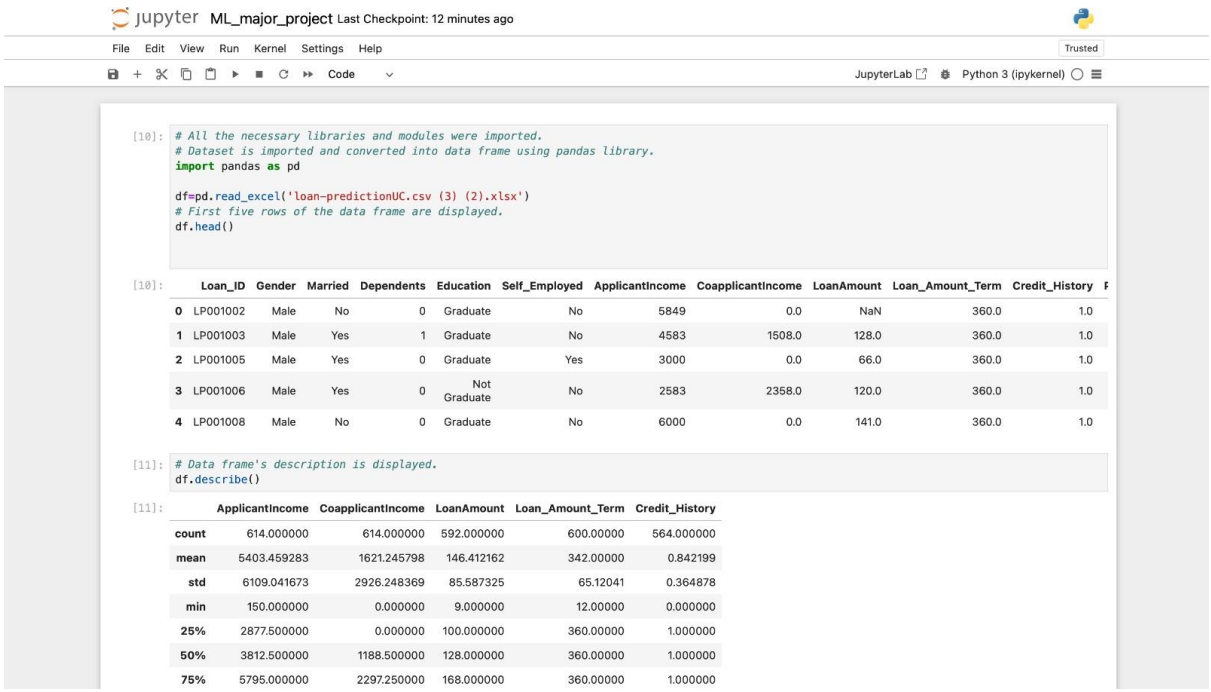
Code and Output Images of Machine Learning Major Project- May Batch, 2024



[10]:
```
# All the necessary libraries and modules were imported.
# Dataset is imported and converted into data frame using pandas library.
import pandas as pd

df=pd.read_excel('loan-predictionUC.csv (3) (2).xlsx')
# First five rows of the data frame are displayed.
df.head()
```

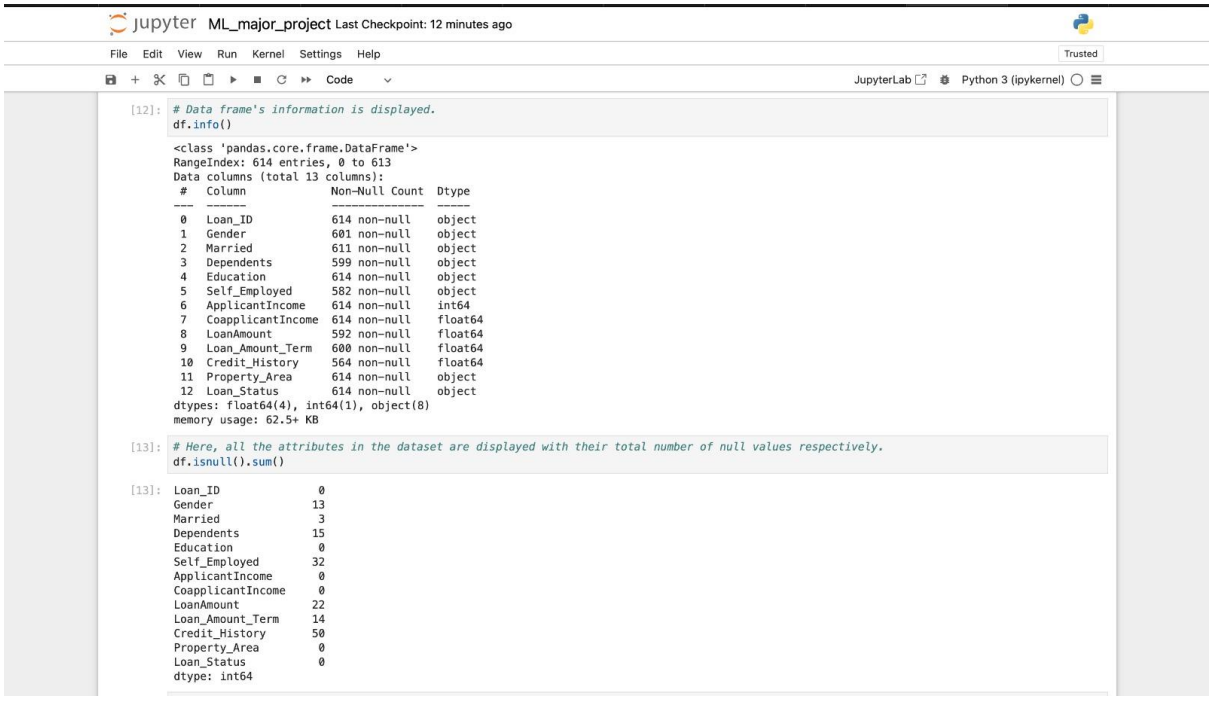
[10]:

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

[11]:
```
# Data frame's description is displayed.
df.describe()
```

[11]:

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



[12]:
```
# Data frame's information is displayed.
df.info()
```

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

[13]:
```
# Here, all the attributes in the dataset are displayed with their total number of null values respectively.
df.isnull().sum()
```

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

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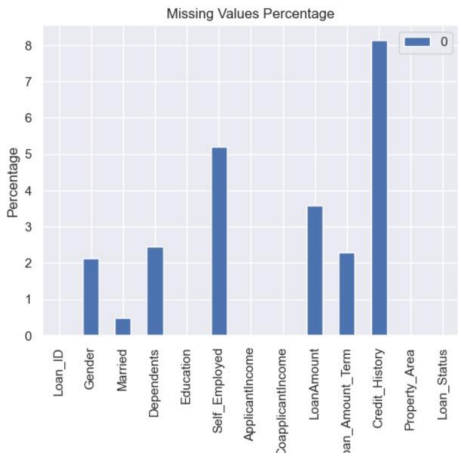
Code

JupyterLab Python 3 (ipykernel)

[14]:
```
# All the necessary libraries and modules were imported.
# Here all the null values percentages for each attribute are plotted in the form of bar graph.
import seaborn as sns
import pandas as pd
sns.set()
miss_val_per=pd.DataFrame((df.isnull().sum()/len(df)*100))
miss_val_per.plot(kind="bar",title="Missing Values Percentage",ylabel="Percentage")
```

[14]:
```
<Axes: title={'center': 'Missing Values Percentage'}, ylabel='Percentage'>
```



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Code

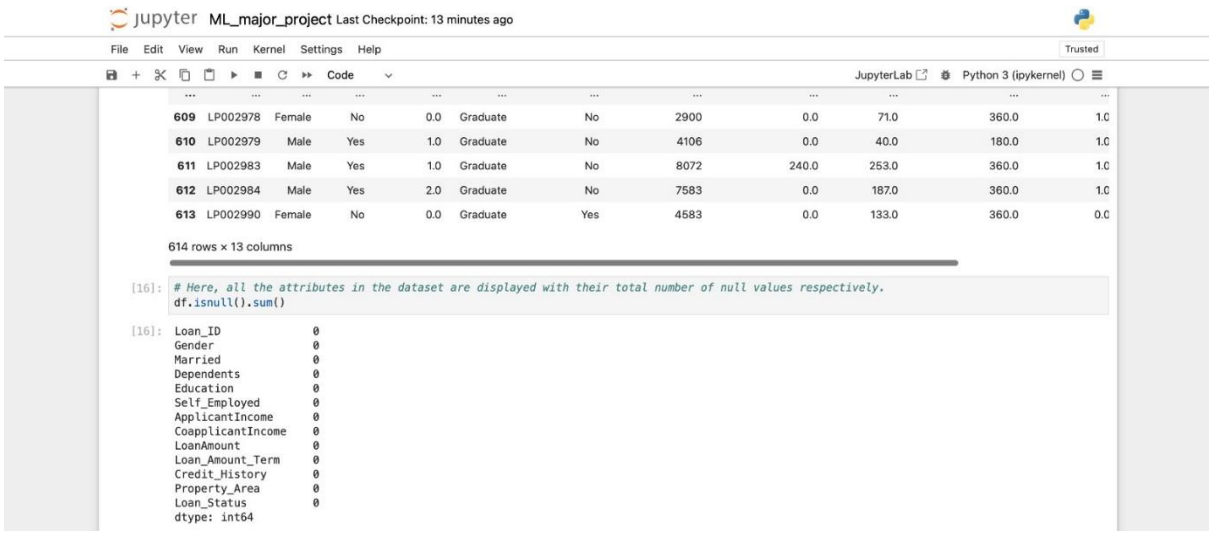
JupyterLab Python 3 (ipykernel)

[15]:
```
# All the necessary libraries and modules were imported.
# Here, all the attribute's null values are filled with sklearn imputer's mean and most_frequent strategies
# according to the requirement.(mean is used for numeric values attributes
# and most_frequent strtegy is used for non-numeric values attributes)

from sklearn.impute import SimpleImputer
import numpy as np
imp_1=SimpleImputer(strategy="mean")
imp_2=SimpleImputer(strategy="most_frequent")
imp_2.fit(df[['Gender']])
df['Gender']=imp_2.fit_transform(df[['Gender']]).ravel()
imp_2.fit(df[['Married']])
df['Married']=imp_2.fit_transform(df[['Married']]).ravel()
imp_2.fit(df[['Self_Employed']])
df['Self_Employed']=imp_2.fit_transform(df[['Self_Employed']]).ravel()
df['Dependents'] = pd.to_numeric(df['Dependents'], errors='coerce')
imp_1.fit(df[['Dependents']])
df['Dependents'] = np.round(imp_1.fit_transform(df[['Dependents']]).ravel())
imp_1.fit(df[['LoanAmount']])
df['LoanAmount'] = np.round(imp_1.fit_transform(df[['LoanAmount']]).ravel())
imp_1.fit(df[['Loan_Amount_Term']])
df['Loan_Amount_Term'] = np.round(imp_1.fit_transform(df[['Loan_Amount_Term']]).ravel())
imp_1.fit(df[['Credit_History']])
df['Credit_History'] = np.round(imp_1.fit_transform(df[['Credit_History']]).ravel())
df
```

[15]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	LP001002	Male	No	0.0	Graduate	No	5849	0.0	146.0	360.0	1.0
1	LP001003	Male	Yes	1.0	Graduate	No	4583	1508.0	128.0	360.0	1.0
2	LP001005	Male	Yes	0.0	Graduate	Yes	3000	0.0	66.0	360.0	1.0
3	LP001006	Male	Yes	0.0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0
4	LP001008	Male	No	0.0	Graduate	No	6000	0.0	141.0	360.0	1.0
...	...	...	...	...	...	...	...	...	...	...	...

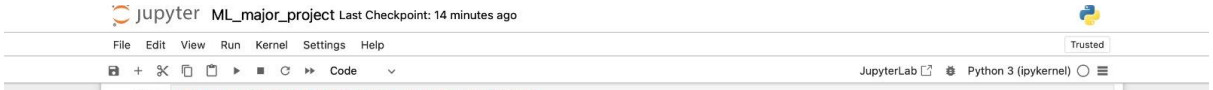


...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0.0	Graduate	No	2900	0.0	71.0	360.0	1.0
610	LP002979	Male	Yes	1.0	Graduate	No	4106	0.0	40.0	180.0	1.0
611	LP002983	Male	Yes	1.0	Graduate	No	8072	240.0	253.0	360.0	1.0
612	LP002984	Male	Yes	2.0	Graduate	No	7583	0.0	187.0	360.0	1.0
613	LP002990	Female	No	0.0	Graduate	Yes	4583	0.0	133.0	360.0	0.0

614 rows × 13 columns

[16]:
```
# Here, all the attributes in the dataset are displayed with their total number of null values respectively.
df.isnull().sum()
```

[16]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```



[17]:
```
# All the necessary libraries and modules were imported.

import pandas as pd
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

# label encoder is used here to convert yes,no and Male,Female into binary 0's and 1's.
# Since we are analyzing the dataset numerically.
label_encoder=LabelEncoder()
for column in ['Gender', 'Married', 'Education', 'Self_Employed', 'Loan_Status']:
    df[column] = label_encoder.fit_transform(df[column])

# get_dummies function is used to convert dependets column to binary values(0,1) and they are sub-divided into
# dependents 1.0 and 2.0(since number is greater than 2)
df = pd.get_dummies(df, columns=['Dependents', 'Property_Area'], drop_first=True)

# Using Feature Engineering we merge ApplicantIncome and CoapplicantIncome to TotalIncome
df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']

# Now, unnecessary ApplicantIncome and CoapplicantIncome columns were removed
df = df.drop(['ApplicantIncome', 'CoapplicantIncome'], axis=1)
df
```

[17]:

	Loan_ID	Gender	Married	Education	Self_Employed	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Dependents_1.0	Dependents_2.0	P
0	LP001002	1	0	0	0	146.0	360.0	1.0	1	False	False	
1	LP001003	1	1	0	0	128.0	360.0	1.0	0	True	False	
2	LP001005	1	1	0	1	66.0	360.0	1.0	1	False	False	
3	LP001006	1	1	1	0	120.0	360.0	1.0	1	False	False	
4	LP001008	1	0	0	0	141.0	360.0	1.0	1	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	
609	LP002978	0	0	0	0	71.0	360.0	1.0	1	False	False	
610	LP002979	1	1	0	0	40.0	180.0	1.0	1	True	False	
611	LP002983	1	1	0	0	253.0	360.0	1.0	1	True	False	

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Code

JupyterLab Python 3 (ipykernel)

...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	0	0	0	0	71.0	360.0	1.0	1	False	False
610	LP002979	1	1	0	0	40.0	180.0	1.0	1	True	False
611	LP002983	1	1	0	0	253.0	360.0	1.0	1	True	False
612	LP002984	1	1	0	0	187.0	360.0	1.0	1	False	True
613	LP002990	0	0	0	1	133.0	360.0	0.0	0	False	False

614 rows × 16 columns

[18]:
```
# All the necessary libraries and modules were imported.
# Here different models are tested for their accuracy for given data set

from sklearn.linear_model import LogisticRegression,LinearRegression
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt

X = df.drop(['Loan_ID', 'Loan_Status'], axis=1)  # Features

y = df['Loan_Status']


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# All the models were given in a dictionary and for loop is used to access each model individually
models = {
    "Logistic Regression": LogisticRegression(max_iter=3000, random_state=42),
    "DecisionTree": DecisionTreeClassifier(random_state=42),
    "RandomForest": RandomForestClassifier(n_estimators=100, random_state=42),
    "GradientBoosting": GradientBoostingClassifier(n_estimators=100, random_state=42),
    "SVM": SVC(random_state=42)
}
```

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Code

JupyterLab Python 3 (ipykernel)

```
# In for loop all the models were fitted with Trianing Data and tested with testing data and the predicted values are stored
# to generate confusion matrix, classification report and accuracy.
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    cm=confusion_matrix(y_test,y_pred)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"{model_name} Classification Report:")
    print(classification_report(y_test, y_pred))
    print("confusion matrix")
    print(cm)
    print(f"accuracy-score is {accuracy}")
    print("\n" + "-"*60 + "\n")

# Then, all the models were made to individually display their outputs and plots.
    if model_name == "DecisionTree":
        plt.figure(figsize=(150,100))
        plot_tree(model, feature_names=X.columns, filled=True, rounded=True, class_names=["N", "Y"])
        plt.show()

    if model_name in ["Logistic Regression", "SVM"]:
        # Plotting decision boundaries for Logistic Regression and SVM
        plt.figure(figsize=(10, 6))
        X_vis = X_train[['Credit_History', 'TotalIncome']].values
        y_vis = y_train
        model.fit(X_vis, y_vis)

        x_min, x_max = X_vis[:, 0].min() - 1, X_vis[:, 0].max() + 1
        y_min, y_max = X_vis[:, 1].min() - 1, X_vis[:, 1].max() + 1
        xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01), np.arange(y_min, y_max, 100))

        Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
        Z = Z.reshape(xx.shape)

        plt.contourf(xx, yy, Z, alpha=0.8)
        plt.scatter(X_vis[:, 0], X_vis[:, 1], c=y_vis, edgecolors='k', marker='o')
        plt.xlabel('Credit_History')
        plt.ylabel('TotalIncome')
        plt.title(f'{model_name} Decision Boundary')
```

```
            plt.show()

        if model_name in ["RandomForest", "GradientBoosting"]:
            # Plotting feature importances for Random Forest and Gradient Boosting
            importances = model.feature_importances_
            indices = np.argsort(importances)[::-1]

            plt.figure(figsize=(10, 6))
            plt.title(f'{model_name} Feature Importances')
            plt.bar(range(X.shape[1]), importances[indices], align='center')
            plt.xticks(range(X.shape[1]), X.columns[indices], rotation=90)
            plt.tight_layout()
            plt.show()


#Linear Regression is written seperately instead of For loop because it does not have confusion matrix. So, only accuracy score is mentioned.
regr = LinearRegression()
regr.fit(X_train, y_train)
y_pred = regr.predict(X_test)
print(f"accuracy-score is {regr.score(X_test, y_test)}")

# Plotting coefficients for linear regression
plt.figure(figsize=(10, 6))
plt.barh(X.columns, regr.coef_)
plt.title("Linear Regression Coefficients")
plt.show()

# From the results, we can say Logistic Regression will perform better(because of high aaccuracy) for the given datset.
```

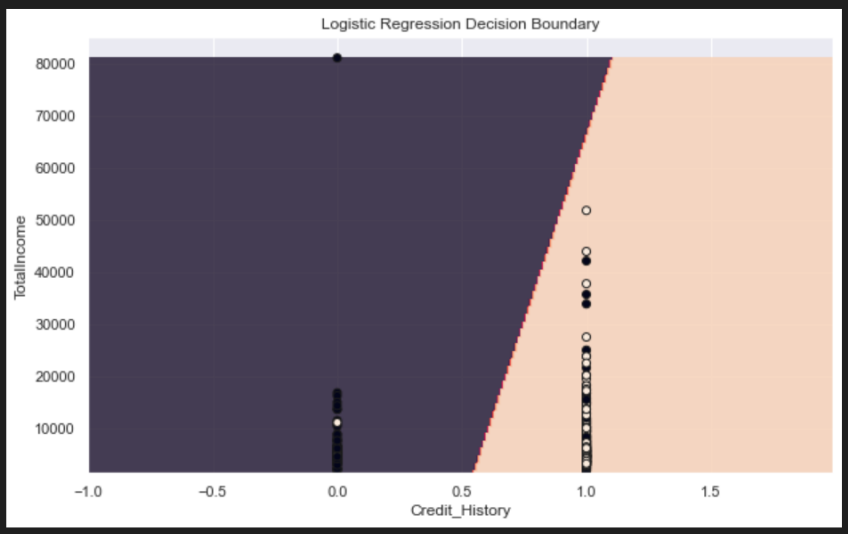
```
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.42      0.58        43
           1       0.76      0.99      0.86        80

    accuracy                           0.79       123
   macro avg       0.85      0.70      0.72       123
weighted avg       0.83      0.79      0.76       123

confusion matrix
[[18 25]
 [ 1 79]]
accuracy-score is 0.7886178861788617

------------------------------------------------------------
```



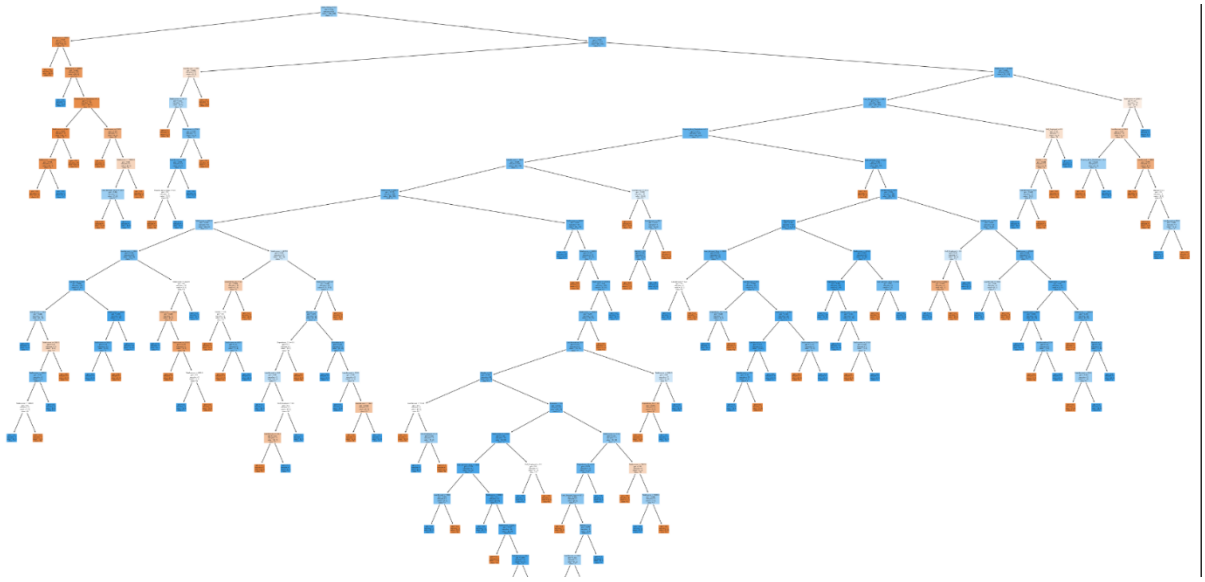
```
DecisionTree Classification Report:
              precision    recall  f1-score   support

           0       0.47      0.47      0.47        43
           1       0.71      0.71      0.71        80

    accuracy                           0.63       123
   macro avg       0.59      0.59      0.59       123
weighted avg       0.63      0.63      0.63       123

confusion matrix
[[20 23]
 [23 57]]
accuracy-score is 0.6260162601626016

------------------------------------------------------------
```



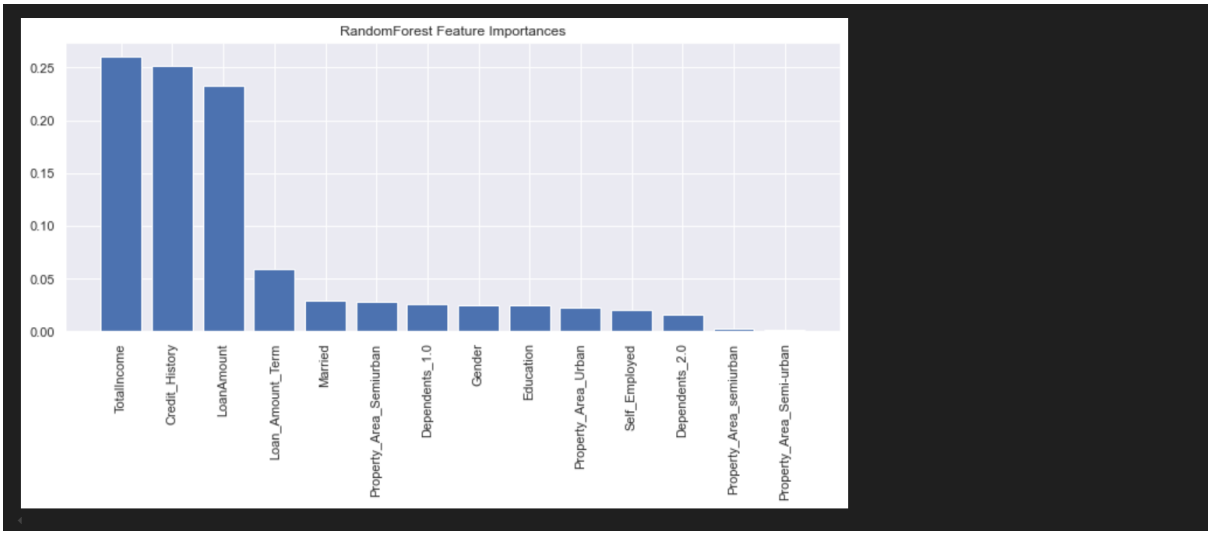
```
RandomForest Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.44      0.58        43
           1       0.76      0.95      0.84        80

    accuracy                           0.77       123
   macro avg       0.79      0.70      0.71       123
weighted avg       0.78      0.77      0.75       123

confusion matrix
[[19 24]
 [ 4 76]]
accuracy-score is 0.7723577235772358

------------------------------------------------------------
```



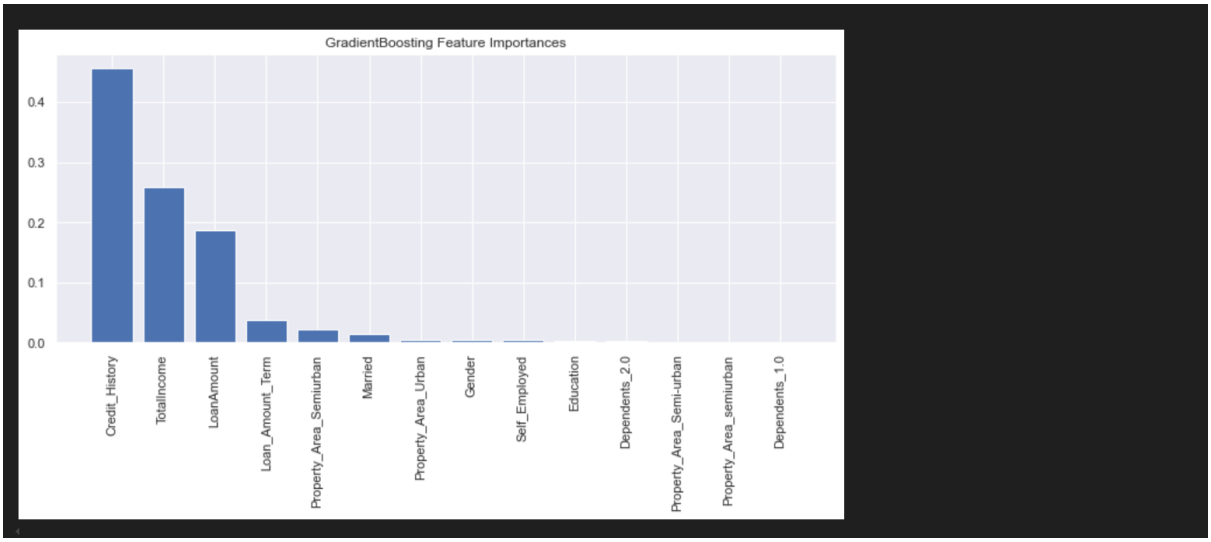

```
GradientBoosting Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.42      0.53        43
           1       0.74      0.91      0.82        80

    accuracy                           0.74       123
   macro avg       0.73      0.67      0.67       123
weighted avg       0.74      0.74      0.72       123

confusion matrix
[[18 25]
 [ 7 73]]
accuracy-score is 0.7398373983739838

------------------------------------------------------------
```



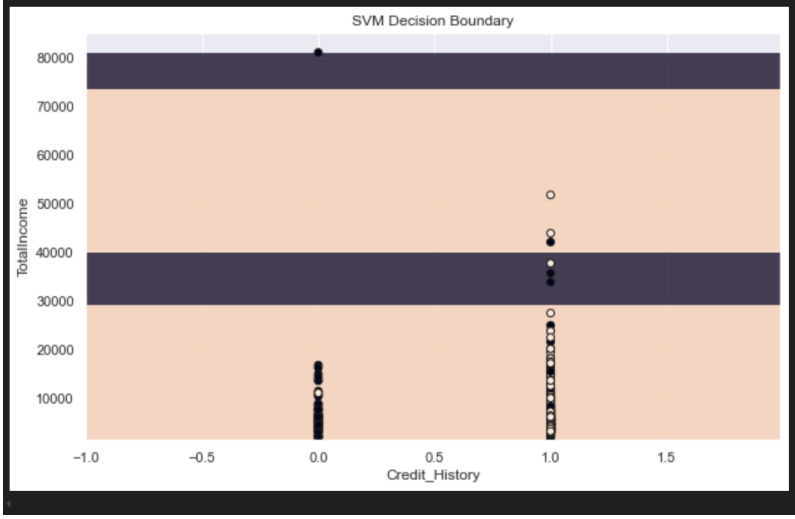
```
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        43
           1       0.65      0.99      0.78        80

    accuracy                           0.64       123
   macro avg       0.32      0.49      0.39       123
weighted avg       0.42      0.64      0.51       123

confusion matrix
[[ 0 43]
 [ 1 79]]
accuracy-score is 0.6422764227642277

------------------------------------------------------------
```




```
accuracy-score is 0.27623037418837315
```