Problem Statement:

This dataset includes details of applicants who have applied for loan. The dataset includes details like credit history, loan amount, their income, dependents etc.You have to build a model that can predict whether the loan of the applicant will be approved or not on the basis of the details provided in the dataset

Importing Required Library

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import scikitplot as skplt
from imblearn.over_sampling import SMOTE
pd.set_option('display.max_columns', None) # # For display maximum column
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sco
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, plot
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.linear_model import LogisticRegression
import xgboost as xgb
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading Data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\csv file\loan_prediction.csv")
df.head()
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplica
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

Check no of row and column

In [3]:
```python
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (614, 13)
```

Checking for Null values

In [4]:
```python
print('================================\n')
print(df.isnull().sum())
print('\n================================')
```

```
================================

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

================================
```

There is null value

Information about dataset

In [5]:
```python
print('==================================================\n')
print(df.info())
print('====================================================')
```

```
==================================================

<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
None
====================================================
```

Categorical data present in our data set

Statistics of Data

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

Out[6]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

Outliers are present in our data set

Drop Unwanted Columns

In [7]:
```
df = df.drop('Loan_ID', axis = 1)
df.head(2)
```

Out[7]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	0	Graduate	No	5849	0.0
1	Male	Yes	1	Graduate	No	4583	1508.0

Analysis of Null value

In [8]:
```
print('================================\n')
print(df.isnull().sum())
print('\n================================')
```

```
================================

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

================================
```

Gender column

In [9]:
```
df['Gender'].value_counts()
```

Out[9]:
```
Male      489
Female    112
Name: Gender, dtype: int64
```

In [10]:
```
df['Gender'].dtype
```

Out[10]:
```
dtype('O')
```

Approach : Gender column is categorical value so, we fill null value with mode

Married column

In [11]:
```
df['Married'].value_counts()
```

Out[11]:
```
Yes    398
No     213
Name: Married, dtype: int64
```

In [12]:
```
df['Married'].dtype
```

Out[12]:
```
dtype('O')
```

Approach : Married column is categorical value so, we fill null value with mode

Dependents columns

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

Out[13]:
```
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```

In [14]:
```
df['Dependents'].dtype
```

Out[14]:
```
dtype('O')
```

In [15]:
```
df['Dependents'] = df['Dependents'].replace(to_replace= '3+', value = 3)
```

In [16]:
```
df['Dependents'].value_counts()
```

Out[16]:
```
0    345
1    102
2    101
3     51
Name: Dependents, dtype: int64
```

Approach 1 : In oreder to do Dependents column analysis we found "3+" value which not acceptable to do analysis so we replace with "3"

Approach 2 : Dependents column is categorical value so, we fill null value with mode

Self Employed columns

In [17]:
```
df['Self_Employed'].value_counts()
```

Out[17]:
```
No     500
Yes     82
Name: Self_Employed, dtype: int64
```

In [18]:
```
df['Self_Employed'].dtype
```

Out[18]:
```
dtype('O')
```

Approach : Self Employed column is categorical value so, we fill null value with mode

Loan Amount column

In [19]:
```
df['LoanAmount'].value_counts()
```

Out[19]:
```
120.0    20
110.0    17
100.0    15
160.0    12
187.0    12
         ..
211.0     1
250.0     1
62.0      1
85.0      1
436.0     1
Name: LoanAmount, Length: 203, dtype: int64
```

In [20]:
```
df['LoanAmount'].dtype
```

Out[20]:
```
dtype('float64')
```

Approach : Loan Amount column is continuous value so, we fill null value with mean

Loan Amount Term column

In [21]:
```
df['Loan_Amount_Term'].value_counts()
```

Out[21]:
```
360.0    512
180.0     44
480.0     15
300.0     13
84.0       4
240.0      4
120.0      3
36.0       2
60.0       2
12.0       1
Name: Loan_Amount_Term, dtype: int64
```

In [22]:
```
df['Loan_Amount_Term'].dtype
```

Out[22]:
```
dtype('float64')
```

Approach : Loan Amount Term column is continuous value so, we fill null value with mean

Credit History column

In [23]:
```
df['Credit_History'].value_counts()
```

Out[23]:
```
1.0    475
0.0     89
Name: Credit_History, dtype: int64
```

In [24]:
```
df['Credit_History'].dtype
```

Out[24]:
```
dtype('float64')
```

Approach : Credit History column is categorical value so, we fill null value with mode

Fill NaN

In [25]:
```
df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0])
df['Married'] = df['Married'].fillna(df['Married'].mode()[0])
df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])
df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])
df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].mean())
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].moc
df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].mode()[0]
```

In [26]:
```
print('================================\n')
print(df.isnull().sum())
print('\n================================')
```

```
================================

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

================================
```

There is no null value

Analysis of data respect to Loan Status

In [27]:
```
df.head(2)
```

Out[27]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	0	Graduate	No	5849	0.0
1	Male	Yes	1	Graduate	No	4583	1508.0

Gender column

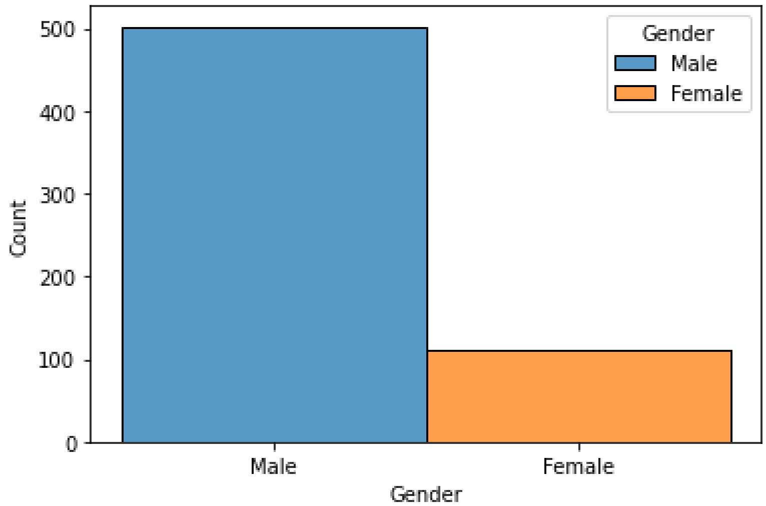
In [28]:
```
df['Gender'].value_counts()
```

Out[28]:
```
Male      502
Female    112
Name: Gender, dtype: int64
```

In [29]:
```
df['Loan_Status'].value_counts()
```

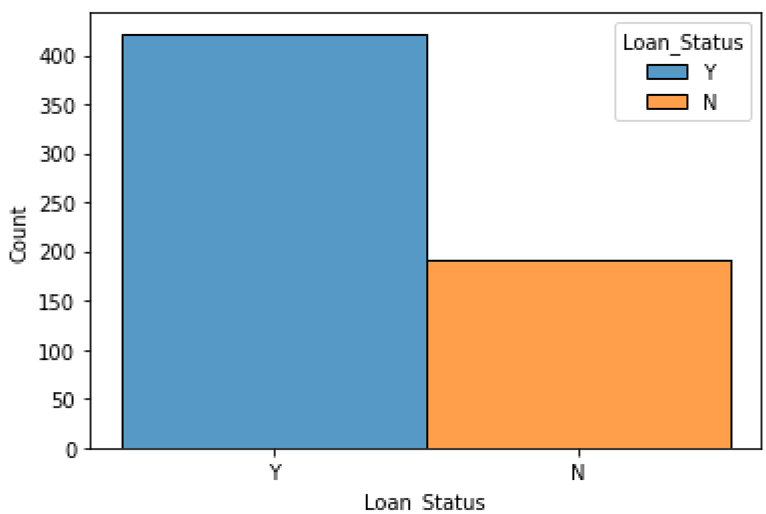
Out[29]:
```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

In [30]:
```
sns.histplot(binwidth=0.5, x="Gender", hue="Gender", data=df, stat="count", multi
plt.show()
```



Male is highest in number

In [31]:
```
sns.histplot(binwidth=0.5, x="Loan_Status", hue="Loan_Status", data=df, stat="cou
plt.show()
```

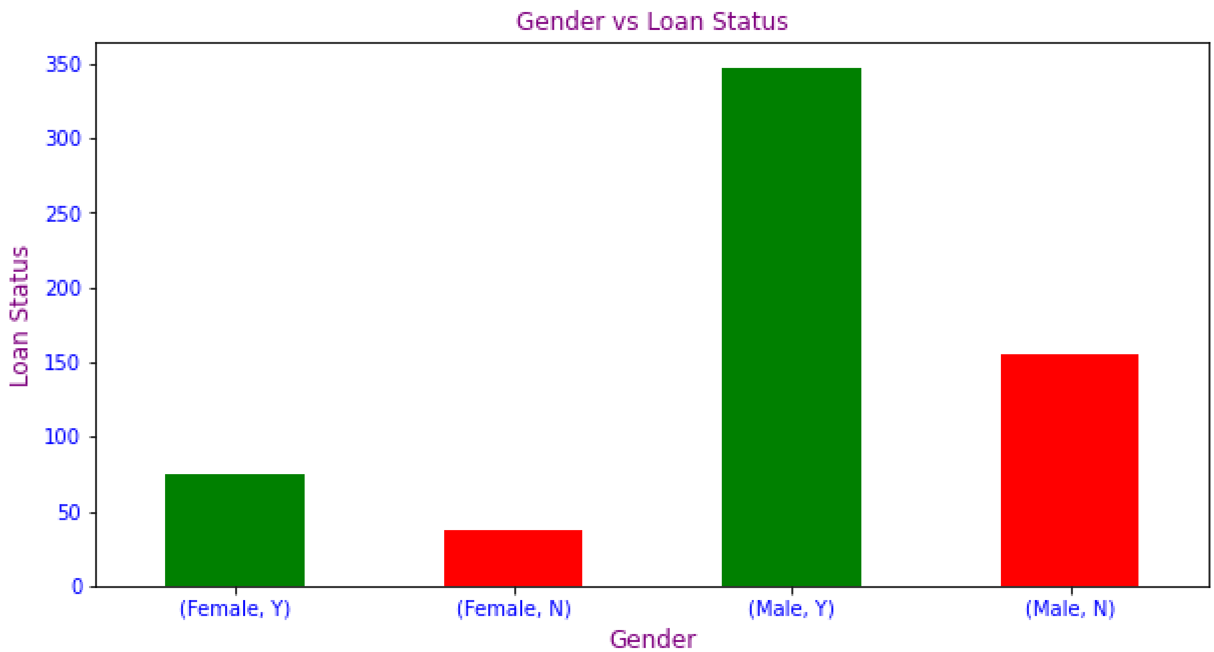


Repayment is high 👍👍

In [32]:
```python
gn = df.groupby('Gender')['Loan_Status'].value_counts()
gn
```

Out[32]:
```
Gender  Loan_Status
Female  Y               75
        N               37
Male    Y              347
        N              155
Name: Loan_Status, dtype: int64
```

In [33]:
```python
gn.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Gender', c = 'purple', fontsize = 12)
plt.ylabel('Loan Status', c = 'purple', fontsize = 12 )
plt.title('Gender vs Loan Status', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



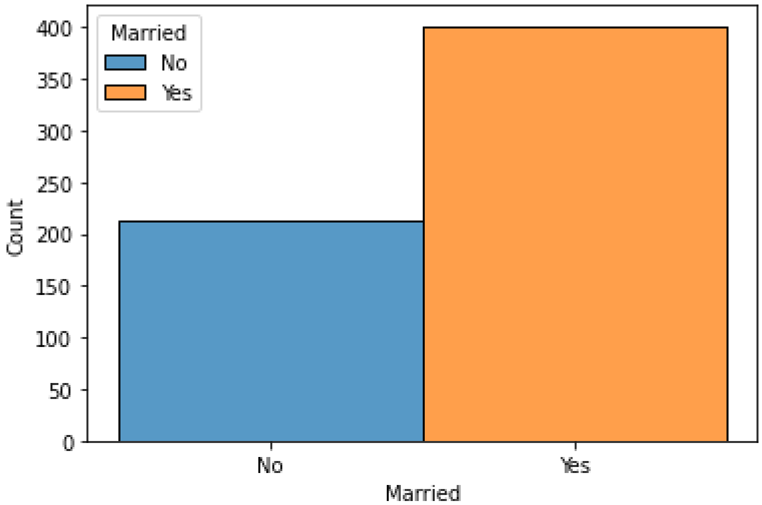
Above plot shows Repayment of Loan in male is higest 347 👍 and in female is 75 which low as compare to male 👎

Married column

In [34]:
```python
df['Married'].value_counts()
```

Out[34]:
```
Yes    401
No     213
Name: Married, dtype: int64
```

In [35]:
```
sns.histplot(binwidth=0.5, x="Married", hue="Married", data=df, stat="count", mul
plt.show()
```

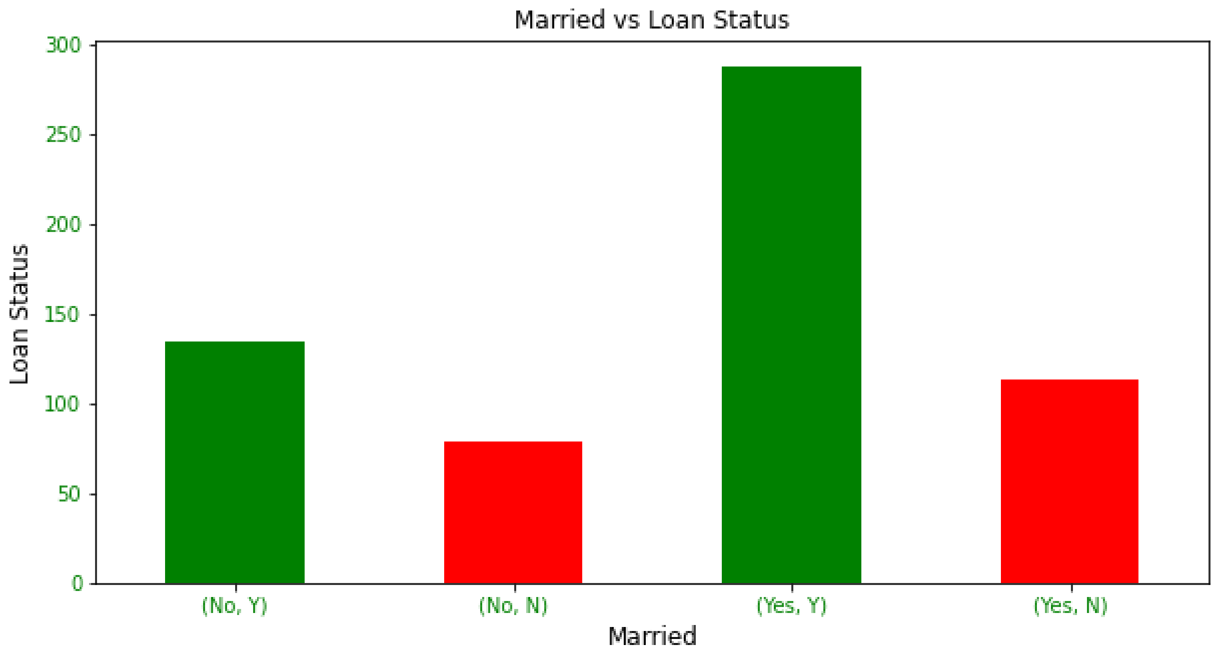


Above plot shows no of Married person is highest

In [36]:
```
m = df.groupby('Married')['Loan_Status'].value_counts()
m
```

Out[36]:
```
Married  Loan_Status
No       Y              134
         N               79
Yes      Y              288
         N              113
Name: Loan_Status, dtype: int64
```

In [37]:
```
m.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Married', c = 'k', fontsize = 12)
plt.ylabel('Loan Status', c = 'k', fontsize = 12 )
plt.title('Married vs Loan Status', c = 'k', fontsize = 12)
plt.xticks(c = 'g')
plt.yticks(c = 'g')
plt.show()
```



Above plot shows Repayment of Loan in Married person is higest 288 👍 and In Not Married is 134 which low as compare to Married person 👎

Dependents column

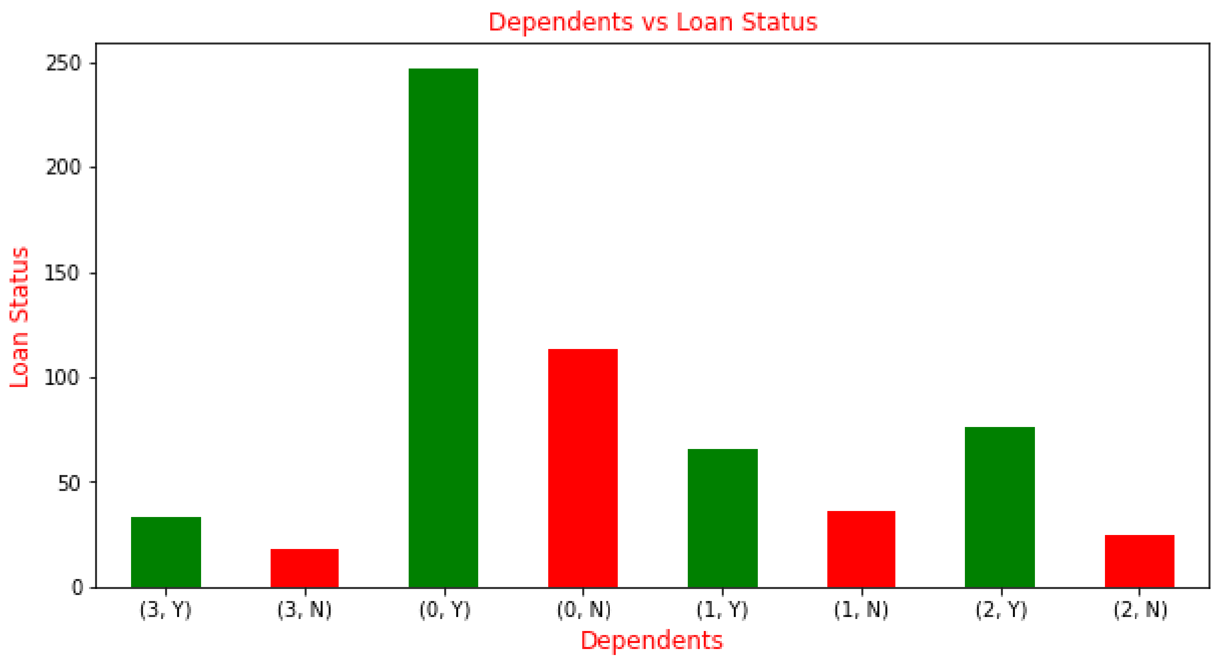
In [38]:
```
df['Dependents'].value_counts()
```

Out[38]:
```
0    360
1    102
2    101
3     51
Name: Dependents, dtype: int64
```

In [39]:
```
d = df.groupby('Dependents')['Loan_Status'].value_counts()
d
```

Out[39]:
```
Dependents  Loan_Status
3           Y               33
            N               18
0           Y              247
            N              113
1           Y               66
            N               36
2           Y               76
            N               25
Name: Loan_Status, dtype: int64
```

In [40]:
```
d.plot.bar(figsize = (10,5), rot = 360, color = ['g', 'r'])
plt.xlabel('Dependents', c = 'r', fontsize = 12)
plt.ylabel('Loan Status', c = 'r', fontsize = 12 )
plt.title('Dependents vs Loan Status', c = 'r', fontsize = 12)
plt.show()
```



Above plot shows Repayment of Loan in Dependents "0" is higest 247 👍 and in Dependents "3" is 18 which low as compare to Dependents "0" 👎

Education column

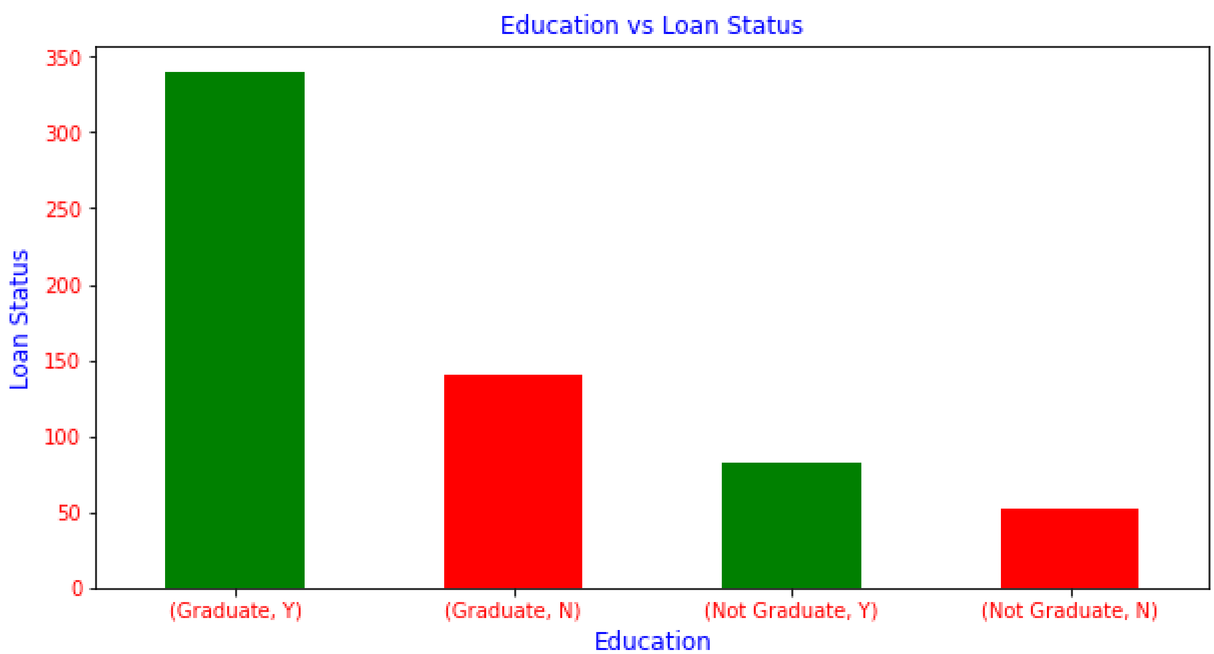
In [41]:
```
df['Education'].value_counts()
```

Out[41]:
```
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```

In [42]:
```
g = df.groupby('Education')['Loan_Status'].value_counts()
g
```

Out[42]:
```
Education     Loan_Status
Graduate      Y              340
              N              140
Not Graduate  Y               82
              N               52
Name: Loan_Status, dtype: int64
```

In [43]:
```
g.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Education', c = 'b', fontsize = 12)
plt.ylabel('Loan Status', c = 'b', fontsize = 12 )
plt.title('Education vs Loan Status', c = 'b', fontsize = 12)
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```



Above plot shows Repayment of Loan in Graduate person is higest 340 👍 and in Not Graduate person is 82 which low as compare to Graduate person 👎

Self Employed column

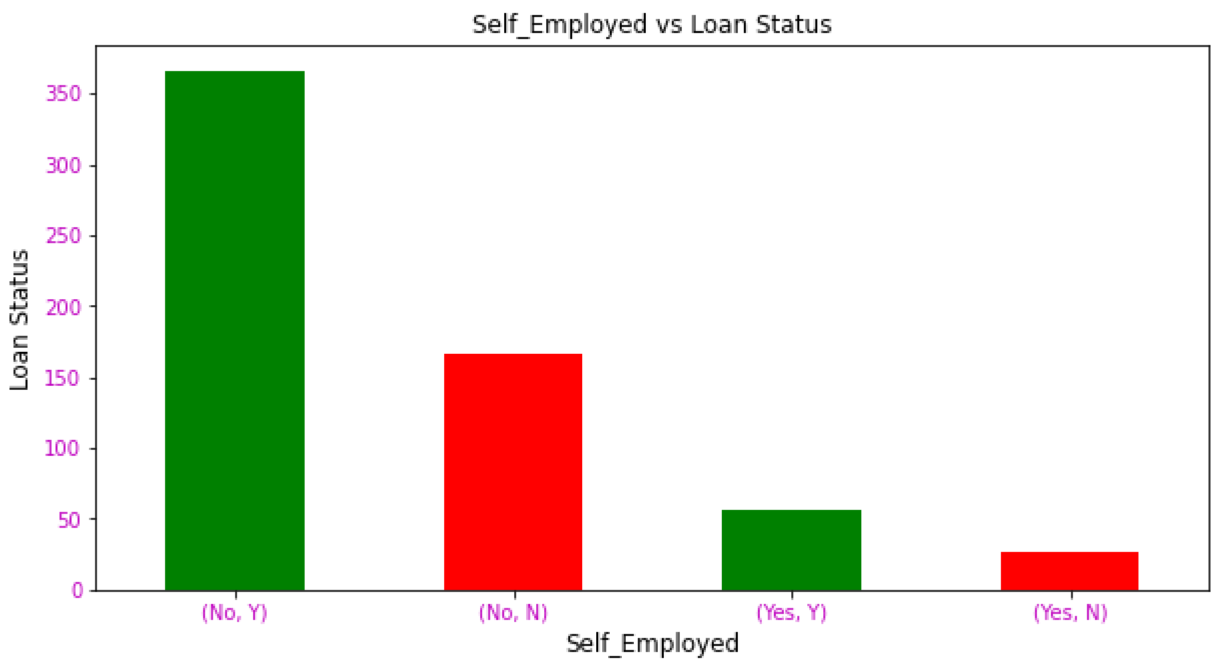
In [44]:
```
df['Self_Employed'].value_counts()
```

Out[44]:
```
No     532
Yes     82
Name: Self_Employed, dtype: int64
```

In [45]:
```
s = df.groupby('Self_Employed')['Loan_Status'].value_counts()
s
```

Out[45]:
```
Self_Employed  Loan_Status
No             Y              366
               N              166
Yes            Y               56
               N               26
Name: Loan_Status, dtype: int64
```

In [46]:
```
s.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Self_Employed', c = 'k', fontsize = 12)
plt.ylabel('Loan Status', c = 'k', fontsize = 12 )
plt.title('Self_Employed vs Loan Status', c = 'k', fontsize = 12)
plt.xticks(c = 'm')
plt.yticks(c = 'm')
plt.show()
```



Above plot shows Repayment of Loan in Self Employed person is 56 which low 👎 😔

Applicant Income column

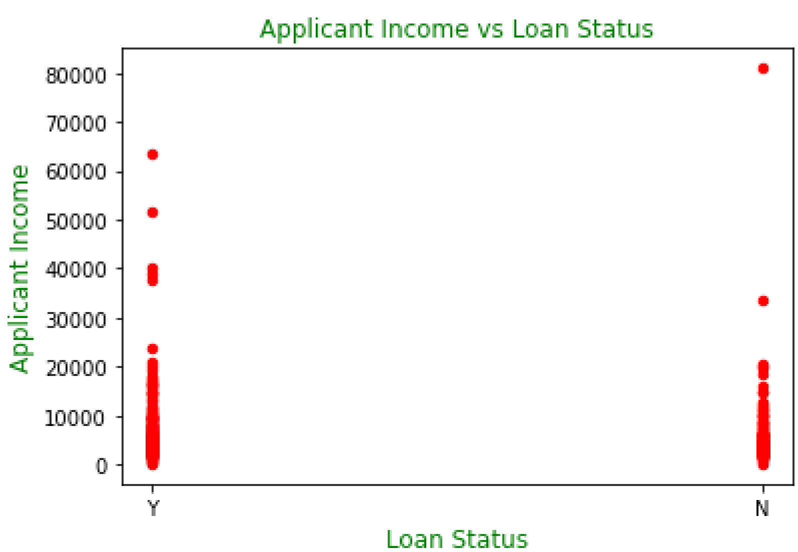
In [47]:
```
df['ApplicantIncome'].value_counts()
```

Out[47]:
```
2500    9
6000    6
2600    6
4583    6
4166    5
       ..
5503    1
3450    1
2425    1
2423    1
4095    1
Name: ApplicantIncome, Length: 505, dtype: int64
```

In [48]:
```
a = df.groupby('ApplicantIncome')['Loan_Status'].value_counts()
a
```

Out[48]:
```
ApplicantIncome  Loan_Status
150              N              1
210              Y              1
416              N              1
645              Y              1
674              Y              1
                               ..
39147            Y              1
39999            Y              1
51763            Y              1
63337            Y              1
81000            N              1
Name: Loan_Status, Length: 536, dtype: int64
```

In [49]:
```
df.plot.scatter(x = 'Loan_Status', y = 'ApplicantIncome', c = 'r')
plt.xlabel('Loan Status', c = 'g', fontsize = 12)
plt.ylabel('Applicant Income', c = 'g', fontsize = 12 )
plt.title('Applicant Income vs Loan Status', c = 'g', fontsize = 12)
plt.show()
```



Above plot shows Applicant Income whoes earning in between (210 to 65000) higest 👍

Loan Amount column

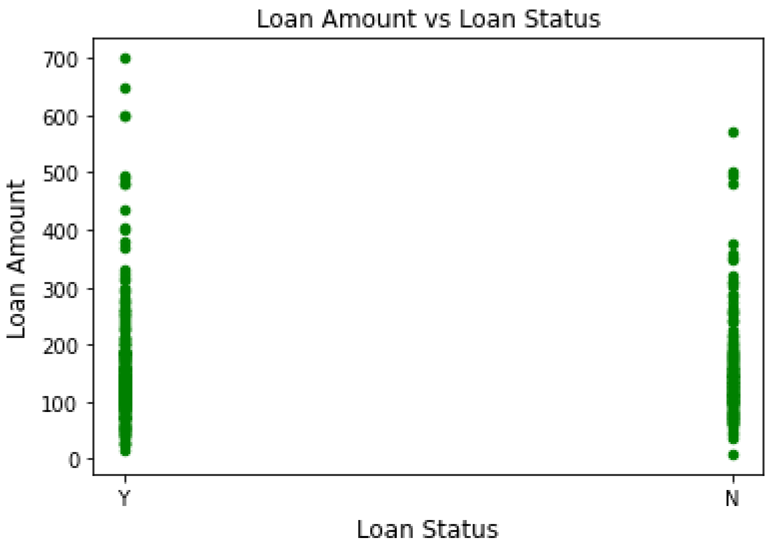
In [50]:
```
df['LoanAmount'].value_counts()
```

Out[50]:
```
146.412162    22
120.000000    20
110.000000    17
100.000000    15
160.000000    12
              ..
211.000000     1
250.000000     1
62.000000      1
85.000000      1
436.000000     1
Name: LoanAmount, Length: 204, dtype: int64
```

In [51]:
```
am = df.groupby('LoanAmount')['Loan_Status'].value_counts()
am
```

Out[51]:
```
LoanAmount  Loan_Status
9.0         N              1
17.0        Y              1
25.0        Y              2
26.0        Y              1
30.0        Y              2
                          ..
500.0       N              1
570.0       N              1
600.0       Y              2
650.0       Y              1
700.0       Y              1
Name: Loan_Status, Length: 282, dtype: int64
```

In [52]:
```
df.plot.scatter(x = 'Loan_Status', y = 'LoanAmount', c = 'g')
plt.xlabel('Loan Status', c = 'k', fontsize = 12)
plt.ylabel('Loan Amount', c = 'k', fontsize = 12 )
plt.title('Loan Amount vs Loan Status', c = 'k', fontsize = 12)
plt.show()
```



Above plot shows Loan amount in between (17 to 700) higest 👍

Property Area column

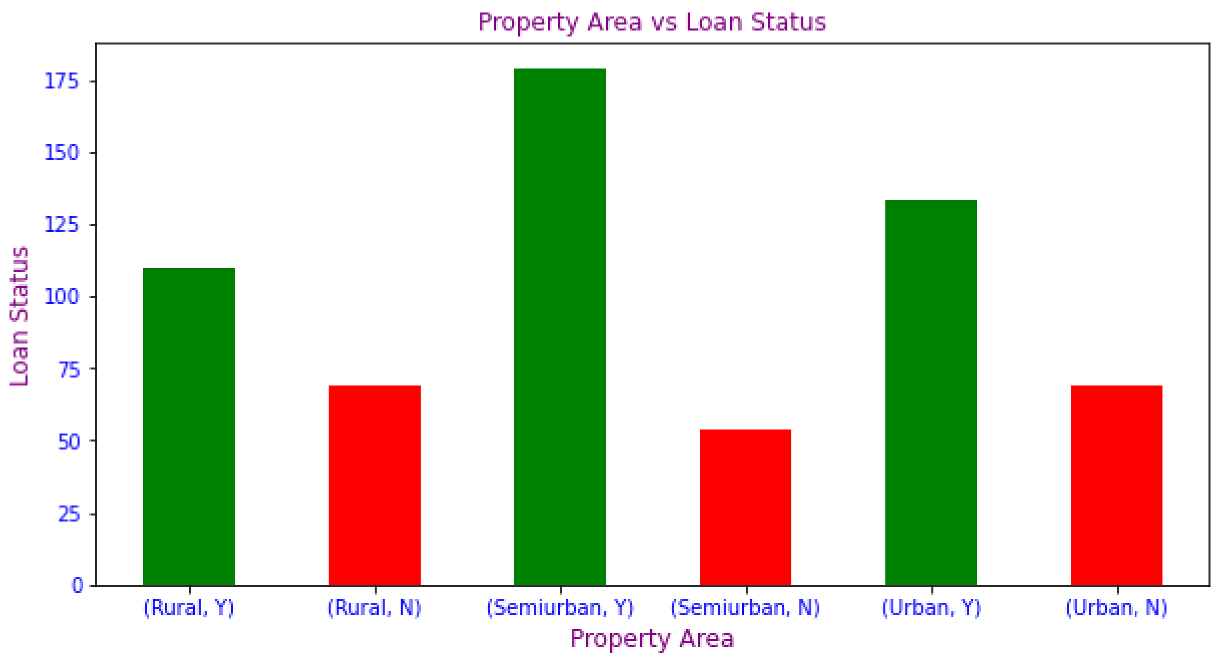
In [53]:
```
df['Property_Area'].value_counts()
```

Out[53]:
```
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```

In [54]:
```
pa = df.groupby('Property_Area')['Loan_Status'].value_counts()
pa
```

Out[54]:
```
Property_Area  Loan_Status
Rural          Y              110
               N               69
Semiurban      Y              179
               N               54
Urban          Y              133
               N               69
Name: Loan_Status, dtype: int64
```

In [55]:
```
pa.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Property Area', c = 'purple', fontsize = 12)
plt.ylabel('Loan Status', c = 'purple', fontsize = 12 )
plt.title('Property Area vs Loan Status', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



Above plot shows Repayment of Loan in Semi urban is higest 179 👍 and lowest is 54 👎

Hypothesis : Applicant whoes gender is Male, Graduated, Married, Annual Income in between (210 to 65000) and lived in Semi Urban area higest chance of Loan Repayment

Encoding columns

In [56]:
```
le = LabelEncoder()
```

In [57]:
```python
df['Gender'] = le.fit_transform(df['Gender'])
df['Married'] = le.fit_transform(df['Married'])
df['Education'] = le.fit_transform(df['Education'])
df['Self_Employed'] = le.fit_transform(df['Self_Employed'])
df['Property_Area'] = le.fit_transform(df['Property_Area'])
df['Loan_Status'] = le.fit_transform(df['Loan_Status'])
```

In [58]:
```python
df['Dependents'] = pd.to_numeric(df['Dependents'])
```

In [59]:
```python
print('==================================================\n')
print(df.info())
print('====================================================')
```

```
==================================================

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             614 non-null    int32  
 1   Married            614 non-null    int32  
 2   Dependents         614 non-null    int64  
 3   Education          614 non-null    int32  
 4   Self_Employed      614 non-null    int32  
 5   ApplicantIncome    614 non-null    int64  
 6   CoapplicantIncome  614 non-null    float64
 7   LoanAmount         614 non-null    float64
 8   Loan_Amount_Term   614 non-null    float64
 9   Credit_History     614 non-null    float64
 10  Property_Area      614 non-null    int32  
 11  Loan_Status        614 non-null    int32  
dtypes: float64(4), int32(6), int64(2)
memory usage: 43.3 KB
None
====================================================
```

In [60]:
```python
df.head(2)
```

Out[60]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	1	0	0	0	0	5849	0.0
1	1	1	1	0	0	4583	1508.0

All columns are encoded

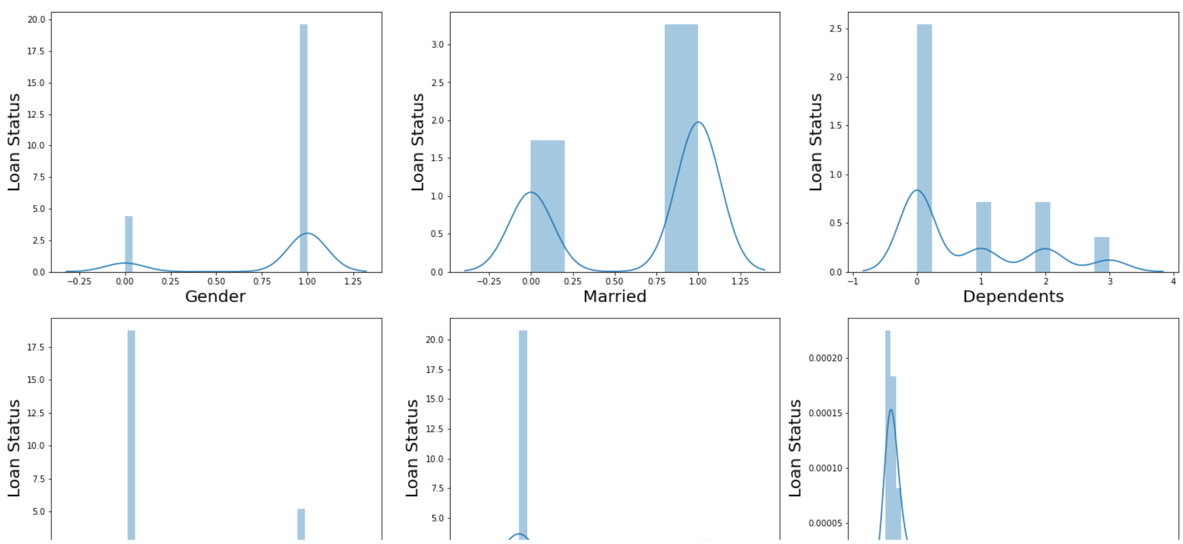
Data distribution and checking outliers and skewness

In [61]:
```python
print('---------------------')
print('Distribution Plot :- ')
print('---------------------')

plt.figure(figsize = (20,25))
plotnumber = 1

for column in df:
    if plotnumber <=15:
        ax = plt.subplot(5,3, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 20)
        plt.ylabel('Loan Status', fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```



In [62]:
```python
df.skew()
```

Out[62]:
```
Gender              -1.648795
Married             -0.644850
Dependents           1.015551
Education            1.367622
Self_Employed        2.159796
ApplicantIncome      6.539513
CoapplicantIncome    7.491531
LoanAmount           2.726601
Loan_Amount_Term    -2.402112
Credit_History      -2.021971
Property_Area       -0.066196
Loan_Status         -0.809998
dtype: float64
```

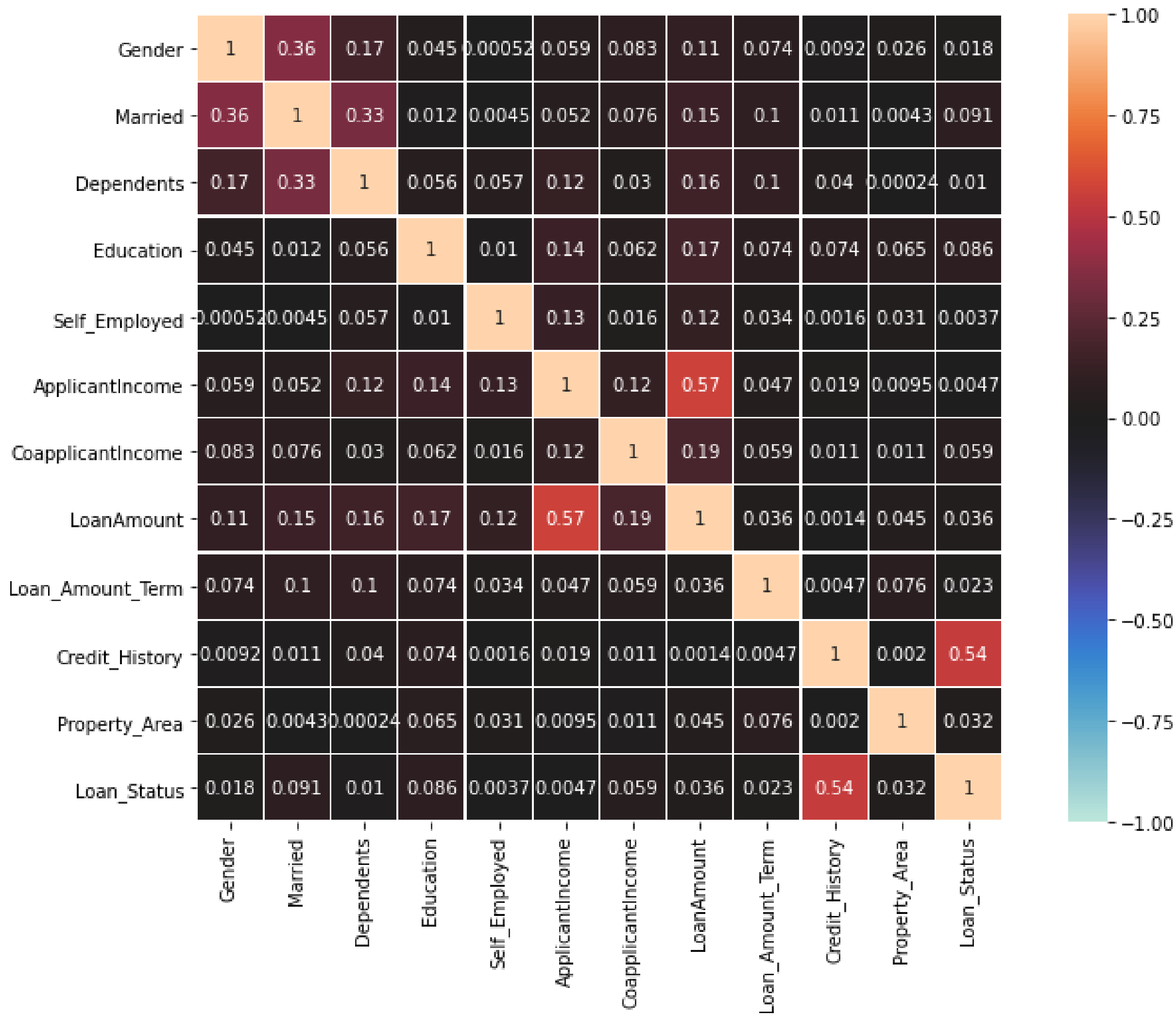
Data has outliers and skewness

Corelation of Feature vs Label using Heat map

In [63]:
```
print('-----------')
print('Heat Map :-')
print('-----------')
df_corr = df.corr().abs()

plt.figure(figsize = (11,8))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '.
plt.tight_layout()
```

```
-----------
Heat Map :-
-----------
```



	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
Gender	1	0.36	0.17	0.045	0.00052	0.059	0.083	0.11	0.074	0.0092	0.026	0.018
Married	0.36	1	0.33	0.012	0.0045	0.052	0.076	0.15	0.1	0.011	0.0043	0.091
Dependents	0.17	0.33	1	0.056	0.057	0.12	0.03	0.16	0.1	0.04	0.00024	0.01
Education	0.045	0.012	0.056	1	0.01	0.14	0.062	0.17	0.074	0.074	0.065	0.086
Self_Employed	0.00052	0.0045	0.057	0.01	1	0.13	0.016	0.12	0.034	0.0016	0.031	0.0037
ApplicantIncome	0.059	0.052	0.12	0.14	0.13	1	0.12	0.57	0.047	0.019	0.0095	0.0047
CoapplicantIncome	0.083	0.076	0.03	0.062	0.016	0.12	1	0.19	0.059	0.011	0.011	0.059
LoanAmount	0.11	0.15	0.16	0.17	0.12	0.57	0.19	1	0.036	0.0014	0.045	0.036
Loan_Amount_Term	0.074	0.1	0.1	0.074	0.034	0.047	0.059	0.036	1	0.0047	0.076	0.023
Credit_History	0.0092	0.011	0.04	0.074	0.0016	0.019	0.011	0.0014	0.0047	1	0.002	0.54
Property_Area	0.026	0.0043	0.00024	0.065	0.031	0.0095	0.011	0.045	0.076	0.002	1	0.032
Loan_Status	0.018	0.091	0.01	0.086	0.0037	0.0047	0.059	0.036	0.023	0.54	0.032	1

Loan Amount has highest corelation

Removing Outliers

In [64]:
```
# we are removing the top 2% data from the Gender column
q = df['Gender'].quantile(0.99)
data_cleaned = df[df['Gender']<q]
# we are removing the top 2% data from the Dependents column
q = df['Dependents'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['Dependents']<q]
# we are removing the top 2% data from the free Self_Employed column
q = df['Self_Employed'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['Self_Employed']<q]
# we are removing the top 2% data from the ApplicantIncome column
q = df['ApplicantIncome'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['ApplicantIncome']<q]
# we are removing the top 2% data from the CoapplicantIncome column
q = df['CoapplicantIncome'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['CoapplicantIncome']<q]
# we are removing the top 2% data from the LoanAmount column
q = df['LoanAmount'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['LoanAmount']<q]
# we are removing the top 2% data from the Loan_Amount_Term column
q = df['Loan_Amount_Term'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['Loan_Amount_Term']<q]
# we are removing the top 2% data from the Credit_History column
q = df['Credit_History'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['Credit_History']<q]
```

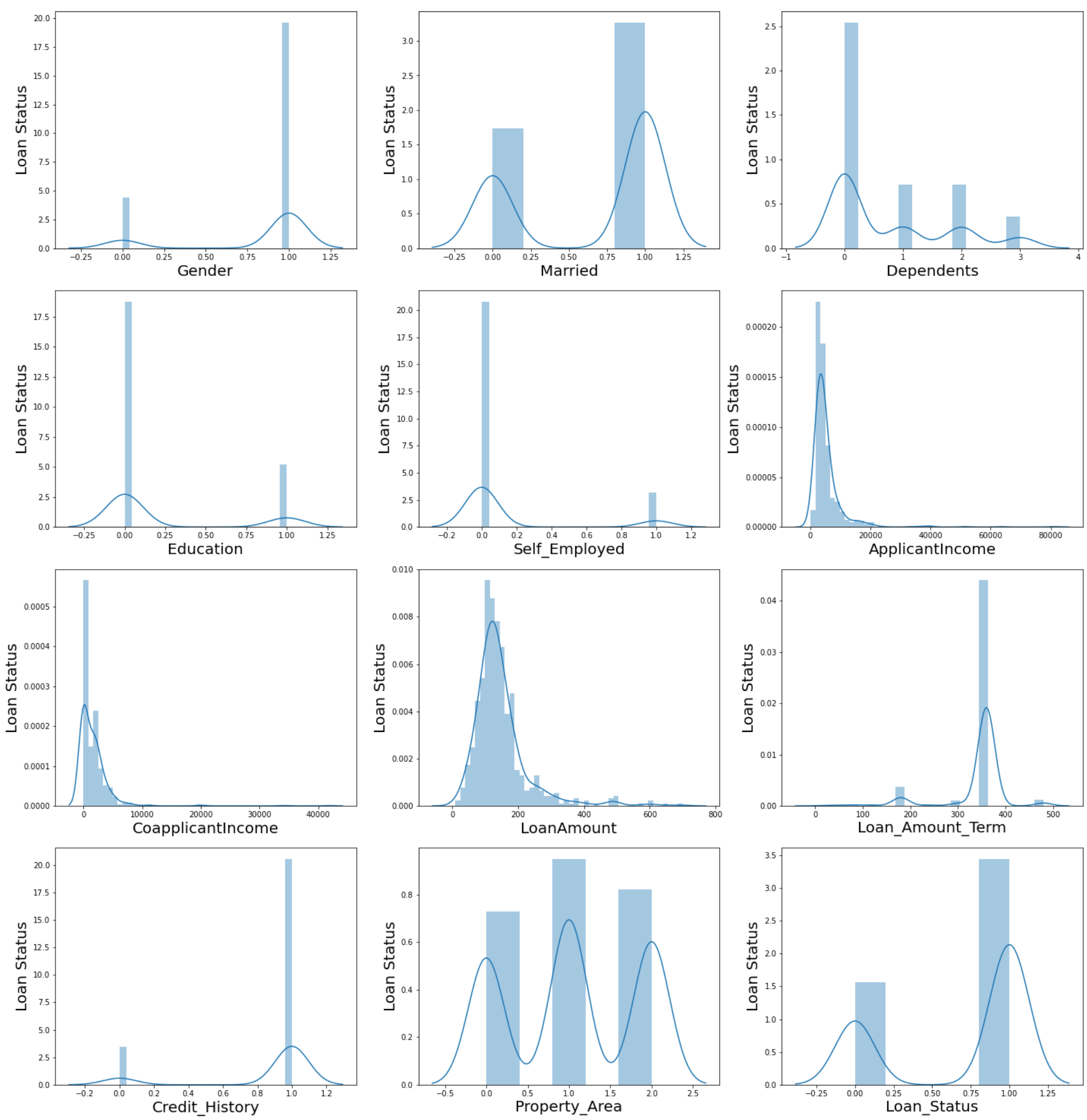
Checking Outliers and skewness removed or not

In [65]:
```python
# Let' see outliers are removed in columns or not.
print('---------------------')
print('Distribution Plot :- ')
print('---------------------')

plt.figure(figsize = (20,25))
plotnumber = 1

for column in df:
    if plotnumber <=15:
        ax = plt.subplot(5,3, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 20)
        plt.ylabel('Loan Status', fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```



Outliers are removed

Spliting Dataset into features and label

In [66]:
```
x = df.drop('Loan_Status', axis = 1)
y = df. Loan_Status
print('Data has been splited')
```

```
Data has been splited
```

In [67]:
```python
# Let' see relation between features and label.
print('-----------------')
print('Scatter Plot :-')
print('-----------------')

plt.figure(figsize = (20,25), facecolor = 'yellow')
plotnumber = 1
for column in x:
    if plotnumber <=15:
        ax = plt.subplot(5,3, plotnumber)
        plt.scatter(x[column],y, c = 'g')
        plt.xlabel(column, fontsize = 18)
        plt.ylabel('Loan_Status', fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
-----------------
Scatter Plot :-
-----------------
```

Checking for class imbalance

In [68]:
```
df['Loan_Status'].value_counts()
```

Out[68]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

Class are not balanced

Handling Class Imbalance

In [69]:
```
sm = SMOTE()
x_over, y_over = sm.fit_resample(x,y)
```

In [70]:
```
print('---------------------')
print('Class are balanced :-')
print('---------------------')
print(y_over.value_counts())
print('---------------------')
```

```
---------------------
Class are balanced :-
---------------------
0    422
1    422
Name: Loan_Status, dtype: int64
---------------------
```

Data Scaling

In [71]:
```
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[71]:
```
array([[1.        , 0.        , 0.        , ..., 0.74358974, 1.        ,
        1.        ],
       [1.        , 1.        , 0.33333333, ..., 0.74358974, 1.        ,
        0.        ],
       [1.        , 1.        , 0.        , ..., 0.74358974, 1.        ,
        1.        ],
       ...,
       [1.        , 1.        , 0.33333333, ..., 0.74358974, 1.        ,
        1.        ],
       [1.        , 1.        , 0.66666667, ..., 0.74358974, 1.        ,
        1.        ],
       [0.        , 0.        , 0.        , ..., 0.74358974, 0.        ,
        0.5       ]])
```

Data has been scaled

Split data into train and test. Model will be bulit on training data and tested on test data

In [72]:
```
x_train, x_test, y_train, y_test = train_test_split(x_over, y_over, test_size = 0
print('Data has been splited.')
```

```
Data has been splited.
```

Model Bulding

Decision Tree model instantiaing, training and evaluating

In [73]:
```
bag_dt = BaggingClassifier(DecisionTreeClassifier(), n_estimators = 15, max_sampl
                           random_state= 3, oob_score = True)
```

In [74]:
```
bag_dt.oob_score
```

Out[74]:
```
True
```

In [75]:
```
bag_dt.fit(x_train, y_train)
print('Bagging DT score ------->', bag_dt.score(x_test, y_test))
```

```
Bagging DT score -------> 0.8056872037914692
```

In [76]:
```
y_pred = bag_dt.predict(x_test)
```

In [77]:
```
print('------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------\n')
```

```
------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.75      0.80       109
           1       0.77      0.86      0.81       102

    accuracy                           0.81       211
   macro avg       0.81      0.81      0.81       211
weighted avg       0.81      0.81      0.81       211

-----------------------------------------------------------
```

Conclusion : Decision Tree model has 81% score

Cross Validation score to check if the model is overfitting

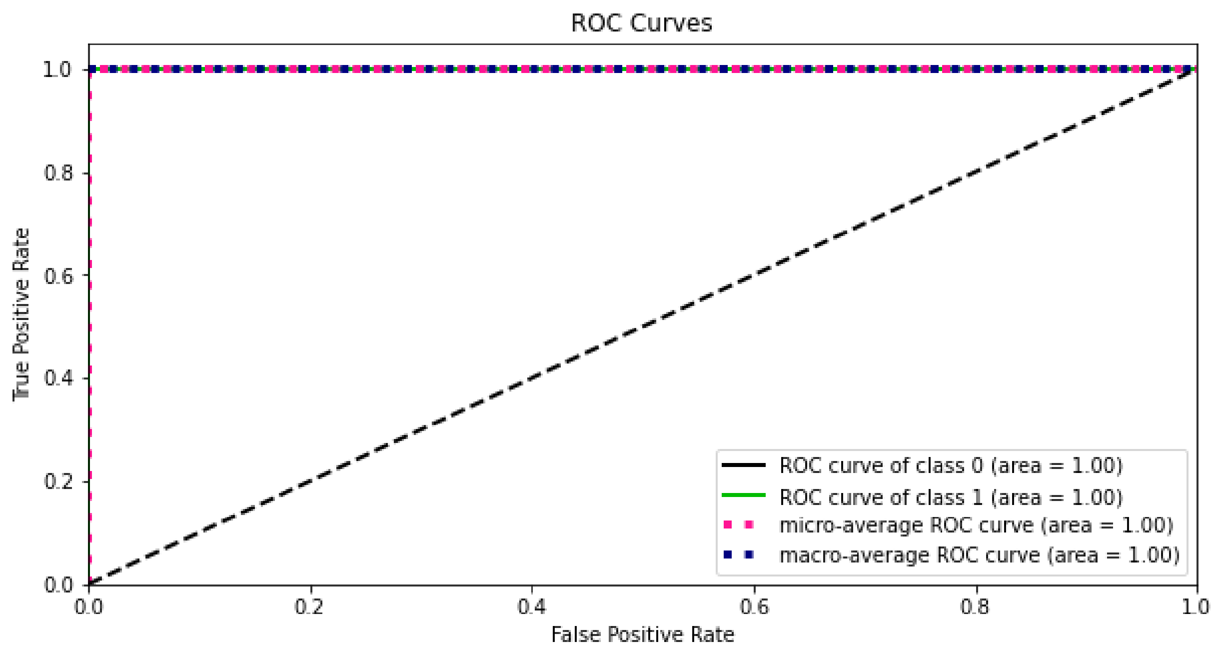
In [78]:
```
cv = cross_val_score(bag_dt, x, y, cv = 5)
print('Cross Validation score of Decision Tree model --->', cv.mean())
```

```
Cross Validation score of Decision Tree model ---> 0.7720111955217913
```

Conclusion : Decision Tree model has 77% Cross Validation score

ROC, AUC Curve

In [79]:
```
prob = bag_dt.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



XGBoost model instantiaing, training and evaluating

In [80]:
```
bag_xgb = BaggingClassifier(xgb.XGBClassifier(eval_metric = 'mlogloss'), n_estima
                                random_state= 3, oob_score = True)
```

In [81]:
```
bag_xgb.oob_score
```

Out[81]:
```
True
```

In [82]:
```
bag_xgb.fit(x_train, y_train)
print('Bagging XGBoost score ------->', bag_xgb.score(x_test, y_test))
```

```
Bagging XGBoost score -------> 0.8009478672985783
```

In [83]:
```
y_pred = bag_xgb.predict(x_test)
```

In [84]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.75      0.80       109
           1       0.76      0.85      0.81       102

    accuracy                           0.80       211
   macro avg       0.80      0.80      0.80       211
weighted avg       0.81      0.80      0.80       211

------------------------------------------------------------
```

Conclusion : XGBoost model has 80% score

Cross Validation score to check if the model is overfitting

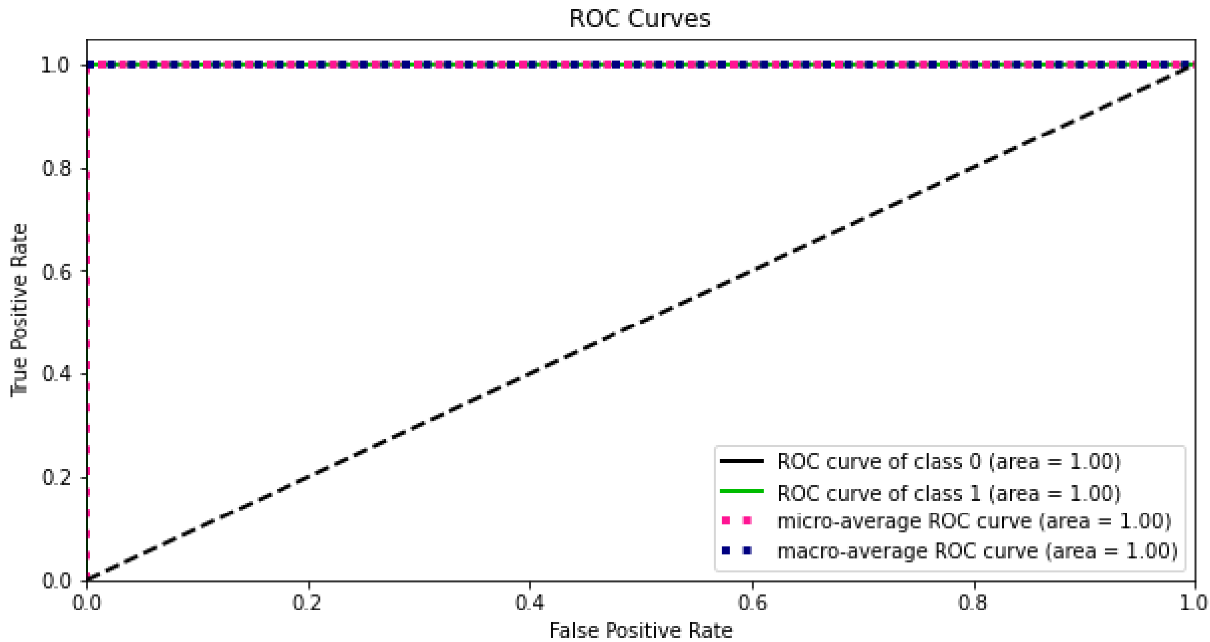
In [85]:
```
cv = cross_val_score(bag_xgb, x, y, cv = 5)
print('Cross Validation score of XGBoost model --->', cv.mean())
```

```
Cross Validation score of XGBoost model ---> 0.8013461282153805
```

Conclusion : XGBoost model has 80% Cross Validation score

ROC, AUC Curve

In [86]:
```
prob = bag_xgb.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Knn model instantiaing, training and evaluating

In [87]:
```
bag_Knn = BaggingClassifier(KNeighborsClassifier(n_neighbors = 5), n_estimators =
                            random_state= 3, oob_score = True)
```

In [88]:
```
bag_Knn.oob_score
```

Out[88]:
```
True
```

In [89]:
```
bag_Knn.fit(x_train, y_train)
print('Bagging KNN score ------->', bag_Knn.score(x_test, y_test))
```

```
Bagging KNN score -------> 0.5876777251184834
```

In [90]:
```
y_pred = bag_dt.predict(x_test)
```

In [91]:
```
print('----------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('---------------------------------------------------------------\n')
```

```
----------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.75      0.80       109
           1       0.77      0.86      0.81       102

    accuracy                           0.81       211
   macro avg       0.81      0.81      0.81       211
weighted avg       0.81      0.81      0.81       211

---------------------------------------------------------------
```

Conclusion : KNN model has 81% score

Cross Validation score to check if the model is overfitting

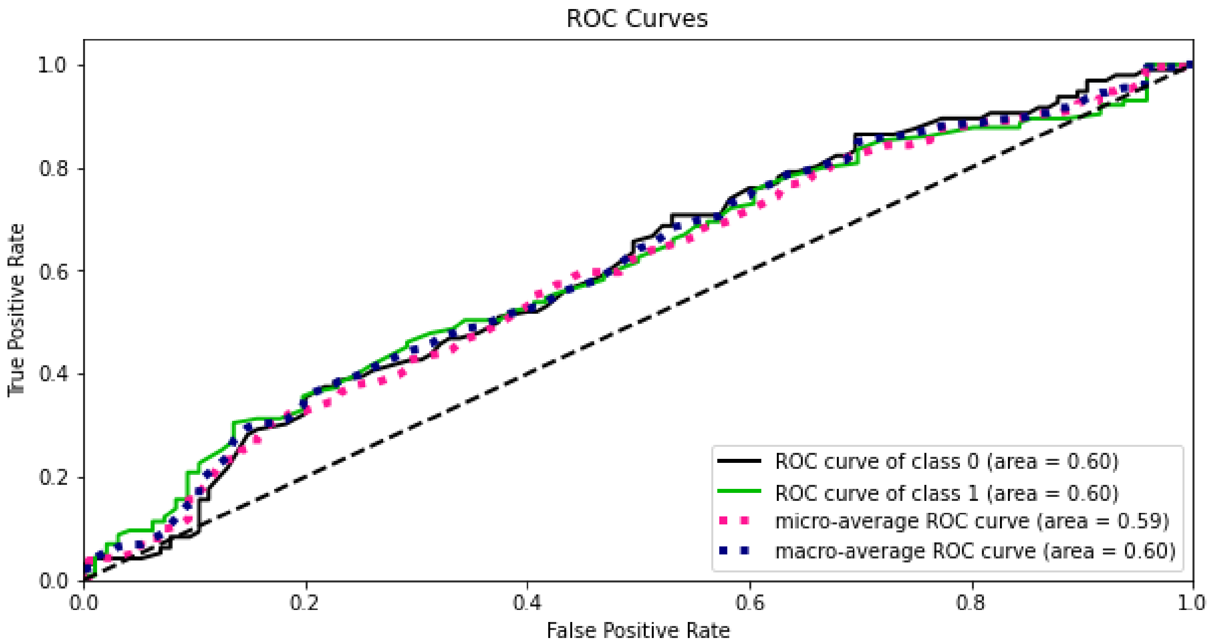
In [92]:
```
cv = cross_val_score(bag_Knn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.6742636278821805
```

Conclusion : Knn model has 67% Cross Validation score

ROC, AUC Curve

In [93]:
```
prob = bag_Knn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Random Forest model instantiaing, training and evaluating

In [94]:
```
bag_Rn = BaggingClassifier(RandomForestClassifier(), n_estimators = 15, max_sampl
                           random_state= 3, oob_score = True)
```

In [95]:
```
bag_Rn.oob_score
```

Out[95]:
```
True
```

In [96]:
```
bag_Rn.fit(x_train, y_train)
print('Bagging Random Forest score ------->', bag_Rn.score(x_test, y_test))
```

```
Bagging Random Forest score -------> 0.8009478672985783
```

In [97]:
```
y_pred = bag_Rn.predict(x_test)
```

In [98]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.73      0.79       109
           1       0.75      0.87      0.81       102

    accuracy                           0.80       211
   macro avg       0.81      0.80      0.80       211
weighted avg       0.81      0.80      0.80       211

------------------------------------------------------------
```

Conclusion : Random Forest model has 80% score

Cross Validation score to check if the model is overfitting

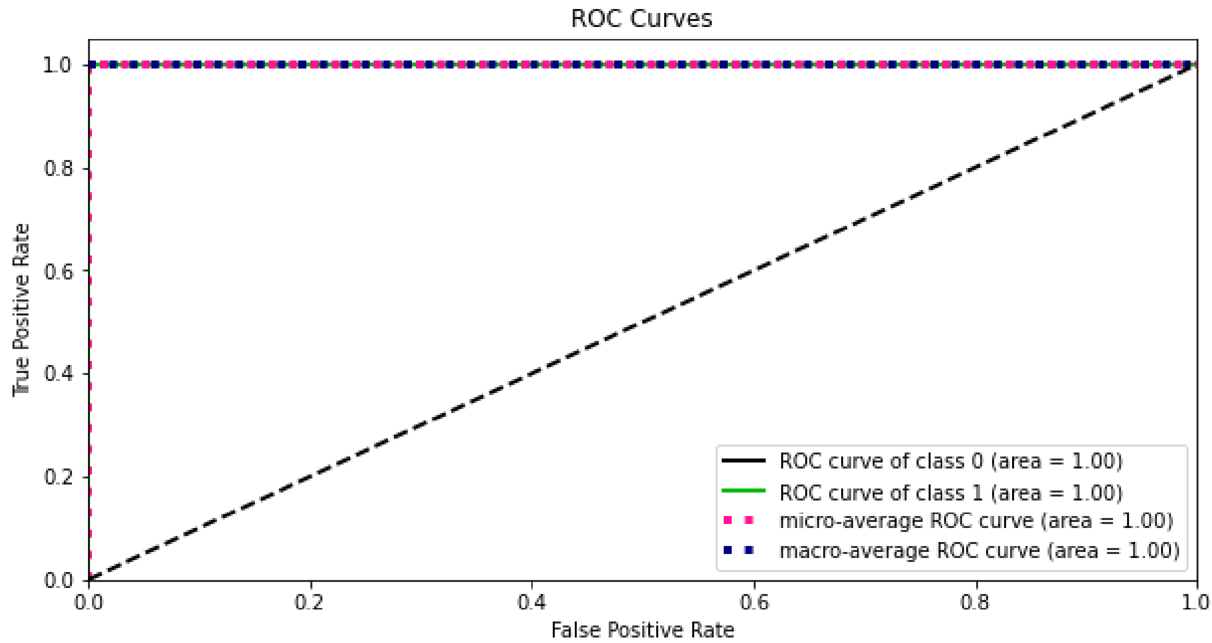
In [99]:
```
cv = cross_val_score(bag_Rn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.8078501932560309
```

Conclusion : Random Forest model has 80% Cross Validation score

ROC, AUC Curve

In [100]:
```
prob = bag_Rn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Logistic Regression model instantiaing, training and evaluating

In [101]:
```
bag_Lr = BaggingClassifier(LogisticRegression(), n_estimators = 15, max_samples =
                          random_state= 3, oob_score = True)
```

In [102]:
```
bag_Lr.oob_score
```

Out[102]: True

In [103]:
```
bag_Lr.fit(x_train, y_train)
print('Bagging Logostic Regression score ------->', bag_Lr.score(x_test, y_test))
```

```
Bagging Logostic Regression score -------> 0.7298578199052133
```

In [104]:
```
y_pred = bag_Lr.predict(x_test)
```

In [105]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.74      0.73      0.74       109
           1       0.72      0.73      0.72       102

    accuracy                           0.73       211
   macro avg       0.73      0.73      0.73       211
weighted avg       0.73      0.73      0.73       211

------------------------------------------------------------
```

Conclusion : Logistic Regression model has 73% score

Cross Validation score to check if the model is overfitting

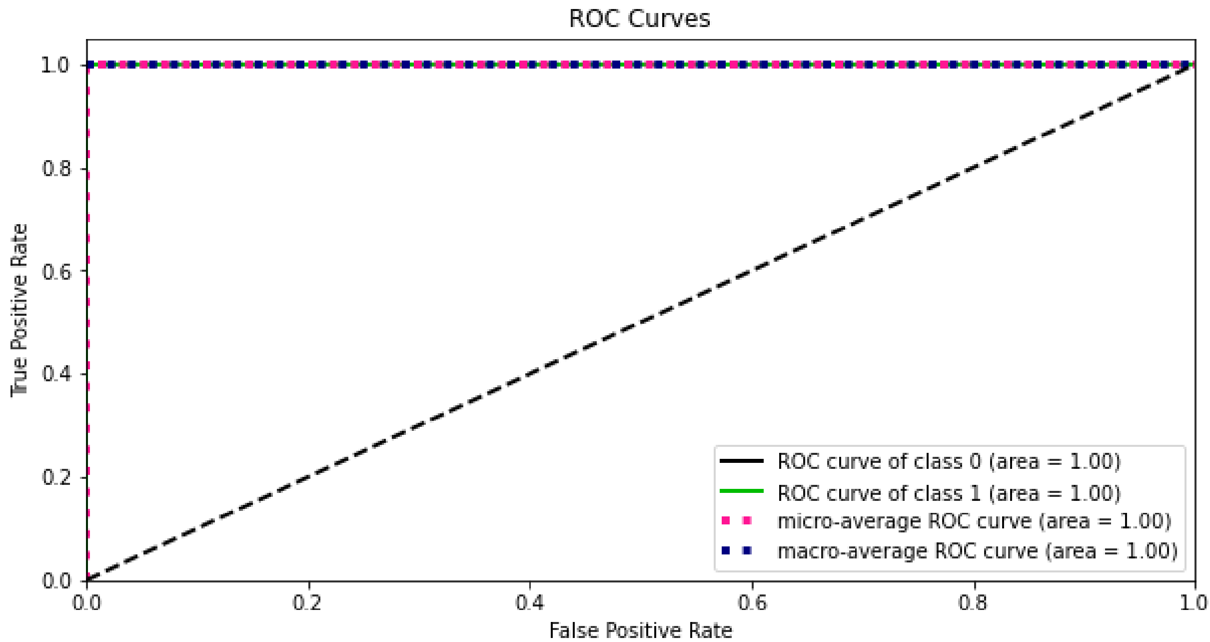
In [113]:
```
cv = cross_val_score(bag_Lr, x, y, cv = 5)
print('Cross Validation score of Logistic regression model --->', cv.mean())
```

```
Cross Validation score of Logistic regression model ---> 0.8062108489937359
```

Conclusion : Logistic Regression model has 80% Cross Validation score

ROC, AUC Curve

In [107]:
```
prob = bag_Lr.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Let's find ROC, AUC score

In [108]:
```
# DecisionTreeClassifier
roc_auc_score(y_test, bag_dt.predict(x_test))
```

Out[108]: 0.8075193380104335

In [109]:
```
# XGBoostClassifier
roc_auc_score(y_test, bag_xgb.predict(x_test))
```

Out[109]: 0.8026173772261198

```
In [110]: # KNeighborsClassifier
          roc_auc_score(y_test, bag_Knn.predict(x_test))
```

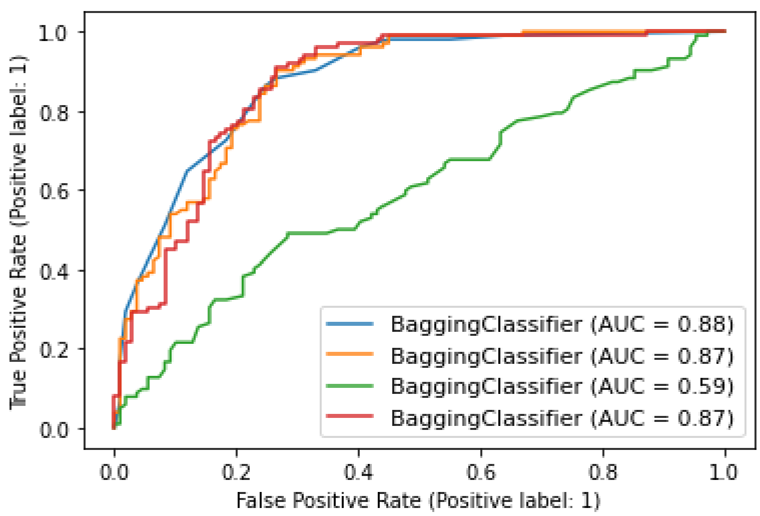
```
Out[110]: 0.5845475805000898
```

```
In [111]: # RandomForestClassifier
          roc_auc_score(y_test, bag_Rn.predict(x_test))
```

```
Out[111]: 0.8032469868681418
```

Let's check ROC, AUC Curve for the fitted model

```
In [112]: dis = plot_roc_curve(bag_dt, x_test, y_test)
          plot_roc_curve(bag_Rn, x_test, y_test, ax = dis.ax_) # ax_ = Axes with confusion
          plot_roc_curve(bag_Knn, x_test, y_test, ax = dis.ax_)
          plot_roc_curve(bag_xgb, x_test, y_test, ax = dis.ax_)
          plt.legend(prop = {'size':11}, loc = 'lower right')
          plt.show()
```



Looking CV score we found Random Forest has best model so we do Hyperparameter Tuning on it.

```
In [114]: param = {'n_estimators': [50,100,750], 'max_samples': [1.0], 'bootstrap': [True]]
```

```
In [115]: grid_search = GridSearchCV(estimator = bag_Rn, param_grid = param, cv = 5 , n_jot
```

In [116]:
```
grid_search.fit(x_train, y_train)
```

Out[116]:
```
GridSearchCV(cv=5,
             estimator=BaggingClassifier(base_estimator=RandomForestClassifier
(),
                                         max_samples=0.5, n_estimators=15,
                                         oob_score=True, random_state=3),
             n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_samples': [1.0],
                         'n_estimators': [50, 100, 750]})
```

In [117]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'bootstrap': True, 'max_samples': 1.0, 'n_estimators': 50}
```

In [118]:
```
hRn = BaggingClassifier(base_estimator=RandomForestClassifier(),max_samples = 1.0
hRn.fit(x_train, y_train)
hRn.score(x_test, y_test)
```

Out[118]:
```
0.8056872037914692
```

In [119]:
```
y_pred = hRn.predict(x_test)
```

In [120]:
```
print('--------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
--------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.75      0.80       109
           1       0.77      0.86      0.81       102

    accuracy                           0.81       211
   macro avg       0.81      0.81      0.81       211
weighted avg       0.81      0.81      0.81       211

------------------------------------------------------------
```

Saving The Model

In [129]:
```
# saving the model to the Local file system
filename = 'Loan Application Status Project.pickle'
pickle.dump(hRn, open(filename, 'wb'))
```

Predict Loan Repayment

In [130]:
```python
model = pickle.load(open('Loan Application Status Project.pickle', 'rb'))
```

In [131]:
```python
a = model.predict(x)
a
```

Out[131]:
```
array([1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1,
       0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1,
       1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1,
       1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1,
       1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0,
       0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0,
       1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0,
       1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1,
       1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1,
       0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
       1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0])
```

In [132]:
```
pred = pd.DataFrame(a)
pred
```

Out[132]:

	0
0	1
1	0
2	1
3	1
4	1
...	...
609	1
610	1
611	1
612	1
613	0

614 rows × 1 columns

In [ ]: