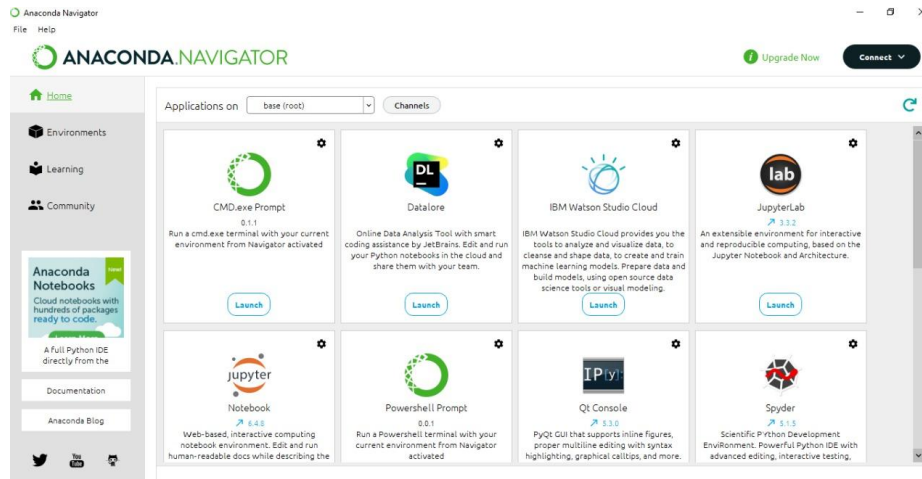


## Screenshots

Date	24 November 2022
Team ID	PNT2022TMID30218
Project Name	Smart Lender - Applicant Credibility Prediction For Loan Approval

## Pre - Requisites



## Visualizing And Analyzing The Data Importing The Libraries

```
[3] import numpy as np
import pandas as ps
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
from sklearn.preprocessing import StandardScaler
from imblearn.combine import SMOTETomek
from sklearn.neighbors import KNeighborsClassifier
```

## Reading The Dataset

```
[4] data = ps.read_csv(r"/content/LOAN_PREDICTION.csv")
```

```
[5] data.head()
```

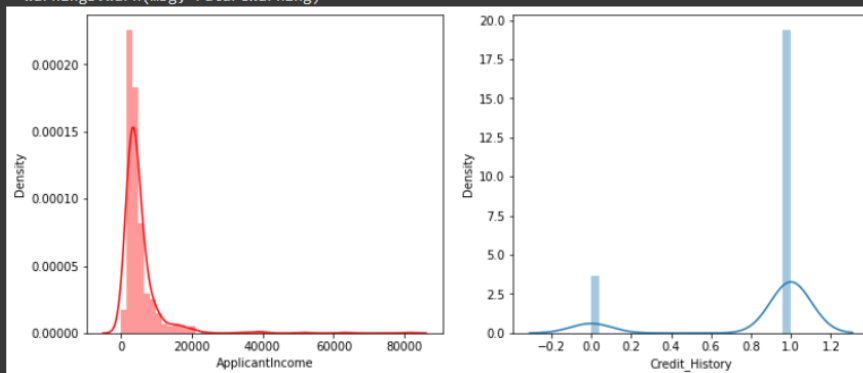
	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	Male	No	0.0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1.0	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2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

## Uni-Variate Analysis

### Uni-Variate Analysis

```
[73] plt.figure(figsize=(12,5))
plt.subplot(121)
sns.distplot(data['ApplicantIncome'], color='r')
plt.subplot(122)
sns.distplot(data['Credit_History'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Use `displot` instead.
warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Use `displot` instead.
warnings.warn(msg, FutureWarning)
```



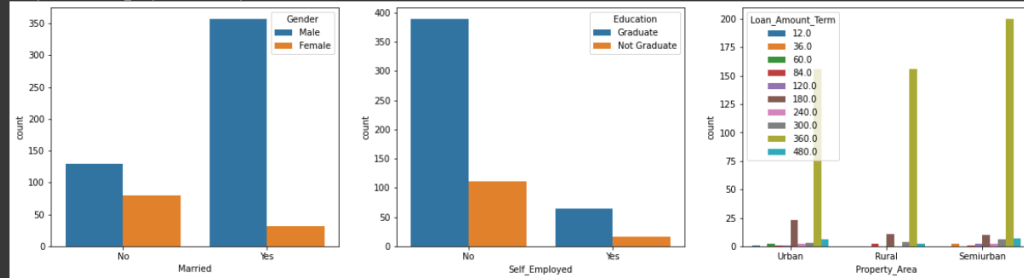
## Bivariate Analysis

### Bi-Variate Analysis

```
plt.figure(figsize=(20,5))
plt.subplot(131)
sns.countplot(data['Married'], hue=data['Gender'])
plt.subplot(132)
sns.countplot(data['Self_Employed'], hue=data['Education'])
plt.subplot(133)
sns.countplot(data['Property_Area'], hue=data['Loan_Amount_Term'])
```

/usr/local/lib/python3.7/dist-packages/seaborn/\_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument is 'x'.  
FutureWarning  
/usr/local/lib/python3.7/dist-packages/seaborn/\_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument is 'x'.  
FutureWarning  
/usr/local/lib/python3.7/dist-packages/seaborn/\_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument is 'x'.  
FutureWarning

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f17eb917610>



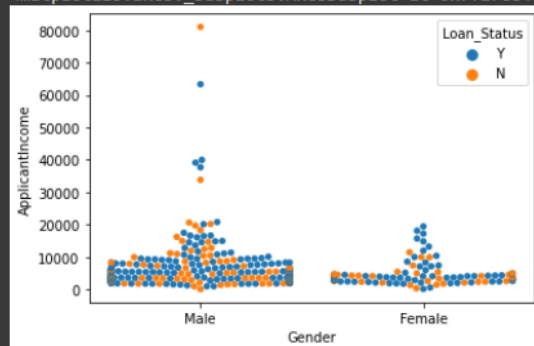
## Multivariate Analysis

### Multivariate Analysis

```
[75] sns.swarmplot(data['Gender'], data['ApplicantIncome'], hue=data['Loan_Status'])
```

/usr/local/lib/python3.7/dist-packages/seaborn/\_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument is 'x'.  
FutureWarning  
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning: 67.5% of the data has missing values in the 'Loan\_Status' variable.  
warnings.warn(msg, UserWarning)  
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning: 33.0% of the data has missing values in the 'ApplicantIncome' variable.  
warnings.warn(msg, UserWarning)

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f17e847aa50>



## Descriptive Analysis

▼ Descriptive Analysis

```
[76] data.describe()
```

	Dependents	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	599.000000	614.000000	614.000000	592.000000	600.000000	564.000000
mean	0.762938	5403.459283	1621.245798	146.412162	342.000000	0.842199
std	1.015216	6109.041673	2926.248369	85.587325	65.12041	0.364878
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	3812.500000	1188.500000	128.000000	360.000000	1.000000
75%	2.000000	5795.000000	2297.250000	168.000000	360.000000	1.000000
max	3.000000	81000.000000	41667.000000	700.000000	480.000000	1.000000

## Data Pre-Processing

### Checking For Null Values

▼ Checking For Null Values

```
[77] data.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   float64
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(5), int64(1), object(7)
memory usage: 62.5+ KB
```

```
[78] data.isnull().sum()
```

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	

0s completed at

## Handling Categorical Values

### ▼ Handling Categorical Values

```
✓ [83] data.select_dtypes(include='object').columns
0s
      Index(['Gender', 'Married', 'Education', 'Self_Employed', 'Property_Area',
            'Loan_Status'],
            dtype='object')
```

```
✓ [84] data['Gender'].unique()
0s
      array(['Male', 'Female'], dtype=object)
```

```
✓ [85] data['Gender'].replace({'Male':1,'Female':0},inplace=True)
0s
```

```
✓ [86] data['Married'].unique()
0s
      array(['No', 'Yes'], dtype=object)
```

```
✓ [87] data['Married'].replace({'Yes':1,'No':0},inplace=True)
0s
```

```
✓ [88] data['Dependents'].unique()
0s
      array([0., 1., 2., 3.])
```

```
✓ [89] data['Dependents'].replace({'0':0,'1':1,'2':2,'3':3},inplace=True)
0s
```

```
✓ [93] data['Property_Area'].replace({'Urban':2,'Rural':0,'Semiurban':1},inplace=True)
0s

✓ [94] data['Loan_Status'].unique()
0s
array(['Y', 'N'], dtype=object)

✓ [95] data['Loan_Status'].replace({'Y':1,'N':0},inplace=True)
0s

✓ [96] data['Education'].unique()
0s
array(['Graduate', 'Not Graduate'], dtype=object)

✓ [97] data['Education'].replace({'Graduate':1,'Not Graduate':0},inplace=True)
0s

✓ [98] data['CoapplicantIncome']=data['CoapplicantIncome'].astype("int64")
0s
data['LoanAmount']=data['LoanAmount'].astype("int64")
data['Loan_Amount_Term']=data['Loan_Amount_Term'].astype("int64")
data['Credit_History']=data['Credit_History'].astype("int64")
```

## Balancing The Dataset

```
✓ Balancing The Dataset

✓ [100] smote = SMOTETomek(0.90)
0s
/usr/local/lib/python3.7/dist-packages/imblearn/utils/_validation.py:591: FutureWarning: Pass sampling_strategy=0.9 as keyword args. From version 0.9.0, passing sampling_strategy as a string will be deprecated.
FutureWarning,

✓ [101] y = data['Loan_Status']
0s
x = data.drop(columns=['Loan_Status'],axis=1)

✓ [102] x_bal,y_bal = smote.fit_resample(x,y)
0s

✓ [103] print(y.value_counts())
0s
print(y_bal.value_counts())

1    422
0    192
Name: Loan_Status, dtype: int64
1    355
0    312
Name: Loan_Status, dtype: int64
```

## Scaling The Data

```
Scaling The Data

[104] sc = StandardScaler()
      x_bal = sc.fit_transform(x_bal)

[105] x_bal = pd.DataFrame(x_bal)

[106] x_bal.head()
```

	0	1	2	3	4	5	6	7	8	9	10
0	0.534007	-1.179271	-0.749348	0.621848	-0.320124	0.081803	-0.528345	-0.273023	0.278859	0.584852	1.348301
1	0.534007	0.847981	0.278126	0.621848	-0.320124	-0.125702	-0.004684	-0.170189	0.278859	0.584852	-1.232235
2	0.534007	0.847981	-0.749348	0.621848	3.123790	-0.385166	-0.528345	-0.967153	0.278859	0.584852	1.348301
3	0.534007	0.847981	-0.749348	-1.608111	-0.320124	-0.453515	0.290483	-0.273023	0.278859	0.584852	1.348301
4	0.534007	-1.179271	-0.749348	0.621848	-0.320124	0.106553	-0.528345	-0.003083	0.278859	0.584852	1.348301

```
[107] data.drop("Property_Area",axis=1,inplace=True)
      data.drop("Loan_Amount_Term",axis=1,inplace=True)

[108] x = data.iloc[:, :-1]
      y = data["Loan_Status"]

[109] x
```

0s completed at 8:57 PM

## Splitting Data Into Train And Test

```
[115] from sklearn.model_selection import train_test_split
      x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.33,random_state=42)
```

## Decision Tree Model

## Decision Tree Model

```
[116] from sklearn.tree import DecisionTreeClassifier
a = DecisionTreeClassifier(max_depth=4,splitter='best',criterion='entropy')
a.fit(x_train,y_train)

DecisionTreeClassifier(criterion='entropy', max_depth=4)

[117] Y= a.predict(x_test)
Y
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1,
        1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
        1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
        1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
        0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
        1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
        1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0,
        0, 1, 1, 1, 1])

[118] y_predict_train =a.predict(x_train)

[119] from sklearn.metrics import accuracy_score,classification_report,confusion_matrix

[120] print('Testing accuracy : ',accuracy_score(y_test,Y))
print("Training accuracy : ",accuracy_score(y_train,y_predict_train))

Testing accuracy : 0.7389162561576355
Training accuracy : 0.8394160583941606
```

```

> Random Forest Model

[121] from sklearn.ensemble import RandomForestClassifier
      m = RandomForestClassifier(n_estimators=10,criterion='entropy')
      m.fit(x_train,y_train)

      RandomForestClassifier(criterion='entropy', n_estimators=10)

[122] ypredict= m.predict(x_test)
      ypredict

array([1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1,
       1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0,
       0, 1, 0, 1, 1])

[123] ypredict_train = m.predict(x_train)

[124] from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
      print('Testing accuracy : ', accuracy_score(y_test,ypredict))
      print('Training accuracy : ',accuracy_score(y_train,ypredict_train))

Testing accuracy :  0.7192118226600985
Training accuracy :  0.9902676399026764

```



## KNN Model

```

KNN Model

[125] S = KNeighborsClassifier()
      S.fit(x_train,y_train)

      KNeighborsClassifier()

[126] y1=S.predict(x_test)
      y2=S.predict(x_train)

[127] kNN = KNeighborsClassifier(n_neighbors=7)
      kNN.fit(x_train, y_train)
      print(kNN.predict(x_test))

[1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0 0 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1
  1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
  1 0 1 1 1 0 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 0 1 1 1 1 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1
  1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1 1 1
  1 1 1 0 1 1 1 1 1 1 1 1 0 1 1 1]

[128] print('Testing accuracy : ',accuracy_score(y_test,y1))
      print('Training accuracy : ',accuracy_score(y_train,y2))

      Testing accuracy :  0.5862068965517241
      Training accuracy :  0.7445255474452555

Double-click (or enter) to edit
```

## Xgboost Model

```

Xgboost Model

[129] from sklearn.ensemble import GradientBoostingClassifier
      from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,f1_score
      V = GradientBoostingClassifier()
      V.fit(x_train,y_train)

      GradientBoostingClassifier()

[130] yp=V.predict(x_test)
      ypr=V.predict(x_train)

[131] print('Testing accuracy : ',accuracy_score(y_test,yp))
      print('Training accuracy : ',accuracy_score(y_train,ypr))

      Testing accuracy :  0.7438423645320197
      Training accuracy :  0.8978102189781022
```

## Compare The Model

### Decision Tree Model

```
decisionTreeClassifier(x_train, x_test, y_train, y_test)

DecisionTreeClassifier
Confusion matrix
[[ 35  37]
 [ 26 105]]
Classification report
      precision    recall  f1-score   support

     0       0.57      0.49      0.53         72
     1       0.74      0.80      0.77        131

   accuracy          0.69         203
  macro avg       0.66      0.64      0.65         203
 weighted avg       0.68      0.69      0.68         203

Testing accuracy : 0.6896551724137931
Training accuracy : 1.0
```

### Random Forest Model

```
randomForestClassifier(x_train, x_test, y_train, y_test)

RandomForestClassifier
Confusion matrix
[[ 36  36]
 [ 10 121]]
Classification report
      precision    recall  f1-score   support

     0       0.78      0.50      0.61         72
     1       0.77      0.92      0.84        131

   accuracy          0.77         203
  macro avg       0.78      0.71      0.73         203
 weighted avg       0.77      0.77      0.76         203

Testing accuracy : 0.7733990147783252
Training accuracy : 1.0
```

## KNN Model

```
kneighborsClassifier(x_train, x_test, y_train, y_test)
```

KNeighborsClassifier  
Confusion matrix  
[[ 30 42]  
 [ 10 121]]  
Classification report

	precision	recall	f1-score	support
0	0.75	0.42	0.54	72
1	0.74	0.92	0.82	131
accuracy			0.74	203
macro avg	0.75	0.67	0.68	203
weighted avg	0.75	0.74	0.72	203

Testing accuracy : 0.5862068965517241  
Training accuracy : 0.7445255474452555

## Xgboost Model

```
print('Training accuracy :', accuracy_score(y_train, predicted))  
xgboost(x_train, x_test, y_train, y_test)
```

Gradient BoostingClassifier  
Confusion matrix  
[[ 29 43]  
 [ 9 122]]  
Classification report

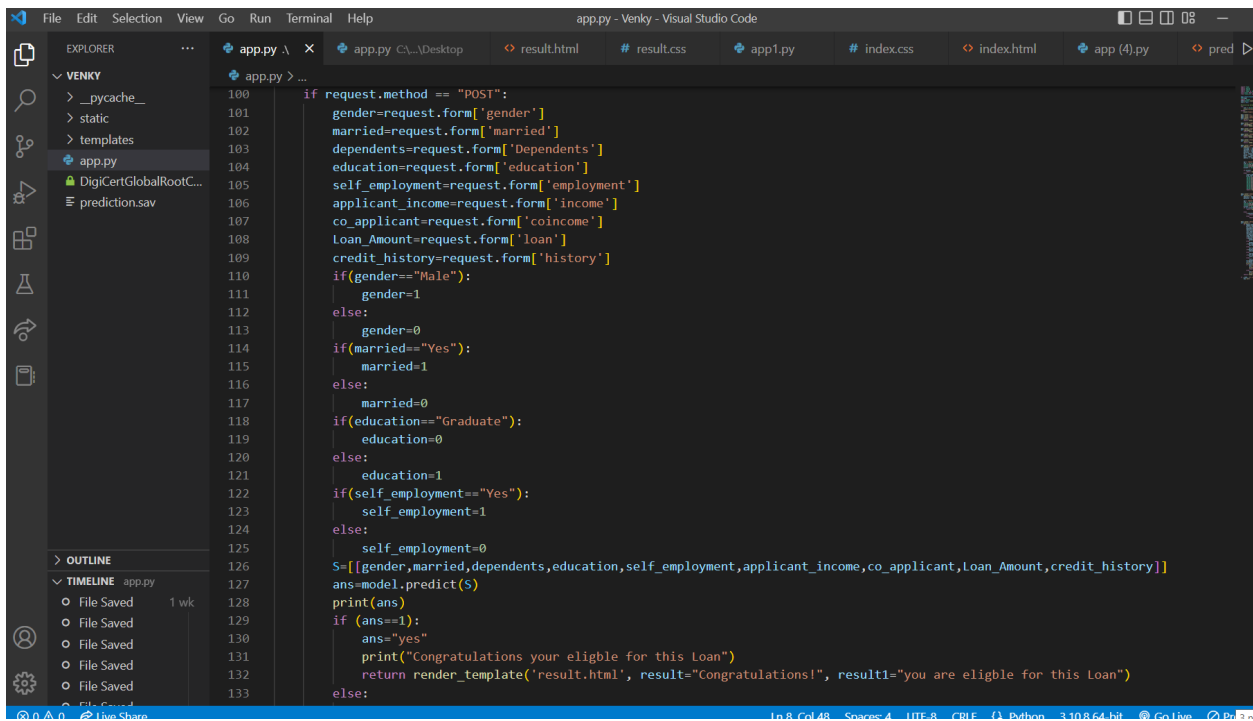
	precision	recall	f1-score	support
0	0.76	0.40	0.53	72
1	0.74	0.93	0.82	131
accuracy			0.74	203
macro avg	0.75	0.67	0.68	203
weighted avg	0.75	0.74	0.72	203

Testing accuracy : 0.7438423645320197  
Training accuracy : 0.8978102189781022

## Save The Model

```
[136] #saving the model
import pickle
filename = 'prediction_loan.sav'
pickle.dump(m,open(filename,"wb"))
```

## Application Building



The screenshot shows a Visual Studio Code editor with a Python web application. The Explorer panel on the left shows a project named 'VENKY' with files like 'app.py', 'prediction.sav', and 'result.html'. The main editor displays the code for 'app.py', which handles POST requests and uses a machine learning model to predict loan eligibility based on various input features.

```
100 if request.method == "POST":
101     gender=request.form['gender']
102     married=request.form['married']
103     dependents=request.form['dependents']
104     education=request.form['education']
105     self_employment=request.form['employment']
106     applicant_income=request.form['income']
107     co_applicant=request.form['coincome']
108     Loan_Amount=request.form['loan']
109     credit_history=request.form['history']
110     if(gender=="Male"):
111         gender=1
112     else:
113         gender=0
114     if(married=="Yes"):
115         married=1
116     else:
117         married=0
118     if(education=="Graduate"):
119         education=0
120     else:
121         education=1
122     if(self_employment=="Yes"):
123         self_employment=1
124     else:
125         self_employment=0
126     S=[[gender,married,dependents,education,self_employment,applicant_income,co_applicant,Loan_Amount,credit_history]]
127     ans=model.predict(S)
128     print(ans)
129     if (ans==1):
130         ans="yes"
131         print("Congratulations your eligible for this Loan")
132         return render_template('result.html', result="Congratulations!", result1="you are eligible for this Loan")
133     else:
```