House Loan Approval Status


```
Objective:-
    The main aim of this project is to build a model for a Dream housing company who wants to automate the loan eligibility
    process (real time) based on customer detail provided while filling online application form.
```

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




from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report,r2_score,accuracy_score,confusion_matrix
```

In [2]:
```python
#Read the data using pandas librarys
df=pd.read_csv('Loan_Data.csv')
```

In [3]:
```python
df.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
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

In [4]:
```
#Complete information of records and features  present in data
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
```

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
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
```

Insight:-from this we had seen there are may null value present in our data.

```
To handle the null values and use the data for prediction we need data cleaning as many columns are in object and null value are also present in data.
```

Data Cleaning(EDA)

In [6]:
```
#Drop the loan id column as it is of no use
df.drop(columns='Loan_ID',inplace=True)
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             601 non-null    object 
 1   Married            611 non-null    object 
 2   Dependents         599 non-null    object 
 3   Education          614 non-null    object 
 4   Self_Employed      582 non-null    object 
 5   ApplicantIncome    614 non-null    int64  
 6   CoapplicantIncome  614 non-null    float64
 7   LoanAmount         592 non-null    float64
 8   Loan_Amount_Term   600 non-null    float64
 9   Credit_History     564 non-null    float64
 10  Property_Area      614 non-null    object 
 11  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 57.7+ KB
```

In [8]:
```
#Replace all the dependents 3+ as 3 and change their data type to float
df['Dependents'].replace('3+','3',inplace=True)
```

In [9]:
```
df['Dependents'].unique()
```
Out[9]:
```
array(['0', '1', '2', '3', nan], dtype=object)
```

In [10]:
```
df['Dependents']=df['Dependents'].astype(float)
```

Insights:-Here we had replace the string value that is of no use to numeric so we can use that feature also for prediction

```
#now we have to handle all the null values.
so as many columns are in object data type and also null value is present so we have to convert object data into
numeric form.so for that we use label encoding
```

1 Label Encoding

In [11]:
```
df_num=df.select_dtypes([int,float])
```

In [12]:
```
df_cat=df.select_dtypes(object)
```

In [13]:
```
df_cat
```
Out[13]:

	Gender	Married	Education	Self_Employed	Property_Area	Loan_Status
0	Male	No	Graduate	No	Urban	Y
1	Male	Yes	Graduate	No	Rural	N
2	Male	Yes	Graduate	Yes	Urban	Y
3	Male	Yes	Not Graduate	No	Urban	Y
4	Male	No	Graduate	No	Urban	Y
...	...	...	...	...	...	...
609	Female	No	Graduate	No	Rural	Y
610	Male	Yes	Graduate	No	Rural	Y
611	Male	Yes	Graduate	No	Urban	Y
612	Male	Yes	Graduate	No	Urban	Y
613	Female	No	Graduate	Yes	Semiurban	N

614 rows × 6 columns

```
Here you can clearly seeing that we had seperated all the object data and now we perform label enoding.
```

In [14]:
```
from sklearn.preprocessing import LabelEncoder
```

In [15]:
```
le=LabelEncoder()
```

In [16]:
```
for i in df_cat:
    df_cat[i]=le.fit_transform(df_cat[i])
```

In [17]:
```
df_cat
```
Out[17]:

	Gender	Married	Education	Self_Employed	Property_Area	Loan_Status
0	1	0	0	0	2	1
1	1	1	0	0	0	0
2	1	1	0	1	2	1
3	1	1	1	0	2	1
4	1	0	0	0	2	1
...	...	...	...	...	...	...
609	0	0	0	0	0	1
610	1	1	0	0	0	1
611	1	1	0	0	2	1
612	1	1	0	0	2	1
613	0	0	0	1	1	0

614 rows × 6 columns

Insights:-Here you can clearly seeing that our data is transform from object to float and all string data is converted into numeric form by one of the most important encoding label encoding.

In [18]:
```
#conact the df
df=pd.concat([df_num,df_cat],axis=1)
```

In [19]:
```
df
```

Out[19]:

	Dependents	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender	Married	Education	Self_Employed	Property_
0	0.0	5849	0.0	NaN	360.0	1.0	1	0	0	0	
1	1.0	4583	1508.0	128.0	360.0	1.0	1	1	0	0	
2	0.0	3000	0.0	66.0	360.0	1.0	1	1	0	1	
3	0.0	2583	2358.0	120.0	360.0	1.0	1	1	1	0	
4	0.0	6000	0.0	141.0	360.0	1.0	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	
609	0.0	2900	0.0	71.0	360.0	1.0	0	0	0	0	
610	3.0	4106	0.0	40.0	180.0	1.0	1	1	0	0	
611	1.0	8072	240.0	253.0	360.0	1.0	1	1	0	0	
612	2.0	7583	0.0	187.0	360.0	1.0	1	1	0	0	
613	0.0	4583	0.0	133.0	360.0	0.0	0	0	0	1	

614 rows × 12 columns

In [20]:
```
#Now we will replace all the null values from our data and move on to prediction
```

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
Dependents           15
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Gender                0
Married               0
Education             0
Self_Employed         0
Property_Area         0
Loan_Status           0
dtype: int64
```

```
Here you can see there are null value present in Dependents,LoanAmount,Loan_Amount_Term,Credit_history so lets
handle it out
```

In [22]:
```
df['LoanAmount'].fillna(df['LoanAmount'].mean(),inplace=True)
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0])
df['Credit_History']=df['Credit_History'].fillna(df['Credit_History'].mode()[0])
```

Insights:- Here we replace all the null value with mean and mode

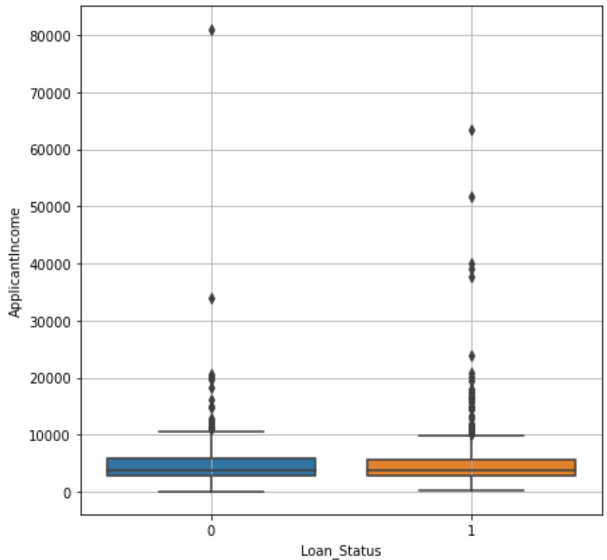
In [23]:
```
df.dropna(inplace=True)
```

In [24]:
```
df.isnull().sum()
```

Out[24]:
```
Dependents           0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Gender               0
Married              0
Education            0
Self_Employed        0
Property_Area        0
Loan_Status          0
dtype: int64
```

Checking Outliers are present or not in our data

In [25]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='Loan_Status',y='ApplicantIncome')
plt.grid(True)
plt.show()
```



Insights:-From above box plot we clearly seeing that there are outlier present in our data.

In [26]:
```
#Removing of outliers
df[(df['Loan_Status']==0)&(df['ApplicantIncome']>30000)]
df[(df['Loan_Status']==1)&(df['ApplicantIncome']>30000)]
```

Out[26]:

	Dependents	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender	Married	Education	Self_Employed	Property_
155	3.0	39999	0.0	600.0	180.0	0.0	1	1	0	0	
171	3.0	51763	0.0	700.0	300.0	1.0	2	1	0	0	
185	0.0	39147	4750.0	120.0	360.0	1.0	1	1	0	1	
333	0.0	63337	0.0	490.0	180.0	1.0	1	1	0	2	
443	1.0	37719	0.0	152.0	360.0	1.0	1	0	0	0	

In [27]:
```
df.drop(index=[155,171,185,333,443],inplace=True)
```

Insights:- So we clear all the outliers which are presnt in our data

```
Hence we finally replace all the null value,also we convert the data types,also remove outliers
 and also data is fully clean now.
```

Model Building

```
Hence for making model we have to remove unnecessary features which is of no use.
```

In [28]:
```
df.drop(columns=['Dependents','Gender','Married'],inplace=True)
```

In [29]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 594 entries, 0 to 613
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   ApplicantIncome    594 non-null    int64  
 1   CoapplicantIncome  594 non-null    float64
 2   LoanAmount         594 non-null    float64
 3   Loan_Amount_Term   594 non-null    float64
 4   Credit_History     594 non-null    float64
 5   Education          594 non-null    int32  
 6   Self_Employed      594 non-null    int32  
 7   Property_Area      594 non-null    int32  
 8   Loan_Status        594 non-null    int32  
dtypes: float64(4), int32(4), int64(1)
memory usage: 37.1 KB
```

Insights:- Here we remove all the unnecessary features and only important features are there in our hand for prediction

In [30]:
```
#To seprate X and Y
x=df.iloc[:,:-1]
```

In [31]:
```
x
```

Out[31]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Education	Self_Employed	Property_Area
0	5849	0.0	146.412162	360.0	1.0	0	0	2
1	4583	1508.0	128.000000	360.0	1.0	0	0	0
2	3000	0.0	66.000000	360.0	1.0	0	1	2
3	2583	2358.0	120.000000	360.0	1.0	1	0	2
4	6000	0.0	141.000000	360.0	1.0	0	0	2
...	...	...	...	...	...	...	...	...
609	2900	0.0	71.000000	360.0	1.0	0	0	0
610	4106	0.0	40.000000	180.0	1.0	0	0	0
611	8072	240.0	253.000000	360.0	1.0	0	0	2
612	7583	0.0	187.000000	360.0	1.0	0	0	2
613	4583	0.0	133.000000	360.0	0.0	0	1	1

594 rows × 8 columns

In [32]:
```
y=df['Loan_Status']
```

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: 594, dtype: int32
```

Insights:-We seperate x and y of our data

In [34]:
```
#To split x and y
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1)
```

In [35]:
```
#first create object for all the model
lr=LogisticRegression()
knn=KNeighborsClassifier()
svm=SVC()
dt=DecisionTreeClassifier()
```

Applying Different Models

In [36]:
```
#build function of mymodel to store all data in mymodel
def mymodel(model):
    model.fit(xtrain, ytrain)
    ypred=model.predict(xtest)
    print(classification_report(ytest, ypred))
```

In [37]:
```
mymodel(lr)
```

```
              precision    recall  f1-score   support

           0       0.86      0.47      0.61        53
           1       0.81      0.97      0.88       126

    accuracy                           0.82       179
   macro avg       0.84      0.72      0.75       179
weighted avg       0.83      0.82      0.80       179
```

In [38]:
```
mymodel(knn)
```

```
              precision    recall  f1-score   support

           0       0.41      0.32      0.36        53
           1       0.74      0.81      0.77       126

    accuracy                           0.66       179
   macro avg       0.58      0.57      0.57       179
weighted avg       0.64      0.66      0.65       179
```

In [39]:
```
mymodel(svm)
```

```
              precision    recall  f1-score   support

           0       1.00      0.02      0.04        53
           1       0.71      1.00      0.83       126

    accuracy                           0.71       179
   macro avg       0.85      0.51      0.43       179
weighted avg       0.79      0.71      0.59       179
```

In [40]:
```
mymodel(dt)
```

```
              precision    recall  f1-score   support

           0       0.52      0.60      0.56        53
           1       0.82      0.76      0.79       126

    accuracy                           0.72       179
   macro avg       0.67      0.68      0.67       179
weighted avg       0.73      0.72      0.72       179
```

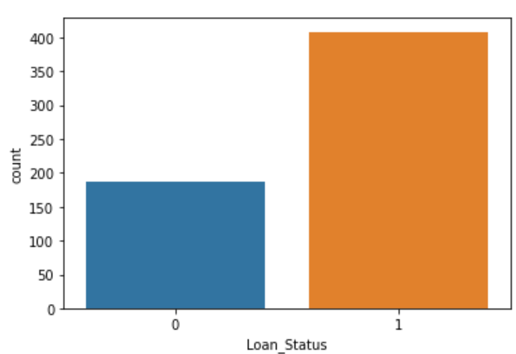
In [41]:
```
#check model balance status
```

In [42]:
```
df['Loan_Status'].value_counts()
```

Out[42]:
```
1    408
0    186
Name: Loan_Status, dtype: int64
```

In [43]:
```
sns.countplot(data=df,x=df['Loan_Status'])
```

Out[43]: <AxesSubplot:xlabel='Loan_Status', ylabel='count'>



Insights:- From this we get to know that our data is highly imbalanced .

```
to over come with this problem we have to balance our data using over fitting
```

Over Fitting

In [44]:
```
!pip install imblearn
```

```
Requirement already satisfied: imblearn in c:\users\maroo\anaconda3\lib\site-packages (0.0)
Requirement already satisfied: imbalanced-learn in c:\users\maroo\anaconda3\lib\site-packages (from imblearn) (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in c:\users\maroo\anaconda3\lib\site-packages (from imbalanced-learn->imblearn)
(1.21.5)
Requirement already satisfied: scipy>=1.3.2 in c:\users\maroo\anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.
7.3)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\maroo\anaconda3\lib\site-packages (from imbalanced-learn->imblea
rn) (1.0.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\maroo\anaconda3\lib\site-packages (from imbalanced-learn->imblearn)
(1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\maroo\anaconda3\lib\site-packages (from imbalanced-learn->imble
arn) (2.2.0)
```

In [45]:
```
from imblearn.over_sampling import RandomOverSampler
```

In [46]:
```
ros=RandomOverSampler(random_state=1)
```

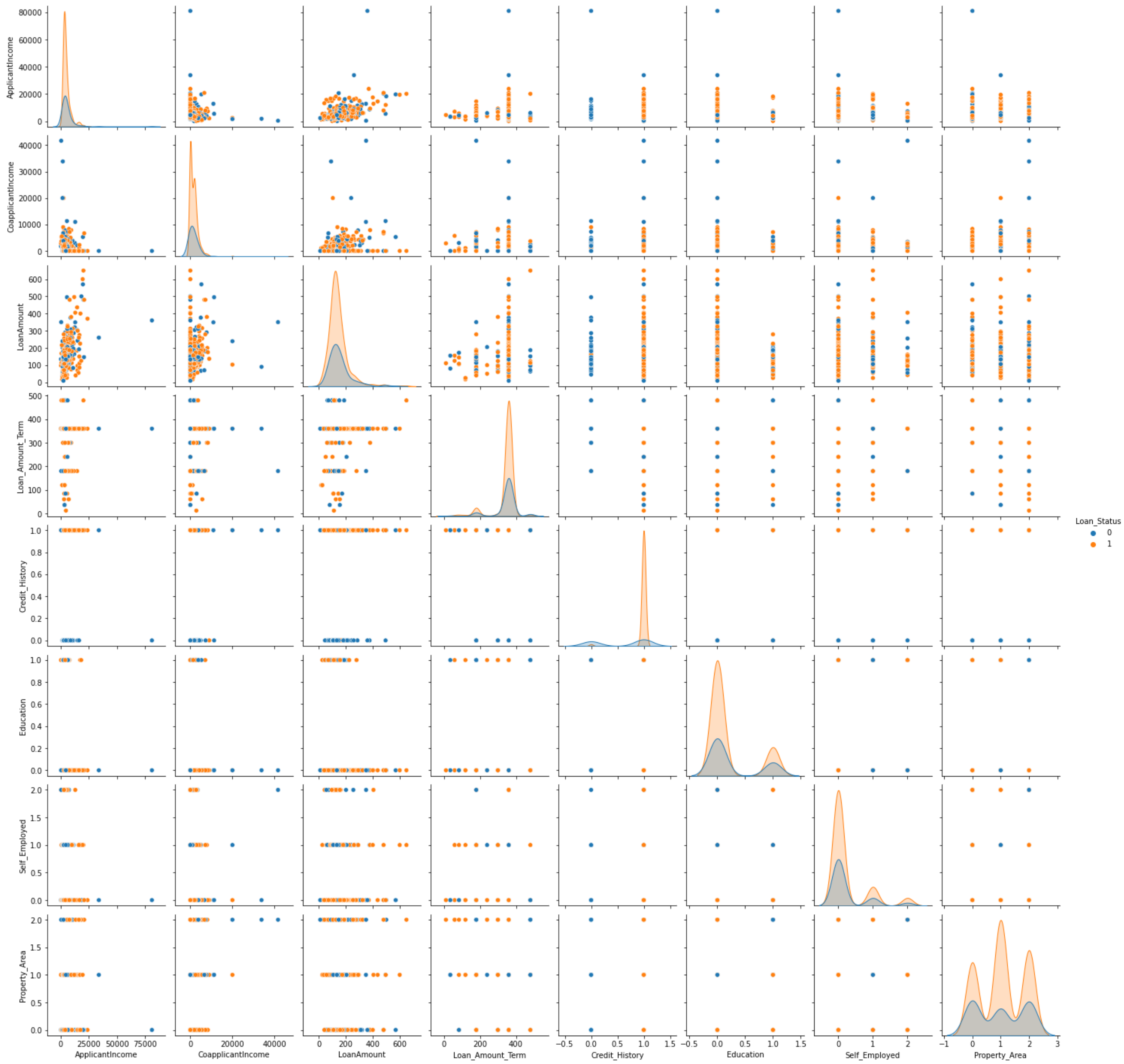
In [47]:
```
x_train,y_train=ros.fit_resample(xtrain,ytrain)
```

In [48]:
```
pd.Series(y_train).value_counts()
```

Out[48]:
```
1    282
0    282
Name: Loan_Status, dtype: int64
```

```
To check how data is distributed
```

In [112]:
```python
sns.pairplot(df,hue='Loan_Status')
plt.show()
```



In [ ]:
```python

```

In [60]:
```python
#build function of mymodel to store all data in mymodel
def mymodel1(model1):
    model1.fit(x_train, y_train)
    ypred=model1.predict(xtest)
    print(classification_report(ytest, ypred))
```

In [61]:
```python
mymodel1(lr)
```

```
              precision    recall  f1-score   support

           0       0.55      0.58      0.57        53
           1       0.82      0.80      0.81       126

    accuracy                           0.74       179
   macro avg       0.69      0.69      0.69       179
weighted avg       0.74      0.74      0.74       179
```

In [62]:
```
mymodel1(dt)
```

```
              precision    recall  f1-score   support

           0       0.45      0.58      0.51        53
           1       0.80      0.70      0.75       126

    accuracy                           0.66       179
   macro avg       0.62      0.64      0.63       179
weighted avg       0.70      0.66      0.68       179
```

In [63]:
```
mymodel(knn)
```

```
              precision    recall  f1-score   support

           0       0.80      0.08      0.14        53
           1       0.72      0.99      0.83       126

    accuracy                           0.72       179
   macro avg       0.76      0.53      0.49       179
weighted avg       0.74      0.72      0.63       179
```

In [64]:
```
mymodel(svm)
```

```
              precision    recall  f1-score   support

           0       1.00      0.02      0.04        53
           1       0.71      1.00      0.83       126

    accuracy                           0.71       179
   macro avg       0.85      0.51      0.43       179
weighted avg       0.79      0.71      0.59       179
```

Insights:-By doing oversampling accuracy has not been increase too much

```
As we can seen clearly accuracy has not been increase too much by sampling the data also so we are trying
by hypertunning the parameter
```

Hypertunning Parameter to increase accuracy

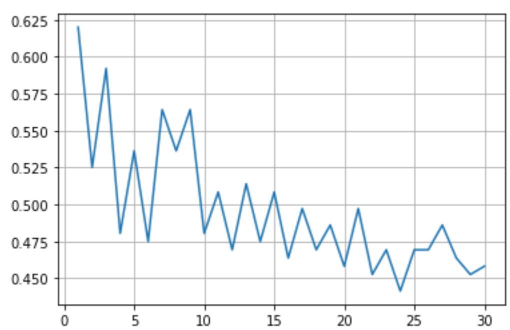
1 KNN

In [66]:
```
accuracy =[]
for i in range(1,31):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(x_train, y_train)
    ypred = knn.predict(xtest)
    ac= accuracy_score(ytest, ypred)
    accuracy.append(ac)
```

In [67]:
```
accuracy
```

Out[67]:
```
[0.6201117318435754,
 0.5251396648044693,
 0.5921787709497207,
 0.48044692737430167,
 0.5363128491620112,
 0.4748603351955307,
 0.5642458100558659,
 0.5363128491620112,
 0.5642458100558659,
 0.48044692737430167,
 0.5083798882681564,
 0.4692737430167598,
 0.5139664804469274,
 0.4748603351955307,
 0.5083798882681564,
 0.46368715083798884,
 0.4972067039106145,
 0.4692737430167598,
 0.4860335195530726,
 0.4581005586592179,
 0.4972067039106145,
 0.45251396648044695,
 0.4692737430167598,
 0.441340782122905,
 0.4692737430167598,
 0.4692737430167598,
 0.4860335195530726,
 0.46368715083798884,
 0.45251396648044695,
 0.4581005586592179]
```

In [68]:
```
plt.plot(range(1,31), accuracy)
plt.grid(True)
plt.show()
```



Insights:- Seeing to graph we are deciding the value of k as 19

In [69]:
```
knn=KNeighborsClassifier(n_neighbors=1)
mymodel1(knn)
```

```
              precision    recall  f1-score   support

           0       0.36      0.38      0.37        53
           1       0.73      0.72      0.73       126

    accuracy                           0.62       179
   macro avg       0.55      0.55      0.55       179
weighted avg       0.62      0.62      0.62       179
```

Insights:-After Hypertunning we are getting accuracy as 62%

Hypertunning the parameter of logistic regression

```
To perform hypertunning for logistic regression we must to need to do feature scaling
```

In [70]:
```
from sklearn.preprocessing import StandardScaler
```

In [71]:
```
sc=StandardScaler()
```

In [72]:
```
x_train=sc.fit_transform(x_train)
```

In [74]:
```
xtest=sc.transform(xtest)
```

In [86]:
```
lr1=LogisticRegression(solver='liblinear')
mymodel1(lr1)
```

```
              precision    recall  f1-score   support

           0       0.64      0.55      0.59        53
           1       0.82      0.87      0.85       126

    accuracy                           0.78       179
   macro avg       0.73      0.71      0.72       179
weighted avg       0.77      0.78      0.77       179
```

In [84]:
```
lr2=LogisticRegression(solver='sag')
mymodel1(lr2)
```

```
              precision    recall  f1-score   support

           0       0.64      0.55      0.59        53
           1       0.82      0.87      0.85       126

    accuracy                           0.78       179
   macro avg       0.73      0.71      0.72       179
weighted avg       0.77      0.78      0.77       179
```

In [83]:
```
lr3=LogisticRegression(solver='saga')
mymodel1(lr3)
```

```
              precision    recall  f1-score   support

           0       0.64      0.55      0.59        53
           1       0.82      0.87      0.85       126

    accuracy                           0.78       179
   macro avg       0.73      0.71      0.72       179
weighted avg       0.77      0.78      0.77       179
```

In [113]:
```
lr4 = LogisticRegression(solver='newton-cg',penalty='l2')
mymodel1(lr4)
```

```
              precision    recall  f1-score   support

           0       0.64      0.55      0.59        53
           1       0.82      0.87      0.85       126

    accuracy                           0.78       179
   macro avg       0.73      0.71      0.72       179
weighted avg       0.77      0.78      0.77       179
```

Insights:-By hypertunning in LogisticRegression we are getting maximum accuracy on liblinear

Hypertunning Decision Tree

In [122]:
```
for i in range(1,50):
    dt5 = DecisionTreeClassifier(max_depth=i)
    dt5.fit(x_train,y_train)
    ypred = dt5.predict(xtest)
    print(f"{i} = {accuracy_score(ytest,ypred)}")
```

```
1 = 0.8212290502793296
2 = 0.8212290502793296
3 = 0.8268156424581006
4 = 0.776536312849162
5 = 0.8044692737430168
6 = 0.5810055865921788
7 = 0.5810055865921788
8 = 0.7374301675977654
9 = 0.6927374301675978
10 = 0.7262569832402235
11 = 0.7318435754189944
12 = 0.7039106145251397
13 = 0.6480446927374302
14 = 0.6480446927374302
15 = 0.7150837988826816
16 = 0.6927374301675978
17 = 0.6871508379888268
18 = 0.6927374301675978
19 = 0.6759776536312849
20 = 0.6815642458100558
21 = 0.6927374301675978
22 = 0.6871508379888268
23 = 0.6703910614525139
24 = 0.6759776536312849
25 = 0.6871508379888268
26 = 0.6759776536312849
27 = 0.6759776536312849
28 = 0.6927374301675978
29 = 0.6983240223463687
30 = 0.6815642458100558
31 = 0.6759776536312849
32 = 0.6703910614525139
33 = 0.6927374301675978
34 = 0.6815642458100558
35 = 0.6759776536312849
36 = 0.6815642458100558
37 = 0.6815642458100558
38 = 0.6983240223463687
39 = 0.6759776536312849
40 = 0.6759776536312849
41 = 0.659217877094972
42 = 0.6871508379888268
43 = 0.6536312849162011
44 = 0.6927374301675978
45 = 0.6815642458100558
46 = 0.664804469273743
47 = 0.6871508379888268
48 = 0.6536312849162011
49 = 0.659217877094972
```

In [123]:
```
dt1=DecisionTreeClassifier(max_depth=3)
mymodel1(dt1)
```

```
              precision    recall  f1-score   support

           0       0.89      0.47      0.62        53
           1       0.81      0.98      0.89       126

    accuracy                           0.83       179
   macro avg       0.85      0.72      0.75       179
weighted avg       0.84      0.83      0.81       179
```

In [124]:
```python
for i in range(2,51):
    dt2 = DecisionTreeClassifier(min_samples_split=i)
    dt2.fit(xtrain,ytrain)
    ypred = dt2.predict(xtest)
    print(f"{i} = {accuracy_score(ytest,ypred)}")
```

```
2 = 0.7039106145251397
3 = 0.7039106145251397
4 = 0.7039106145251397
5 = 0.7039106145251397
6 = 0.29608938547486036
7 = 0.29608938547486036
8 = 0.29608938547486036
9 = 0.29608938547486036
10 = 0.29608938547486036
11 = 0.29608938547486036
12 = 0.29608938547486036
13 = 0.29608938547486036
14 = 0.29608938547486036
15 = 0.29608938547486036
16 = 0.29608938547486036
17 = 0.29608938547486036
18 = 0.29608938547486036
19 = 0.29608938547486036
20 = 0.29608938547486036
21 = 0.29608938547486036
22 = 0.29608938547486036
23 = 0.29608938547486036
24 = 0.29608938547486036
25 = 0.29608938547486036
26 = 0.29608938547486036
27 = 0.29608938547486036
28 = 0.29608938547486036
29 = 0.29608938547486036
30 = 0.29608938547486036
31 = 0.29608938547486036
32 = 0.29608938547486036
33 = 0.29608938547486036
34 = 0.29608938547486036
35 = 0.29608938547486036
36 = 0.29608938547486036
37 = 0.29608938547486036
38 = 0.29608938547486036
39 = 0.29608938547486036
40 = 0.29608938547486036
41 = 0.29608938547486036
42 = 0.29608938547486036
43 = 0.29608938547486036
44 = 0.29608938547486036
45 = 0.29608938547486036
46 = 0.29608938547486036
47 = 0.29608938547486036
48 = 0.29608938547486036
49 = 0.29608938547486036
50 = 0.29608938547486036
```

In [125]:
```python
dt5=DecisionTreeClassifier(min_samples_split=2)
mymodel1(dt5)
```

```
              precision    recall  f1-score   support

           0       0.48      0.58      0.53        53
           1       0.81      0.73      0.77       126

    accuracy                           0.69       179
   macro avg       0.64      0.66      0.65       179
weighted avg       0.71      0.69      0.70       179
```

In [93]:
```python
dt4=DecisionTreeClassifier(min_samples_leaf=10)
mymodel1(dt4)
```

```
              precision    recall  f1-score   support

           0       0.43      0.70      0.53        53
           1       0.83      0.61      0.70       126

    accuracy                           0.64       179
   macro avg       0.63      0.65      0.62       179
weighted avg       0.71      0.64      0.65       179
```

In [126]:

```
for i in range(1,51):
    dt3 = DecisionTreeClassifier(min_samples_leaf=i)
    dt3.fit(x_train,y_train)
    ypred = dt3.predict(xtest)
    print(f"{i} = {accuracy_score(ytest,ypred)}")
```

```
1 = 0.7039106145251397
2 = 0.6536312849162011
3 = 0.6759776536312849
4 = 0.659217877094972
5 = 0.6424581005586593
6 = 0.659217877094972
7 = 0.6759776536312849
8 = 0.664804469273743
9 = 0.6927374301675978
10 = 0.6368715083798883
11 = 0.6759776536312849
12 = 0.7094972067039106
13 = 0.7094972067039106
14 = 0.6424581005586593
15 = 0.6424581005586593
16 = 0.6536312849162011
17 = 0.6759776536312849
18 = 0.6256983240223464
19 = 0.6256983240223464
20 = 0.6312849162011173
21 = 0.6312849162011173
22 = 0.6089385474860335
23 = 0.6089385474860335
24 = 0.6201117318435754
25 = 0.6201117318435754
26 = 0.6480446927374302
27 = 0.6480446927374302
28 = 0.6815642458100558
29 = 0.6368715083798883
30 = 0.6480446927374302
31 = 0.6480446927374302
32 = 0.6480446927374302
33 = 0.6145251396648045
34 = 0.6145251396648045
35 = 0.6145251396648045
36 = 0.6145251396648045
37 = 0.6424581005586593
38 = 0.6424581005586593
39 = 0.664804469273743
40 = 0.6815642458100558
41 = 0.6759776536312849
42 = 0.6033519553072626
43 = 0.7374301675977654
44 = 0.7374301675977654
45 = 0.7318435754189944
46 = 0.7318435754189944
47 = 0.6815642458100558
48 = 0.6815642458100558
49 = 0.6815642458100558
50 = 0.6815642458100558
```

In [128]:

```
dt4 = DecisionTreeClassifier(max_depth=3,min_samples_leaf=43,min_samples_split=2)
mymodel1(dt4)
```

```
              precision    recall  f1-score   support

           0       0.68      0.53      0.60        53
           1       0.82      0.90      0.86       126

    accuracy                           0.79       179
   macro avg       0.75      0.71      0.73       179
weighted avg       0.78      0.79      0.78       179
```

Insights:-Hence we are getting maximum accuracy when max_depth is 3

Hypertunning svm parameter

In [97]:
```
svm1=SVC(kernel='linear')
mymodel1(svm1)
```

```
              precision    recall  f1-score   support

           0       0.86      0.47      0.61        53
           1       0.81      0.97      0.88       126

    accuracy                           0.82       179
   macro avg       0.84      0.72      0.75       179
weighted avg       0.83      0.82      0.80       179
```

In [98]:
```
svm2=SVC(kernel='poly')
mymodel1(svm2)
```

```
              precision    recall  f1-score   support

           0       0.57      0.53      0.55        53
           1       0.81      0.83      0.82       126

    accuracy                           0.74       179
   macro avg       0.69      0.68      0.68       179
weighted avg       0.74      0.74      0.74       179
```

In [99]:
```
svm3=SVC(kernel='sigmoid')
mymodel1(svm3)
```

```
              precision    recall  f1-score   support

           0       0.45      0.55      0.50        53
           1       0.79      0.72      0.76       126

    accuracy                           0.67       179
   macro avg       0.62      0.63      0.63       179
weighted avg       0.69      0.67      0.68       179
```

Insights:-In this from linear solver we are getting best accuracy

Ensemble learning

```
It is used to improve predicted power of algorithm.
```

In [100]:
```
models=[]
accuracy=[]
models.append(('logistic',LogisticRegression()))
models.append(('DT',DecisionTreeClassifier()))
models.append(('svm',SVC(probability=True)))
```

In [101]:
```
for name,model_obj in models:
    model_obj.fit(xtrain,ytrain)
    ypred=model_obj.predict(xtest)
    ac=accuracy_score(ytest,ypred)
    accuracy.append(ac)
```

In [102]:
```
accuracy
```

Out[102]:
```
[0.8212290502793296, 0.7039106145251397, 0.7039106145251397]
```

In [103]:
```
ac_accuracy=np.array(accuracy)
np.mean(ac_accuracy)
```

Out[103]:
```
0.7430167597765364
```

Bagging

In [104]:
```
from sklearn.ensemble import BaggingClassifier
```

In [105]:
```
bg=BaggingClassifier(LogisticRegression())
bg.fit(x_train,y_train)
ypred=bg.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.53      0.58        53
           1       0.82      0.88      0.85       126

    accuracy                           0.78       179
   macro avg       0.73      0.70      0.72       179
weighted avg       0.77      0.78      0.77       179
```

In [106]:
```
bg1=BaggingClassifier(DecisionTreeClassifier())
bg1.fit(x_train,y_train)
ypred=bg1.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.52      0.60      0.56        53
           1       0.82      0.76      0.79       126

    accuracy                           0.72       179
   macro avg       0.67      0.68      0.67       179
weighted avg       0.73      0.72      0.72       179
```

In [107]:
```
bg2=BaggingClassifier(SVC())
bg2.fit(x_train,y_train)
ypred=bg2.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.55      0.55      0.55        53
           1       0.81      0.81      0.81       126

    accuracy                           0.73       179
   macro avg       0.68      0.68      0.68       179
weighted avg       0.73      0.73      0.73       179
```

In [108]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [110]:
```
rf=RandomForestClassifier()
#In random forest default value is 100 and build a
#Machine model in 100 subset model
rf.fit(x_train,y_train)
ypred=rf.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.63      0.64      0.64        53
           1       0.85      0.84      0.84       126

    accuracy                           0.78       179
   macro avg       0.74      0.74      0.74       179
weighted avg       0.78      0.78      0.78       179
```

In [129]:
```
from sklearn.ensemble import VotingClassifier
```

In [130]:
```
vc=VotingClassifier(models,voting='hard')
rf.fit(x_train,y_train)
ypred=rf.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.70      0.62      0.66        53
           1       0.85      0.89      0.87       126

    accuracy                           0.81       179
   macro avg       0.78      0.76      0.76       179
weighted avg       0.81      0.81      0.81       179
```

In [131]:
```
vc=VotingClassifier(models,voting='soft')
rf.fit(x_train,y_train)
ypred=rf.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.59      0.62      0.61        53
           1       0.84      0.82      0.83       126

    accuracy                           0.76       179
   macro avg       0.71      0.72      0.72       179
weighted avg       0.76      0.76      0.76       179
```

Boosting

In [132]:
```
from sklearn.ensemble import AdaBoostClassifier,GradientBoostingClassifier
```

In [133]:
```
ad = AdaBoostClassifier()
gbc = GradientBoostingClassifier()
from xgboost import XGBClassifier
xgb=XGBClassifier()
```

In [134]:
```
mymodel1(ad)
```

```
              precision    recall  f1-score   support

           0       0.57      0.62      0.59        53
           1       0.83      0.80      0.82       126

    accuracy                           0.75       179
   macro avg       0.70      0.71      0.71       179
weighted avg       0.76      0.75      0.75       179
```

In [136]:
```
mymodel1(gbc)
```

```
              precision    recall  f1-score   support

           0       0.59      0.57      0.58        53
           1       0.82      0.83      0.83       126

    accuracy                           0.75       179
   macro avg       0.70      0.70      0.70       179
weighted avg       0.75      0.75      0.75       179
```

In [137]:
```
mymodel1(xgb)
```

```
              precision    recall  f1-score   support

           0       0.67      0.66      0.67        53
           1       0.86      0.87      0.86       126

    accuracy                           0.80       179
   macro avg       0.77      0.76      0.76       179
weighted avg       0.80      0.80      0.80       179
```

Final Model

In [138]:
```
dt1=DecisionTreeClassifier(max_depth=3)
mymodel1(dt1)
```

```
              precision    recall  f1-score   support

           0       0.89      0.47      0.62        53
           1       0.81      0.98      0.89       126

    accuracy                           0.83       179
   macro avg       0.85      0.72      0.75       179
weighted avg       0.84      0.83      0.81       179
```

After doing boosting and bagging we can see still our accuracy is same i.e 80% our accuracy didn't increased

So as we can see that we are getting almost same accuracy by using Logistic Regression, Support vector machine and Random Forest Classifier

So we are selecting Decision Tree Classifier for our model prediction as its values are best suited for our model.

Prescriptive analysis

- **_After studying the dataset, we can see that there are few main parameters based on which there are high chances of rejection**

```
1 ApplicantIncome
2 LoanAmount
3 Loan_Amount_Term
4 Credit_History
5 Education
6 Self_Employed
```

- **Measures to take in order to avoid Avoid Rejection status**

```
1 Applicant should have income more than 10000.
2 Loan_Amount_Term must be of 360 days.
3 Education must be necessary.
```