Loan Approval Prediction Machine Learning

In this article we are going to solve the loan approval prediction .This is the classification type problem in which we need to classify whether the loan will be approved or not for the persons who applied for loan

Quick summary (steps involved in the solving the problem)

1) Reading the problem statement

2) After reading the problem statement we need to identify the dependent column and independent columns

3) Loading the essential python libraries for solving the given problem

4) Data preprocessing

5) Exploratory data analysis (EDA)

6) Feature Engineering

8) Splitting the dataset columns into train columns and test columns

9) Building machine learning model, by training the model with train values

10) Make prediction on the test dataset values

11) Conclusion, selecting the best model and saving the best model

Understanding the Problem Statements

Finance company deals in all kinds of loan. The customer first applies for a loan and after that the company validates the customer's eligibility for the loan.

The company wants to automate the loan eligibility process based on the customers details provided while filling the online application form s. The details given by the customers are Loan ID, Gender, Married, Dependents, Education, Self employed, Applicant Income, Co applican

Income, Loan Amount, Loan Amount Term, Credit History, Properly Area, Loan Status

By seeing the target column (Loan Status) we can say that, this is the binary classification problem in which we need to predict our target label which is loan status

Loan Status column is having the two values

YES: If the loan is approved

NO: If the loan is not approved

So using the training dataset we will train our model and try to predict target column that is Loan Status on the test dataset

About the dataset

The dataset consists of the following columns as shown below

Variable	Description
Loan_ID	Unique Loan ID
Gender	Male/ Female
Married	Applicant married (Y/N)
Dependents	Number of dependents
Education	Applicant Education (Graduate/ Under Graduate)
Self_Employed	Self employed (Y/N)
ApplicantIncome	Applicant income
CoapplicantIncome	Coapplicant income
LoanAmount	Loan amount in thousands
Loan_Amount_Term	Term of loan in months
Credit_History	credit history meets guidelines
Property_Area	Urban/ Semi Urban/ Rural
Loan_Status	(Target) Loan approved (Y/N)

The above table shows the dataset columns name, in that loan status is the dependent column which is target column, and except that column all other columns are independent columns

Loading Essential Python Libraries

1) Pandas for reading and importing the dataset to data frame

2) Numpy for converting the dataset into arrays for any calculation

3) Visualization libraries like matplotlib.pyplot and sea born for analysis study

4) Importing the algorithm's for model learning and prediction

5) Importing the pickel for saving the best model

After importing the libraries we need to define variable name for loading the dataset .In this problem df is the variable name for which the dataset is imported to variable df and the dataset converted to data frame with the help pandas as shown below

In [2]:
```
#Importing the libreris like pandas, numpy for selecing the data and convering the data to dataframe as shown below
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
#Creating the variable df and loading the dataset to the variable df
df=pd.read_csv('loanstatus.csv')
df
```

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
...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0	1.0
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0	1.0
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0	1.0

After importing, we need to check the variable information, if we consider our problem df.info gives us the information about the df dataset weather df dataset consists null values or not, columns dtype

In our problem df dataset having the null values and three dtype values (int(64), float(64),object) as shown below

In [6]:
```
#cheking the datatype of df dataframe columns
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 [4]:
```
#Checking the df dataframe for null values, if null value present we need to remove (or) fill the null values
df.isnull().sum()
```

Out[4]:
```
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
```

null values present in the df dataset we need to remove(or) fill the null values

The df dataset consists of categorical and numerical columns, Categorical Columns: Gender (Male/Female), Married (Yes/No), Number of dependents (Possible values:0,1,2,3+), Education (Graduate / Not Graduate), Self-Employed (No/Yes), credit history(Yes/No), Property Area (Rural/Semi-Urban/Urban) and Loan Status (Y/N)(i. e. Target variable)

Numerical Columns: Loan ID, Applicant Income, Co-applicant Income, Loan Amount, and Loan amount term

Data Pre-processing

Data pre-processing is the important step in the machine learning project because in the real world the data is highly susceptible to be missing, inconsistent, and noisy due to their heterogeneous origin.

By doing the data pre-processing on the dataset we can reduce the missing values, removing the irrelevant columns from the dataset, removing the outliers which helps to give the quality data to the machine for learning which results in obtaining the good results

In our project we come to know that the df dataset having the null values so we are filling the null values by mode function where all the null values filled by the mode values

In [9]:
```
#filling the missing data
print("Before filling missing values\n\n","#"*50,"\n")
null_cols = ['Credit_History', 'Self_Employed', 'LoanAmount','Dependents', 'Loan_Amount_Term', 'Gender', 'Married']


for col in null_cols:
    print(f"{col}:\n{df[col].value_counts()}\n","-"*50)
    df[col] = df[col].fillna(
    df[col].dropna().mode().values[0] )


df.isnull().sum().sort_values(ascending=False)
print("After filling missing values\n\n","#"*50,"\n")
for col in null_cols:
    print(f"\n{col}:\n{df[col].value_counts()}\n","-"*50)
```

After filling the null values by mode function, checking the still null values present in the df dataset

In [11]:
```
# checking for null values
df.isnull().sum()
```

Out[11]:
```
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
```

null values is filled and now the dataset df doesnot have any null values

In our project label encoder done to convert all the categorical columns into numerical columns by converting categorical values to numerical values as shown below

In [31]:
```
# converting the categorical columns to numerical columns by LabelEncoder
from sklearn.preprocessing import LabelEncoder
for col in df.columns:
    if df[col].dtype=='object':
        encode=LabelEncoder()
        df[col]=encode.fit_transform(df[col])
df
```

Out[31]:

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

614 rows × 13 columns

The column Loan ID is not having any impact on the target column so we are dropping from df dataset

```
In [40]: # Loan_id doesnot have any impact on target column so we can drop the loan_id column
df=df.drop(columns='Loan_ID')
df
```

Out[40]:

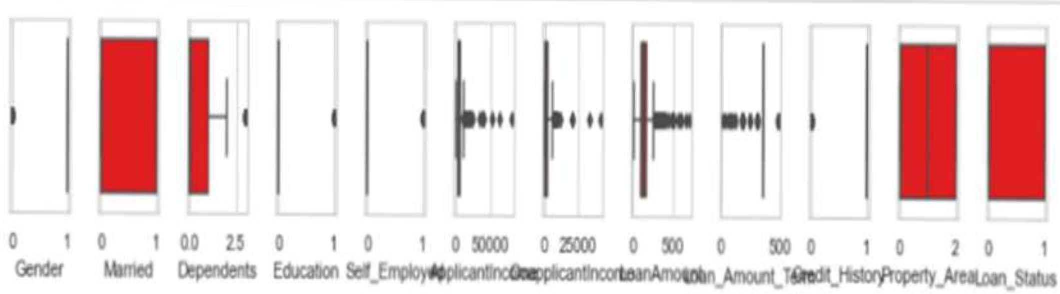
	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_
0	1	0	0	0	0	5849	0.0	120.0	360.0	1.0	
1	1	1	1	0	0	4583	1508.0	128.0	360.0	1.0	
2	1	1	0	0	1	3000	0.0	66.0	360.0	1.0	
3	1	1	0	1	0	2583	2358.0	120.0	360.0	1.0	
4	1	0	0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

614 rows × 12 columns

In the above dataframe df Loan_id is droped

By plotting the box plot we also come to know that the df dataset having the outliers so outliers need to be calculated by using the zscore. After zscore calculation we come to know that df dataset consists 41 outliers, so now we need to remove the outliers after removing the outliers, df dataset renamed to df_new dataset and the shape reduced from (614*12) to (577*12)

```
In [41]: #check for outliers with the help of box plot
columns_list=df.columns.values
ncol=100
nrows=50
plt.figure(figsize=(ncol,ncol))
for i in range (0,len(columns_list)):
    plt.subplot(nrows,ncol,i+1)
    sns.boxplot(df[columns_list[i]],color='red',orient='h')
    plt.tight_layout()
```



From the graph we can see that the outliers present in the dataset , so we need to remove

In [42]:
```python
# checking how much number of outliers are present in the dataframe
from scipy.stats import zscore
z=np.abs(zscore(df))
print(df.shape)
print(z.shape)
threshold=3
print(np.where(z>3))
len(np.where(z>3)[0])
```

```
(614, 12)
(614, 12)
(array([  9,  14,  68,  94, 126, 130, 133, 155, 155, 171, 171, 177, 177,
       183, 185, 242, 262, 278, 308, 313, 333, 333, 369, 402, 409, 417,
       432, 443, 487, 495, 497, 506, 523, 525, 546, 561, 575, 581, 585,
       600, 604], dtype=int64), array([6, 8, 8, 8, 5, 7, 8, 5, 7, 5, 7, 6, 7, 5, 5, 8, 8, 7, 7, 8, 5, 7,
       7, 6, 5, 6, 7, 5, 7, 8, 8, 7, 7, 7, 8, 7, 8, 6, 8, 6, 7],
      dtype=int64))
```

Out[42]: 41

41 numbers outliers present in the dataset df

In [43]:
```python
# 41 outliers are present in the df data frame, now we are removing the outliers
df_new=df[(z<3).all(axis=1)]
print(df_new.shape)
```

```
(577, 12)
```

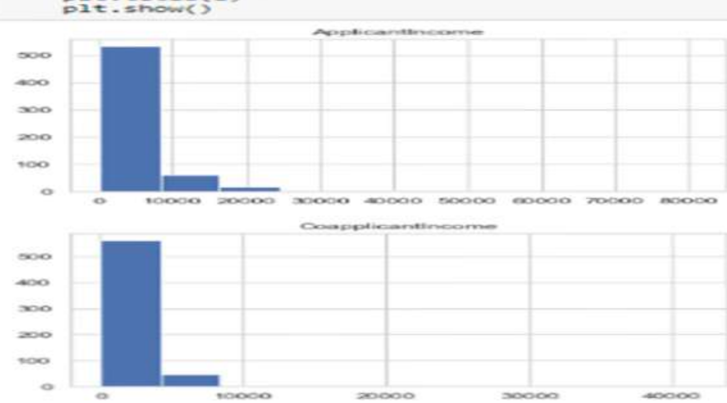
df_new is the dataset obtained after removing the 41 outliers

Exploratory Data Analysis (EDA)

EDA is an important step in any data analysis or data science project, EDA generally involves statistical summary for numerical data in the dataset and creating various graphical representation to understand the data better

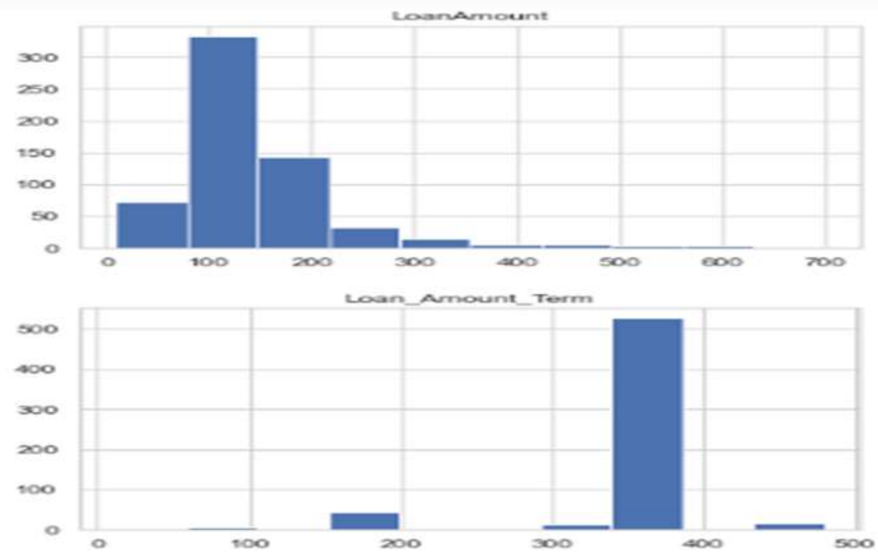
In our project first univariant analysis is done for which the column like Loan status, Application, Co-applicant income, Loan Amount, Loan Amount term, Credit History graph is as shown below

In [16]:
```python
# plotting the numerical columns data
for i in loan_num:
    plt.hist(loan_num[i])
    plt.title(i)
    plt.show()
```

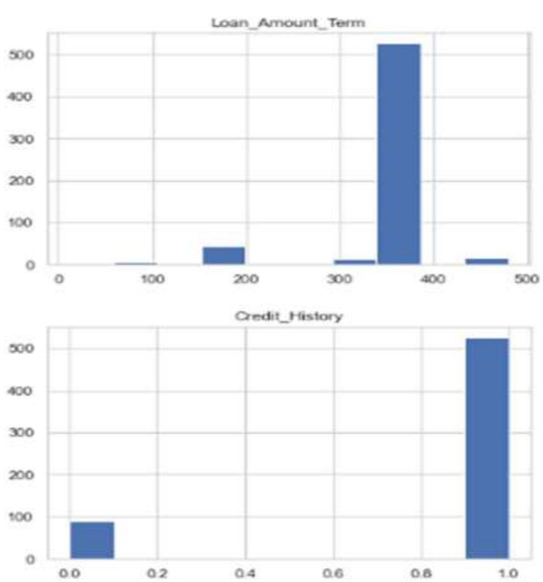


If we consider the applicant income column, graph shows that the persons who applied for loan maximum people having the income between the range 0 to 10000

If we consider the coapplicantincome column, graph shows that the person's coapplicant income ranges from 0 to 10000



If we consider the loan amount column, graph shows that the maximum people applied for loan in the range of 100 to 200



- if we consider the applicantincome column, graph shows that the persons who applied for loan maximum people having the income between the range 0 to 10000
- if we consider the coapplicantincome column, graph shows that the person's coapplicant income ranges from 0 to 10000
- if we consider the loan amount column, graph shows that the maximum people applied for loan in the range of 100 to 200
- The above table also shows the loan_ amount_term and credit history

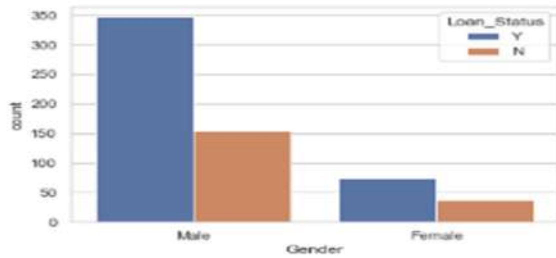
The above table also shows the loan_ amount term and credit history

Bivariate analysis

The columns like Gender, Married, Dependent, Education, Self employed,

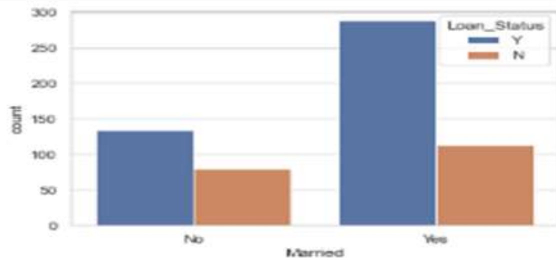
Property area are compared with the target columns (loan status) and the observation written below the graph itself in the screenshot

In [25]:
```
# categorical columns ( spliting by loan status columns values)
sns.countplot(x='Gender',hue='Loan_Status', data=df)
plt.show()
```



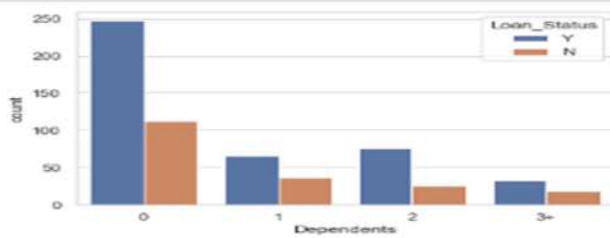
- from graph we can say , loan approved for male is more when compare to female

In [26]:
```
sns.countplot(x='Married',hue='Loan_Status',data=df)
plt.show()
```

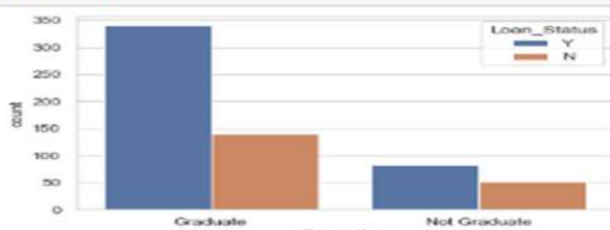


From graph we can say, the loan approved for married person is more when we compare loan_status column with married column in dataset

In [27]:
```
sns.countplot(x='Dependents',hue='Loan_Status',data=df)
plt.show()
```

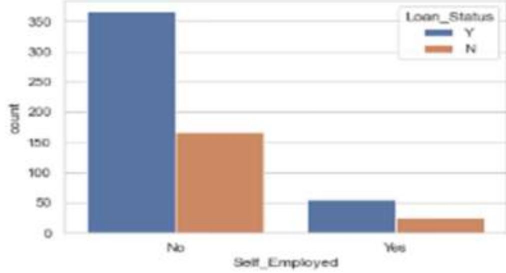


In [28]:
```
sns.countplot(x='Education',hue='Loan_Status',data=df)
plt.show()
```



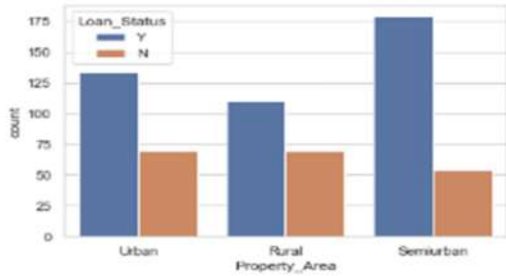
From graph we can say that, the loan approved for graduate is more when compte to not graduate

In [29]:
```python
sns.countplot(x='Self_Employed',hue='Loan_Status',data=df)
plt.show()
```



From graph we can say that, the loan approved for people with no self employed status is more(mean people who are working for salary) when compared to self employed status yes

In [30]:
```python
sns.countplot(x='Property_Area',hue='Loan_Status',data=df)
plt.show()
```

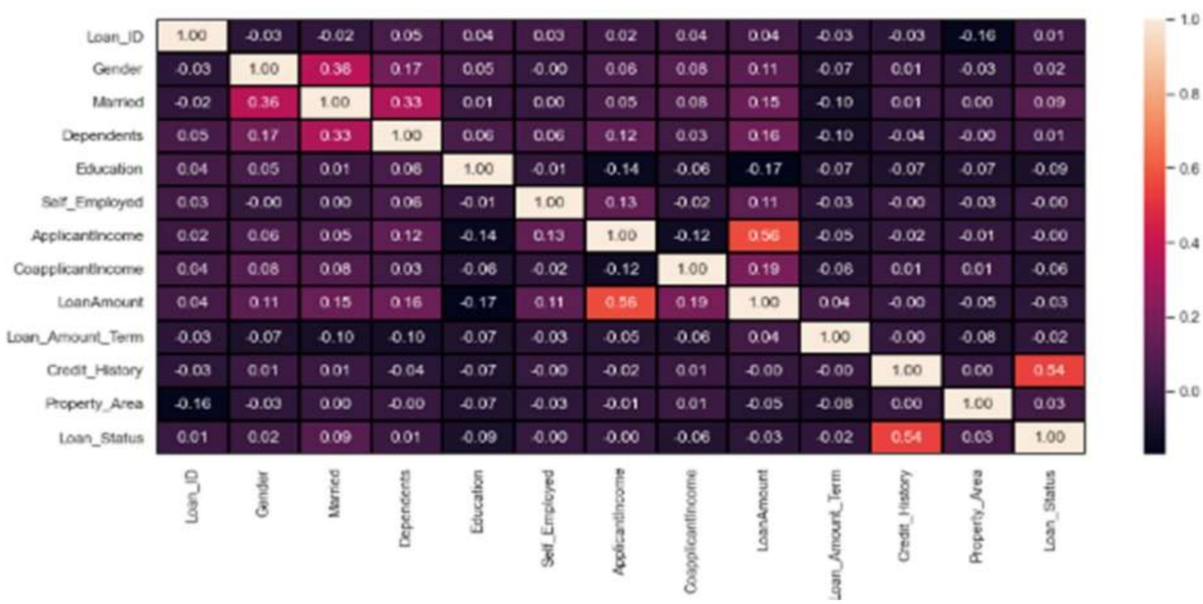


From graph we can say that , the loan approved for semiurban is more then followed by urban and rural area as showm in the graph above

Co-Relation also calculated and display with the help of heat map

In [32]:
```python
# Corelation can also be reprasented by heatmap
import matplotlib.pyplot as plt
plt.figure(figsize=(15,6))
sns.heatmap(df.corr(),annot=True,linewidth=0.1,linecolor='black',fmt='0.2f')
```

Out[32]: <AxesSubplot:>



From The correlation heat map we can say that the column credit_history having the good co relation value with loan_status, therefore our target value is highly dependent on credit_history column

Statistical summary of the df dataset also calculated

```
In [12]: # to know the statistical data we use describe function
         df.describe()
```

Out[12]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	145.465798	342.410423	0.855049
std	6109.041673	2926.248369	84.180967	64.428629	0.352339
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.250000	360.000000	1.000000
50%	3812.500000	1188.500000	125.000000	360.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

1) After filling all the null values,number of counts in each columns are same which means there is no null value in the data set

2) by seeing the 75% percentail value and max value we can say that outliers are present in the dataset which need to be removed

3) With the help of obove table we can know the statistical information of each columns in the data set

By this table we can know the each column mean, standard deviation, columns min and maximum values and also 25^{th} 50^{th} 75^{th} percentile values

Feature Engineering

Feature Engineering refers to manipulation, addition, deletion, combination, mutation of your dataset to improve machine learning model training, leading to better performance and greater accuracy

In our project after splitting the data values into x and y. For x values we are applying the yeo-Johnson method to remove the skewness and also we are doing the min max scalar technique to bring the values in the range between 0 to 1

```
In [46]: #removing the skewness by yeo johnson method
         from sklearn.preprocessing import power_transform
         x=power_transform(x,method='yeo-johnson')
         x

Out[46]: array([[ 4.72342640e-01, -1.37208932e+00, -8.27104306e-01, ...,
                  1.75540037e-01,  4.11732692e-01,  1.19356680e+00],
                [ 4.72342640e-01,  7.28815525e-01,  8.54259122e-01, ...,
                  1.75540037e-01,  4.11732692e-01, -1.35000343e+00],
                [ 4.72342640e-01,  7.28815525e-01, -8.27104306e-01, ...,
                  1.75540037e-01,  4.11732692e-01,  1.19356680e+00],
                ...,
                [ 4.72342640e-01,  7.28815525e-01,  8.54259122e-01, ...,
                  1.75540037e-01,  4.11732692e-01,  1.19356680e+00],
                [ 4.72342640e-01,  7.28815525e-01,  1.31670248e+00, ...,
                  1.75540037e-01,  4.11732692e-01,  1.19356680e+00],
                [-2.11710719e+00, -1.37208932e+00, -8.27104306e-01, ...,
                  1.75540037e-01, -2.42876026e+00,  2.36103342e-03]])
```

```
In [50]: from sklearn.preprocessing import MinMaxScaler
         mms=MinMaxScaler()
         x1=mms.fit_transform(x)
```

```
In [51]: # importing all the algorithems for checking the accuracy_score  and model perforfance
         from sklearn.linear_model import LogisticRegression
         from sklearn.model_selection import train_test_split,cross_val_score,GridSearchCV
         from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,f1_score
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.svm import SVC
         from sklearn.naive bayes import GaussianNB
```

Building Machine Learning Model

Creating x (input variable) and Y (target variable)

Using the train test split on the training data for validation we have a 67:33 split on the training data and for training the model we need to import the algorithms depending up on the target column. In our project the target column is of classifier type, so we imported the different classifier type algorithm’s such as Random Forest classifier, Decision Tree classifier, Support vector classifier, KNeighbours classifier, GaussionNB, Logistic Regression. Among all the algorithms support vector classifier (SVC) gives the best accuracy score 86.206

```
In [51]: # importing all the algorithems for checking the accuracy_score  and model perforfance
         from sklearn.linear_model import LogisticRegression
         from sklearn.model_selection import train_test_split,cross_val_score,GridSearchCV
         from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,f1_score
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.svm import SVC
         from sklearn.naive_bayes import GaussianNB
         from sklearn.ensemble import RandomForestClassifier
```

```
In [64]: model=[RandomForestClassifier(),DecisionTreeClassifier(),SVC(),KNeighborsClassifier(),GaussianNB(),LogisticRegression()]
         max_r2_score=0
         for i_state in range(0,10):
             x_train,x_test,y_train,y_test=train_test_split(x1,y,random_state=i_state,test_size=0.33)
             for a in model:
                 a.fit(x_train,y_train)
                 pred=a.predict(x_test)
                 score=accuracy_score(y_test,pred)
                 print('score for random_state',i_state,'is',score)
                 if score>max_r2_score:
                     max_r2_score=score
                     Final_state=i_state
                     Final_model= a
         print('accuracy_score ',max_r2_score,'for random state ',Final_state, 'and model is ',Final_model)
```

In the above table , I wrote the program for importing the best algorithm and for best random state value. After all the calculation best model was SVC for random state 8 which is also shown in the below screen short

```
score for random_state 9 is 0.7881773399014779
accuracy_score  0.8620689655172413 for random state  8 and model is  SVC()
```

```
In [71]: # we are training the model with SVC() for randomstate 8 and checking the accuracy_score
svc=SVC()
x_train,x_test,y_train,y_test=train_test_split(x1,y,random_state=8,test_size=0.33)
svc.fit(x_train,y_train)
svc.score(x_train,y_train)
pred_y=svc.predict(x_test)
svcs=accuracy_score(y_test,pred_y)
print('accuracy_score =',svcs*100)
print(classification_report(y_test,pred_y))
print(confusion_matrix(y_test,pred_y))
print('F1_score = ',f1_score(y_test,pred_y)*100)
from sklearn.model_selection import cross_val_score
cv_score=cross_val_score(svc,x1,y,cv=5)
cv_mean=cv_score.mean()
print("cross_val_score=",cv_mean*100)
```

```
accuracy_score = 86.20689655172413
              precision    recall  f1-score   support

           0       0.97      0.53      0.68        57
           1       0.84      0.99      0.91       146

    accuracy                           0.86       203
   macro avg       0.91      0.76      0.80       203
weighted avg       0.88      0.86      0.85       203

[[ 30  27]
 [  1 145]]
F1_score =  91.19496855345913
cross_val_score= 80.9462881514061
```

After getting the accuracy score of 86.206, I tried fine tuning it to improve the accuracy score using the GridSearchCV

```
In [72]: from sklearn.model_selection import GridSearchCV
# defining parameter range
param_grid = {'C': [0.1, 1, 10, 100],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'kernel': ['rbf']}

grid = GridSearchCV(SVC(), param_grid, refit = True, verbose = 3)

# fitting the model for grid search
grid.fit(x_train,y_train)
print(grid.best_params_)
```

The best parameter I got after the fine tuning is

```
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[CV 5/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.671 total time=   0.0s
{'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}

74]: smv1=SVC(C=1, gamma=0.1, kernel='rbf')
```
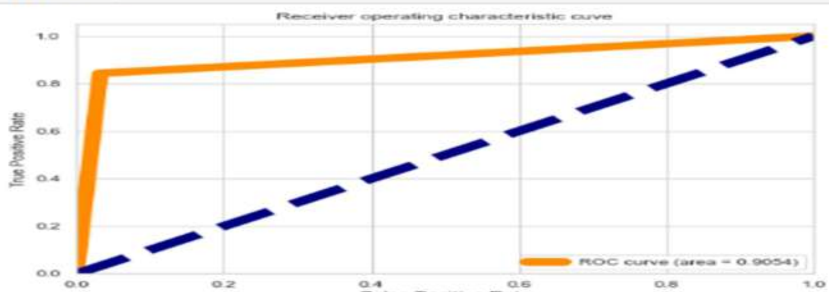

After fine tuning SVC, in our project we are not seeing the much difference in the accuracy score

```
In [74]: smv1=SVC(C=1,gamma=0.1,kernel='rbf')
         smv1.fit(x_train,y_train)
         pred_smv=smv1.predict(x_test)
         score=accuracy_score(y_test,pred_smv)
         print('accuracy_score= ',score*100)
         cv_score=cross_val_score(smv1,x,y,cv=5)
         cv_mean=cv_score.mean()
         print('mean_cv value = ',cv_mean*100)
         print(confusion_matrix(y_test,pred_y))
         print(classification_report(y_test,pred_y))
```

```
accuracy_score=  86.20689655172413
mean_cv value =  80.94495535119283
[[ 30  27]
 [  1 145]]
              precision    recall  f1-score   support

           0       0.97      0.53      0.68        57
           1       0.84      0.99      0.91       146

    accuracy                           0.86       203
   macro avg       0.91      0.76      0.80       203
weighted avg       0.88      0.86      0.85       203
```

AOC and ROC curve also drawn, area under the curve is 90.54 which is good value

```
In [75]: #aoc-roc curve
         from sklearn.metrics import roc_curve,auc
         fpr, tpr, thresholds = roc_curve(pred_smv,y_test)
         roc_auc=auc(fpr,tpr)

         plt.figure(figsize=(8, 6))
         plt.plot( fpr, tpr,color='darkorange',lw=10,label='ROC curve (area = %0.4f)' % roc_auc)
         plt.plot([0, 1], [0, 1],color='navy',lw=10,linestyle='--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver operating characteristic cuve')
         plt.legend(loc="lower right")
         plt.show()
```



<u>Conclusion</u>

1) The support vector classifier SVC() giving the best accuracy value

2) SVC Accuracy_score, F1_score, Classification report, Confussion_matrix, and also ROC value is also shown in the above table

3) Last step of the project ,we know the better performance algorithm which is Support Vector Classifier hyper parameter tuning also done, after that we need to save the model by using pickel