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Project Name : Loan Approval Prediction using Machine Learning classification algorithm

Objective of project:

The goal is to develop a machine learning model for Loan Approval Prediction, to potentially replace the updatable supervised machine learning classification .models by predicting results in the form of best accuracy.

The dataset contains 13 features are listed below:

Loan : A unique id

Gender :Gender of the applicant Male/female

Married :Marital Status of the applicant, values will be Yes/ No

Dependents :It tells whether the applicant has any dependents or not.

Education :It will tell us whether the applicant is Graduated or not.

Self_Employed :This defines that the applicant is self-employed i.e. Yes/ No

ApplicantIncome :Applicant income

CoapplicantIncome :Co-applicant income

LoanAmount :Loan amount (in thousands)

Loan_Amount_Term :Terms of loan (in months)

Credit_History :Credit history of individual's repayment of their debts

Property_Area :Area of property i.e. Rural/Urban/Semi-urban

Loan_Status :Status of Loan Approved or not i.e. Y- Yes, N-No

Firstly we have to import libraries :

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
import os
os.getcwd()
```

Out[2]:
```
'C:\\Users\\pawar'
```

Reading Data

In [3]:
```
df = pd.read_csv('LOAN_DATA_OG.csv')
df
```

Out[3]:

	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	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y
...	...	...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0	1.0	Rural	Y
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0	1.0	Rural	Y
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0	1.0	Urban	Y
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.0	1.0	Urban	Y
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.0	0.0	Semiurban	N

614 rows × 13 columns

In [4]:
```
df.head() #It display first five row
```

Out[4]:

	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	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

In [5]:
```
df.tail() #It display last five row
```

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0	1.0	Rural	Y
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0	1.0	Rural	Y
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0	1.0	Urban	Y
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.0	1.0	Urban	Y
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.0	0.0	Semiurban	N

EDA process part in Dataset

In [6]:
```
df.info() #It display the information about data
```

```
<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
```

We can observe 13 attributes. Out of which 4 attributes are in float, 1 attribute is in integer and the other 8 are in objects.

In [7]:
```
df.isnull().sum() #Handling missing values
```

Out[7]:
```
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
```

We have found 6 columns having NULL values. And we have to replace the NULL values with some common values.

In [8]:
```
df.isna().sum()
```

Out[8]:
```
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
```

In [9]:
```
df.describe() #It displays the stastical information of the data
```

Out[9]:

	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
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

describe() is used to give Statistical Information of Dataset. The total count column displays some missing values .The ['credit_history'] attributes are in the range of 0 to 1. The ['CoapplicantIncome'] attributes has min values are 0 so we have to replace it with nan and after that replace with mean

In [10]:
```
df["CoapplicantIncome"].replace(0, np.nan, inplace=True)
```

In [11]:
```
df["CoapplicantIncome"].replace(np.nan,df["CoapplicantIncome"].mean(),inplace=True)
```

In [12]:
```
df.shape
```

Out[12]: (614, 13)

In [13]:
```
df.describe() # after the above process final statistical information displayed.
```

Out[13]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	2919.193314	146.412162	342.00000	0.842199
std	6109.041673	2540.709504	85.587325	65.12041	0.364878
min	150.000000	16.120001	9.000000	12.00000	0.000000
25%	2877.500000	2064.750000	100.000000	360.00000	1.000000
50%	3812.500000	2919.193314	128.000000	360.00000	1.000000
75%	5795.000000	2919.193314	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

Let us fill in the missing values for numerical terms using mode operation.

In [14]:
```
df['Gender'].fillna(df['Gender'].mode()[0], inplace = True)
df['Married'].fillna(df['Married'].mode()[0],inplace = True)
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0],inplace=True)
df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)

df.LoanAmount = df.LoanAmount.fillna(df.LoanAmount.mean())


df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)

df.isnull().sum()
```

Out[14]:
```
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
```

In [15]:
```
df.isnull().sum()
```

Out[15]:
```
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
```

All the missing values will be filled with the most frequently occurring values. Modes give the result in their terms of the data frame, so we only need the values. We will specify 0th index to display the values.

In [16]:
```
df.shape # the number of elements in each dimension
```

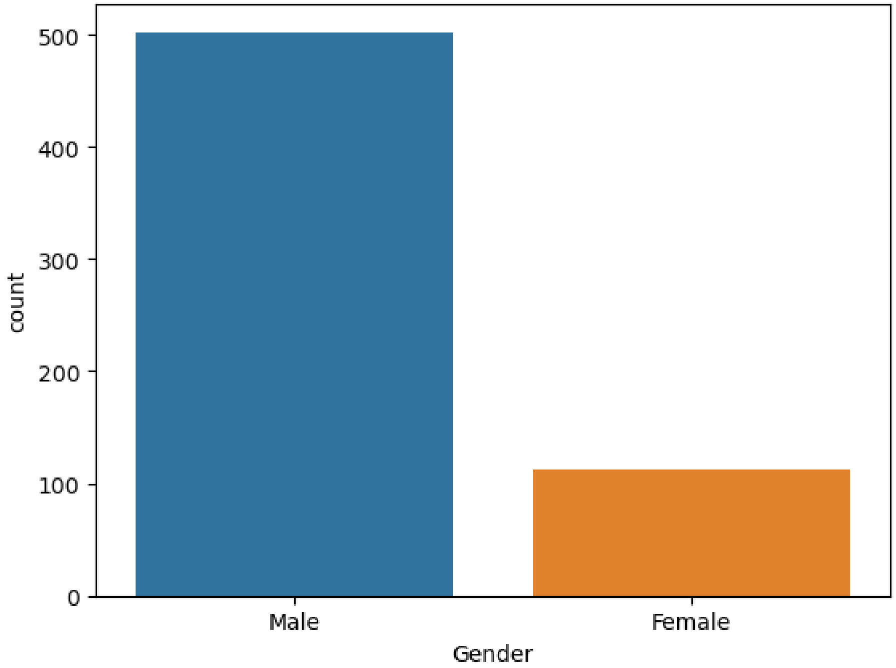
Out[16]:
```
(614, 13)
```

Data visualization for categorical dataset

In [17]:
```
#we will see the number of people who take loan as group by gender
print("number of people who take loan as group by gender:")
print(df['Gender'].value_counts())
sns.countplot(x='Gender', data=df)
```

```
number of people who take loan as group by gender:
Male      502
Female    112
Name: Gender, dtype: int64
```

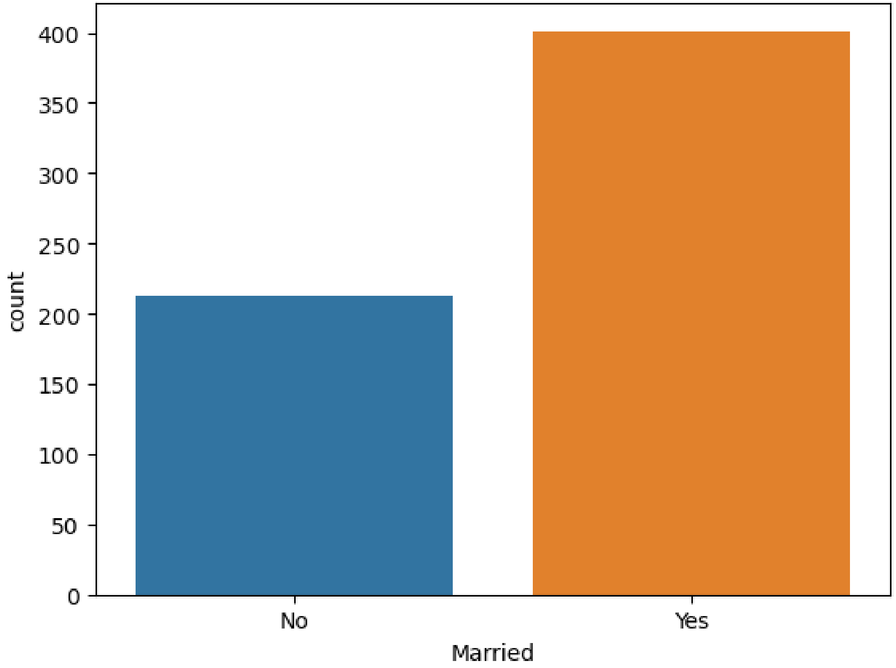
Out[17]:
```
<Axes: xlabel='Gender', ylabel='count'>
```



As per the number of oberervation in each category bins are displayed using bar so the gender are male and female. so Male take loan as count 502 and female take loan as count 112.

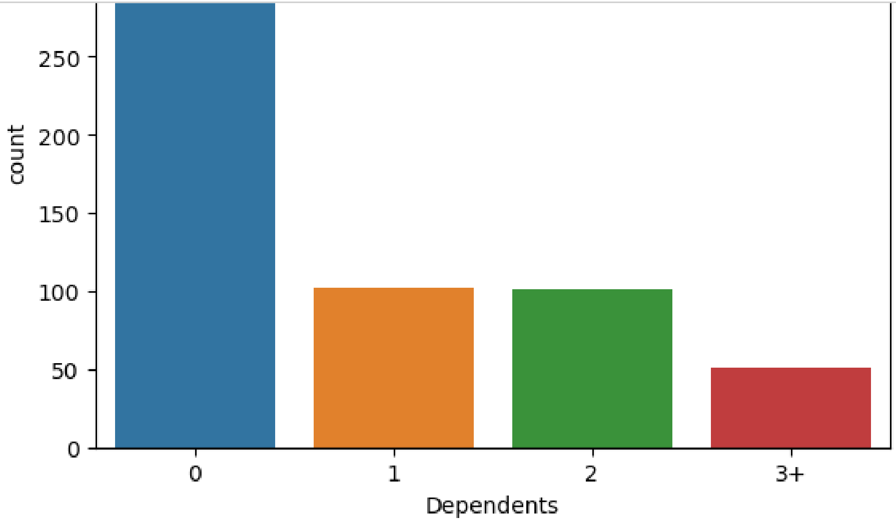
In [18]:
```
#we will see the number of people who take loan as group by marital status
print("number of people who take loan as group by marital_status:")
print(df['Married'].value_counts())
sns.countplot(x='Married', data=df)
plt.show()
```

```
number of people who take loan as group by marital_status:
Yes    401
No     213
Name: Married, dtype: int64
```



As per the observation the marital_status wise Yes means they are Married and take loan as count 401 and No means unmarried take loan as count 213.

In [19]:
```
#we will see the number of people who take loan as group by Dependents
print("number of people who take loan as group by Dependents:")
print(df['Dependents'].value_counts())
sns.countplot(x='Dependents', data=df)
```

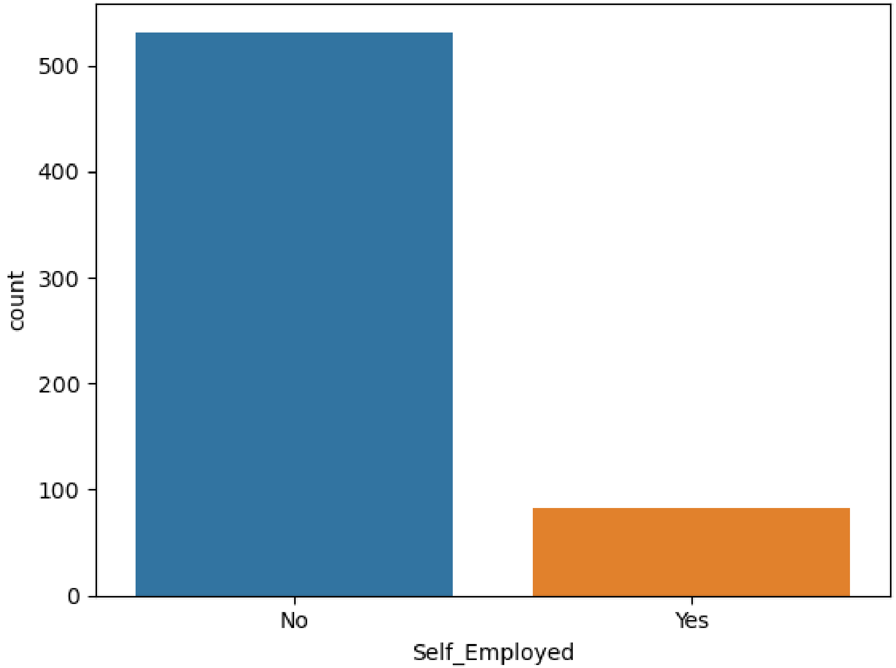


As per the observation the dependents 0 dependents are take loan as count 360 ,1 dependents are take loan as 102 and 2 dependents are take loan as 101 and 3+ dependents take loan as count 51

In [20]:
```
#we will see the number of people who take loan as group by Self_Employed
print("number of people who take loan as group by Self_Employed:")
print(df['Self_Employed'].value_counts())
sns.countplot(x='Self_Employed', data=df)
```

```
number of people who take loan as group by Self_Employed:
No     532
Yes     82
Name: Self_Employed, dtype: int64
```

Out[20]: <Axes: xlabel='Self_Employed', ylabel='count'>

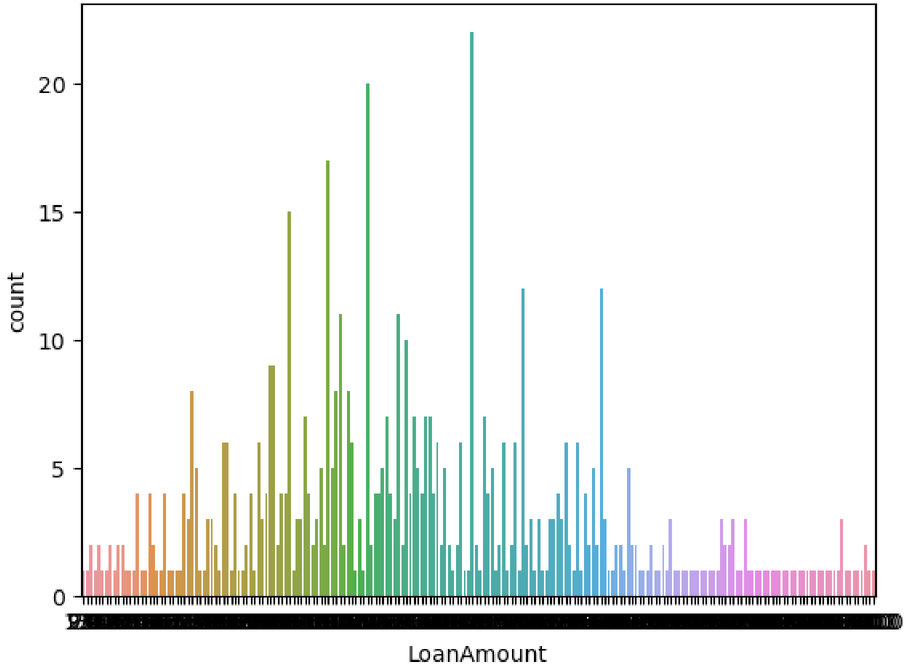


As per the observation the No they are take loan as count 532 and yes as count is 82

In [21]:
```
#we will see the number of people who take loan as group by LoanAmount
print("number of people who take loan as group by LoanAmount:")
print(df['LoanAmount'].value_counts())
sns.countplot(x='LoanAmount', data=df)
```

```
number of people who take loan as group by LoanAmount:
146.412162    22
120.000000    20
110.000000    17
100.000000    15
160.000000    12
              ..
240.000000     1
214.000000     1
59.000000      1
166.000000     1
253.000000     1
Name: LoanAmount, Length: 204, dtype: int64
```

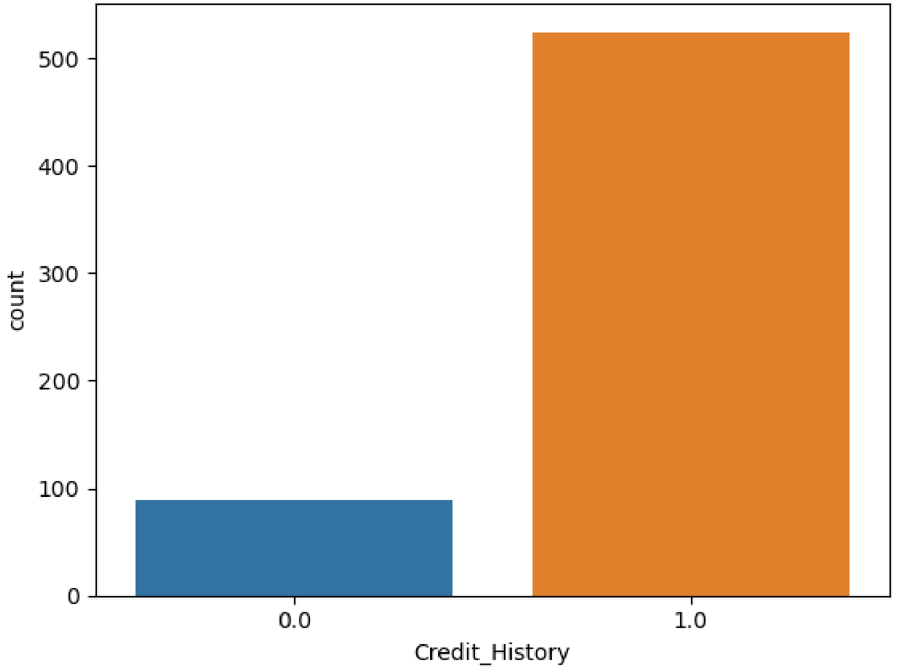
Out[21]: <Axes: xlabel='LoanAmount', ylabel='count'>



In [22]:
```
#we will see the number of people who take loan as group by Credit_History
print("number of people who take loan as group by Credit_History:")
print(df['Credit_History'].value_counts())
sns.countplot(x='Credit_History', data=df)
```

```
number of people who take loan as group by Credit_History:
1.0    525
0.0     89
Name: Credit_History, dtype: int64
```

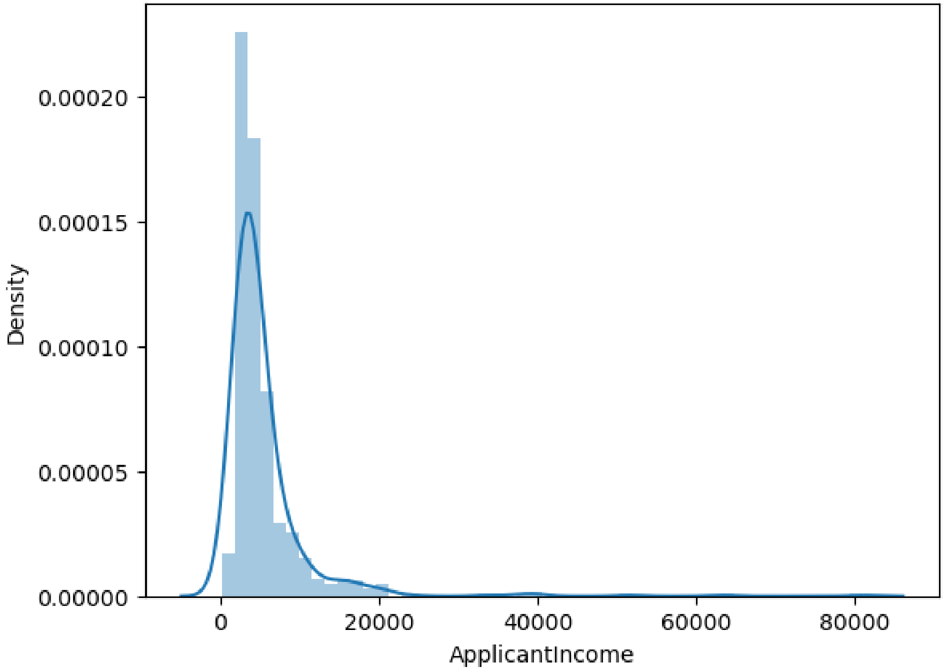
Out[22]: `<Axes: xlabel='Credit_History', ylabel='count'>`



Data visualization for numerical dataset

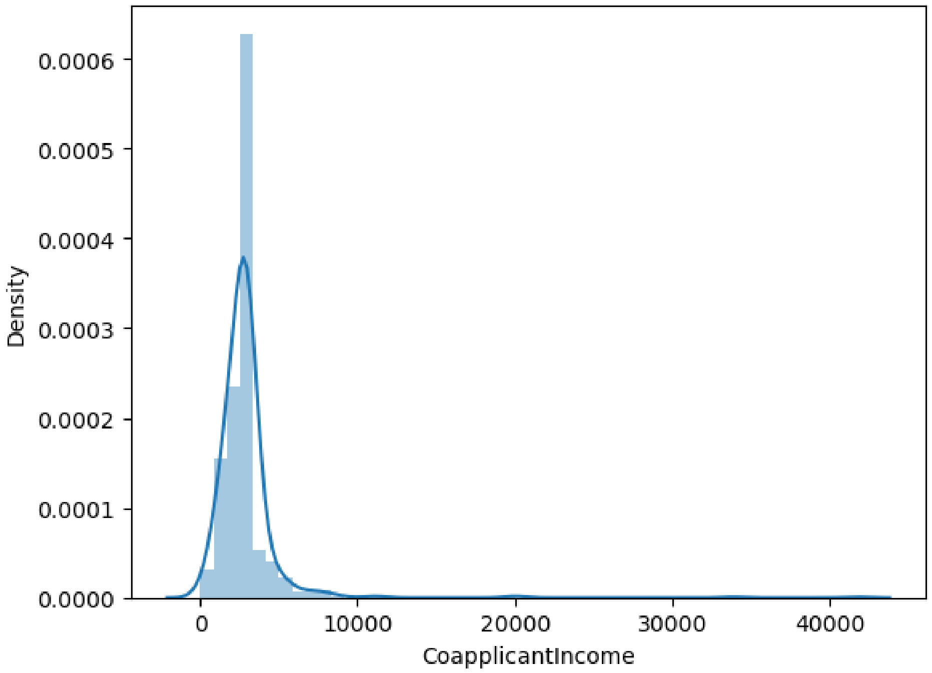
In [23]:
```
sns.distplot(df["ApplicantIncome"])
```

Out[23]: <Axes: xlabel='ApplicantIncome', ylabel='Density'>



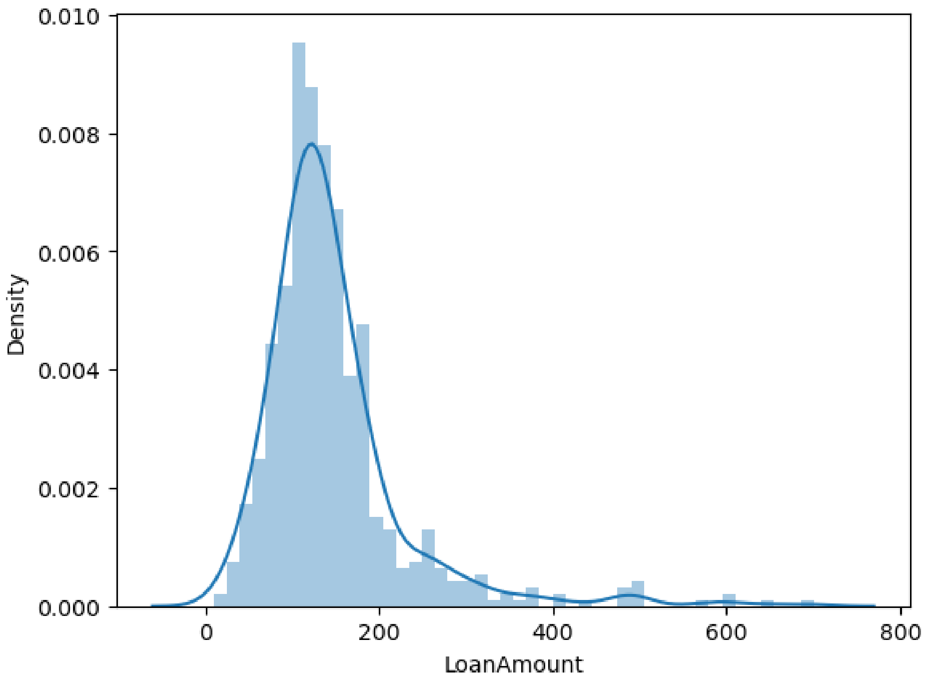
In [24]:
```
sns.distplot(df["CoapplicantIncome"])
```

Out[24]: <Axes: xlabel='CoapplicantIncome', ylabel='Density'>



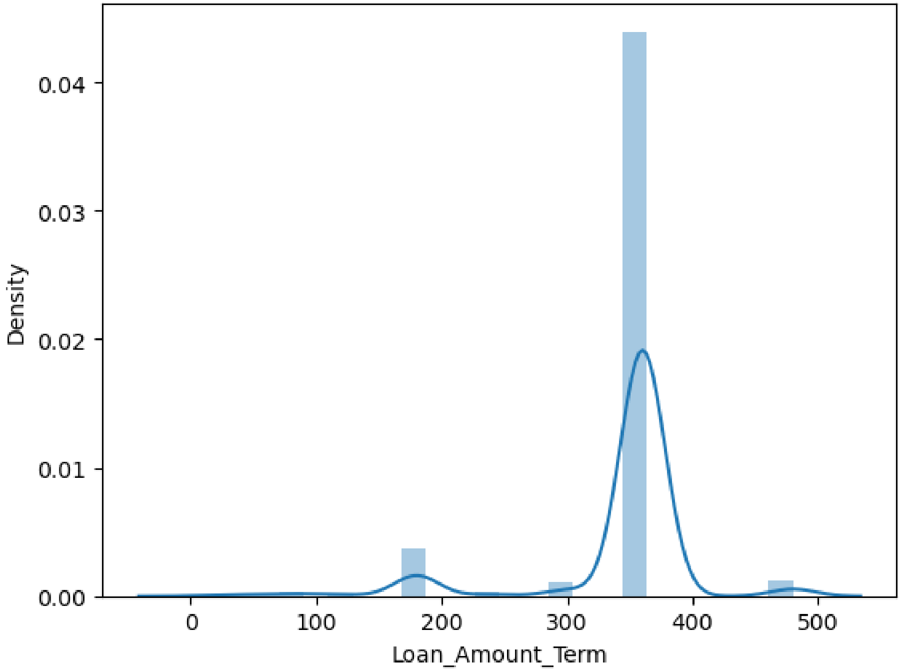
In [25]:
```
sns.distplot(df["LoanAmount"])
```

Out[25]: <Axes: xlabel='LoanAmount', ylabel='Density'>



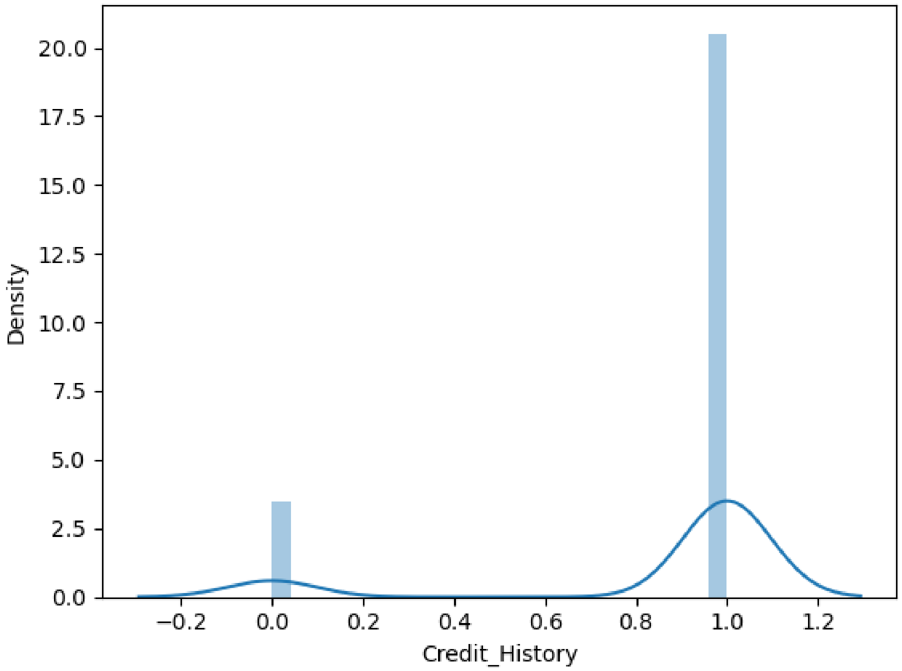
In [26]:
```
sns.distplot(df['Loan_Amount_Term'])
```

Out[26]: <Axes: xlabel='Loan_Amount_Term', ylabel='Density'>



In [27]:
```
sns.distplot(df['Credit_History'])
```

Out[27]: <Axes: xlabel='Credit_History', ylabel='Density'>



In [28]:
```
df
```

Out[28]:

	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	Graduate	No	5849	2919.193314	146.412162	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.000000	128.000000	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	2919.193314	66.000000	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.000000	120.000000	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	2919.193314	141.000000	360.0	1.0	Urban	Y
...	...	...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	No	2900	2919.193314	71.000000	360.0	1.0	Rural	Y
610	LP002979	Male	Yes	3+	Graduate	No	4106	2919.193314	40.000000	180.0	1.0	Rural	Y
611	LP002983	Male	Yes	1	Graduate	No	8072	240.000000	253.000000	360.0	1.0	Urban	Y
612	LP002984	Male	Yes	2	Graduate	No	7583	2919.193314	187.000000	360.0	1.0	Urban	Y
613	LP002990	Female	No	0	Graduate	Yes	4583	2919.193314	133.000000	360.0	0.0	Semiurban	N

614 rows × 13 columns

Label Encoding

label encoding is a technique used in machine learning and data analysis to convert categorical variables into numerical format.

In [29]:
```
from sklearn.preprocessing import LabelEncoder
cols = ['Gender',"Married","Education",'Self_Employed',"Property_Area","Loan_Status","Dependents"]
le = LabelEncoder()
for col in cols:
    df[col] = le.fit_transform(df[col])
```

In [30]:
```
df
```

Out[30]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	1	0	0	0	0	5849	2919.193314	146.412162	360.0	1.0	2	1
1	LP001003	1	1	1	0	0	4583	1508.000000	128.000000	360.0	1.0	0	0
2	LP001005	1	1	0	0	1	3000	2919.193314	66.000000	360.0	1.0	2	1
3	LP001006	1	1	0	1	0	2583	2358.000000	120.000000	360.0	1.0	2	1
4	LP001008	1	0	0	0	0	6000	2919.193314	141.000000	360.0	1.0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	0	0	0	0	0	2900	2919.193314	71.000000	360.0	1.0	0	1
610	LP002979	1	1	3	0	0	4106	2919.193314	40.000000	180.0	1.0	0	1
611	LP002983	1	1	1	0	0	8072	240.000000	253.000000	360.0	1.0	2	1
612	LP002984	1	1	2	0	0	7583	2919.193314	187.000000	360.0	1.0	2	1
613	LP002990	0	0	0	0	1	4583	2919.193314	133.000000	360.0	0.0	1	0

614 rows × 13 columns

Our data is converted ito numerical format

Splitting the data into x and y

In [31]:
```
x = df.iloc[:,:-1].values
y = df['Loan_Status']
```

In [32]:
```
x
```

Out[32]:
```
array([['LP001002', 1, 0, ..., 360.0, 1.0, 2],
       ['LP001003', 1, 1, ..., 360.0, 1.0, 0],
       ['LP001005', 1, 1, ..., 360.0, 1.0, 2],
       ...,
       ['LP002983', 1, 1, ..., 360.0, 1.0, 2],
       ['LP002984', 1, 1, ..., 360.0, 1.0, 2],
       ['LP002990', 0, 0, ..., 360.0, 0.0, 1]], dtype=object)
```

In [33]:
```
y
```

Out[33]:
```
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 614, dtype: int32
```

Separate features (x) and target variable (y)

Target Variable (y) : we to worked on target variable so we can check the how many values are present on respective column

In [34]:
```
df['Loan_Status'].value_counts()
```

Out[34]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

As per the result the target column are unbalanced so we need to balanced it first

Random OverSampling is technique for rebalancing the class distribution for an imbalanced dataset.

Steps for balanced data by using Oversampling method

OverSampling: Duplicating samples from minority class

In [35]:
```
from imblearn.over_sampling import RandomOverSampler
from collections import Counter
```

In [36]:
```
ros=RandomOverSampler(random_state=1)
x_ros,y_ros=ros.fit_resample(x,y)
```

In [37]:
```
print("Original Dataset",Counter(y))
print("Resampled Dataset",Counter(y_ros))
```

```
Original Dataset Counter({1: 422, 0: 192})
Resampled Dataset Counter({1: 422, 0: 422})
```

As per the obesrvation is data is now balanced perfectly

Splitting the data into Train-Test set

In [38]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,random_state=42)
```

Model Training

In [39]:
```
from sklearn.preprocessing import LabelEncoder
LabelEncoder_x = LabelEncoder()
```

In [40]:
```
for i in range(0,5):
    x_train[:,i]= LabelEncoder_x.fit_transform(x_train[:,i])
    x_train[:,i]= LabelEncoder_x.fit_transform(x_train[:,7])
x_train
```

Out[40]:
```
array([[118, 118, 118, ..., 360.0, 1.0, 1],
       [157, 157, 157, ..., 360.0, 1.0, 1],
       [62, 62, 62, ..., 360.0, 1.0, 1],
       ...,
       [159, 159, 159, ..., 360.0, 1.0, 2],
       [159, 159, 159, ..., 240.0, 1.0, 1],
       [159, 159, 159, ..., 360.0, 1.0, 2]], dtype=object)
```

In [41]:
```python
LabelEncoder_y = LabelEncoder()
y_train = LabelEncoder_y.fit_transform(y_train)
y_train
```

Out[41]:
```
array([0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1,
       1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0,
       1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
       0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0,
       0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
       1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 0, 1, 1, 1, 1, 1], dtype=int64)
```

In [42]:
```python
for i in range(0,5):
    x_test[:,i]= LabelEncoder_x.fit_transform(x_test[:,i])
    x_test[:,7]= LabelEncoder_x.fit_transform(x_test[:,7])
x_test
```

Out[42]:
```
array([[75, 1, 1, ..., 360.0, 1.0, 1],
       [80, 1, 1, ..., 360.0, 1.0, 1],
       [37, 1, 1, ..., 360.0, 1.0, 0],
       ...,
       [56, 1, 1, ..., 480.0, 1.0, 1],
       [3, 1, 1, ..., 360.0, 1.0, 2],
       [73, 1, 1, ..., 180.0, 1.0, 2]], dtype=object)
```

In [43]:
```
LabelEncoder_y = LabelEncoder()

y_test = LabelEncoder_y.fit_transform(y_test)
y_test
```

Out[43]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1,
       1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0,
       1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1], dtype=int64)
```

In [44]:
```
from sklearn.preprocessing import MinMaxScaler

ss= MinMaxScaler()
x_train = ss.fit_transform(x_train)
x_test = ss.fit_transform(x_test)
```

In [45]:
```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier()
rf_clf.fit(x_train,y_train)
```

Out[45]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

Accuracy checking for random forest classifier is

In [52]:
```
from sklearn import metrics
from sklearn.metrics import accuracy_score

y_pred = rf_clf.predict(x_test)

print("Accuracy of random forest classifier is ", accuracy_score(y_pred,y_test))
```

```
Accuracy of random forest classifier is  0.7154471544715447
```

Classification Report for random forest classifier

In [47]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)


print(f'Confusion Matrix:\n{conf_matrix}')
print(f'Classification Report for random forest classifier:\n{classification_rep}')
```

```
Confusion Matrix:
[[26 17]
 [18 62]]
Classification Report for random forest classifier:
              precision    recall  f1-score   support

           0       0.59      0.60      0.60        43
           1       0.78      0.78      0.78        80

    accuracy                           0.72       123
   macro avg       0.69      0.69      0.69       123
weighted avg       0.72      0.72      0.72       123
```

Accuracy checking for LogisticRegression

In [48]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
model = LogisticRegression(solver="sag")

# Train the model
model.fit(x_train, y_train)

# Predict on test data
y_pred = model.predict(x_test)

# Evaluate the model
print('Accuracy of LogisticRegression:', accuracy_score(y_test, y_pred))
```

```
Accuracy of LogisticRegression: 0.7886178861788617
```

Classification Report for Logistic Regression classifier

In [49]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)


print(f'Confusion Matrix:\n{conf_matrix}')
print(f'Classification Report for Logistic Regression classifier:\n{classification_rep}')
```

```
Confusion Matrix:
[[18 25]
 [ 1 79]]
Classification Report for Logistic Regression classifier:
              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
```

Accuracy checking for DecisionTreeClassifier

In [50]:
```
from sklearn.tree import DecisionTreeClassifier

# Same preprocessing steps as above...

# Create decision tree model
model = DecisionTreeClassifier(max_depth=7,min_samples_leaf=5,random_state=42)

# Train the model
model.fit(x_train, y_train)

# Predict on test data
y_pred = model.predict(x_test)

# Evaluate the model
print('Accuracy of DecisionTreeClassifier :', accuracy_score(y_test, y_pred))
```

```
Accuracy of DecisionTreeClassifier : 0.7723577235772358
```

Classification Report for DecisionTree Classifier

In [51]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)


print(f'Confusion Matrix:\n{conf_matrix}')
print(f'Classification Report for DecisionTree Classifier:\n{classification_rep}')
```

```
Confusion Matrix:
[[24 19]
 [ 9 71]]
Classification Report for DecisionTree Classifier:
              precision    recall  f1-score   support

           0       0.73      0.56      0.63        43
           1       0.79      0.89      0.84        80

    accuracy                           0.77       123
   macro avg       0.76      0.72      0.73       123
weighted avg       0.77      0.77      0.76       123
```

conclusion:

The LogisticRegression algorithm gives us maximum Accuracy score is 0.7886178861788617. compared to the other 2 machine learnig classification algorithm.The best accuracy with an accuracy score of 78%.