Loan Prediction with Machine Learning

Dissertation submitted in fulfilment of the requirements for the Degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

With Specialization in Data Science (AI & ML)

By

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GITHUB LINK: https://github.com/omkar3334/loanprediction

LOAN PREDICTION USING MACHINE LEARNING.

0.0.1 Abstract: -

0.0.2 Loans are the core business of banks. The main profit comes directly from the loan's interest. The loan companies grant a loan after an intensive process of verification and validation.However, they still don't have assurance if the applicant is able to repay the loan with nodifficulties.In this tutorial, we'll build a predictive model to predict if an applicant is able to repay the lending company or not. We will prepare the data using Jupyter Notebook and use various models to predict the target variable.

0.0.3 Introduction:-

0.0.4 Loans are the core business of banks. The main profit comes directly from the loan's interest. The loan companies grant a loan after an intensive process of verification and validation.However, they still don't have assurance if the applicant is able to repay the loan with nodifficulties.In this tutorial, we'll build a predictive model to predict if an applicant is able to repay the lending company or not. We will prepare the data using Jupyter Notebook and use various models to predict the target variable.

0.0.5 Problem Statement & Dataset Information:-

0.0.6 Dream Housing Finance company deals in all home loans. They have presence across all urban, semi urban and rural areas. Customer first apply for home loan after that company validates the customer eligibility for loan. Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details areGender, Marital Status, Education,

Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have given a problem to identify the customers

0.0.7 segments, those are eligible for loan amount so that they can specifically target these customers.This is a standard supervised classification task.A classification problem where we have to predict whether a loan would be approved or not. Below is the dataset attributes with description.

0.0.8 Variable Description

0.0.9 Loan_ID Unique Loan ID

0.0.10 Gender Male/ Female

0.0.11 Married Applicant married (Y/N)

0.0.12 Dependents Number of dependents

0.0.13 Education Applicant Education (Graduate/ Under Graduate)

0.0.14 Self_Employed Self employed (Y/N)

0.0.15 ApplicantIncome Applicant income

0.0.16 CoapplicantIncome Coapplicant income

0.0.17 LoanAmount Loan amount in thousands

0.0.18 Loan_Amount_Term Term of loan in months

0.0.19 Credit_History credit history meets guidelines

0.0.20 Property_Area Urban/ Semi Urban/ Rural

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

0.0.23 Loading the dataset

[2]:
```
df=pd.read_csv(r"C:\Users\P.omkar\OneDrive\Desktop\LoanApprovalPrediction.csv")
```

0.0.24 it will show top 5 rows of a dataset

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

[3]:
```
    Loan_ID Gender Married  Dependents     Education Self_Employed  \
0  LP001002   Male      No         0.0      Graduate            No
1  LP001003   Male     Yes         1.0      Graduate            No
2  LP001005   Male     Yes         0.0      Graduate           Yes
3  LP001006   Male     Yes         0.0  Not Graduate            No
4  LP001008   Male      No         0.0      Graduate            No

   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

   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
```

[4]:
```
df.tail()
```

[4]:
```
      Loan_ID  Gender Married  Dependents Education Self_Employed  \
593  LP002978  Female      No         0.0  Graduate            No
594  LP002979    Male     Yes         3.0  Graduate            No
595  LP002983    Male     Yes         1.0  Graduate            No
596  LP002984    Male     Yes         2.0  Graduate            No
597  LP002990  Female      No         0.0  Graduate           Yes
```

```
     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
593             2900                0.0        71.0             360.0
594             4106                0.0        40.0             180.0
595             8072              240.0       253.0             360.0
596             7583                0.0       187.0             360.0
597             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
593             1.0         Rural           Y
594             1.0         Rural           Y
595             1.0         Urban           Y
596             1.0         Urban           Y
597             0.0     Semiurban           N
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 598 entries, 0 to 597
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            598 non-null    object
 1   Gender             598 non-null    object
 2   Married            598 non-null    object
 3   Dependents         586 non-null    float64
 4   Education          598 non-null    object
 5   Self_Employed      598 non-null    object
 6   ApplicantIncome    598 non-null    int64
 7   CoapplicantIncome  598 non-null    float64
 8   LoanAmount         577 non-null    float64
 9   Loan_Amount_Term   584 non-null    float64
 10  Credit_History     549 non-null    float64
 11  Property_Area      598 non-null    object
 12  Loan_Status        598 non-null    object
dtypes: float64(5), int64(1), object(7)
memory usage: 60.9+ KB
```

[6]:
```
df.describe()
```

[6]:
```
       Dependents  ApplicantIncome  CoapplicantIncome  LoanAmount  \
count  586.000000       598.000000         598.000000  577.000000
mean     0.755973      5292.252508        1631.499866  144.968804
std      1.007751      5807.265364        2953.315785   82.704182
min      0.000000       150.000000           0.000000    9.000000
25%      0.000000      2877.500000           0.000000  100.000000
50%      0.000000      3806.000000        1211.500000  127.000000
```

```
75%       1.750000       5746.000000          2324.000000  167.000000
max       3.000000      81000.000000         41667.000000  650.000000

       Loan_Amount_Term  Credit_History
count        584.000000      549.000000
mean         341.917808        0.843352
std           65.205994        0.363800
min           12.000000        0.000000
25%          360.000000        1.000000
50%          360.000000        1.000000
75%          360.000000        1.000000
max          480.000000        1.000000
```

0.0.25 from below we can say there are 598 rows and 13 coloumns in a dataset

[7]:
```
df.shape
```

[7]:
```
(598, 13)
```

0.0.26 checking the null values from the dataset and removing the null values

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

[8]:
```
Loan_ID               0
Gender                0
Married               0
Dependents           12
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           21
Loan_Amount_Term     14
Credit_History       49
Property_Area         0
Loan_Status           0
dtype: int64
```

[9]:
```
df=df.dropna()
```

0.0.27 removed all the null values

[10]:
```
df.isna().sum()
```

[10]:
```
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
```

[11]:
```
df
```

[11]:
```
      Loan_ID  Gender Married  Dependents     Education Self_Employed  \
1    LP001003    Male     Yes         1.0      Graduate            No
2    LP001005    Male     Yes         0.0      Graduate           Yes
3    LP001006    Male     Yes         0.0  Not Graduate            No
4    LP001008    Male      No         0.0      Graduate            No
5    LP001011    Male     Yes         2.0      Graduate           Yes
..        ...     ...     ...         ...           ...           ...
593  LP002978  Female      No         0.0      Graduate            No
594  LP002979    Male     Yes         3.0      Graduate            No
595  LP002983    Male     Yes         1.0      Graduate            No
596  LP002984    Male     Yes         2.0      Graduate            No
597  LP002990  Female      No         0.0      Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
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
5               5417             4196.0       267.0             360.0
..               ...                ...         ...               ...
593             2900                0.0        71.0             360.0
594             4106                0.0        40.0             180.0
595             8072              240.0       253.0             360.0
596             7583                0.0       187.0             360.0
597             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
1               1.0         Rural           N
2               1.0         Urban           Y
3               1.0         Urban           Y
4               1.0         Urban           Y
5               1.0         Urban           Y
```

```
..              …         …       …
593           1.0     Rural        Y
594           1.0     Rural        Y
595           1.0     Urban        Y
596           1.0     Urban        Y
597           0.0 Semiurban        N

[505 rows x 13 columns]
```

0.0.28 finding the unique values in a dependent

[12]:
```
df['Dependents'].unique()
```

[12]:
```
array([1., 0., 2., 3.])
```

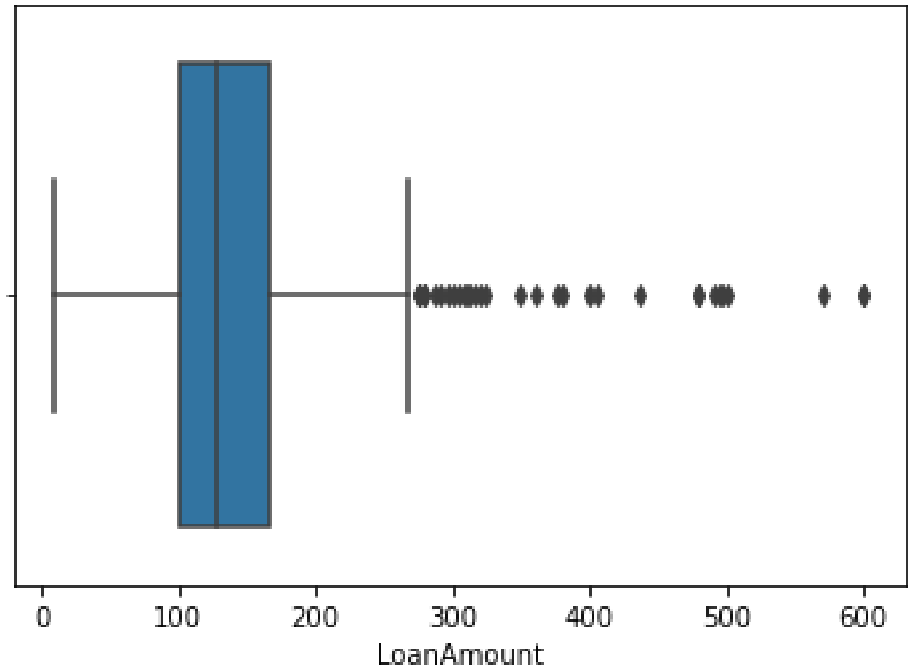
[13]:
```
df['Dependents'].value_counts()
```

[13]:
```
0.0    289
2.0     90
1.0     84
3.0     42
Name: Dependents, dtype: int64
```

0.0.29 exploratory data analysis

[14]:
```
sns.boxplot(df['LoanAmount'])
```

[14]:
```
<AxesSubplot:xlabel='LoanAmount'>
```

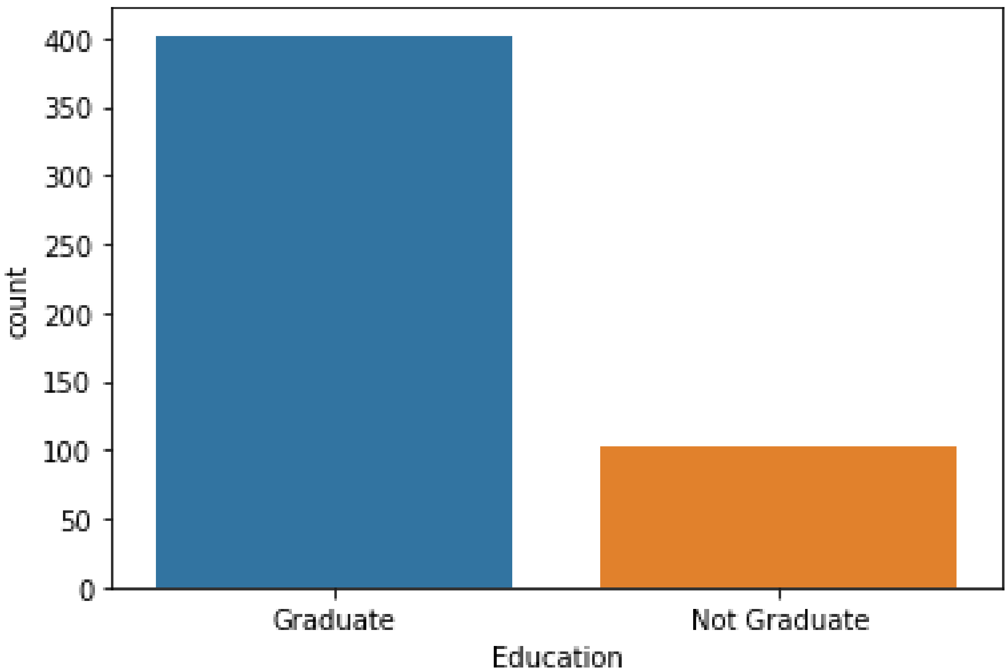


[15]:
```
print(np.where(df["LoanAmount"]>280))
```

```
(array([  8,  18,  28,  43,  55, 105, 125, 144, 212, 230, 255, 264, 265,
       272, 285, 300, 303, 311, 336, 356, 401, 422, 430, 431, 440, 461,
       496], dtype=int64),)
```

[16]:
```
#visualizing eduaction
sns.countplot(df['Education'])
```

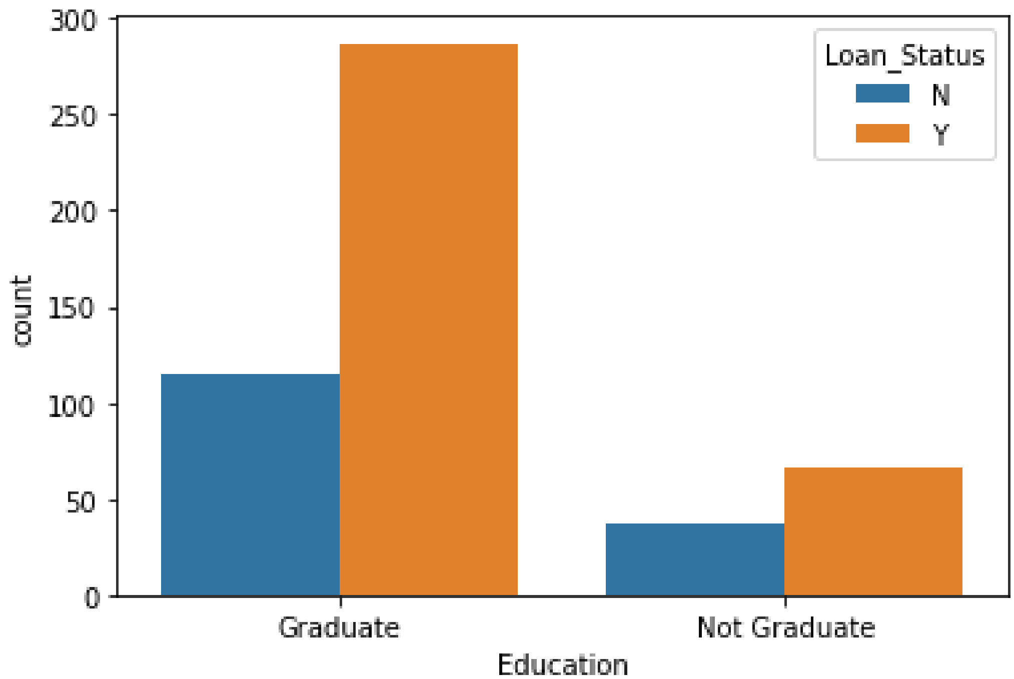
[16]: <AxesSubplot:xlabel='Education', ylabel='count'>



0.0.30 From the above most of the educated person are applied from the loan

[17]:
```
#combining educatin status with loan status
sns.countplot(x = 'Education',hue = 'Loan_Status',data=df)
```

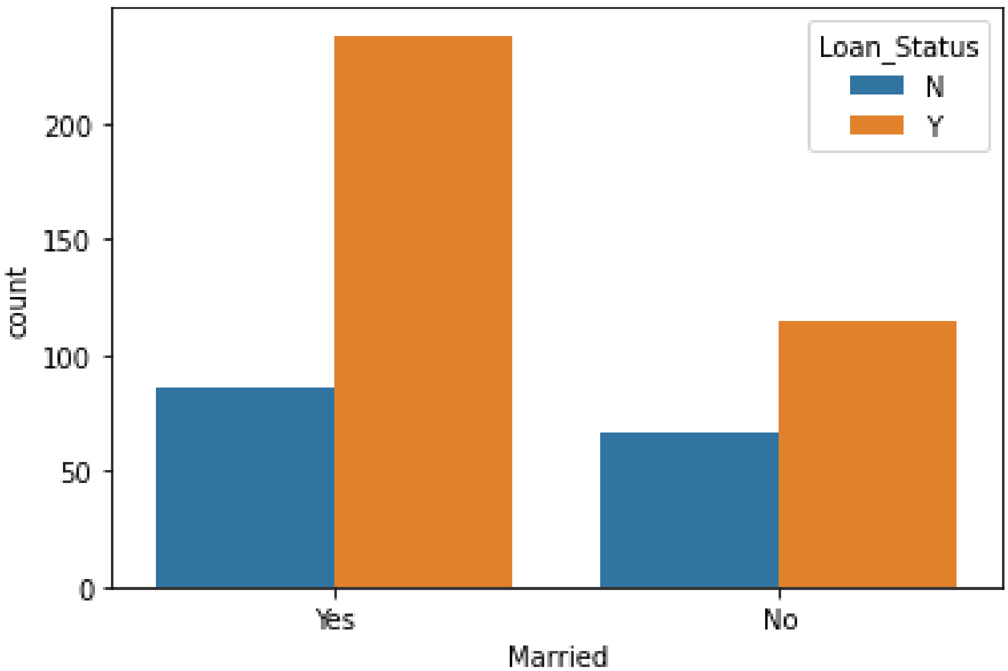
[17]: <AxesSubplot:xlabel='Education', ylabel='count'>



0.0.31 from the above figure loan status was approved for the educated persons

[18]:
```
sns.countplot(x = 'Married',hue = 'Loan_Status',data=df)
```

[18]: <AxesSubplot:xlabel='Married', ylabel='count'>

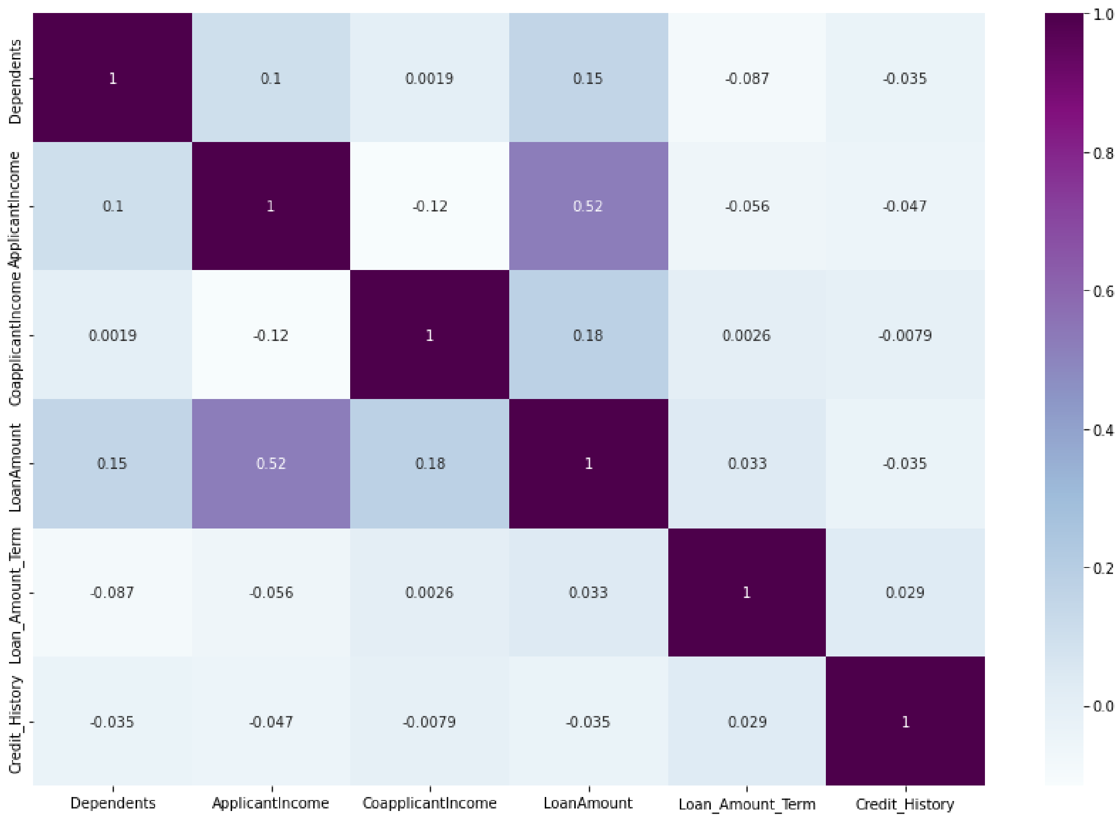


0.0.32 from the above figure loan status was approved for the married persons

0.0.33 finidng correlation between the variables using heatmap

[19]:
```
#finidng correlation between the variables using heatmap
corr = df.corr()
plt.figure(figsize=(15,10))
sns.heatmap(corr, annot = True, cmap="BuPu")
```

[19]: <AxesSubplot:>



[20]:
```python
df['Married'].unique()
```

[20]:
```
array(['Yes', 'No'], dtype=object)
```

Encoding the categories values

[21]:
```python
df.head()
```

[21]:
```
    Loan_ID Gender Married  Dependents     Education Self_Employed  \
1  LP001003   Male     Yes         1.0      Graduate            No
2  LP001005   Male     Yes         0.0      Graduate           Yes
3  LP001006   Male     Yes         0.0  Not Graduate            No
4  LP001008   Male      No         0.0      Graduate            No
5  LP001011   Male     Yes         2.0      Graduate           Yes

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
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
5             5417             4196.0       267.0             360.0
```

```
   Credit_History Property_Area Loan_Status
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
5             1.0         Urban           Y
```

0.0.34 replace the categorical coloumns of married,gender ,education,self employed,property_area into 1 or 0 for the convience of predictions

[22]:
```
df.replace({'Married':{'Yes':1,'No':0},'Gender':{'Male':1,'Female':
↪0},'Education':{'Graduate':1,'Not Graduate':0},'Self_Employed':{'Yes':1,'No':
↪0},'Property_Area':{'Rural':1,'Urban':0,'Semiurban':0}},inplace=True)
```

[23]:
```
df.head()
```

[23]:
```
    Loan_ID  Gender  Married  Dependents  Education  Self_Employed  \
1  LP001003       1        1         1.0          1              0
2  LP001005       1        1         0.0          1              1
3  LP001006       1        1         0.0          0              0
4  LP001008       1        0         0.0          1              0
5  LP001011       1        1         2.0          1              1

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
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
5             5417             4196.0       267.0             360.0

   Credit_History  Property_Area Loan_Status
1             1.0              1           N
2             1.0              0           Y
3             1.0              0           Y
4             1.0              0           Y
5             1.0              0           Y
```

0.0.35 converting the data type of dependents of float into int

[53]:
```
df['Dependents']=df['Dependents'].astype('int')
```

[54]:
```
X=df.iloc[: ,2 :-1].values
```

[55]:
```
X[0]
```

```
[55]: array([1.000e+00, 1.000e+00, 1.000e+00, 0.000e+00, 4.583e+03, 1.508e+03,
              1.280e+02, 3.600e+02, 1.000e+00, 1.000e+00])
```

```
[56]: df.replace({'Loan_Status':{'Y':1,'N':0}},inplace=True)
```

```
[57]: Y=df.iloc[: ,-1].values
```

```
[58]: Y
```

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

```
[59]: X
```

```
[59]: array([[  1.,    1.,    1., …, 360.,    1.,    1.],
              [  1.,    0.,    1., …, 360.,    1.,    0.],
              [  1.,    0.,    0., …, 360.,    1.,    0.],
              …,
              [  1.,    1.,    1., …, 360.,    1.,    0.],
              [  1.,    2.,    1., …, 360.,    1.,    0.],
              [  0.,    0.,    1., …, 360.,    0.,    0.]])
```

0.0.36 Train-Test Split

[31]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.
↪25,random_state=42)
```

[32]:
```
x_train.shape
```

[32]: (378, 10)

[33]:
```
x_test.shape
```

[33]: (127, 10)

0.0.37 Model Training

0.0.38 After creating new features, we can continue the model building process. So we will start with the logistic regression model and then move over to more complex models like RandomForest and XGBoost. We will build the following models in this section.

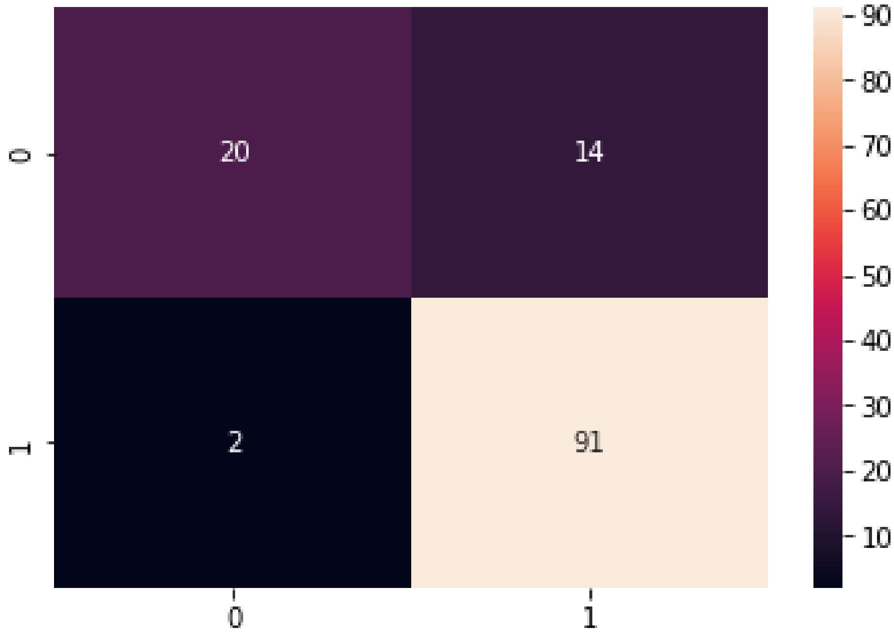
[34]:
```
from sklearn.linear_model import LogisticRegression
log_classifier=LogisticRegression()
log_classifier.fit(x_train ,y_train)
```

[34]: LogisticRegression()

[35]:
```
log_y_pred=log_classifier.predict(x_test)
```

[36]:
```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,log_y_pred)
cm
sns.heatmap(cm,annot=True)
```

[36]: <AxesSubplot:>



[37]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,log_y_pred)
```

[37]: 0.8740157480314961

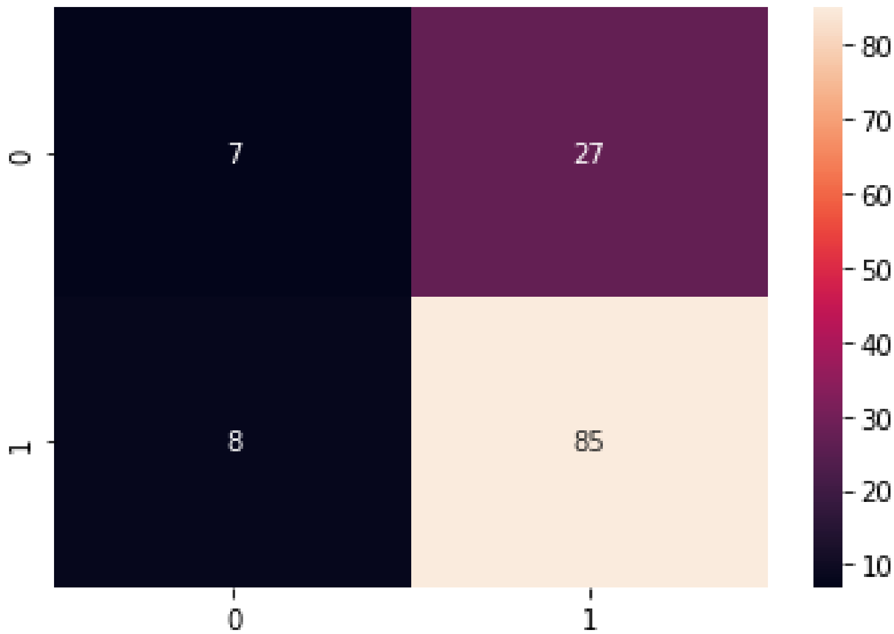
[38]:
```
from sklearn.neighbors import KNeighborsClassifier
k_classifier=KNeighborsClassifier()
k_classifier.fit(x_train,y_train)
```

[38]: KNeighborsClassifier()

[39]:
```
k_y_pred=k_classifier.predict(x_test)
```

[40]:
```
sns.heatmap(confusion_matrix(y_test,k_y_pred),annot=True)
```

[40]: <AxesSubplot:>



[41]:
```
accuracy_score(y_test,k_y_pred)
```

[41]: 0.7244094488188977

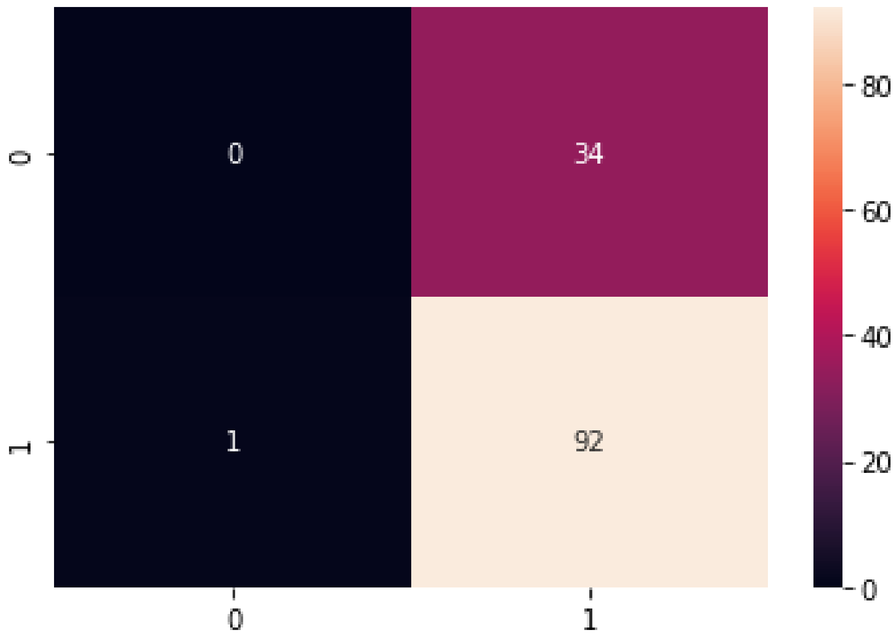
[42]:
```
from sklearn.svm import SVC
s_classifier=SVC(kernel='rbf',random_state=42)
s_classifier.fit(x_train,y_train)
```

[42]: SVC(random_state=42)

[43]:
```
s_y_pred=s_classifier.predict(x_test)
```

[44]:
```
sns.heatmap(confusion_matrix(y_test,s_y_pred),annot=True)
```

[44]: <AxesSubplot:>



[46]:
```
accuracy_score(y_test,s_y_pred)
```

[46]: 0.7244094488188977

0.0.39 RandomForest Classifier:-

0.0.40 RandomForest is a tree-based bootstrapping algorithm wherein a certain no. of weak learners (decision trees) are combined to make a powerful prediction model.For every individual learner, a random sample of rows and a few randomly chosen variables are used to build a decision tree model.Final prediction can be a function of all the predictions made by the individual learners.

[47]:
```
from sklearn.ensemble import RandomForestClassifier
classifier=RandomForestClassifier(n_estimators=25,criterion='entropy')
classifier.fit(x_train,y_train)
```

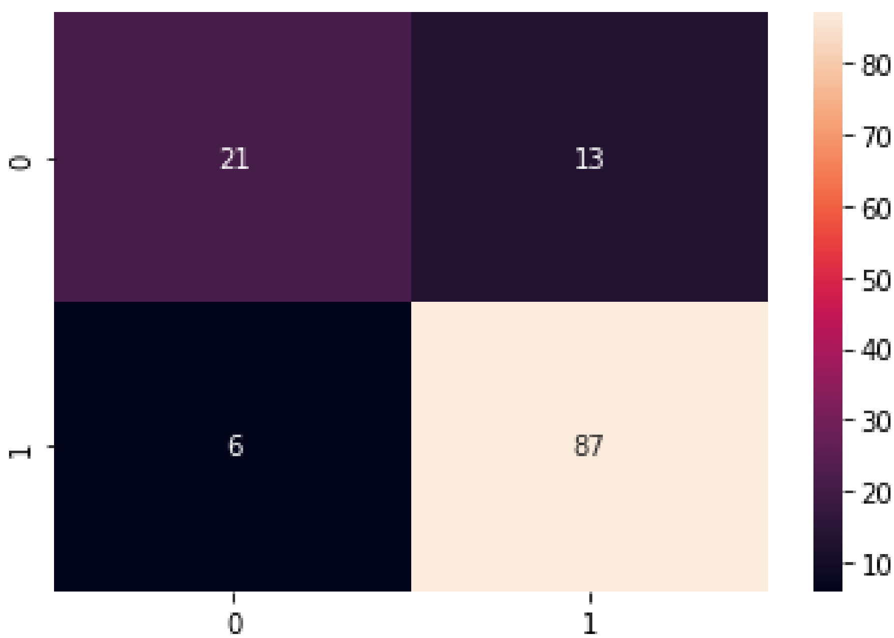
[47]: RandomForestClassifier(criterion='entropy', n_estimators=25)

[48]:
```
y_pred=classifier.predict(x_test)
```

Confusion Matrix
A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made.

[49]:
```
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
```

[49]: <AxesSubplot:>



[61]:
```
accuracy_score(y_test,y_pred)
```

[61]: 0.8503937007874016

Conclusion

We have built our classification model and prediction, we notice that Logistic Regression algorithm gives the best results for our dataset, the accuracy results are around 87% and 85% with Random forest classifier