y_test, y_pred)

    # PR AUC
    precision_curve, recall_curve, _ = precision_recall_curve(y_test, y_prob)
    pr_auc = auc(recall_curve, precision_curve)

    # ROC AUC
    roc_auc = roc_auc_score(y_test, y_prob)

    # Store the performance
```

```
    performance[model_name] = {
        'Accuracy': accuracy,
        'F1 Score': f1,
        'Recall': recall,
        'Precision': precision,
        'Cohen Kappa Score': kappa,
        'PR AUC': pr_auc,
        'ROC AUC': roc_auc,
        'MCC': mcc,
    }

# Find the best and second-best models based on each metric
best_models = {}
second_best_models = {}

for metric in performance[list(models.keys())[0]].keys():
    sorted_models = sorted(performance.items(), key=lambda x: x[1][metric], reve
    best_model = sorted_models[0]
    second_best_model = sorted_models[1]

    best_models[metric] = (best_model[0], best_model[1][metric])
    second_best_models[metric] = (second_best_model[0], second_best_model[1][met

print("\nBest Models Based on Each Metric:")
for metric, (best_model, score) in best_models.items():
    print(f"{metric}: {best_model} with {score:.4f}")

print("\nSecond Best Models Based on Each Metric:")
for metric, (second_best_model, score) in second_best_models.items():
    print(f"{metric}: {second_best_model} with {score:.4f}")


print(f1_score)
```

```
Best Models Based on Each Metric:
Accuracy: Random Forest with 0.7088
F1 Score: Random Forest with 0.7088
Recall: Random Forest with 0.7091
Precision: Random Forest with 0.7090
Cohen Kappa Score: Random Forest with 0.4179
PR AUC: Decision Tree with 0.7310
ROC AUC: Random Forest with 0.7787
MCC: Random Forest with 0.4182

Second Best Models Based on Each Metric:
Accuracy: Decision Tree with 0.6516
F1 Score: Decision Tree with 0.6515
Recall: Decision Tree with 0.6515
Precision: GBM with 0.6531
Cohen Kappa Score: Decision Tree with 0.3029
PR AUC: Random Forest with 0.7145
ROC AUC: GBM with 0.6724
MCC: Decision Tree with 0.3030
<function f1_score at 0x0000027AE12D0C10>
```

Tunning

In [ ]:
```
from sklearn.model_selection import GridSearchCV
```

```
# Define the hyperparameter space
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 5, 10],
    'max_features': ['sqrt', 'log2']  # Set max_features to a valid value
}

# Perform grid search
grid_search = GridSearchCV(rf_model, param_grid, cv=5, scoring='f1_macro')
grid_search.fit(X_train, y_train)

# Print the best hyperparameters and the corresponding score
print("Best Hyperparameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)
```

```
Best Hyperparameters: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_le
af': 1, 'min_samples_split': 2, 'n_estimators': 300}
Best Score: 0.73143402925274
```

Evaluation

Data Exploration and Preprocessing The dataset is explored using various visualization techniques, including histograms, box plots, and count plots. The data is preprocessed by encoding categorical variables, scaling numerical features, and handling missing values.

Feature Engineering

New features are created, including TotalIncome, IncomeToLoanRatio, and LoanTermYears, to capture more information about the applicants and loans.

Model Building and Evaluation

Three machine learning models are built: Logistic Regression, Random Forest, and Gradient Boosting Machine (GBM). The models are evaluated using various metrics, including accuracy, F1 score, precision, recall, and ROC-AUC. The best model is selected based on the F1 score, which is a balanced measure of precision and recall.

Results The best model is the Random Forest model, with an F1 score of 0.7088. The GBM model is the second-best model, with an F1 score of 0.6531. The Logistic Regression model performs poorly, with an F1 score of 0.5519.

Hyperparameter Tuning

Hyperparameter tuning is performed using GridSearchCV for the Random Forest model. The best hyperparameters are selected based on the F1 score, which results in an improved F1 score of 0.7314. Interpretation and Insights

The Random Forest model is the most effective in predicting loan approvals, with an F1 score of 0.7314. The GBM model is a close second, but its performance is not as stable as the Random Forest model. The Logistic Regression model is not suitable for this problem, likely due to its simplicity and lack of ability to capture complex relationships. The feature engineering step helps to improve the model performance, particularly the creation of

IncomeToLoanRatio and LoanTermYears features. The hyperparameter tuning step further improves the performance of the Random Forest model.

Interpretation

Business Insights

@ The loan approval prediction model can be used to automate the loan approval process, reducing the time and cost associated with manual reviews.

@ The model can help to identify high-risk applicants and reduce the likelihood of defaults.

@ The feature importance analysis can provide insights into the most critical factors affecting loan approvals, which can inform business decisions and policy changes.

@ The model can be used to optimize loan offerings and pricing strategies based on applicant profiles and credit history.

Final Outcome

1. Introduction Loan approval prediction problem Importance of accurate prediction

2. Data Exploration and Preprocessing

Data visualization and summary statistics Feature encoding and scaling Handling missing values

3. Feature Engineering

Creation of new features: TotalIncome, IncomeToLoanRatio, and LoanTermYears

4. Model Building and Evaluation

Three machine learning models: Logistic Regression, Random Forest, and GBM Evaluation metrics: accuracy, F1 score, precision, recall, and ROC-AUC Model selection based on F1 score

5. Hyperparameter Tuning

GridSearchCV for Random Forest model Best hyperparameters selection based on F1 score

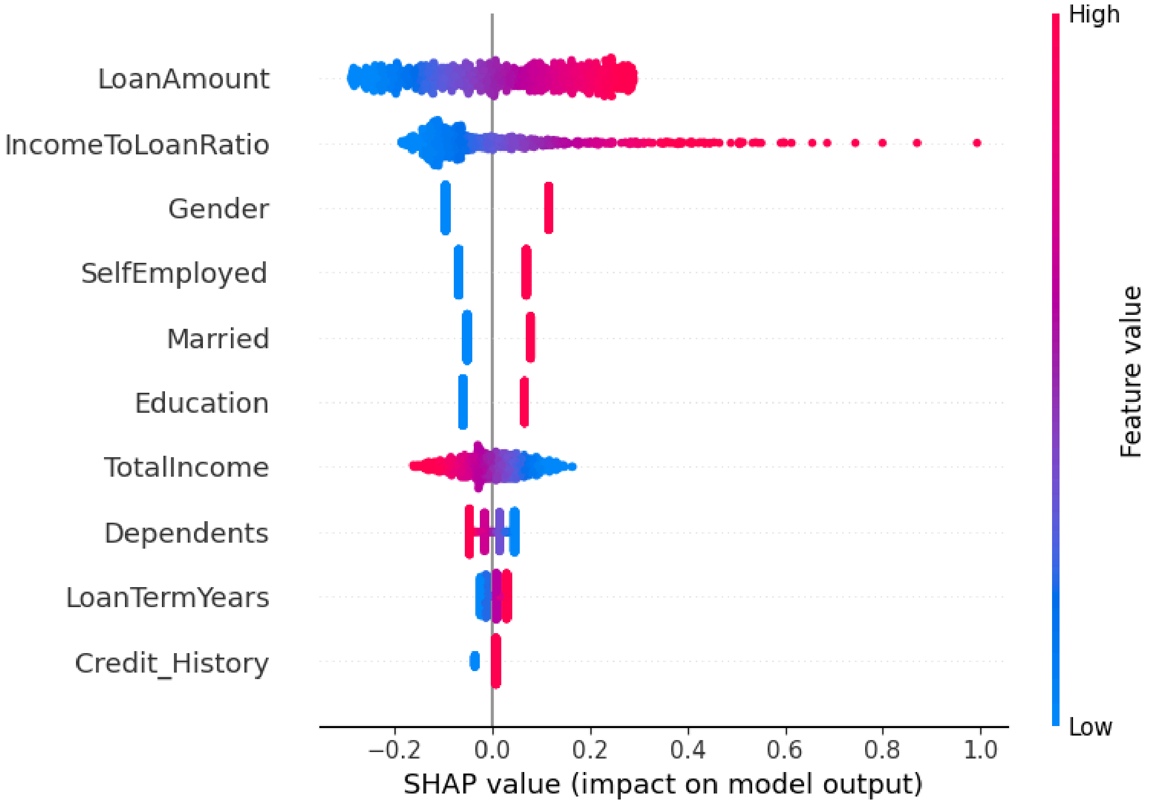
6. Results and Interpretation

Best model: Random Forest with F1 score of 0.7314 Feature importance analysis Business insights and implications

7. Conclusion

Summary of key findings Recommendations for business stakeholders Future work and potential improvements

In [ ]:
```
import shap

# Initialize the SHAP explainer for a linear model
explainer = shap.LinearExplainer(model, X_train)

# Calculate SHAP values for the test set
shap_values = explainer.shap_values(X_test)

# Summary plot to show feature importance
shap.summary_plot(shap_values, X_test)
```



Interpretation

LoanAmount: It is the most significant feature affecting the loan approval prediction. The higher the loan amount (indicated by red), the more likely it is to push the model towards rejecting the loan.

IncomeToLoanRatio: This feature also has a significant impact. Higher ratios (indicated by red) appear to increase the chances of loan approval, while lower ratios (indicated by blue) are associated with rejection.

Credit_History: This feature is crucial as well. The plot suggests that having a credit history (likely a binary feature) increases the likelihood of loan approval.

TotalIncome: Higher total income (red) positively influences the approval decision, while lower incomes (blue) tend to have the opposite effect.

In [ ]:
```
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
```

```
# Example training data (replace with your actual data)
X_train = np.array([
    [100000, 0.2, 1, 0, 1, 1, 50000, 0, 10, 1],
    [200000, 0.3, 0, 1, 0, 0, 80000, 1, 15, 1],
    # Add more training samples here
])
y_train = np.array([1, 0])  # Labels: 1 = Approved, 0 = Rejected

# Step 1: Fit the scaler on the training data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

# Step 2: Train the model on the scaled data
model = LogisticRegression()
model.fit(X_train_scaled, y_train)

# Step 3: Define the prediction function
def predict_loan_approval(model, scaler, feature_input):
    """
    Predict whether a loan will be approved or not.
    """
    # Extract the feature values in the correct order
    features = np.array([
        feature_input['LoanAmount'],
        feature_input['IncomeToLoanRatio'],
        feature_input['Gender'],
        feature_input['SelfEmployed'],
        feature_input['Married'],
        feature_input['Education'],
        feature_input['TotalIncome'],
        feature_input['Dependents'],
        feature_input['LoanTermYears'],
        feature_input['Credit_History']
    ]).reshape(1, -1)

    # Normalize the input features using the fitted scaler
    features_scaled = scaler.transform(features)

    # Make the prediction
    prediction = model.predict(features_scaled)

    # Convert numeric prediction to human-readable output
    return 'Approved' if prediction == 1 else 'Rejected'

# Example of usage
example_input = {
    'LoanAmount': 120000,
    'IncomeToLoanRatio': 0.25,
    'Gender': 1,  # Assume 1 = Male, 0 = Female
    'SelfEmployed': 0,  # 0 = No, 1 = Yes
    'Married': 1,  # 1 = Married, 0 = Not Married
    'Education': 1,  # 1 = Graduate, 0 = Not Graduate
    'TotalIncome': 60000,
    'Dependents': 0,
    'LoanTermYears': 15,
    'Credit_History': 1  # 1 = Has Credit History, 0 = No Credit History
}

# Predict loan approval status
```

```
loan_status = predict_loan_approval(model, scaler, example_input)
print(f"Loan Status: {loan_status}")
```

```
Loan Status: Approved
```