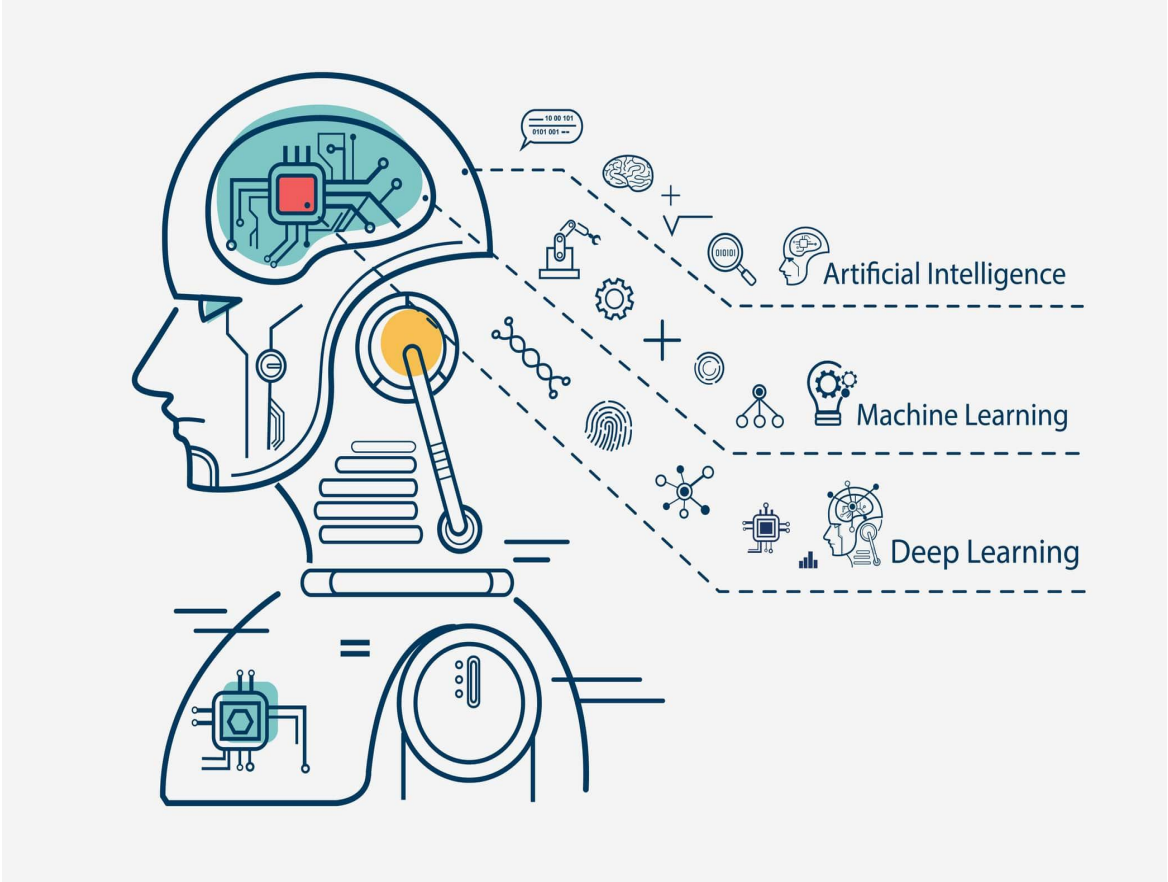
Loan Status Eligibility Prediction Using Machine Learning

- RISHI RAJ
(Analyst Task Report)



Problem Statement

- The objective of this project is to develop a machine learning model to predict loan approval status based on applicant details and financial information.
- The project involves preprocessing the data, performing exploratory data analysis, engineering features, selecting and evaluating classification models, and optimizing hyperparameters.
- The deliverables include a detailed report of the entire process, the trained predictive model with performance metrics, and a deployable version of the model.

Column Details

1. Loan_ID : Unique Loan ID
2. Gender : Male/ Female
3. Married : Applicant married (Y/N)
4. Dependents : Number of dependents
5. Education : Applicant Education (Graduate/ Under Graduate)
6. Self_Employed : Self employed (Y/N)
7. ApplicantIncome : Applicant income
8. CoapplicantIncome : Coapplicant income
9. LoanAmount : Loan amount in thousands of dollars
10. Loan_Amount_Term : Term of loan in months
11. Credit_History : Credit history meets guidelines yes or no
12. Property_Area : Urban/ Semi Urban/ Rural
13. Loan_Status : Loan approved (Y/N) this is the target variable

About Datasets

```
<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
```

`data.info()`

`data.dtypes`

```
Loan_ID              object
Gender               object
Married              object
Dependents           object
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
```

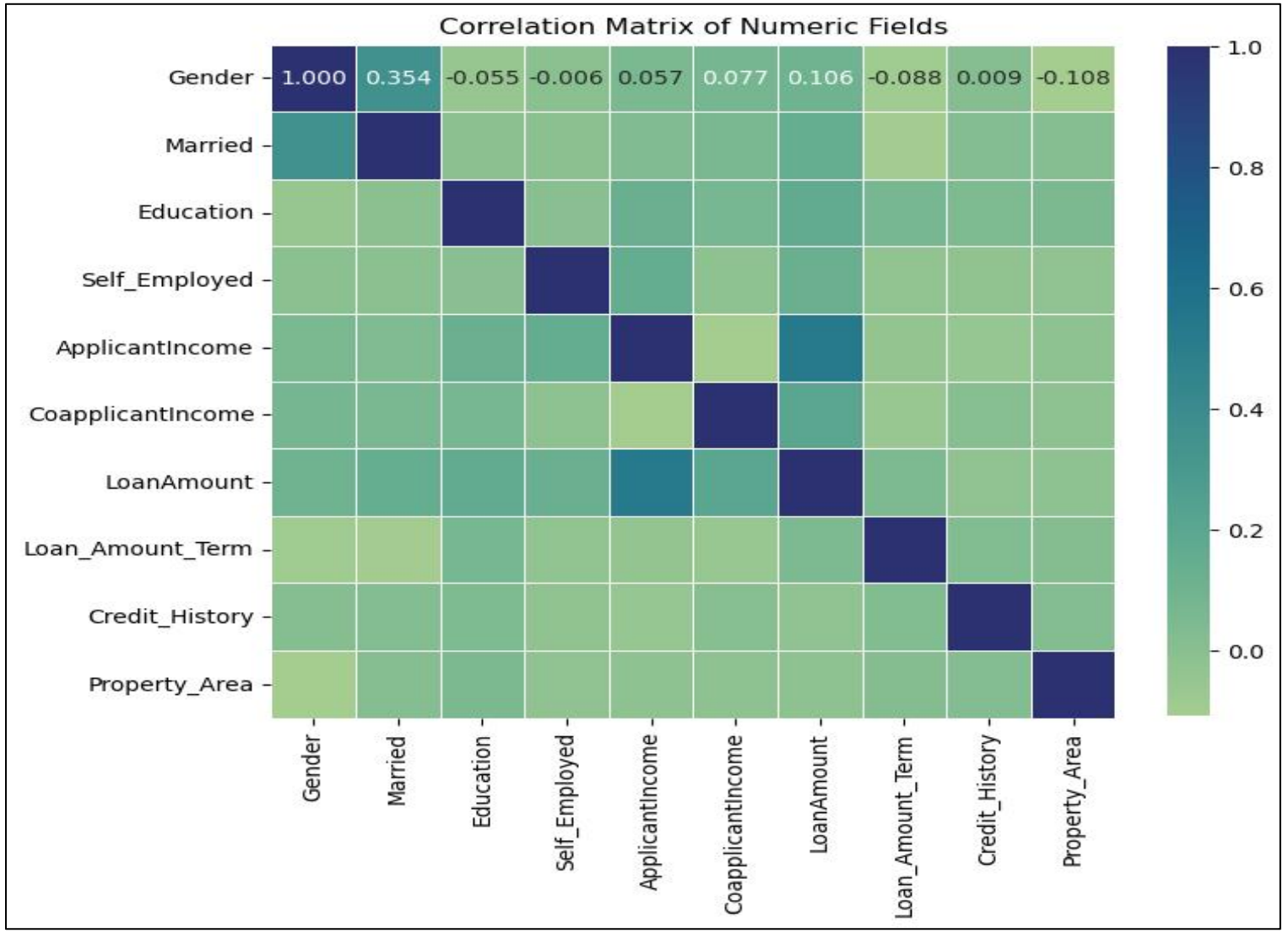
Workflow Overview

1. Data Reading
2. Data Exploration
3. Data Visualization and Analysis
4. Data Preparation and Data Scaling
5. Train Test Split of Data
6. Model Training
7. Model Prediction and Accuracy Metrics
8. Building a GUI Application

Read Data and Analyse

```
<class 'pandas.core.frame.DataFrame'>
Index: 553 entries, 1 to 613
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gender             553 non-null    int32
 1   Married            553 non-null    int32
 2   Dependents         553 non-null    object
 3   Education          553 non-null    int32
 4   Self_Employed      553 non-null    int32
 5   ApplicantIncome    553 non-null    int64
 6   CoapplicantIncome  553 non-null    float64
 7   LoanAmount         553 non-null    float64
 8   Loan_Amount_Term   553 non-null    float64
 9   Credit_History     553 non-null    float64
 10  Property_Area      553 non-null    int32
dtypes: float64(4), int32(5), int64(1), object(1)
memory usage: 41.0+ KB
```

Dataset Info



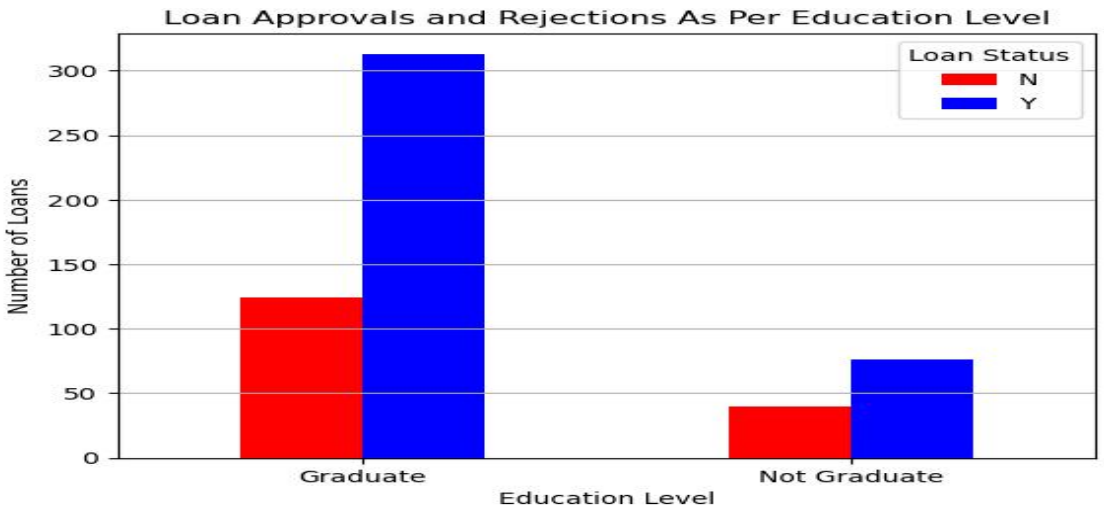
Correlation Matrix of Dataset Fields

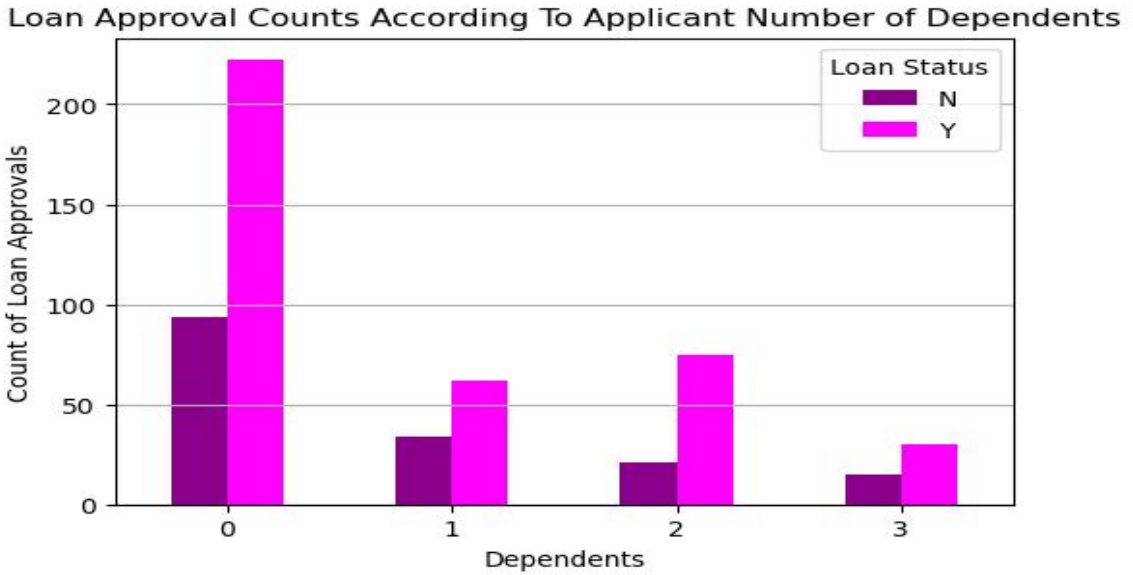
Data Exploration and Correction

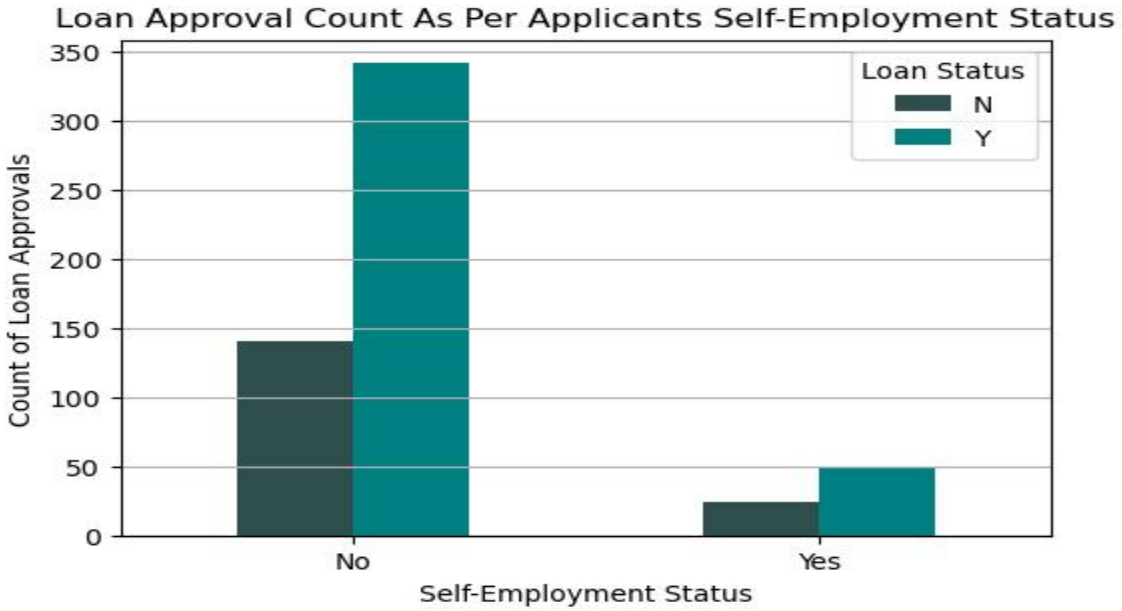
Important Steps:-

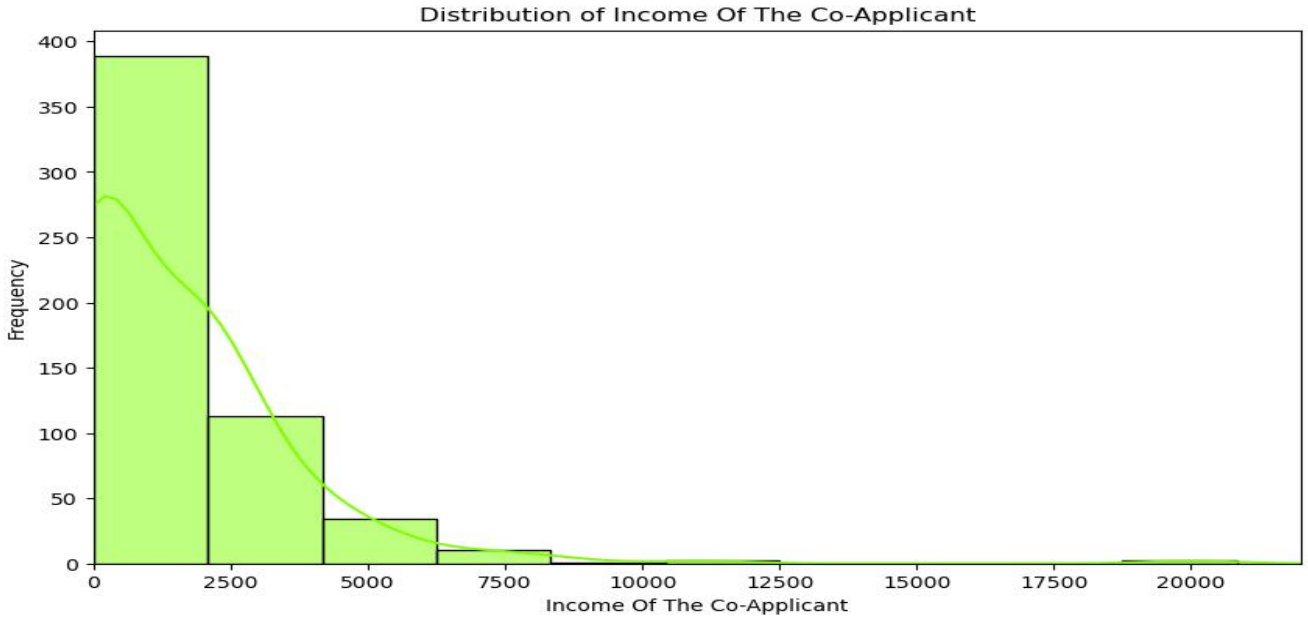
1. Checking Data Types of columns.
2. Checking for null values.
3. Correlation among data.
4. Getting descriptive statistics of the data.
5. Removing some negative values

Data Analysis: Plotting and Charting

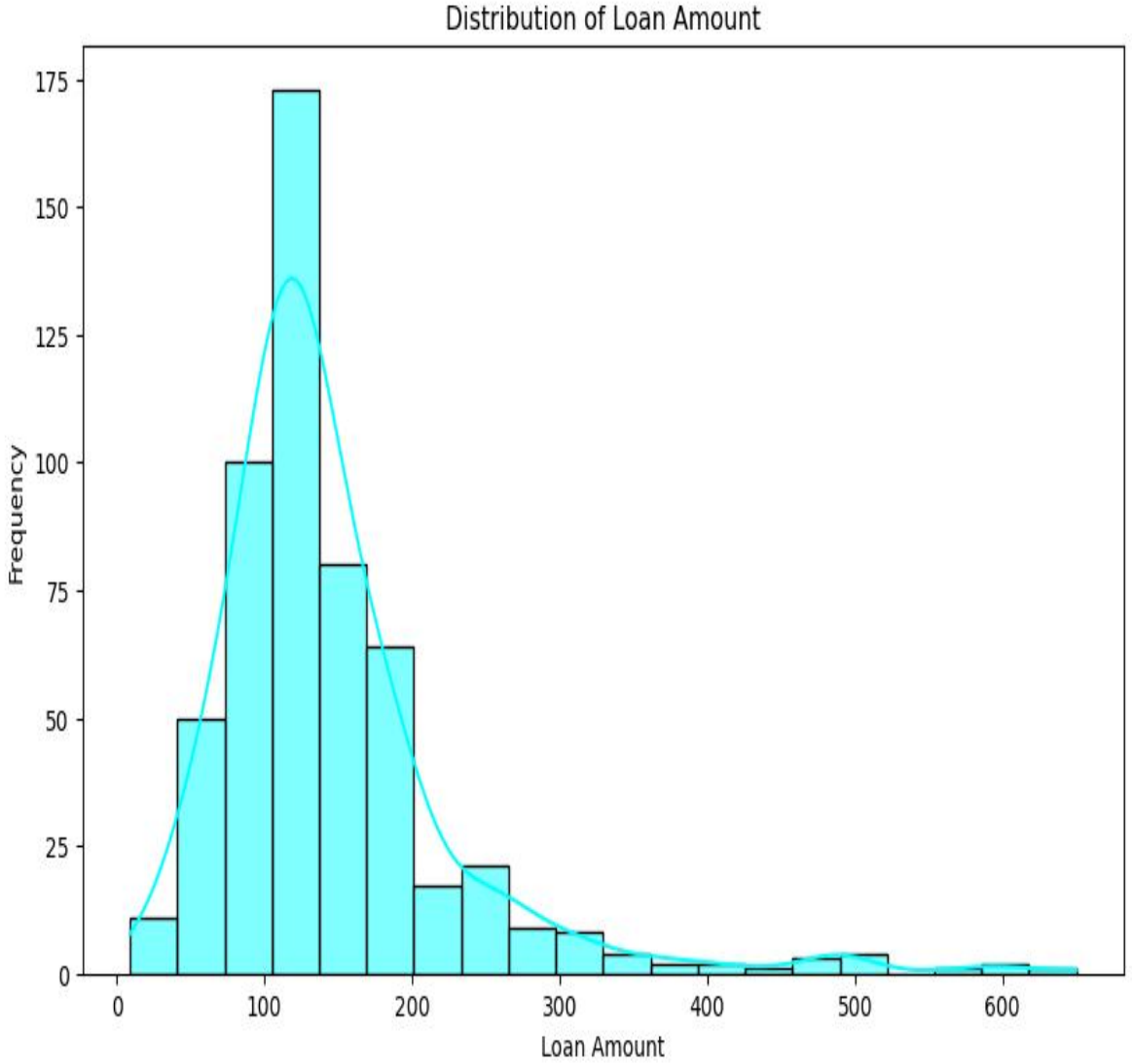


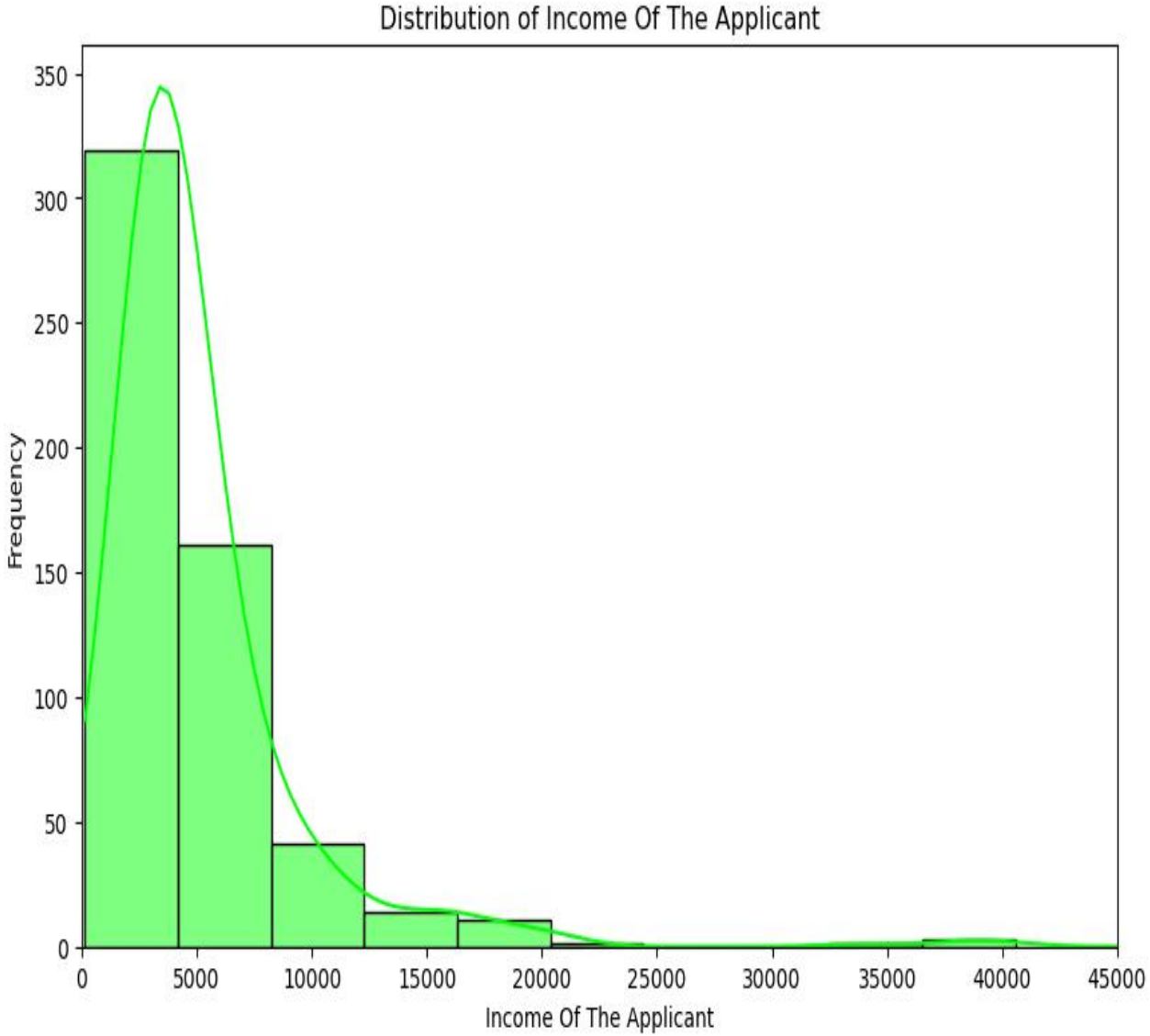




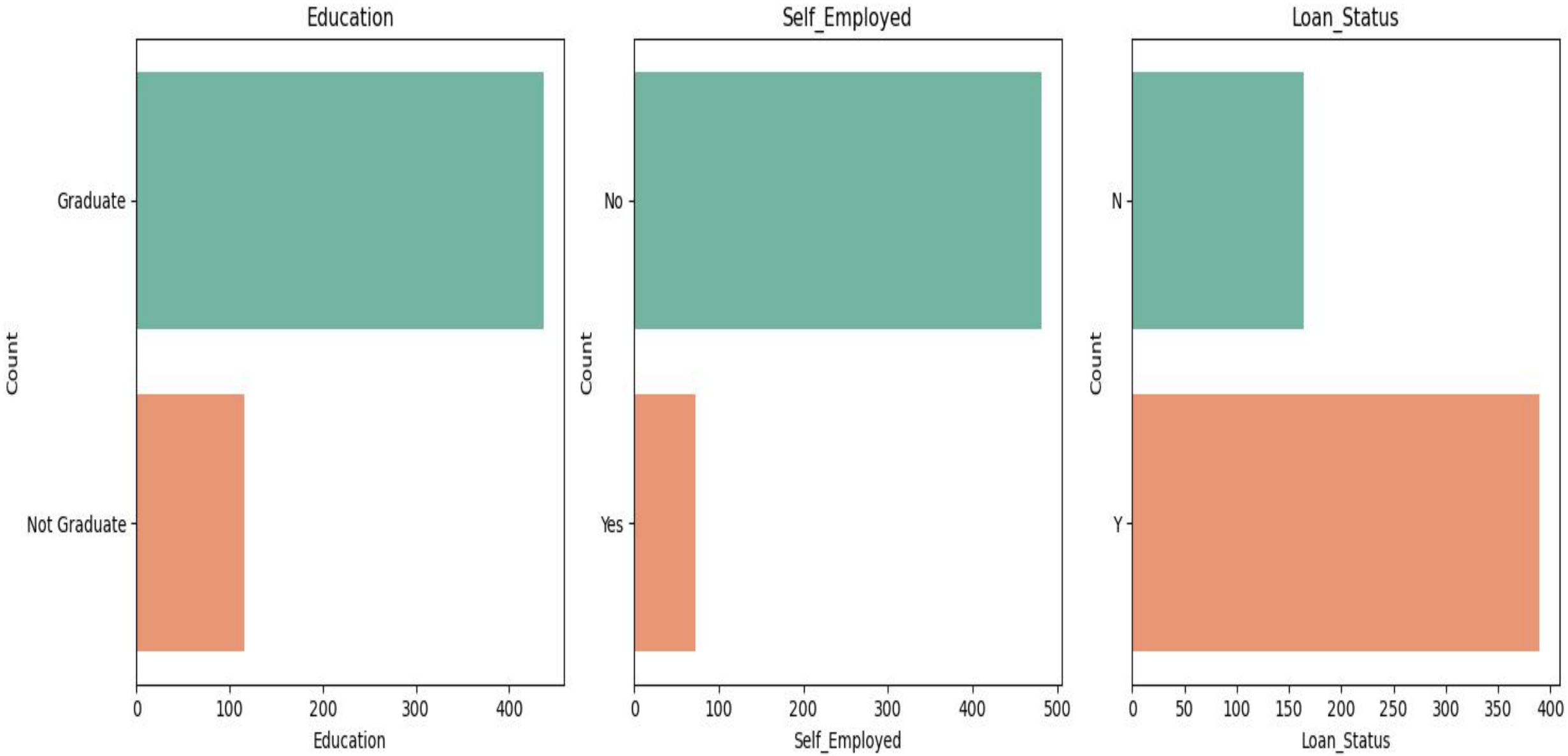


Data Analysis: Plotting and Charting

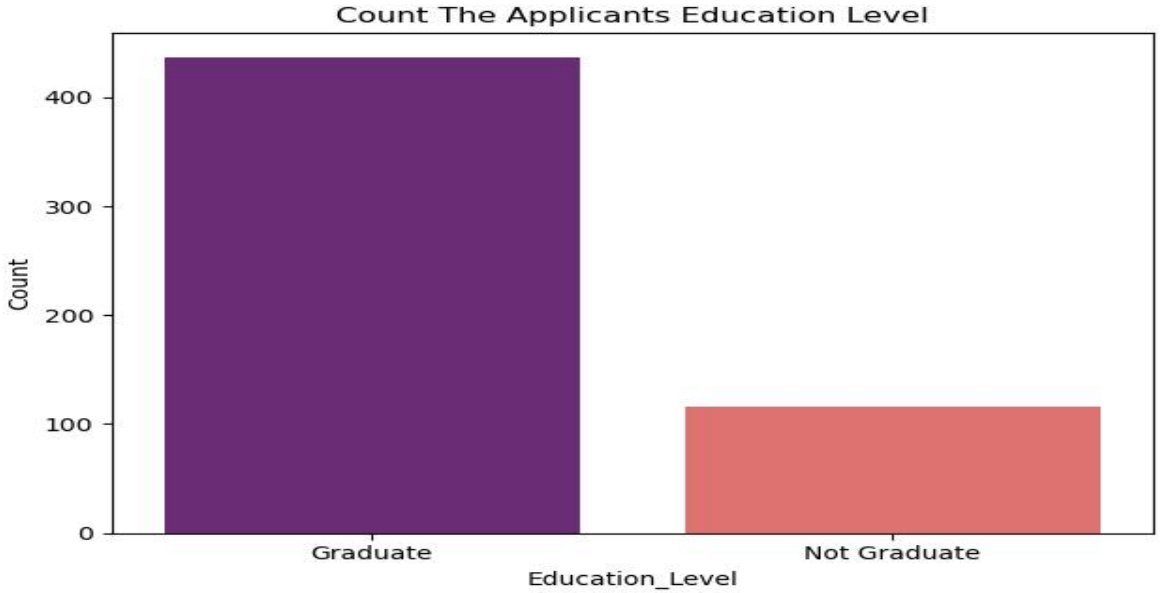


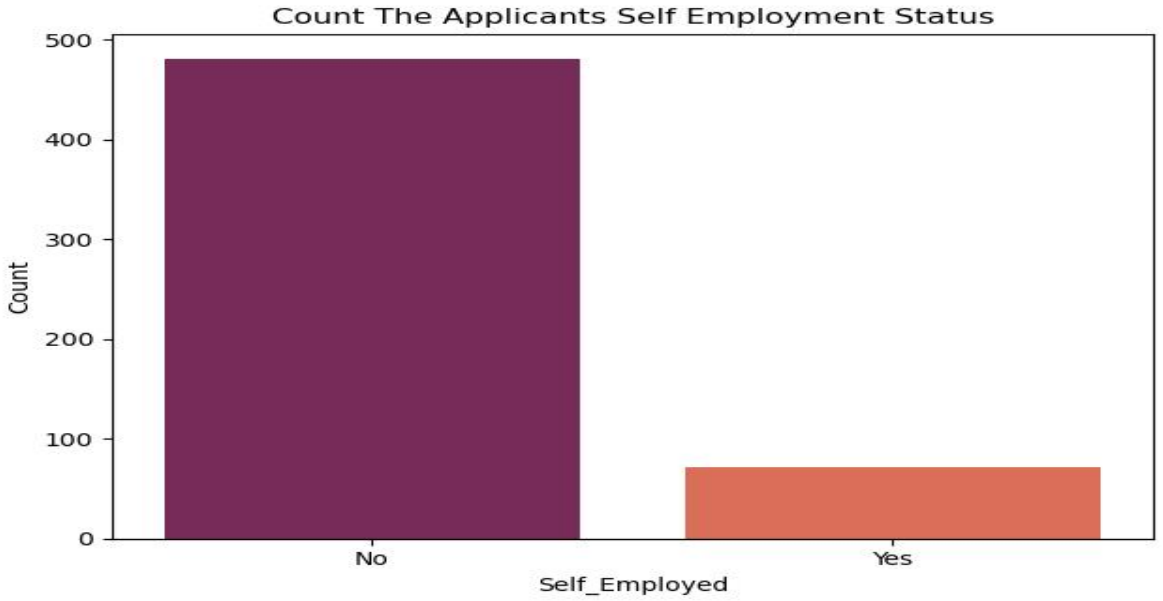


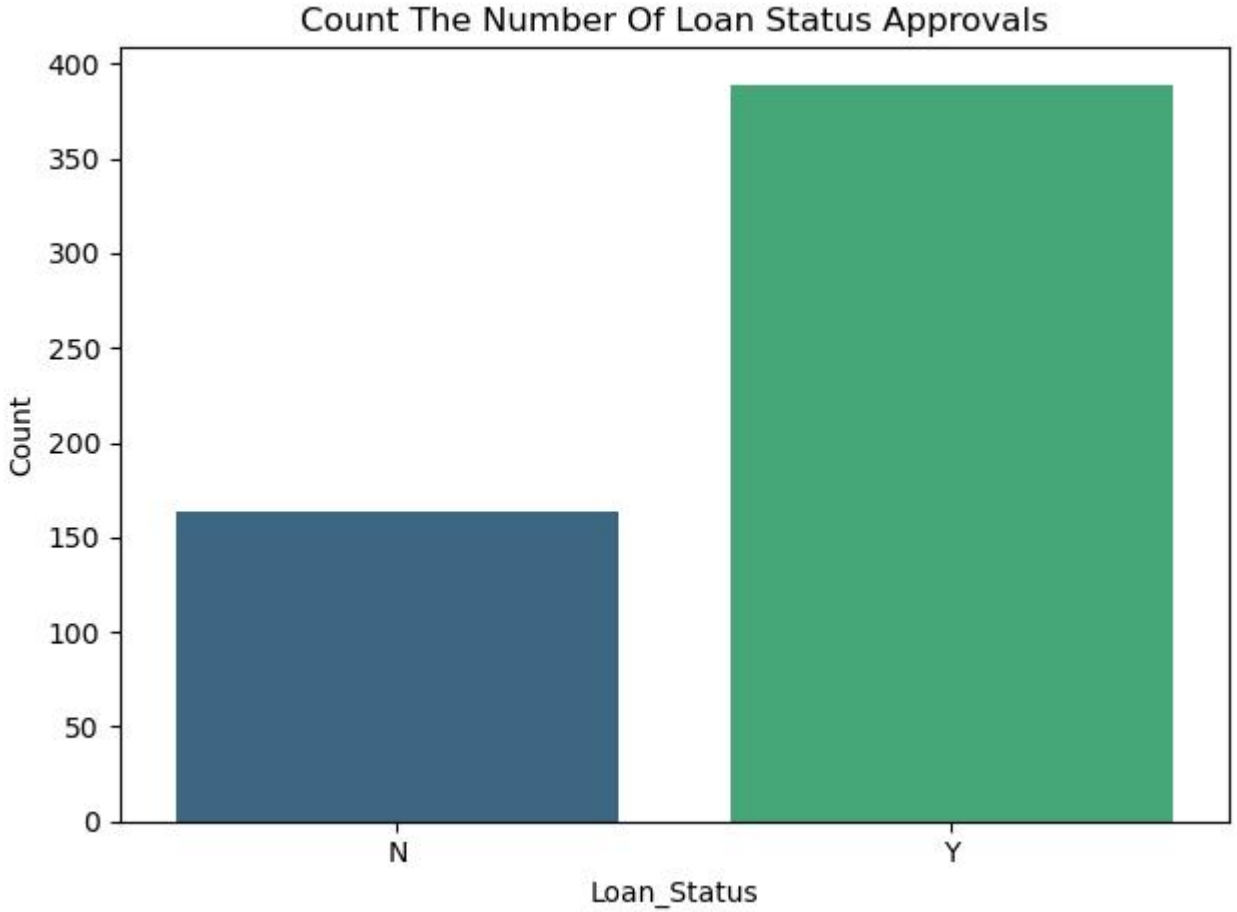
Data Analysis: Plotting and Charting



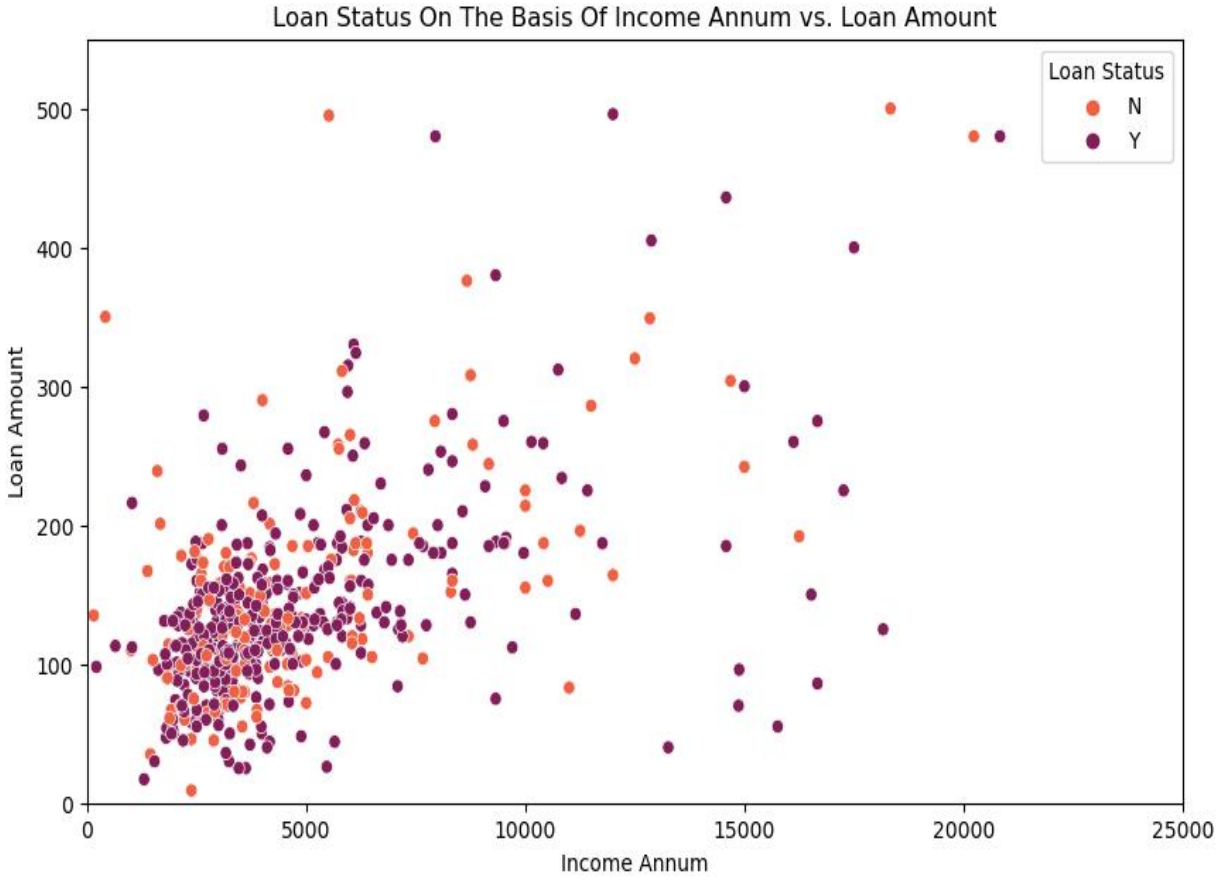
Data Analysis: Plotting and Charting

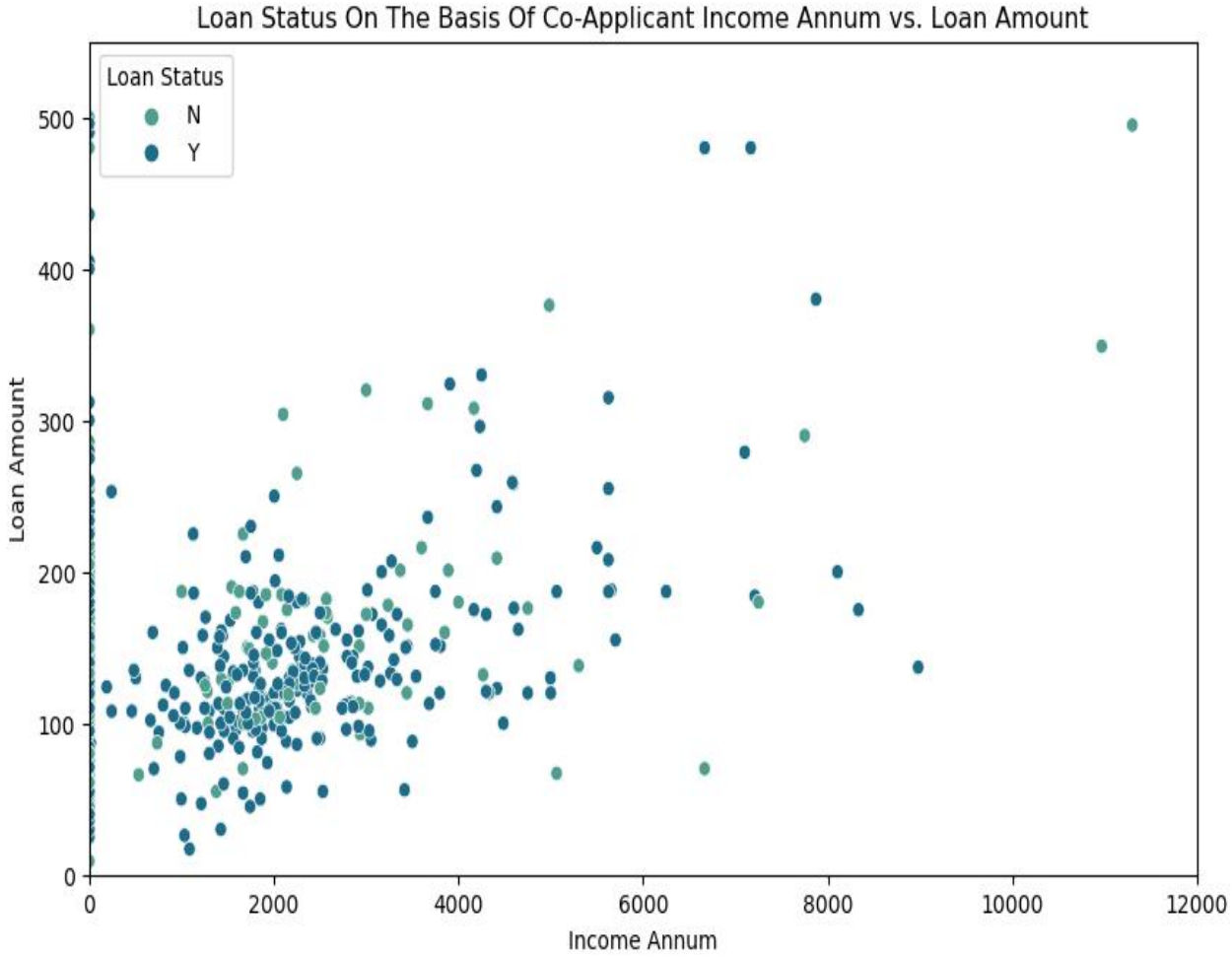






Data Analysis: Plotting and Charting





Column Details For CIBIL Data

1. Loan_ID : Unique Loan ID
2. Dependents : Number of dependents
3. Education : Applicant Education (Graduate/ Under Graduate)
4. Self_Employed : Self employed (Y/N)
5. ApplicantIncome : Applicant income
6. LoanAmount : Loan amount in thousands of dollars
7. Loan_Amount_Term : Term of loan in months
8. Cibil_Score : Cibil Score
9. Residential_Assets_Value: Value Of Residential Assets
10. Commercial_Assets_Value: Value Of Commercial Assets
11. Luxury_Assets_Value: Value Of Luxury Assets
12. Bank_Asset_Value: Value Of Bank Assets
13. Loan_Status: Loan approved (Y/N) this is the target variable

About Datasets

```
<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
```

`data.info()`

`data.dtypes`

```
loan_id                    int64
 no_of_dependents          int64
 education                object
 self_employed            object
 income_annum              int64
 loan_amount               int64
 loan_term                 int64
 cibil_score               int64
 residential_assets_value  int64
 commercial_assets_value   int64
 luxury_assets_value       int64
 bank_asset_value          int64
 loan_status              object
dtype: object
```

Read Data and Analyse

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4269 entries, 0 to 4268
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
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 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
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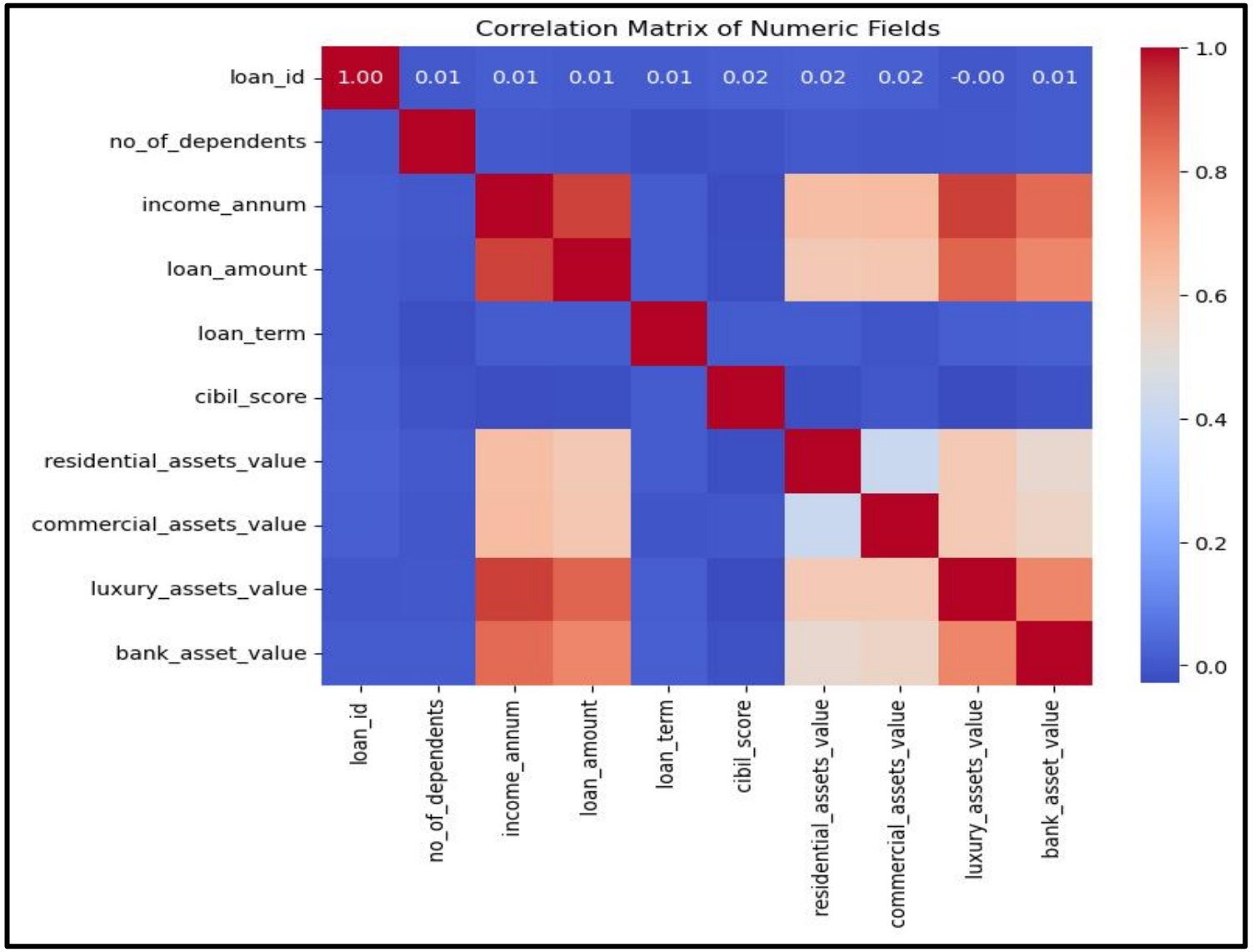
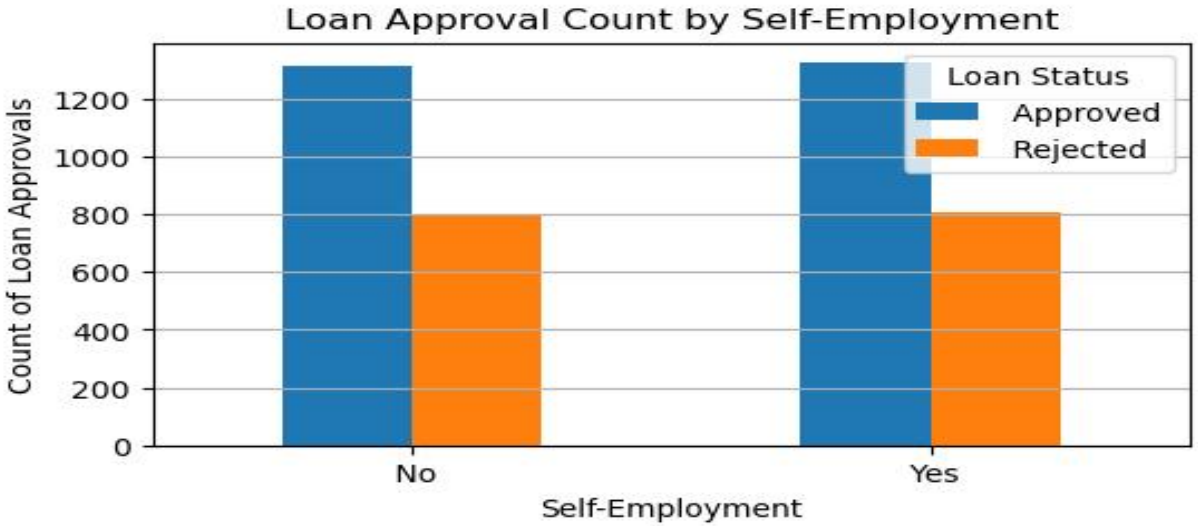
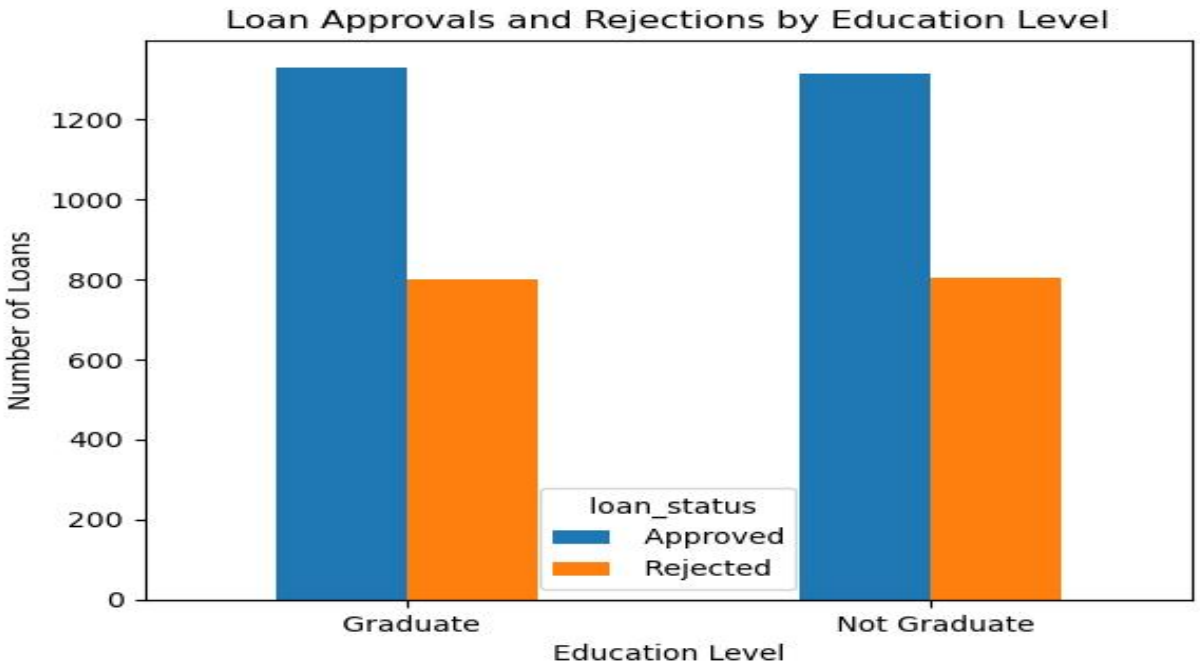
Dataset Info

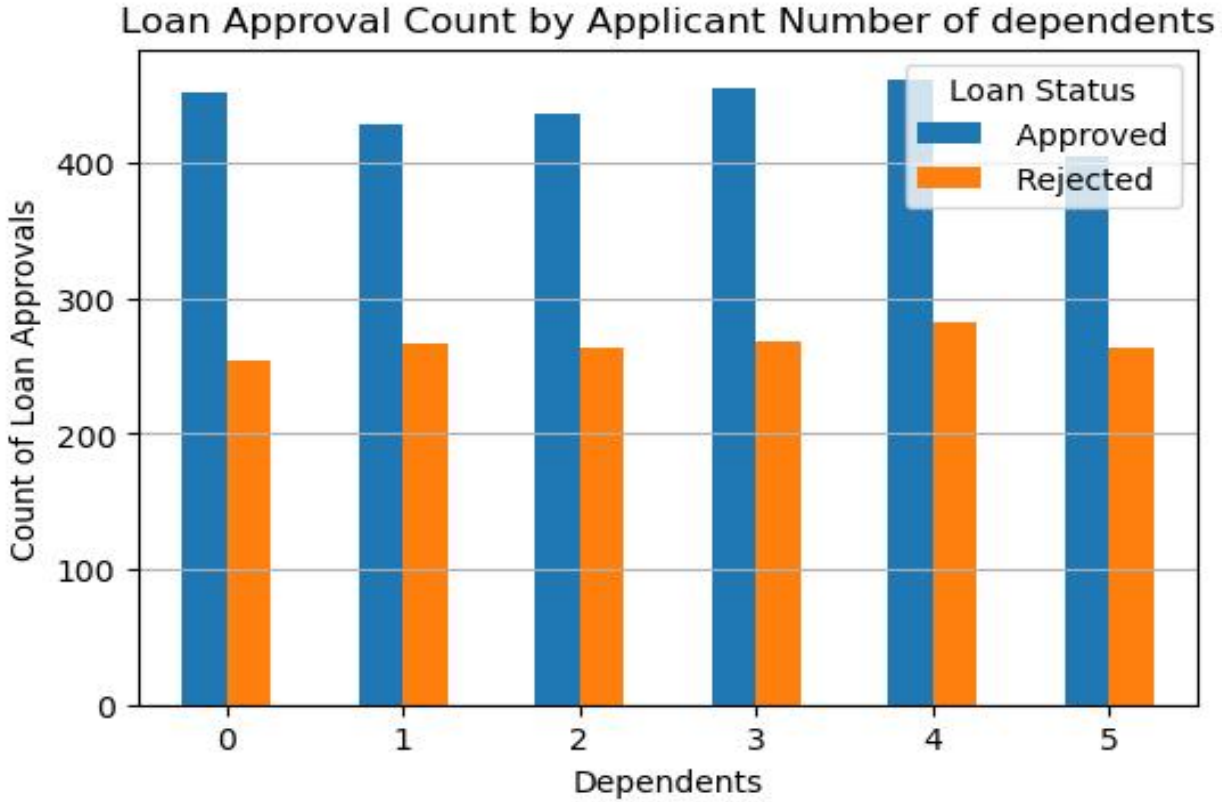


Correlation Matrix of Dataset Fields

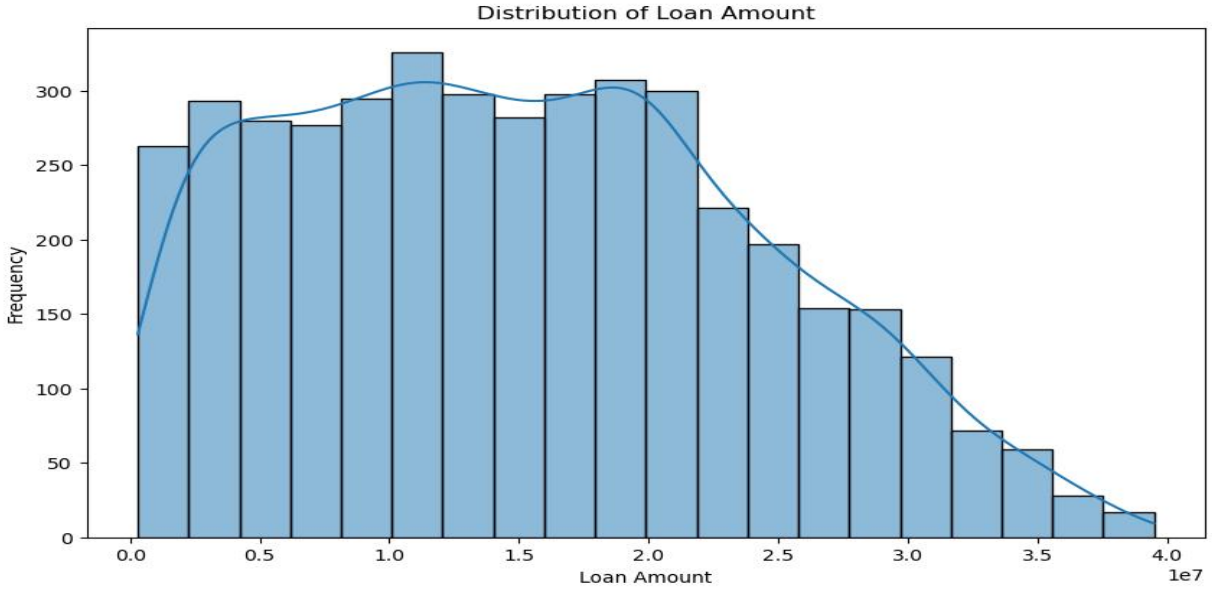
Data Analysis: Plotting and Charting

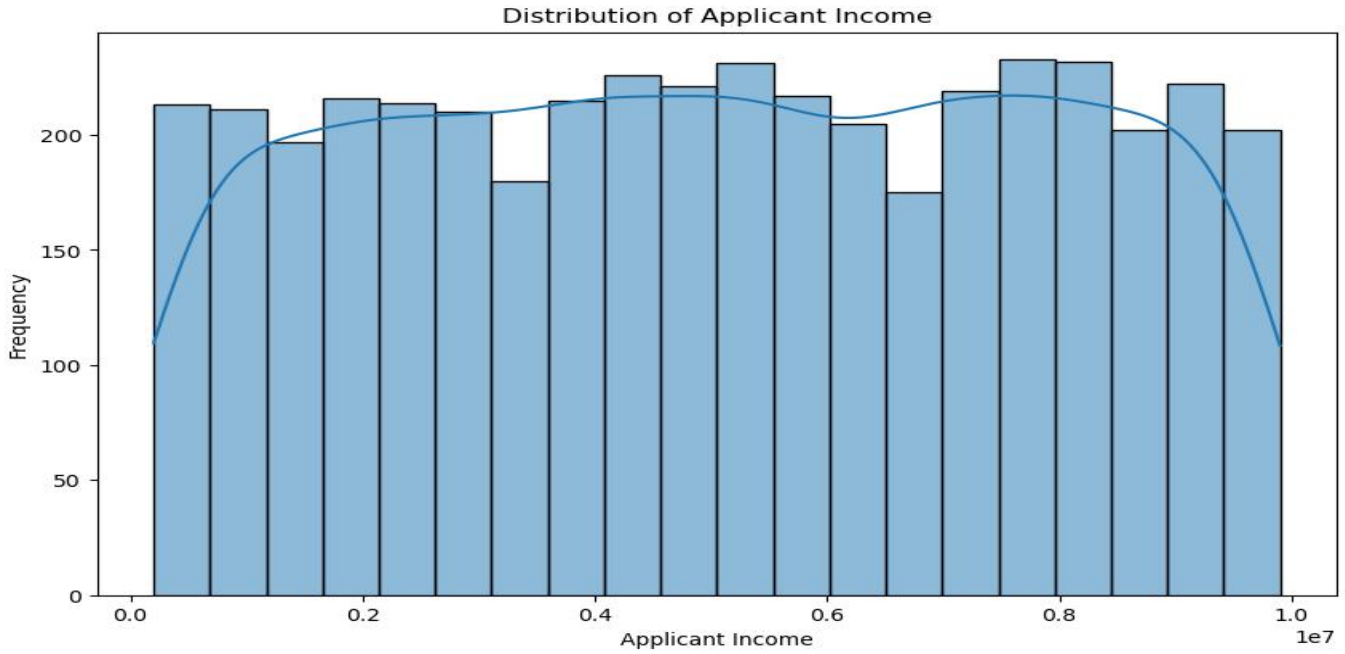




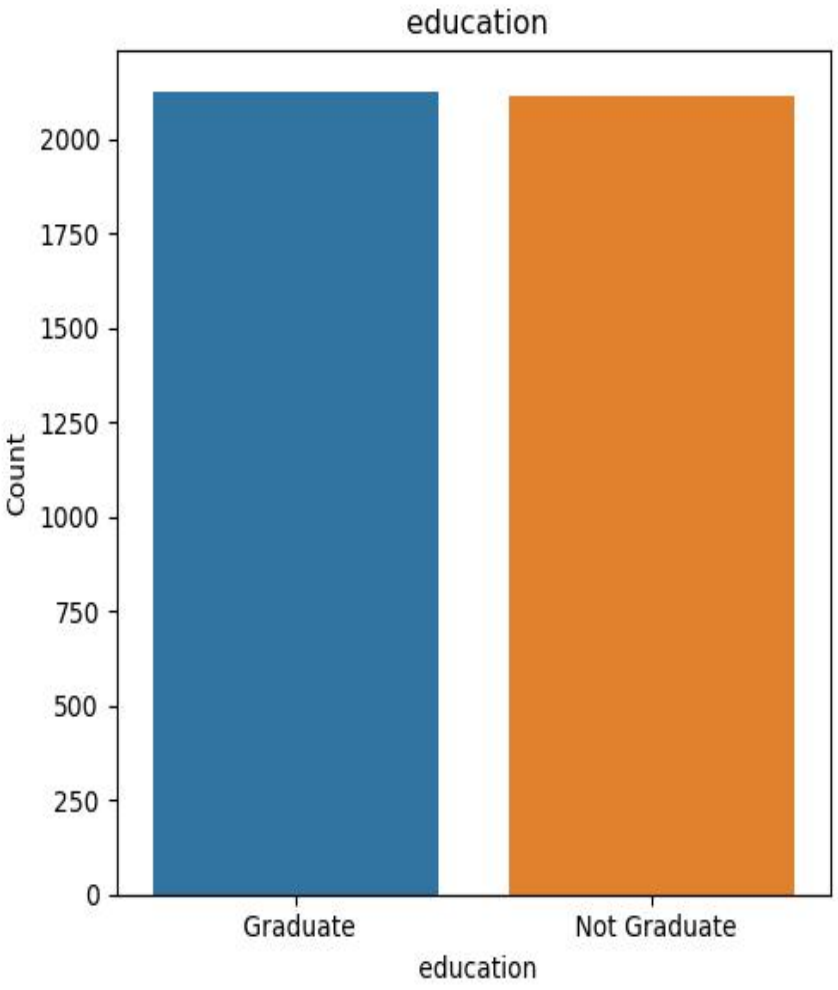


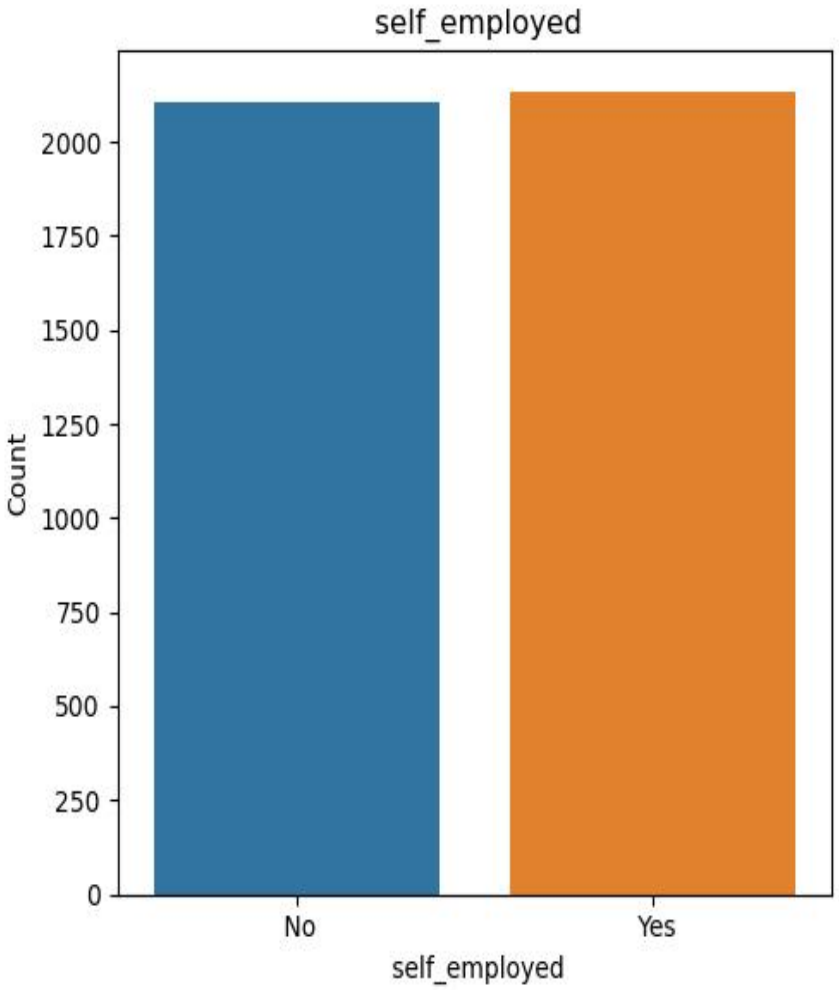
Data Analysis: Plotting and Charting

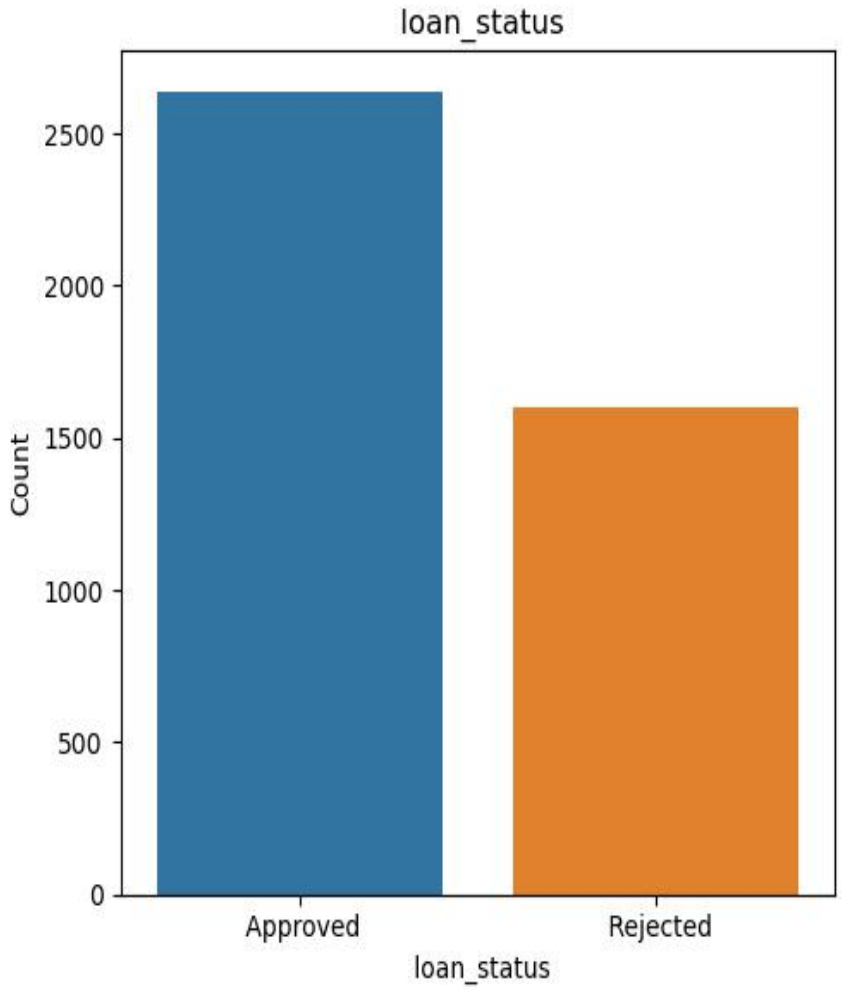




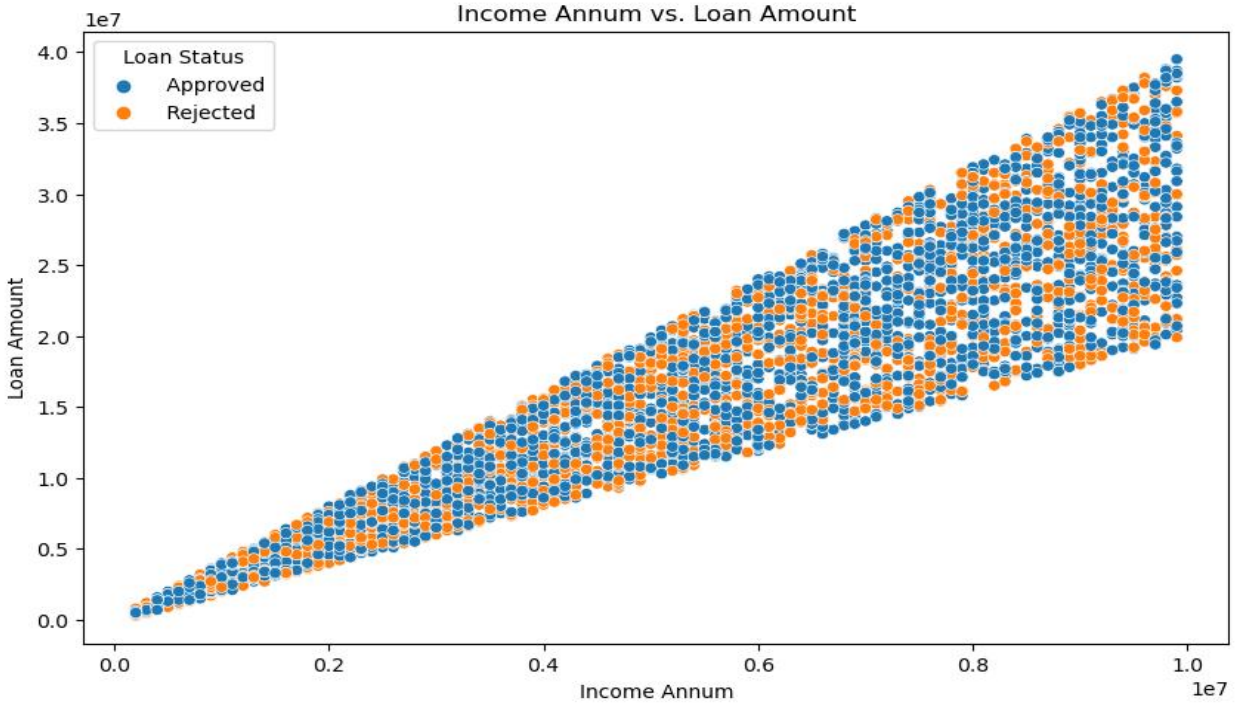
Data Analysis: Plotting and Charting

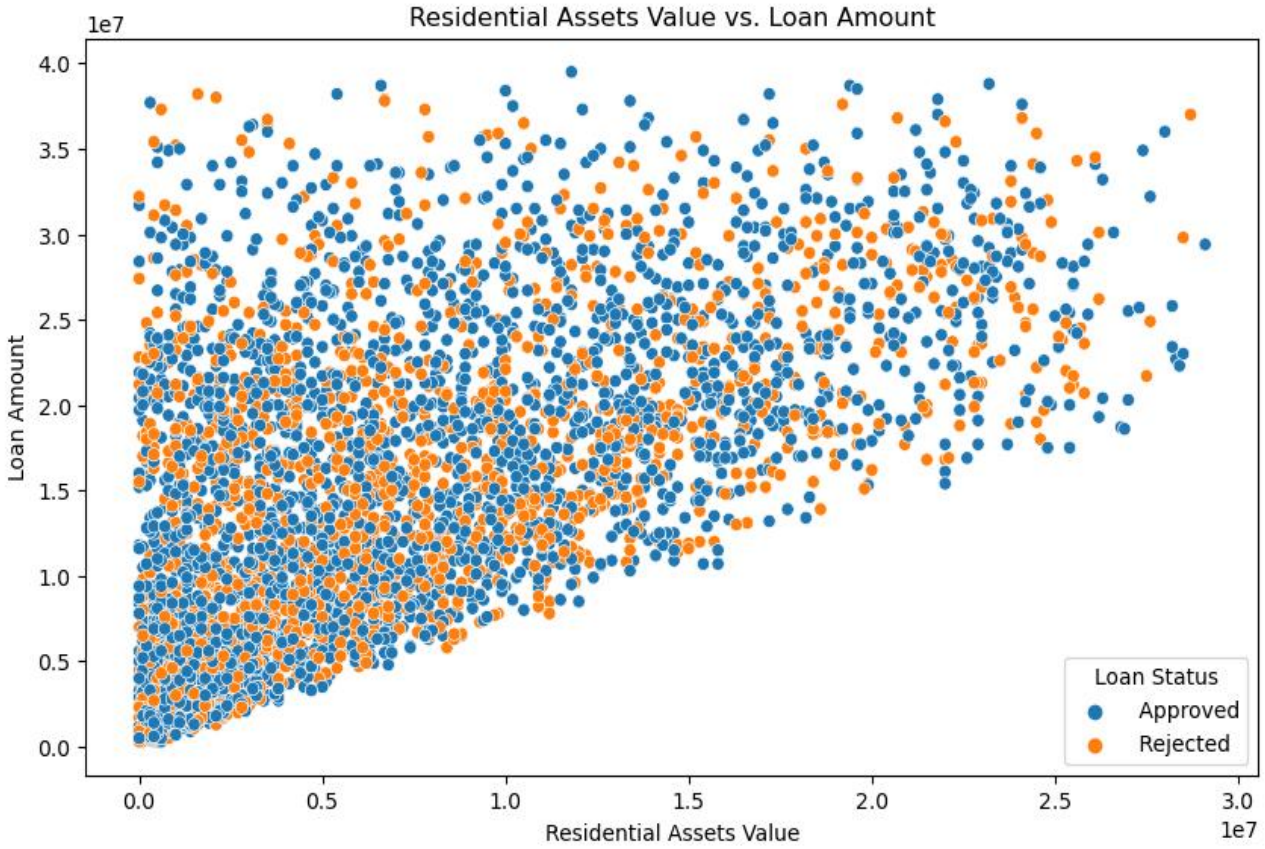




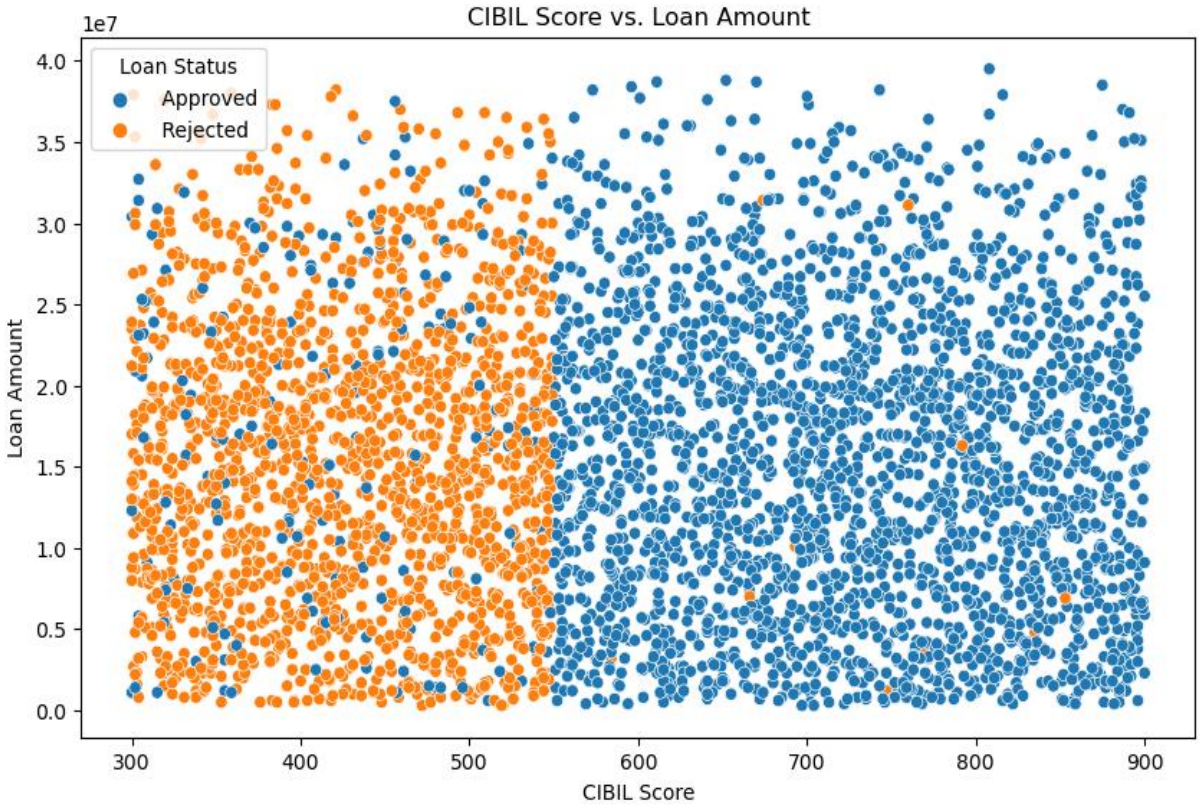


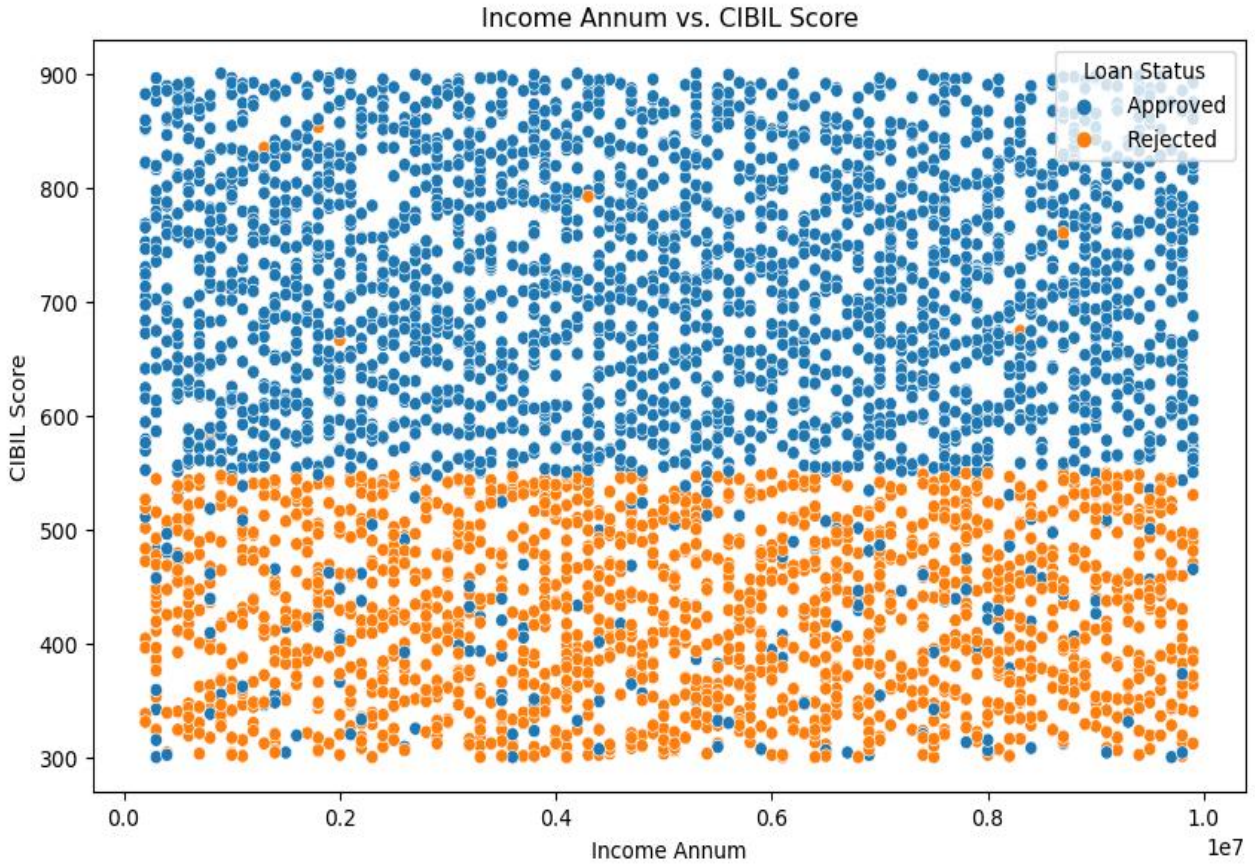
Data Analysis: Plotting and Charting





Data Analysis: Plotting and Charting





Convert Categorical Variables To Numeric

- Categorical features refer to string data types and can be easily understood by human beings.
- However, machines cannot interpret the categorical data directly. Therefore, the categorical data must be converted into numerical data for further processing.
- We mapped categorical variables to numerical values for better processing by machine learning algorithms.

```
'Graduate': 1, 'Not Graduate’: 0
 'Yes': 1, ' No': 0
'Approved': 1, 'Rejected': 0
```

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Min-max Scaling

- Min-max scaling, also known as normalization, is a technique commonly used in data preprocessing. It is used to transform numerical features into a specific range, typically between 0 and 1. However, machines cannot interpret the categorical data directly.
- Many machine learning algorithms perform better when the input features are normalized. By scaling the features to a specific range, you can prevent any particular feature from dominating the learning process.

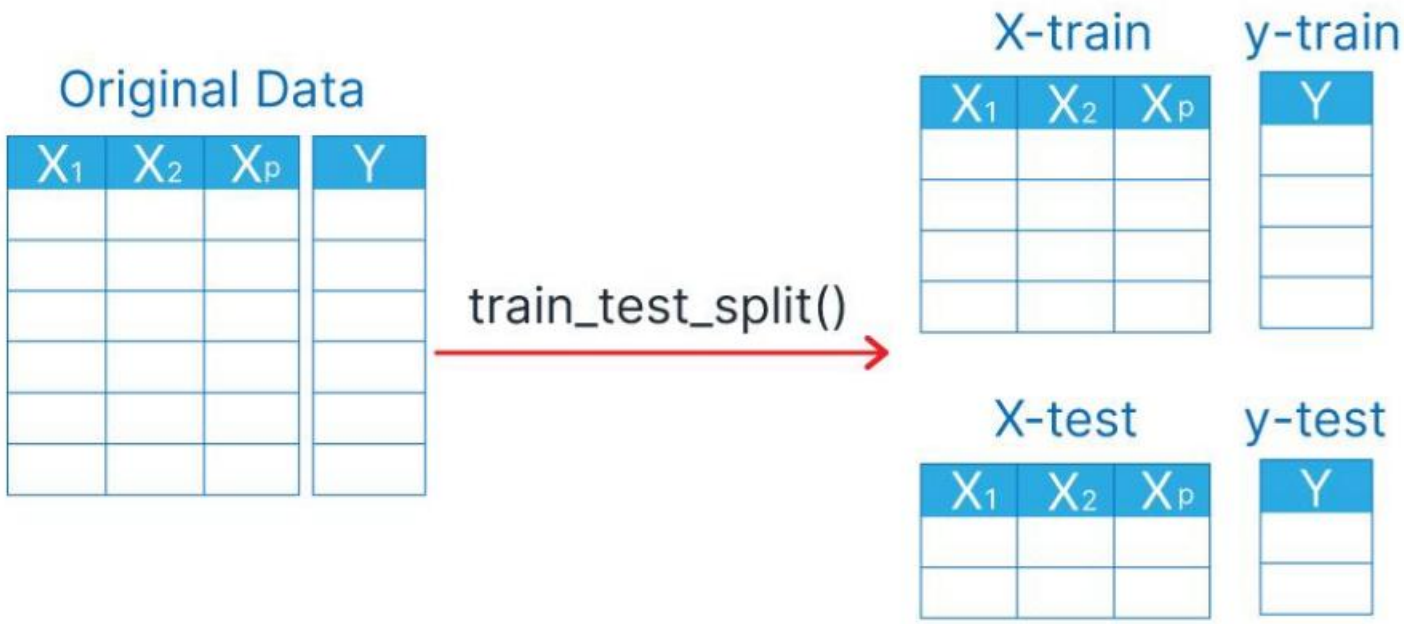
Data Preparation

Input : X
Output : Y

Supervised machine learning is a type of machine learning that learns the relationship between input and output. The inputs are known as features or X variables and output is generally referred to as the target or y variable. The type of data which contains both the features, and the target is known as labeled data.

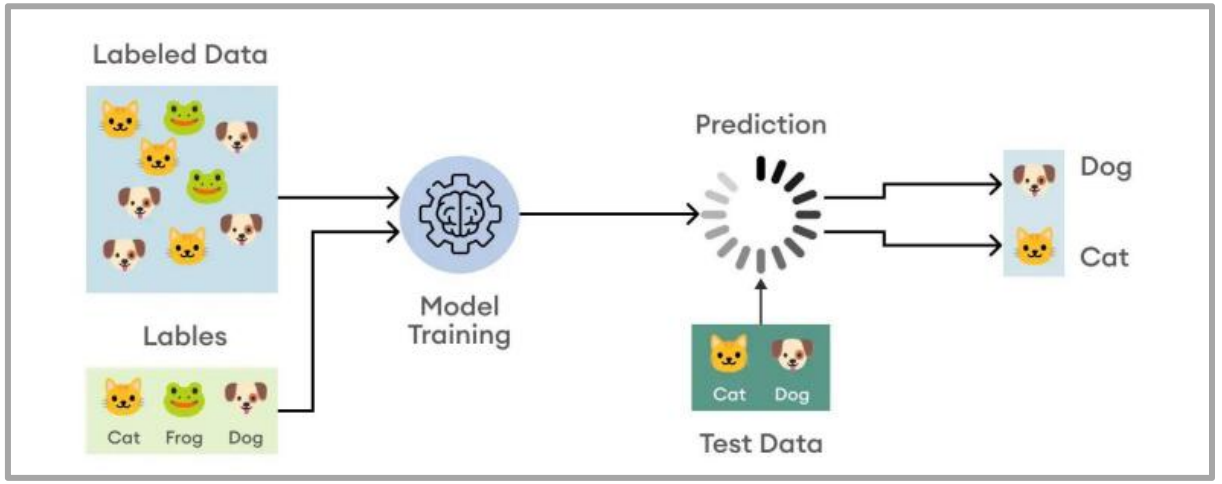
Train Test Split :-

Train-test split divides the data once into distinct training and test sets used for model evaluation.



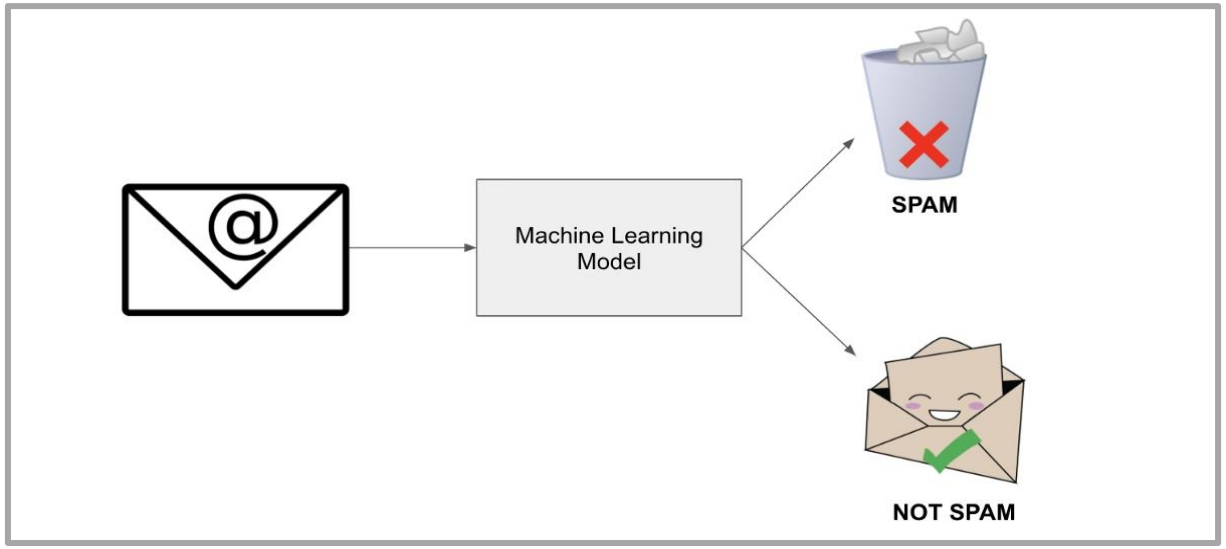
Machine Learning : Classification

- Classification is a supervised machine learning method where the model tries to predict the correct label of a given input data.
- In classification, the model is fully trained using the training data, and then it is evaluated on test data before being used to perform prediction on new unseen data.



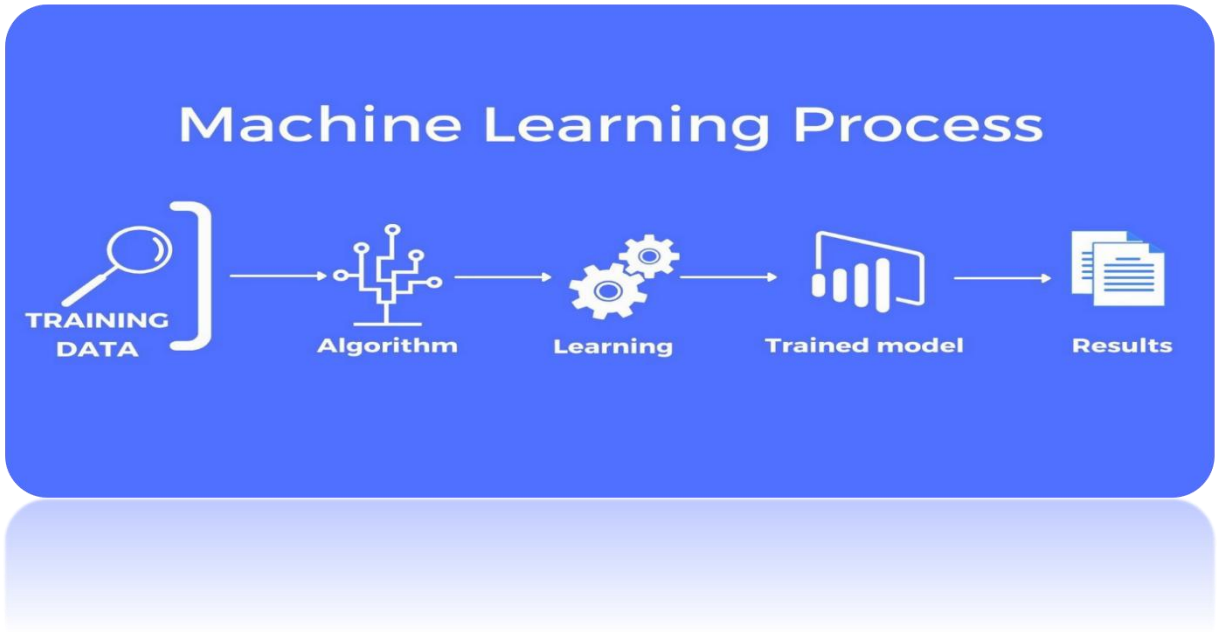
Binary Classification:-

- In a binary classification task, the goal is to classify the input data into two mutually exclusive categories.
- The training data in such a situation is labeled in a binary format: true and false; positive and negative; O and 1; spam and not spam, etc. depending on the problem being tackled.
- The loan approvals prediction is a binary classification problem.



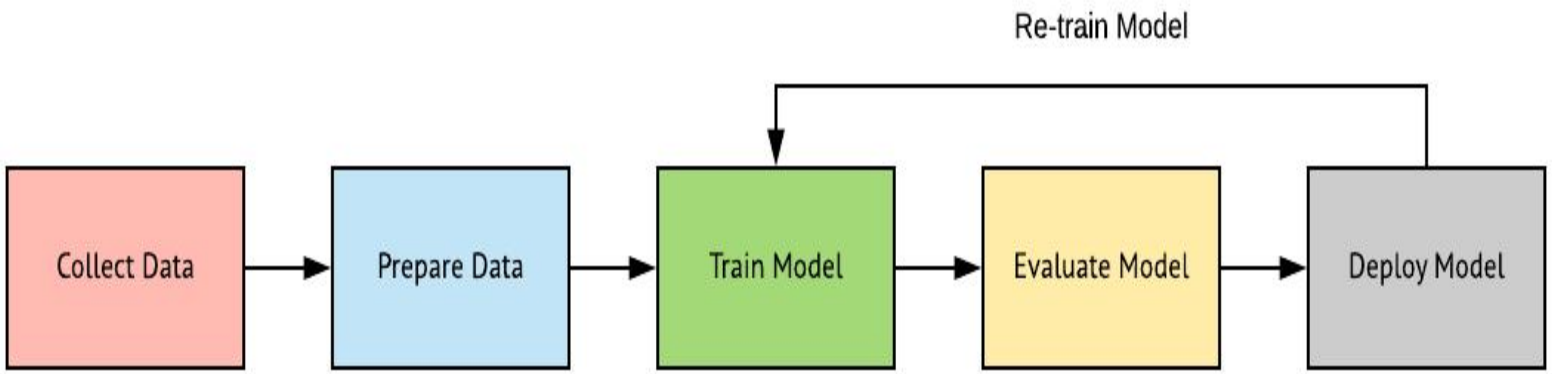
Model Training

- A training model is a dataset that is used to train an ML algorithm.
- It consists of the sample output data and the corresponding sets of input data that have an influence on the output.
- The training model is used to run the input data through the algorithm to correlate the processed output against the sample output.



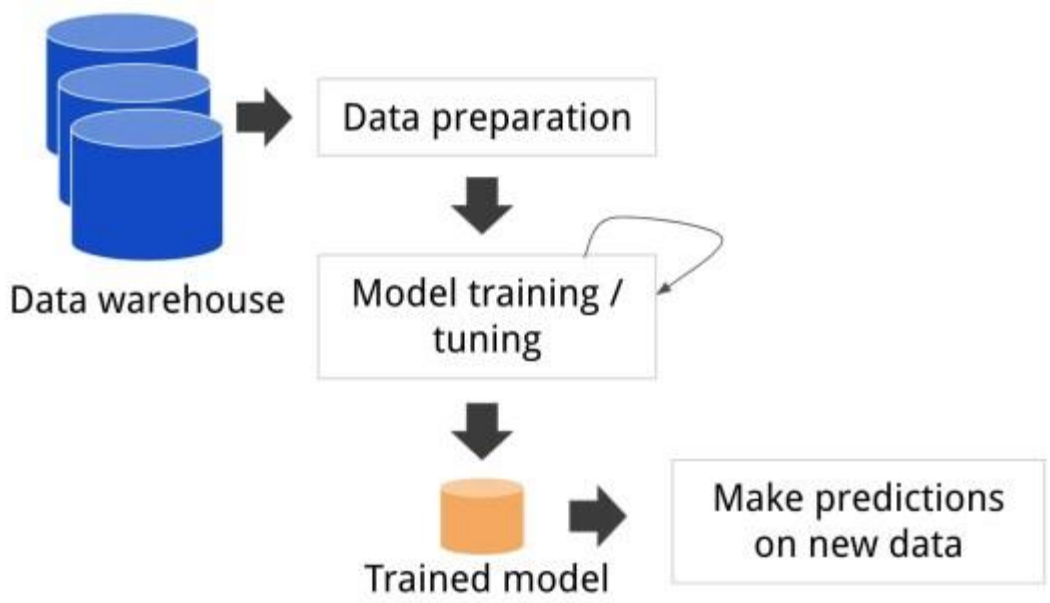
Models Used: Package-Sci-Kit Learn

- Logistic Regression
- Support Vector Machine (SVM)
- Decision Tree Classifier
- Random Forest Classifier
- Gradient Boosting Classifier
- Random Search CV



Model Prediction and Evaluation

Each input variable gets a label marking a category. In other words, the classification technique is used to map the input data to one of the categorial output labels.

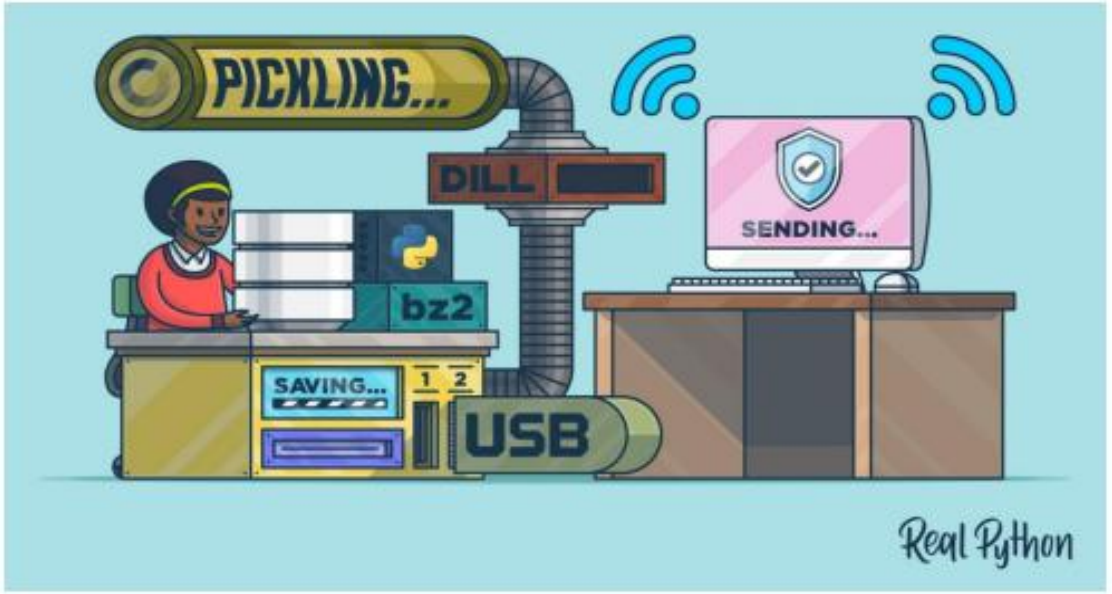


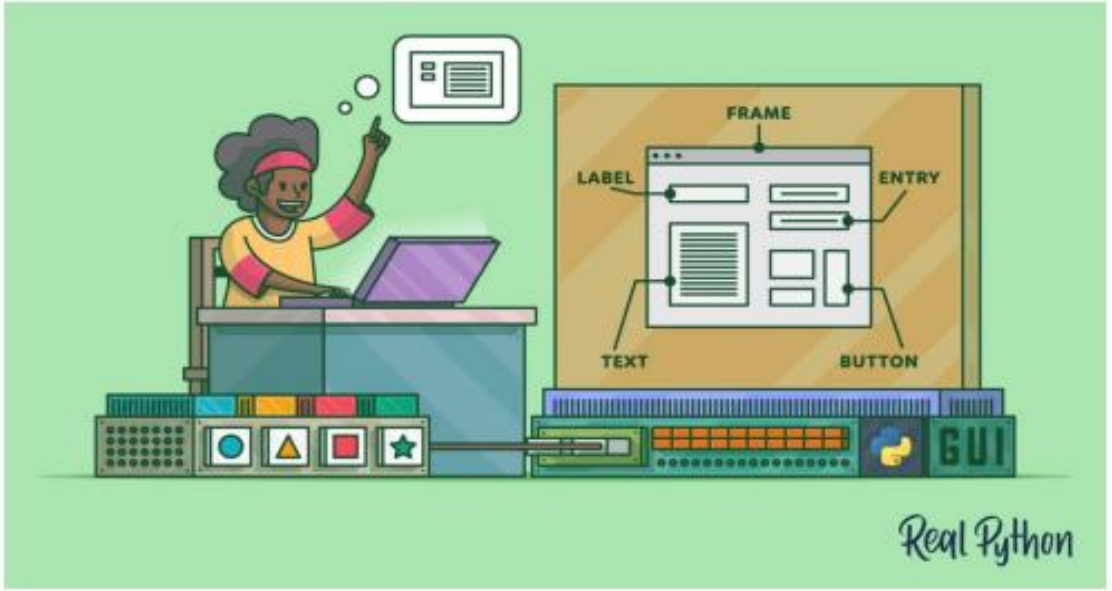
Model Evaluation

Evaluating the performance of your classification model is crucial to ensure its accuracy and effectiveness.

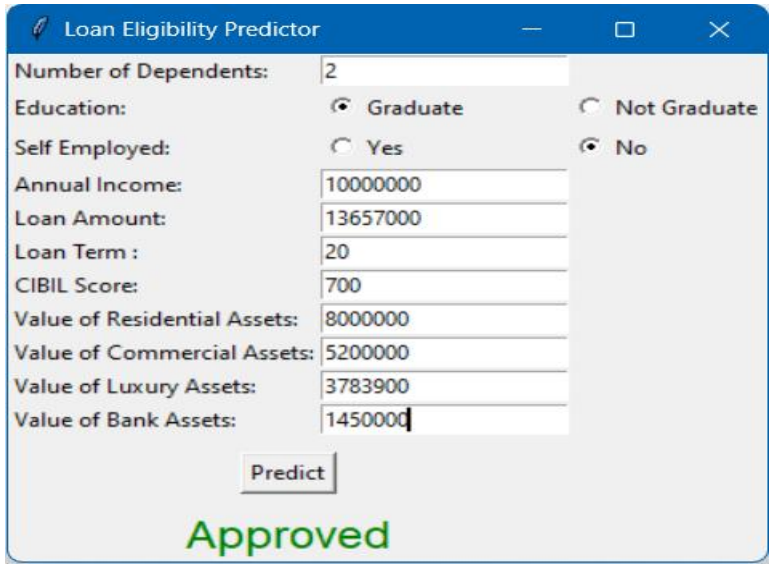
Building GUI Application

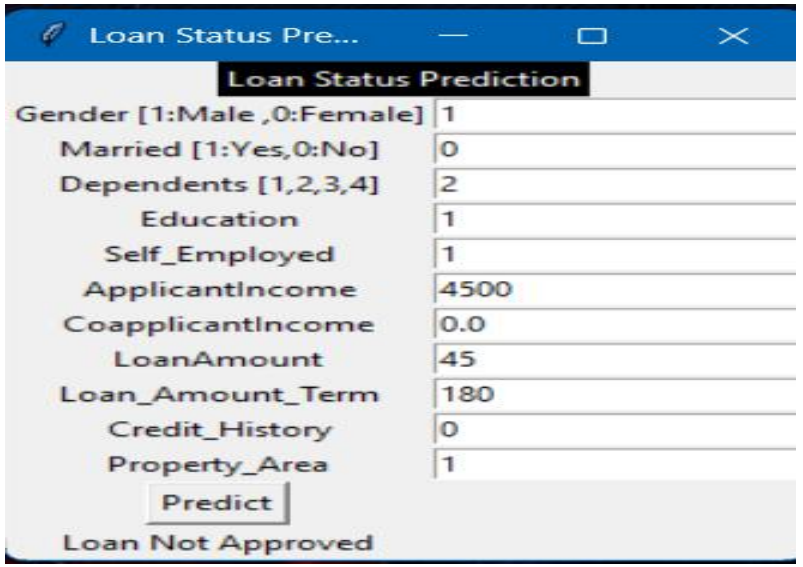
1. Saving the Model and Scaler.
2. Taking test Inputs.
3. Scaling the Inputs.
4. Passing the inputs to the model.
5. Getting the Output.
6. Displaying if Loan will be Approved or Rejected.
7. Building a GUI

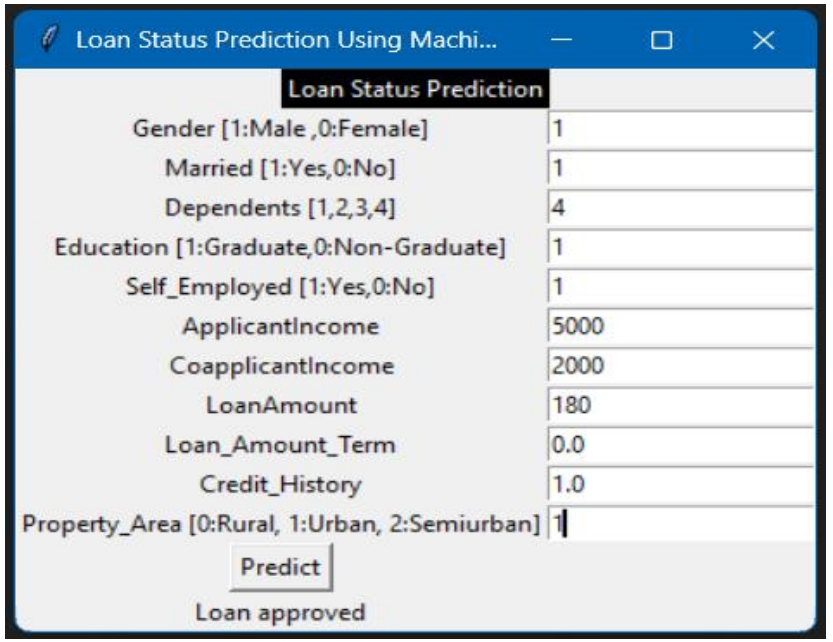


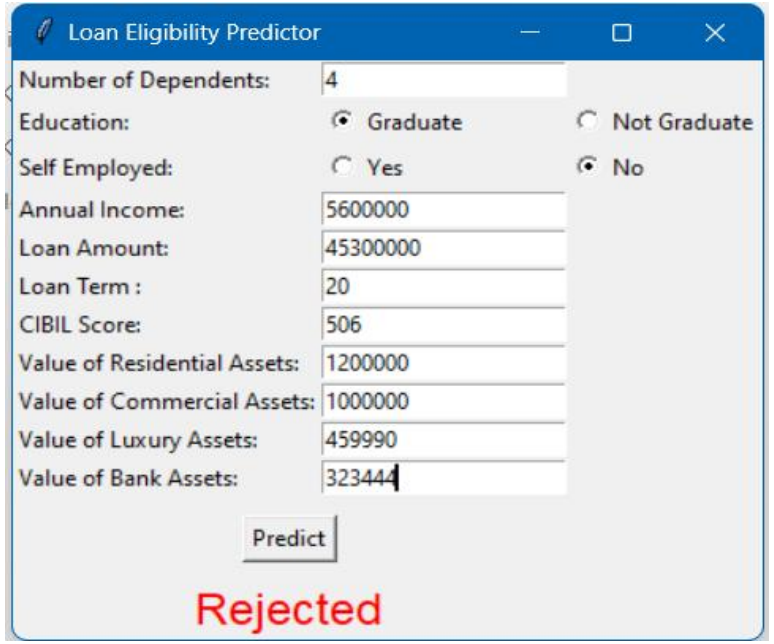


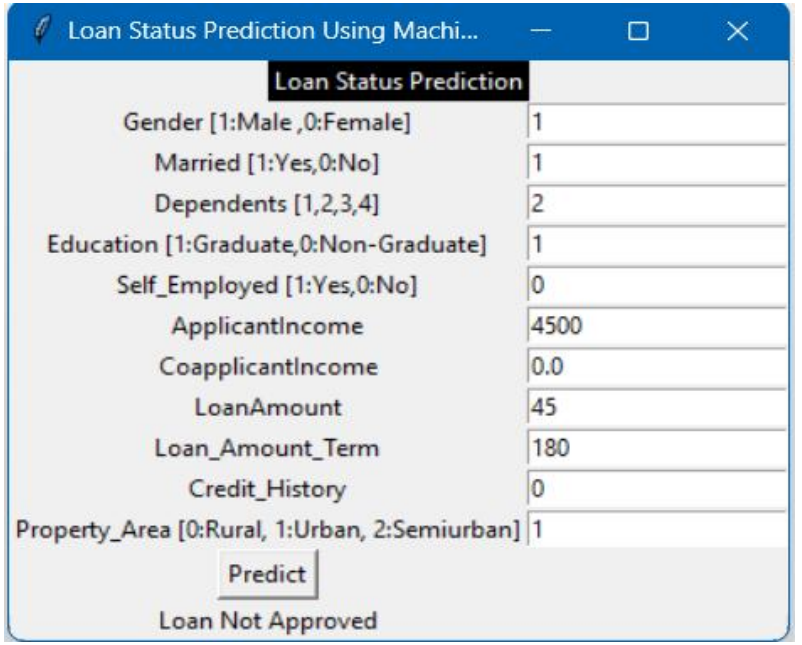
GUI Interface



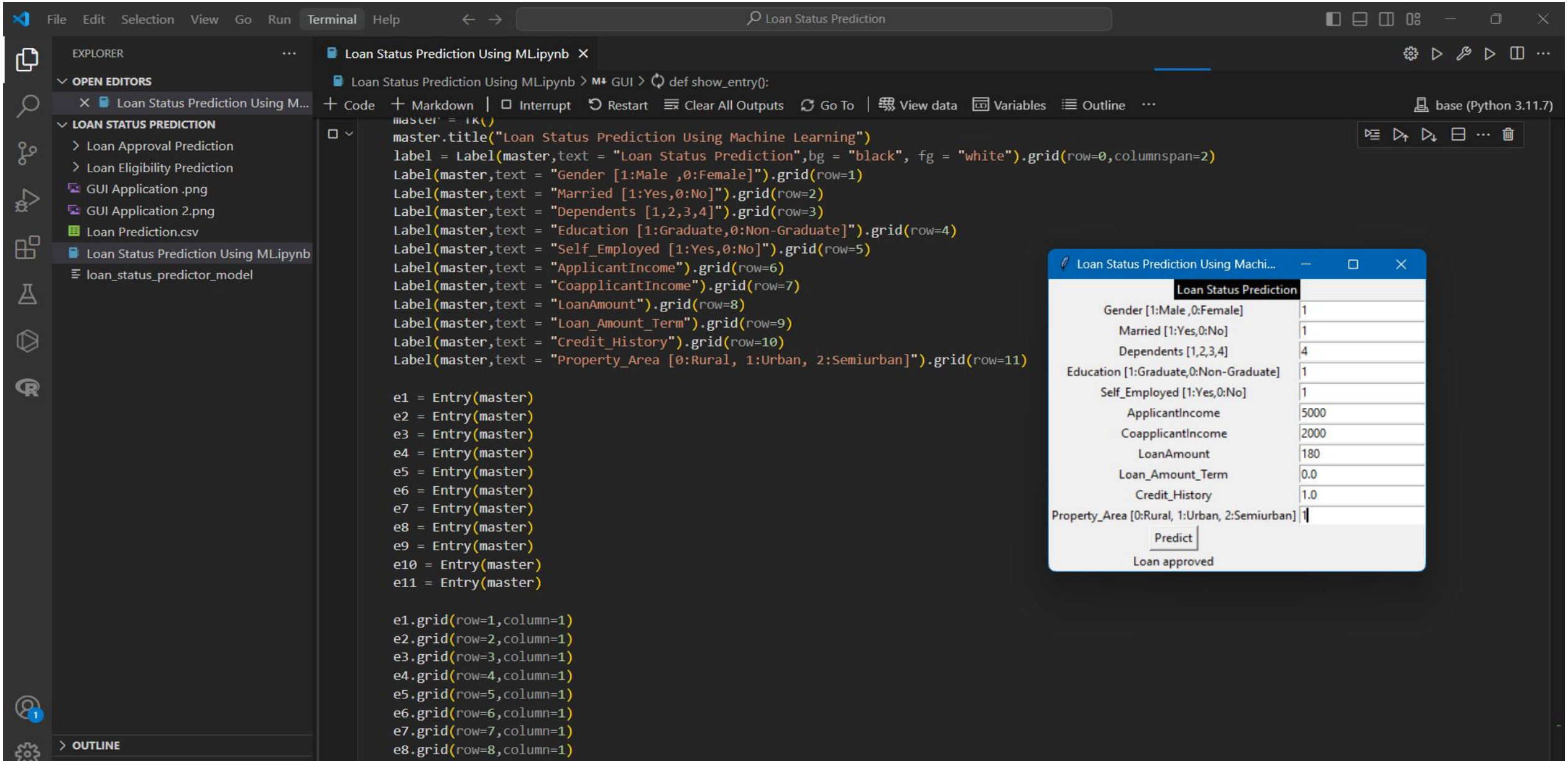




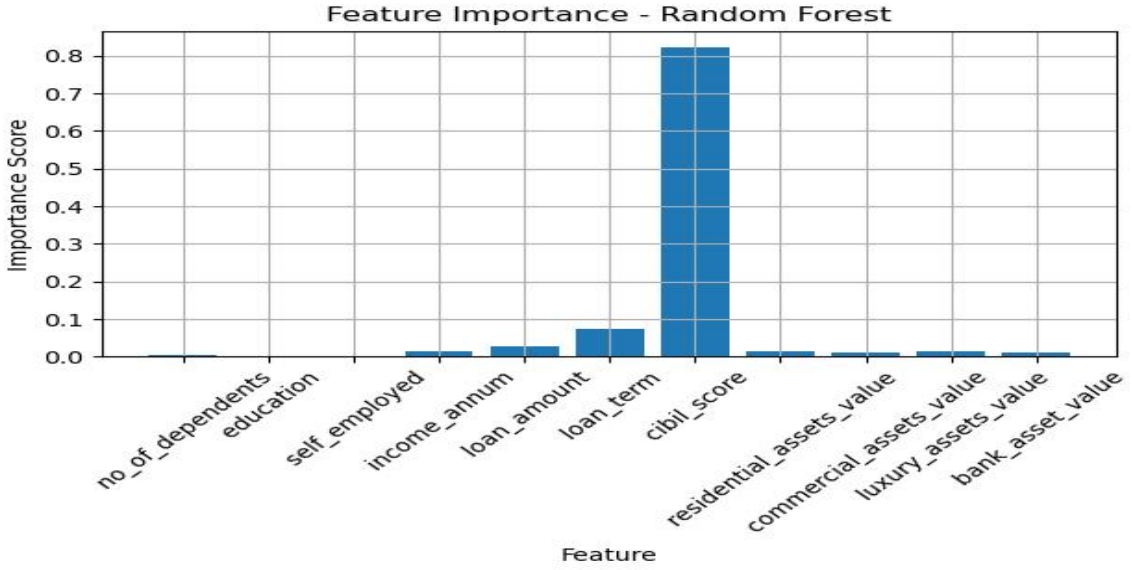


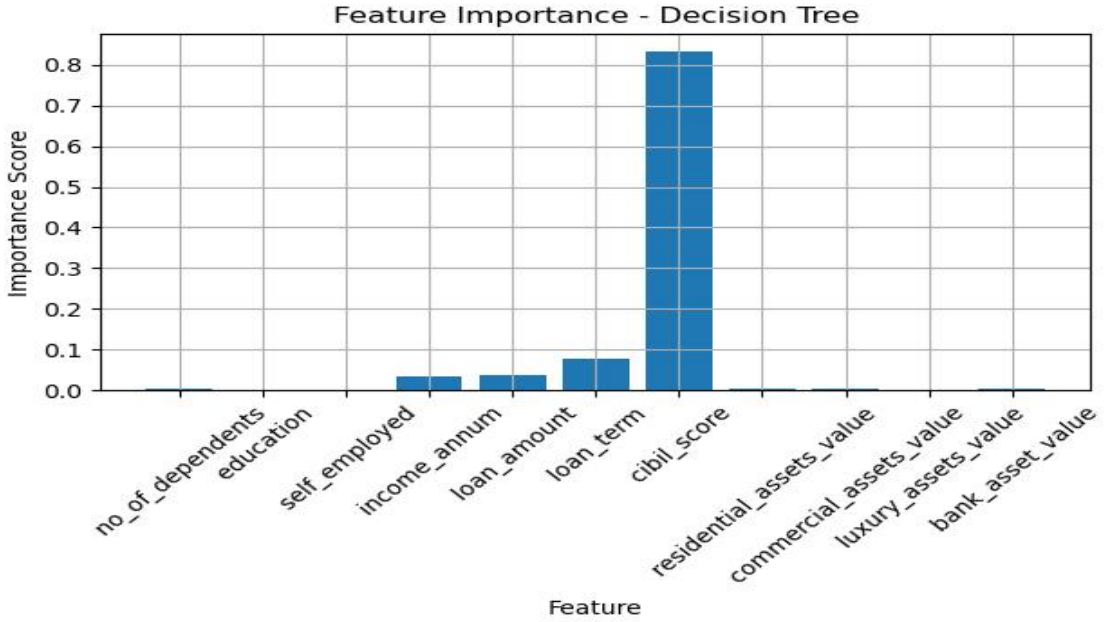


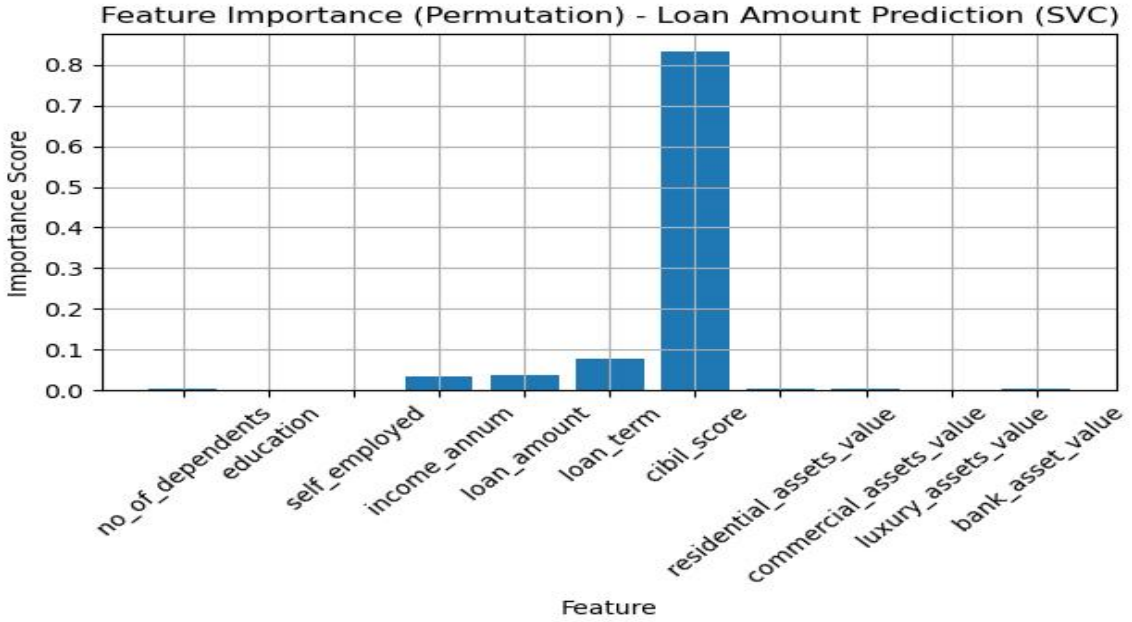
GUI Interface



Feature Importance







Conclusion:-

1. The project involved assessing the performance of different machine learning models on a dataset. To improve the model, more data can be collected.
2. The models used were Decision Tree, Random Forest, Logistic Regression, and SVC.
3. Among the models examined, the Random Forest Classifier had the most accuracy in the project.
4. Based on current data, model can be built on 4-5 important features for future prospects.
5. The UI based application can be used by the bank to predict if a loan application should be approved or not.
6. Optimal hyper parameters can be found to improve the model.
7. With more data, Neural Networks can be used.
8. Feature importance refers to techniques that assign a score to input features based on how useful they are at predicting a target variable.