

```
import pandas as pd
```

```
df = pd.read_csv("C:/Users/RUCHI/Documents/riya/data  
science/loan_data_set.csv")  
df
```

| | Loan_ID | Gender | Married | Dependents | Education | |
|-----------------|----------|--------|---------|------------|--------------|-----|
| Self_Employed \ | | | | | | |
| 0 | LP001002 | Male | No | 0 | Graduate | No |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No |
| 4 | LP001008 | Male | No | 0 | Graduate | No |
| .. | ... | ... | ... | ... | ... | ... |
| 609 | LP002978 | Female | No | 0 | Graduate | No |
| 610 | LP002979 | Male | Yes | 3+ | Graduate | No |
| 611 | LP002983 | Male | Yes | 1 | Graduate | No |
| 612 | LP002984 | Male | Yes | 2 | Graduate | No |
| 613 | LP002990 | Female | No | 0 | Graduate | Yes |

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term |
|-----|-----------------|-------------------|------------|------------------|
| \ | | | | |
| 0 | 5849 | 0.0 | NaN | 360.0 |
| 1 | 4583 | 1508.0 | 128.0 | 360.0 |
| 2 | 3000 | 0.0 | 66.0 | 360.0 |
| 3 | 2583 | 2358.0 | 120.0 | 360.0 |
| 4 | 6000 | 0.0 | 141.0 | 360.0 |
| .. | ... | ... | ... | ... |
| 609 | 2900 | 0.0 | 71.0 | 360.0 |
| 610 | 4106 | 0.0 | 40.0 | 180.0 |
| 611 | 8072 | 240.0 | 253.0 | 360.0 |
| 612 | 7583 | 0.0 | 187.0 | 360.0 |

| | | | | |
|-----|------|-----|-------|-------|
| 613 | 4583 | 0.0 | 133.0 | 360.0 |
|-----|------|-----|-------|-------|

| | Credit_History | Property_Area | Loan_Status |
|-----|----------------|---------------|-------------|
| 0 | 1.0 | Urban | Y |
| 1 | 1.0 | Rural | N |
| 2 | 1.0 | Urban | Y |
| 3 | 1.0 | Urban | Y |
| 4 | 1.0 | Urban | Y |
| .. | ... | ... | ... |
| 609 | 1.0 | Rural | Y |
| 610 | 1.0 | Rural | Y |
| 611 | 1.0 | Urban | Y |
| 612 | 1.0 | Urban | Y |
| 613 | 0.0 | Semiurban | N |

[614 rows x 13 columns]

df.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 |

df.describe()

| | ApplicantIncome | CoapplicantIncome | LoanAmount |
|--------------------|-----------------|-------------------|------------|
| Loan_Amount_Term \ | | | |
| count | 614.000000 | 614.000000 | 592.000000 |
| mean | 5403.459283 | 1621.245798 | 146.412162 |
| std | 6109.041673 | 2926.248369 | 85.587325 |
| min | 150.000000 | 0.000000 | 9.000000 |
| 25% | 2877.500000 | 0.000000 | 100.000000 |
| 50% | 3812.500000 | 1188.500000 | 128.000000 |

```

360.000000
75%          5795.000000          2297.250000  168.000000
360.000000
max          81000.000000          41667.000000  700.000000
480.000000

```

```

      Credit_History
count          564.000000
mean           0.842199
std            0.364878
min            0.000000
25%            1.000000
50%            1.000000
75%            1.000000
max            1.000000

```

```
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
```

```
len(df)
```

```
614
```

Data Cleaning

```
df.drop_duplicates()
```

```

      Loan_ID  Gender Married Dependents  Education
Self_Employed \

```

| | | | | | | |
|-----|-----------------|-------------------|-------------|------------------|--------------|-----|
| 0 | LP001002 | Male | No | 0 | Graduate | No |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No |
| 4 | LP001008 | Male | No | 0 | Graduate | No |
| .. | ... | ... | ... | ... | ... | ... |
| 609 | LP002978 | Female | No | 0 | Graduate | No |
| 610 | LP002979 | Male | Yes | 3+ | Graduate | No |
| 611 | LP002983 | Male | Yes | 1 | Graduate | No |
| 612 | LP002984 | Male | Yes | 2 | Graduate | No |
| 613 | LP002990 | Female | No | 0 | Graduate | Yes |
| | | | | | | |
| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | | |
| \ | | | | | | |
| 0 | 5849 | 0.0 | NaN | 360.0 | | |
| 1 | 4583 | 1508.0 | 128.0 | 360.0 | | |
| 2 | 3000 | 0.0 | 66.0 | 360.0 | | |
| 3 | 2583 | 2358.0 | 120.0 | 360.0 | | |
| 4 | 6000 | 0.0 | 141.0 | 360.0 | | |
| .. | ... | ... | ... | ... | | |
| 609 | 2900 | 0.0 | 71.0 | 360.0 | | |
| 610 | 4106 | 0.0 | 40.0 | 180.0 | | |
| 611 | 8072 | 240.0 | 253.0 | 360.0 | | |
| 612 | 7583 | 0.0 | 187.0 | 360.0 | | |
| 613 | 4583 | 0.0 | 133.0 | 360.0 | | |
| | | | | | | |
| | Credit_History | Property_Area | Loan_Status | | | |
| 0 | 1.0 | Urban | Y | | | |
| 1 | 1.0 | Rural | N | | | |

| | | | |
|-----|-----|-----------|-----|
| 2 | 1.0 | Urban | Y |
| 3 | 1.0 | Urban | Y |
| 4 | 1.0 | Urban | Y |
| ... | ... | ... | ... |
| 609 | 1.0 | Rural | Y |
| 610 | 1.0 | Rural | Y |
| 611 | 1.0 | Urban | Y |
| 612 | 1.0 | Urban | Y |
| 613 | 0.0 | Semiurban | N |

[614 rows x 13 columns]

```
df.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
```

```
df["Gender"].mode()[0]
```

```
'Male'
```

```
df["Gender"] = df["Gender"].fillna(df["Gender"].mode()[0])
```

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

```
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
```

```

df["Credit_History"].mode()[0]

1.0

df["Credit_History"] =
df["Credit_History"].fillna(df["Credit_History"].mode()[0])

df.isnull().sum()

Loan_ID          0
Gender           13
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

x = df["Credit_History"].astype("object")
x.mode()

0    1.0
Name: Credit_History, dtype: object

df["Married"].mode()[0]

'Yes'

x = df["Married"] = df["Married"].fillna(df["Married"].mode()[0])
x

0      No
1      Yes
2      Yes
3      Yes
4      No
...
609    No
610    Yes
611    Yes
612    Yes
613    No
Name: Married, Length: 614, dtype: object

df["Dependents"].mode()[0]

```

```
'0'
```

```
df["Dependents"] = df["Dependents"].fillna(df["Dependents"].mode()[0])
df["Self_Employed"] =
df["Self_Employed"].fillna(df["Self_Employed"].mode()[0])

df["Loan_Amount_Term"] =
df["Loan_Amount_Term"].fillna(df["Loan_Amount_Term"].mode()[0])

df["LoanAmount"] = df["LoanAmount"].fillna(df["LoanAmount"].median())

df.isnull().sum()

Loan_ID      0
Gender       13
Married       3
Dependents    0
Education     0
Self_Employed 0
ApplicantIncome 0
CoapplicantIncome 0
LoanAmount    0
Loan_Amount_Term 0
Credit_History 50
Property_Area 0
Loan_Status   0
dtype: int64
```

identify the ml model suitable for the dataset

```
df
```

| | Loan_ID | Gender | Married | Dependents | Education | |
|-----------------|----------|--------|---------|------------|--------------|-----|
| Self_Employed \ | | | | | | |
| 0 | LP001002 | Male | No | 0 | Graduate | No |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No |
| 4 | LP001008 | Male | No | 0 | Graduate | No |
| .. | ... | ... | ... | ... | ... | ... |
| 609 | LP002978 | Female | No | 0 | Graduate | No |
| 610 | LP002979 | Male | Yes | 3+ | Graduate | No |

| | | | | | | |
|-----|----------|--------|-----|---|----------|-----|
| 611 | LP002983 | Male | Yes | 1 | Graduate | No |
| 612 | LP002984 | Male | Yes | 2 | Graduate | No |
| 613 | LP002990 | Female | No | 0 | Graduate | Yes |

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term |
|-----|-----------------|-------------------|------------|------------------|
| \ | | | | |
| 0 | 5849 | 0.0 | 128.0 | 360.0 |
| 1 | 4583 | 1508.0 | 128.0 | 360.0 |
| 2 | 3000 | 0.0 | 66.0 | 360.0 |
| 3 | 2583 | 2358.0 | 120.0 | 360.0 |
| 4 | 6000 | 0.0 | 141.0 | 360.0 |
| .. | ... | ... | ... | ... |
| 609 | 2900 | 0.0 | 71.0 | 360.0 |
| 610 | 4106 | 0.0 | 40.0 | 180.0 |
| 611 | 8072 | 240.0 | 253.0 | 360.0 |
| 612 | 7583 | 0.0 | 187.0 | 360.0 |
| 613 | 4583 | 0.0 | 133.0 | 360.0 |

| | Credit_History | Property_Area | Loan_Status |
|-----|----------------|---------------|-------------|
| 0 | 1.0 | Urban | Y |
| 1 | 1.0 | Rural | N |
| 2 | 1.0 | Urban | Y |
| 3 | 1.0 | Urban | Y |
| 4 | 1.0 | Urban | Y |
| .. | ... | ... | ... |
| 609 | 1.0 | Rural | Y |
| 610 | 1.0 | Rural | Y |
| 611 | 1.0 | Urban | Y |
| 612 | 1.0 | Urban | Y |
| 613 | 0.0 | Semiurban | N |

[614 rows x 13 columns]

df.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

```

```
df.drop("Loan_ID", axis=1, inplace=True)
```

```
df
```

| | Gender | Married | Dependents | Education | Self_Employed |
|-------------------|--------|---------|------------|--------------|---------------|
| ApplicantIncome \ | | | | | |
| 0 | Male | No | 0 | Graduate | No |
| 5849 | | | | | |
| 1 | Male | Yes | 1 | Graduate | No |
| 4583 | | | | | |
| 2 | Male | Yes | 0 | Graduate | Yes |
| 3000 | | | | | |
| 3 | Male | Yes | 0 | Not Graduate | No |
| 2583 | | | | | |
| 4 | Male | No | 0 | Graduate | No |
| 6000 | | | | | |
| .. | ... | ... | ... | ... | ... |
| ... | | | | | |
| 609 | Female | No | 0 | Graduate | No |
| 2900 | | | | | |
| 610 | Male | Yes | 3+ | Graduate | No |
| 4106 | | | | | |
| 611 | Male | Yes | 1 | Graduate | No |
| 8072 | | | | | |
| 612 | Male | Yes | 2 | Graduate | No |
| 7583 | | | | | |
| 613 | Female | No | 0 | Graduate | Yes |
| 4583 | | | | | |

| | CoapplicantIncome | LoanAmount | Loan_Amount_Term | |
|------------------|-------------------|------------|------------------|-----|
| Credit_History \ | | | | |
| 0 | 0.0 | 128.0 | 360.0 | 1.0 |
| 1 | 1508.0 | 128.0 | 360.0 | 1.0 |

| | | | | |
|-----|--------|-------|-------|-----|
| 2 | 0.0 | 66.0 | 360.0 | 1.0 |
| 3 | 2358.0 | 120.0 | 360.0 | 1.0 |
| 4 | 0.0 | 141.0 | 360.0 | 1.0 |
| .. | ... | ... | ... | ... |
| 609 | 0.0 | 71.0 | 360.0 | 1.0 |
| 610 | 0.0 | 40.0 | 180.0 | 1.0 |
| 611 | 240.0 | 253.0 | 360.0 | 1.0 |
| 612 | 0.0 | 187.0 | 360.0 | 1.0 |
| 613 | 0.0 | 133.0 | 360.0 | 0.0 |

| | Property_Area | Loan_Status |
|-----|---------------|-------------|
| 0 | Urban | Y |
| 1 | Rural | N |
| 2 | Urban | Y |
| 3 | Urban | Y |
| 4 | Urban | Y |
| .. | ... | ... |
| 609 | Rural | Y |
| 610 | Rural | Y |
| 611 | Urban | Y |
| 612 | Urban | Y |
| 613 | Semiurban | N |

[614 rows x 12 columns]

```
df_1 = pd.get_dummies(df, columns = ["Gender", "Married",
"Dependents", "Education", "Self_Employed", "Property_Area"])
```

```
x = df.drop("Loan_Status", axis=1).values
```

```
y = df["Loan_Status"].values
```

```
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
```

```
y = le.fit_transform(y)
```

```
x
```

```
array([[ 1.,  0.,  0., ..., 360.,  1.,  2.],
       [ 1.,  1.,  1., ..., 360.,  1.,  0.],
       [ 1.,  1.,  0., ..., 360.,  1.,  2.],
       ...,
       [ 1.,  1.,  1., ..., 360.,  1.,  2.]
```

```
[ 1., 1., 2., ..., 360., 1., 2.],  
[ 0., 0., 0., ..., 360., 0., 1.]])
```

y

```
array([1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0,  
1,  
0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1,  
1,  
1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0,  
0,  
0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1,  
1,  
1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,  
1,  
1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1,  
1,  
1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0,  
0,  
1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0,  
1,  
1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1,  
1,  
1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0,  
1,  
0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,  
0,  
1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0,  
1,  
1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0,  
1,  
0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1,  
0,  
0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0,  
1,  
1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1,  
0,  
1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1,  
0,  
1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,  
1,  
0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0,  
0,  
1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,  
1,  
1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1,  
1,  
1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1,  
1,  
1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1,
```

```

1,
    1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1,
1,
    1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0,
1,
    0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1,
0,
    1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1,
1,
    1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0])

```

```

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y,
train_size=0.2, random_state = 10)

```

x_train

```

array([[ 1.,  1.,  1., ..., 180.,  1.,  0.],
       [ 1.,  1.,  0., ..., 360.,  1.,  1.],
       [ 0.,  0.,  0., ..., 360.,  1.,  2.],
       ...,
       [ 1.,  1.,  1., ..., 360.,  0.,  1.],
       [ 0.,  0.,  0., ..., 360.,  1.,  0.],
       [ 1.,  0.,  0., ..., 360.,  1.,  0.]])

```

```

from sklearn.linear_model import LogisticRegression
model = LogisticRegression(max_iter=1000)
model.fit(x_train, y_train)

```

LogisticRegression(max_iter=1000)

y_pred = model.predict(x_test)

y_test

```

array([1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
1,
    1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0,
1,
    0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
0,
    0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0,
0,
    0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
0,
    0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
1,
    1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1,
1,
    0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1,
1,

```



```

1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1,
1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1,
1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 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, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0,
1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1,
1, 1, 0, 1, 1, 1, 0, 0, 1])

```

```
model.score(x_train, y_train)
```

```
0.7868852459016393
```

```

from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy score of the model is: ",accuracy)

```

```
Accuracy score of the model is: 0.7764227642276422
```

```

from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
cm = confusion_matrix(y_test,y_pred)
sns.heatmap(cm, annot=True, cmap="Purples")
plt.xlabel("Predicted values")
plt.ylabel("Actual")
plt.title("Confusion Matrix")

```

```
Text(0.5, 1.0, 'Confusion Matrix')
```

