

```
import numpy as np
import pandas as pd
df=pd.read_csv('/content/LoanApprovalPrediction.csv')
df
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amc
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	
...	
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	

614 rows × 13 columns



```
df.head()
```

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



```
df.tail()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amc
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	



```
df.columns
```

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
      'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
      'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
#   Column              Non-Null Count  Dtype
---  -
Loan_ID      614 non-null    object
Gender       614 non-null    object
Married      614 non-null    object
Dependents   614 non-null    object
Education    614 non-null    object
Self_Employed 614 non-null    object
ApplicantIncome 614 non-null    float64
CoapplicantIncome 614 non-null    float64
LoanAmount   614 non-null    float64
Loan_Amount_Term 614 non-null    object
Credit_History 614 non-null    object
Property_Area 614 non-null    object
Loan_Status  614 non-null    object
```

```

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

```

Find Missing Values

```
df.isna().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

```

Fill missing Values

```

columns=['Gender','Married','Dependents','Self_Employed','LoanAmount','Loan_Amount_Term','Credit_History']
for i in columns:
    x=df[i].mode()[0]
    df[i].fillna(x,inplace=True)
df.isna().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

```

Drop unwanted column

```

df1=df.drop(['Loan_ID'],axis=1)
df1

```

Convert to numerical data

```

from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
columns1=['Gender','Married','Dependents','Education','Self_Employed','Property_Area','Loan_Status']
for i in df1[columns1]:
    df1[i]=le.fit_transform(df1[i])
df1

```

Split into input and output

Allocate data for training and testing

Normalization done by Standard Scaler method

<https://colab.research.google.com/drive/1eydQigrMQjrcFCv748RqnIZK9JjBONuL#scrollTo=fhn0FOw21Uds&printMode=true>

```

0.40323892, -1.34950589],
[ 0.49343516, -1.29019234, -0.71703534, ..., 0.30437507,
 0.40323892, -0.071497 ],
...,
[-2.02660871, -1.29019234, -0.71703534, ..., 0.30437507,
 0.40323892, 1.20651188],
[-2.02660871, 0.77507823, -0.71703534, ..., -1.45542149,
 0.40323892, -0.071497 ],
[ 0.49343516, 0.77507823, -0.71703534, ..., 0.30437507,
 0.40323892, 1.20651188]]])

```

▼ Model Creation using KNN, Naive Bayes, SVM

```

from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
knn=KNeighborsClassifier(n_neighbors=3)
bayes=GaussianNB()
svc=SVC()
lst1=[knn,bayes,svc]

```

▼ Performance Evaluation using FOR LOOP

```

for i in lst1:
    i.fit(x_train,y_train)
    y_pred=i.predict(x_test)
    print('Accuracy Score of',i,':',accuracy_score(y_test,y_pred))
    print('Confusion matrix for',i,':')
    print(confusion_matrix(y_test,y_pred))
    print('classification report of',i,':')
    print(classification_report(y_test,y_pred))
    print('*****')

Accuracy Score of KNeighborsClassifier(n_neighbors=3) : 0.7567567567567568
Confusion matrix for KNeighborsClassifier(n_neighbors=3) :
[[ 27  38]
 [  7 113]]
classification report of KNeighborsClassifier(n_neighbors=3) :
      precision    recall  f1-score   support

     0       0.79      0.42      0.55         65
     1       0.75      0.94      0.83        120

 accuracy                   0.76         185
 macro avg              0.77      0.68      0.69         185
 weighted avg           0.76      0.76      0.73         185

*****
Accuracy Score of GaussianNB() : 0.7675675675675676
Confusion matrix for GaussianNB() :
[[ 28  37]
 [  6 114]]
classification report of GaussianNB() :
      precision    recall  f1-score   support

     0       0.82      0.43      0.57         65
     1       0.75      0.95      0.84        120

 accuracy                   0.77         185
 macro avg              0.79      0.69      0.70         185
 weighted avg           0.78      0.77      0.74         185

*****
Accuracy Score of SVC() : 0.7891891891891892
Confusion matrix for SVC() :
[[ 27  38]
 [  1 119]]
classification report of SVC() :
      precision    recall  f1-score   support

     0       0.96      0.42      0.58         65
     1       0.76      0.99      0.86        120

 accuracy                   0.79         185
 macro avg              0.86      0.70      0.72         185
 weighted avg           0.83      0.79      0.76         185

*****

```