Loan Approval Status Prediction

Problem Statement:

Have you ever thought the apps which can predict whether you will get your loan approved or not work? Develope one such model which can predict whether a person will get his/her loan approved or not by using some of the background information of the applicant like the applicant's gender, marital status, income, etc.

Independent Variables:

Loan_ID

Gender

Married

Dependents

Education

Self_Employed

ApplicantIncome

CoapplicantIncome

Loan_Amount

Loan_Amount_Term

Credit History

Property_Area

Dependent Variable (Target Variable):

Loan_Status

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 libraries

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

#Loading dataset
df = pd.read_csv('loan.csv')

df
```

```
      Loan_ID  Gender Married Dependents     Education
Self_Employed  \
0    LP001002    Male      No          0      Graduate             No

1    LP001003    Male     Yes          1      Graduate             No

2    LP001005    Male     Yes          0      Graduate            Yes

3    LP001006    Male     Yes          0  Not Graduate             No

4    LP001008    Male      No          0      Graduate             No

..        ...     ...     ...        ...           ...            ...

609  LP002978  Female      No          0      Graduate             No

610  LP002979    Male     Yes         3+      Graduate             No

611  LP002983    Male     Yes          1      Graduate             No

612  LP002984    Male     Yes          2      Graduate             No

613  LP002990  Female      No          0      Graduate            Yes


     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

..               ...                ...         ...               ...

609             2900                0.0        71.0             360.0
```

```
610              4106                    0.0        40.0              180.0

611              8072                  240.0       253.0              360.0

612              7583                    0.0       187.0              360.0

613              4583                    0.0       133.0              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
..              ...           ...         ...
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

[614 rows x 13 columns]
```

```
#Let's check the shape of dataset
df.shape
```

```
(614, 13)
```

There are 614 rows and 13 columns including our target variable present in our dataset

```
#Let's see first 5 values of data.
df.head()
```

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

#Let's see last 5 values of data.
df.tail()

      Loan_ID  Gender Married Dependents Education Self_Employed  \
609  LP002978  Female      No          0  Graduate            No
610  LP002979    Male     Yes         3+  Graduate            No
611  LP002983    Male     Yes          1  Graduate            No
612  LP002984    Male     Yes          2  Graduate            No
613  LP002990  Female      No          0  Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term
\
609             2900                0.0        71.0             360.0

610             4106                0.0        40.0             180.0

611             8072              240.0       253.0             360.0

612             7583                0.0       187.0             360.0

613             4583                0.0       133.0             360.0


     Credit_History Property_Area Loan_Status
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

#Let's check the info & datatype of dataset
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
```

There are 8 object, 4 flot and 1 integer attributes in our dataset

```
# checking statistical summary
df.describe()
```

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

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

We can clearly see Applicantincome, Coapplicantincome, LoanAmount are Right skewed because Mean values is greater than the Median Values.

Loan Amount & Loan_amount term are left skewed because Median is greater than Mean values.

There is a compartively high difference between 3rd quantile (75%) and max values which also proves that outiliers are present in dataset

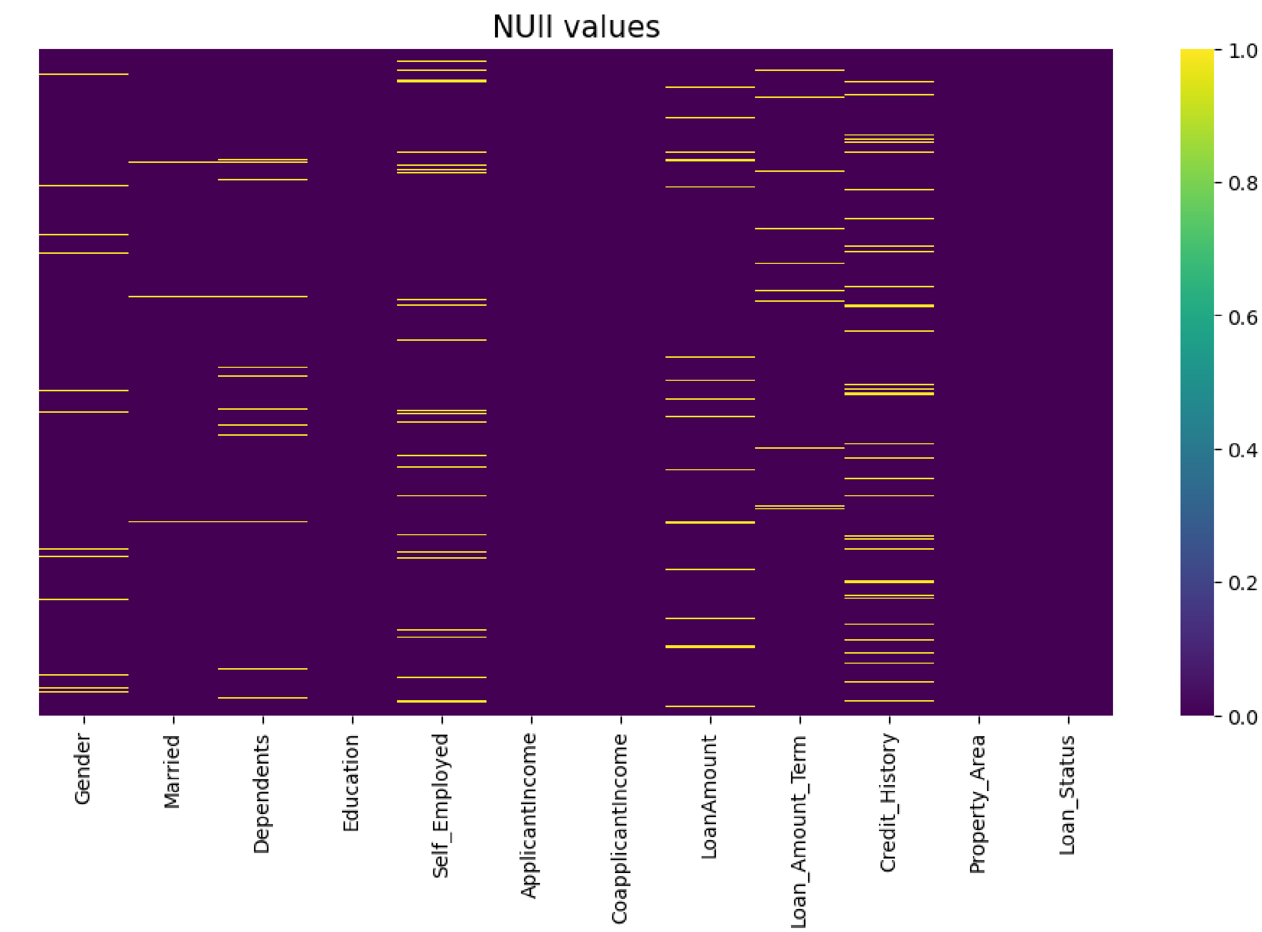
```python
#Checking Null values
df.isnull().sum()
```

```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

So, We can clearly see that there are few attributes where Null values are present

```python
# Dropping unnecessary columns. Loan Id has no significance to predict our Loan Status.
df.drop(['Loan_ID'],axis=1,inplace=True)

#Let's see null values by heatmap
plt.figure(figsize=(12,6))
plt.title('NUll values',fontsize=15)
sns.heatmap(df.isnull(),yticklabels=False,cmap='viridis')
```

```
<AxesSubplot:title={'center':'NUll values'}>
```



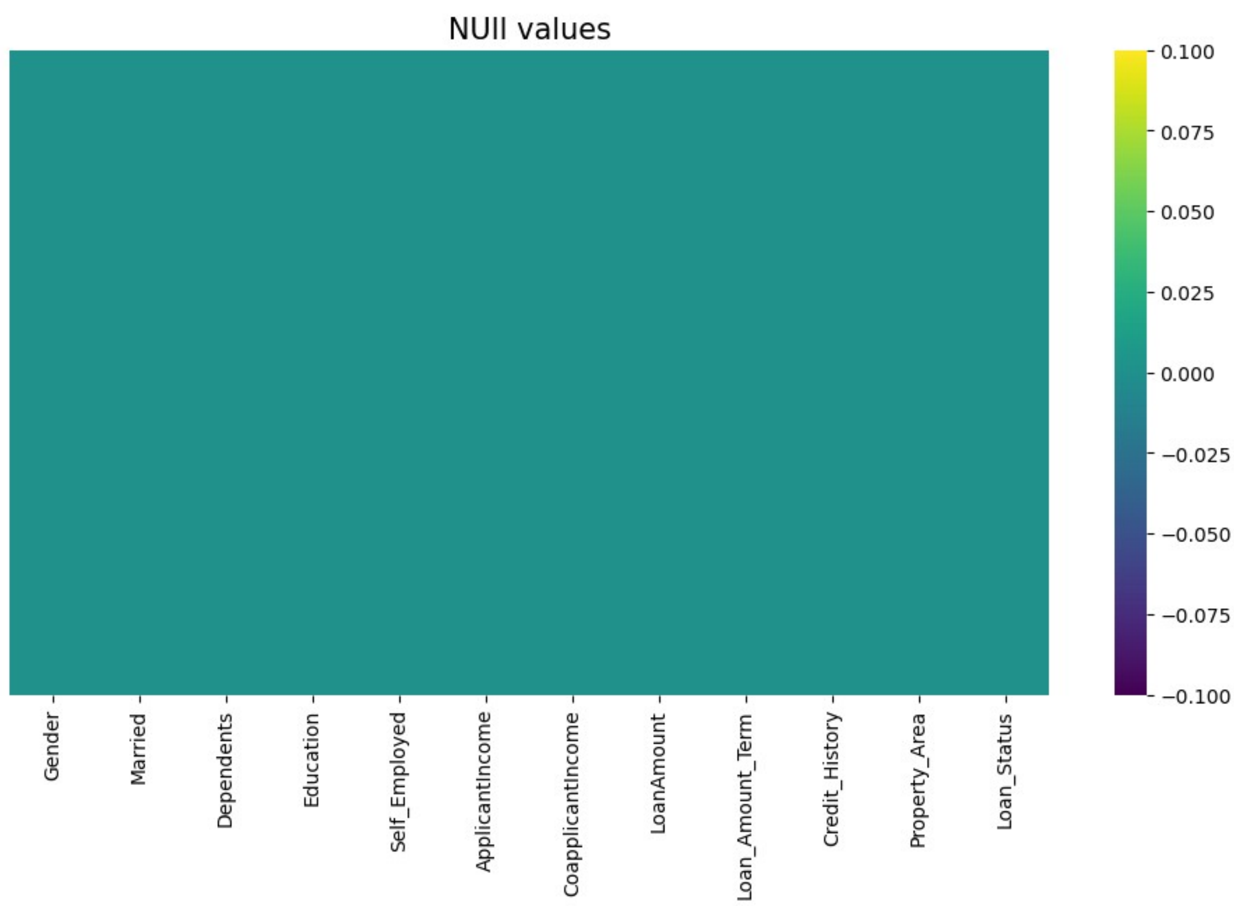
This dataset has few Null Values which we will deal later.

```
# filling the missing values for numerical terms by - median
df['LoanAmount']=df['LoanAmount'].fillna(df['LoanAmount'].median())
df['Loan_Amount_Term']=df['Loan_Amount_Term'].fillna(df['Loan_Amount_T
erm'].median())
df['Credit_History']=df['Credit_History'].fillna(df['Credit_History'].
median())

# Filling the missing values for categorical terms by - mode
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'].mod
e()[0])

#Let's check Null values now
df.isnull().sum()

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
```

So, Now there is no Null values in our dataset

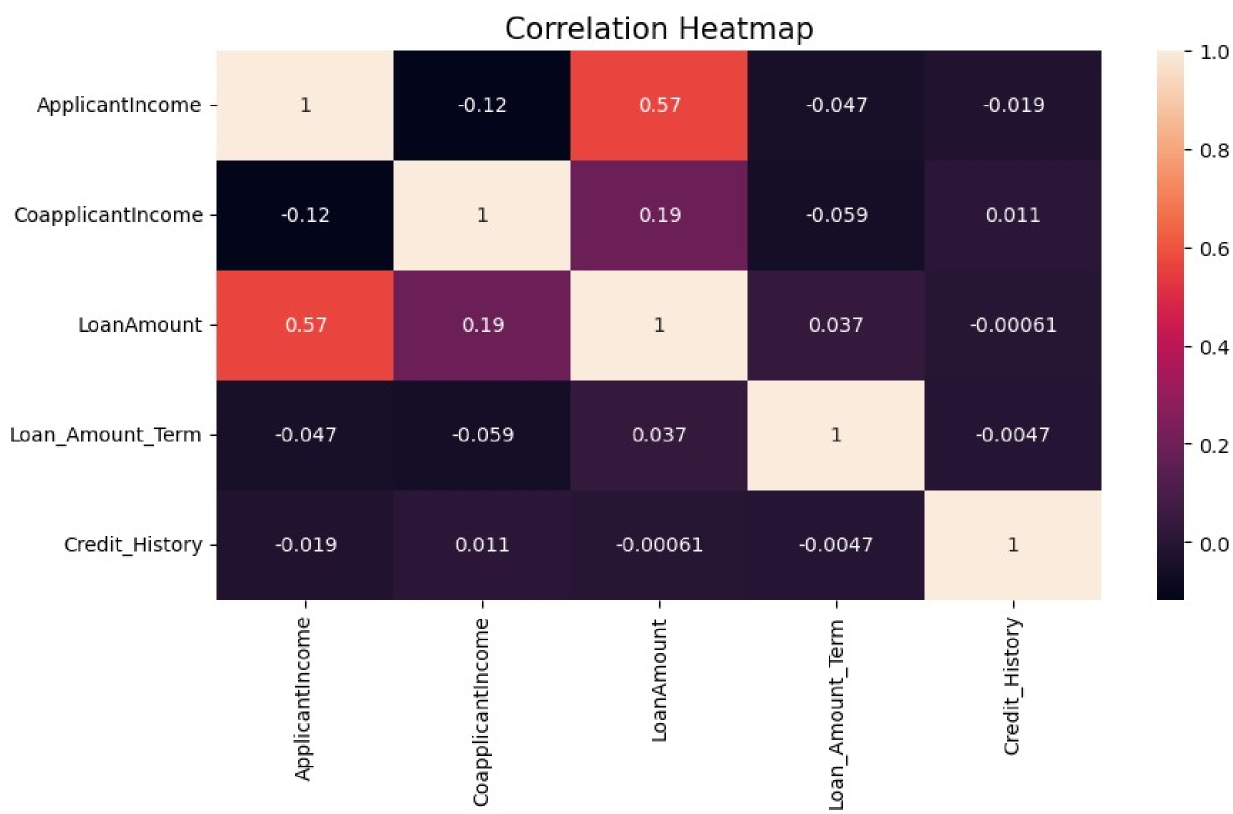
```
#Let's see null values by heatmap
plt.figure(figsize=(12,6))
plt.title('NUll values',fontsize=15)
sns.heatmap(df.isnull(),yticklabels=False,cmap='viridis')

<AxesSubplot:title={'center':'NUll values'}>
```



There is no Null values now in dataset

Segregation of Object and Numeric DataType for Analysis

```
## for Numeric Attributes
num_df=df.select_dtypes(exclude='object')

## for categorical Attributes
obj_df=df.select_dtypes(include='object')

## correlation Plot
plt.figure(figsize=(10,5))
plt.title('Correlation Heatmap',fontsize=15)
sns.heatmap(df.corr(),annot=True)

<AxesSubplot:title={'center':'Correlation Heatmap'}>
```



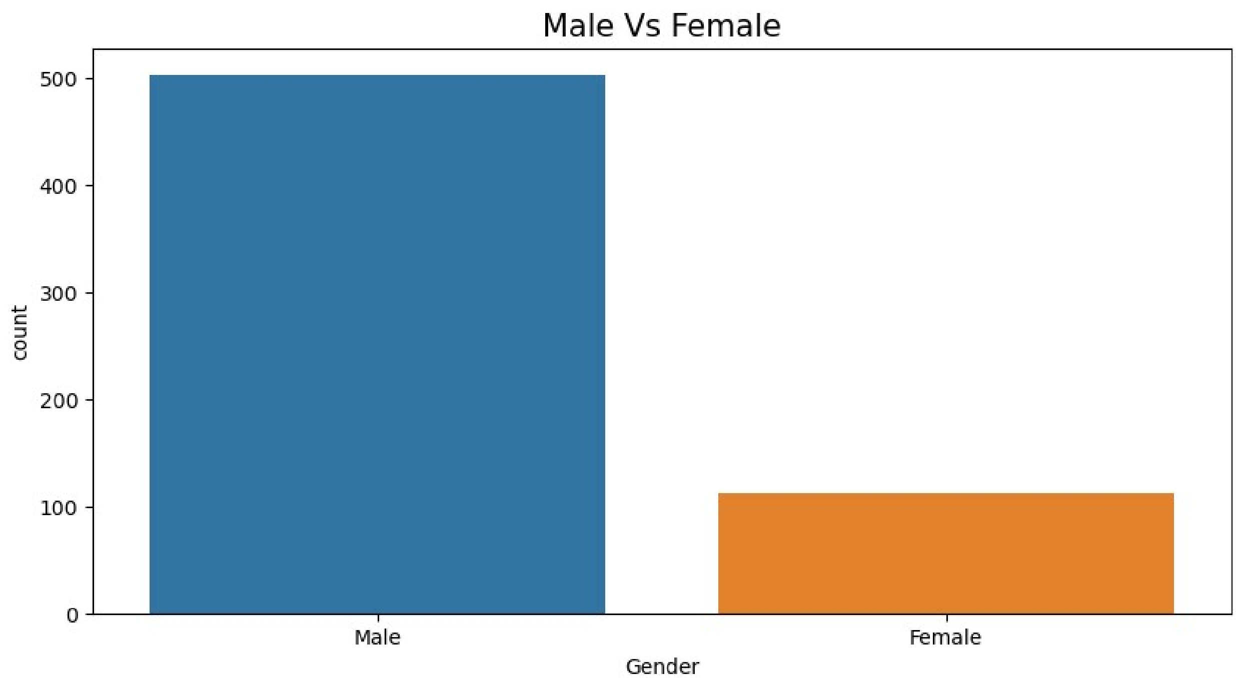
Our Loan amount is highly correlated with Applicant Income which is .57.

Neither the strong positive nor the strong negative correlation present in any variable.

Data Visualization

```
plt.figure(figsize=(10,5))
plt.title('Male Vs Female',fontsize=15)
sns.countplot(df['Gender'],data=df)
```

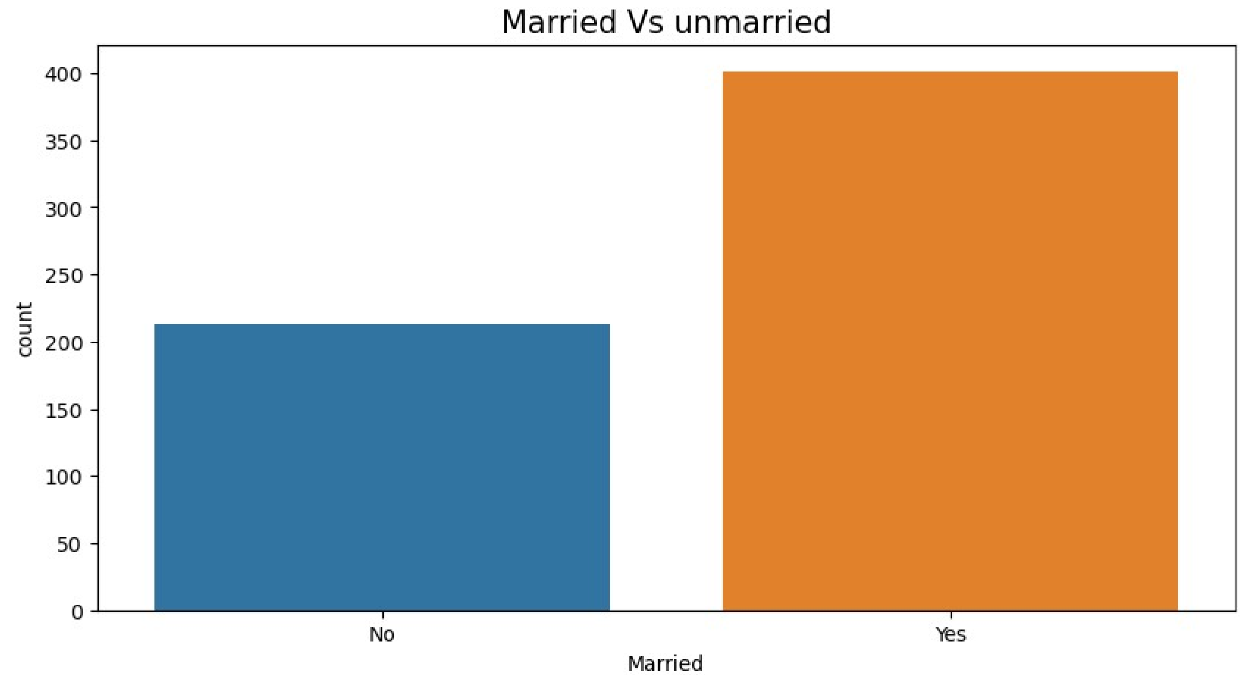
```
<AxesSubplot:title={'center':'Male Vs Female'}, xlabel='Gender',
ylabel='count'>
```



Almost 500 Male and 100 Female applied for the loan.

```
plt.figure(figsize=(10,5))
plt.title('Married Vs unmarried',fontsize=15)
sns.countplot(df['Married'])
```

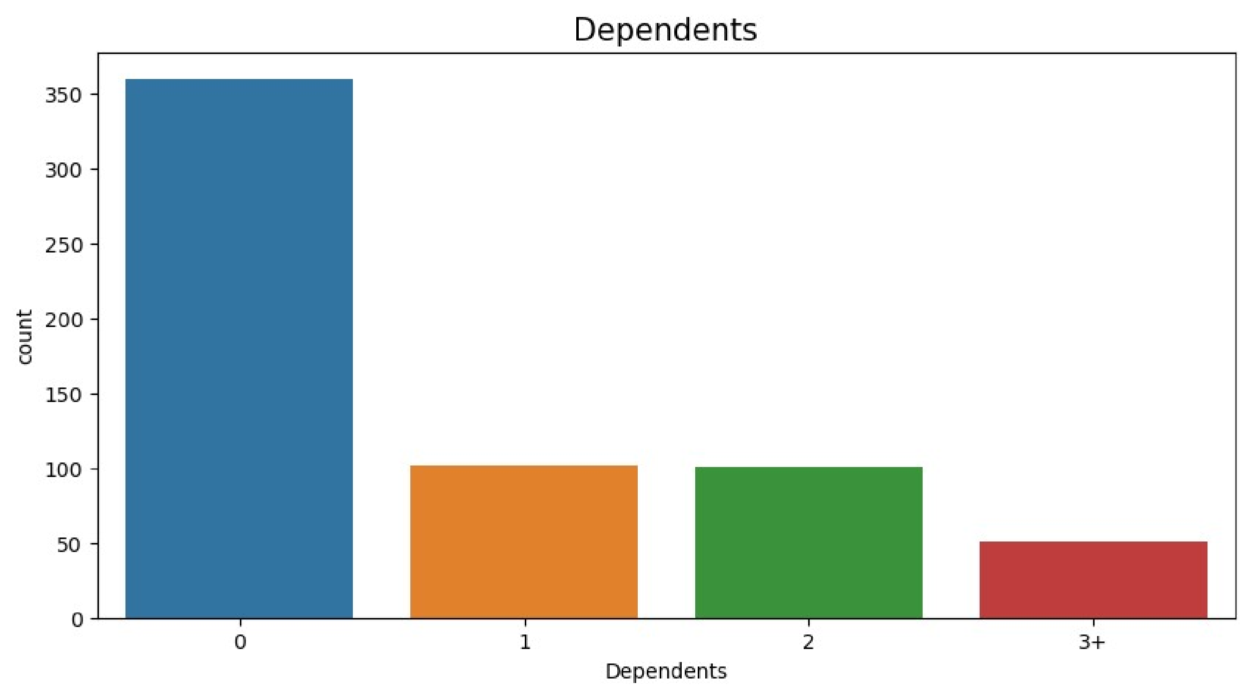
```
<AxesSubplot:title={'center':'Married Vs unmarried'},
xlabel='Married', ylabel='count'>
```



Almost 400 married & more than 200 unmarried people applied for loan

```
plt.figure(figsize=(10,5))
plt.title('Dependents',fontsize=15)
sns.countplot(df['Dependents'])
```

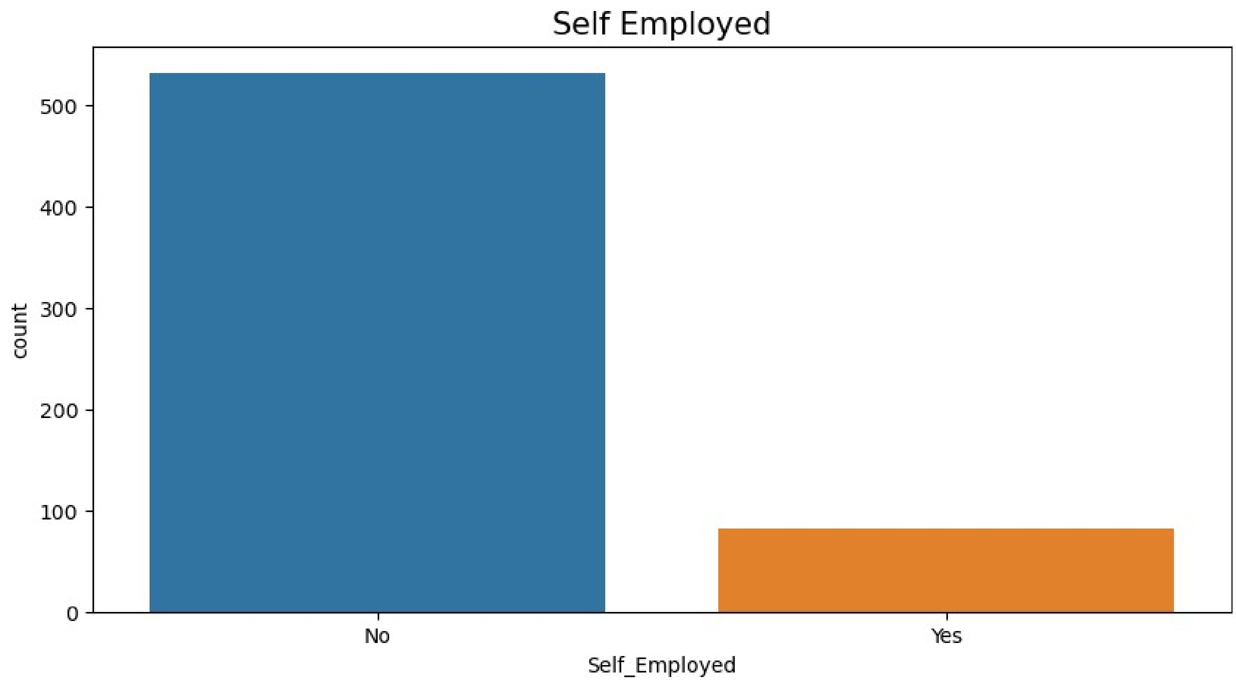
```
<AxesSubplot:title={'center':'Dependents'}, xlabel='Dependents',
ylabel='count'>
```



More than 350 people doesn't have any dependents and around 100 people have either 1 or 2 dependents in family. Less than 50 people are there who has more than 3 dependents in family.

```
plt.figure(figsize=(10,5))
plt.title('Self Employed',fontsize=15)
sns.countplot(df['Self_Employed'])
```

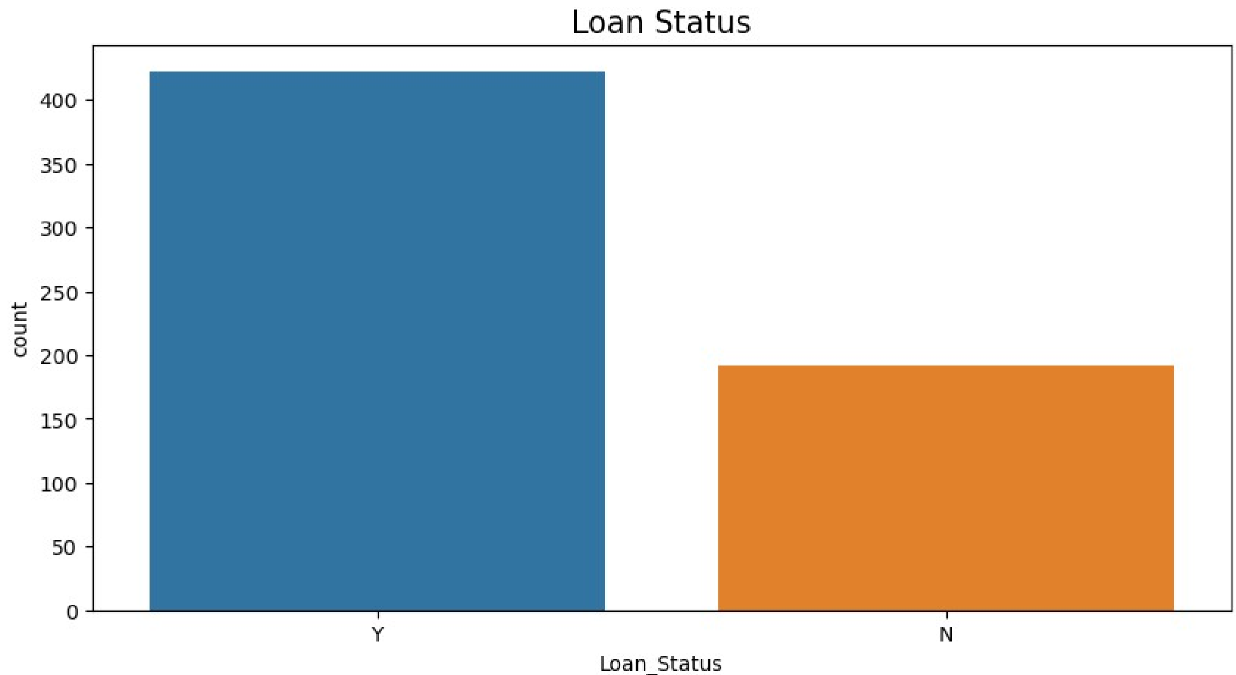
```
<AxesSubplot:title={'center':'Self Employed'}, xlabel='Self_Employed', ylabel='count'>
```



more than 500 people applied for loan aren't self employed and more than 50 people are self employed.

```
plt.figure(figsize=(10,5))
plt.title('Loan Status',fontsize=15)
sns.countplot(df['Loan_Status'])
```

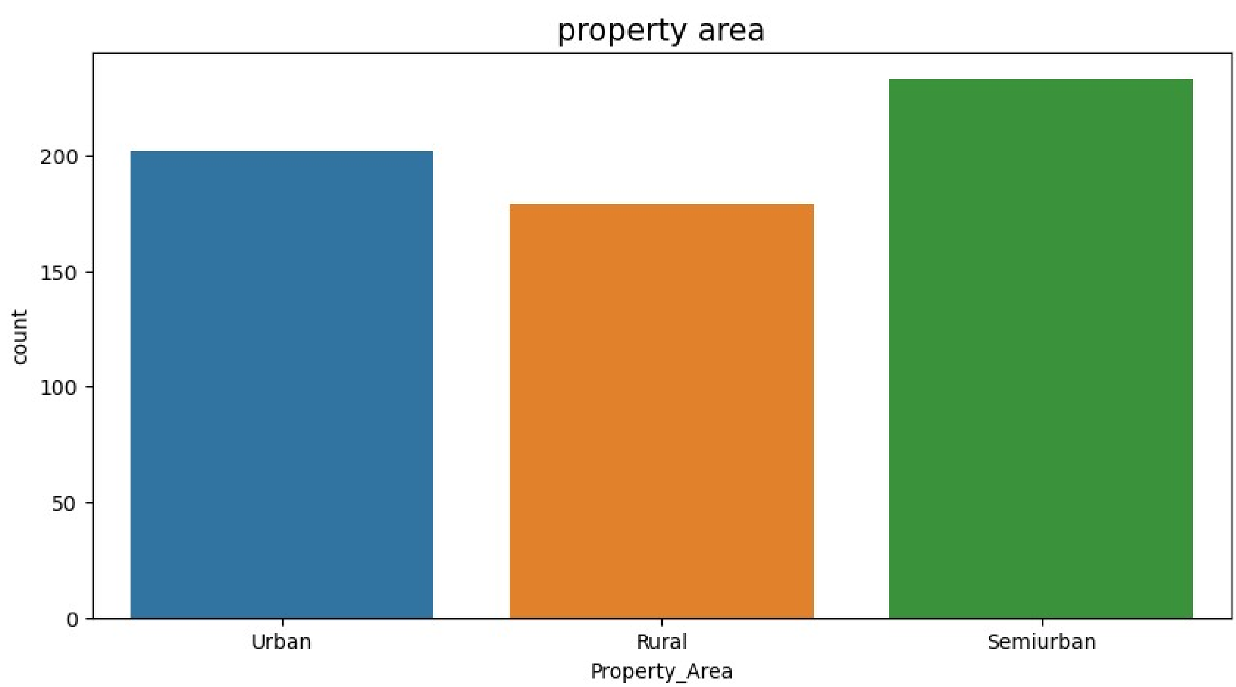
```
<AxesSubplot:title={'center':'Loan Status'}, xlabel='Loan_Status', ylabel='count'>
```



more than 400 peoples loan aproved and more than 150 peoples loan not aproved.

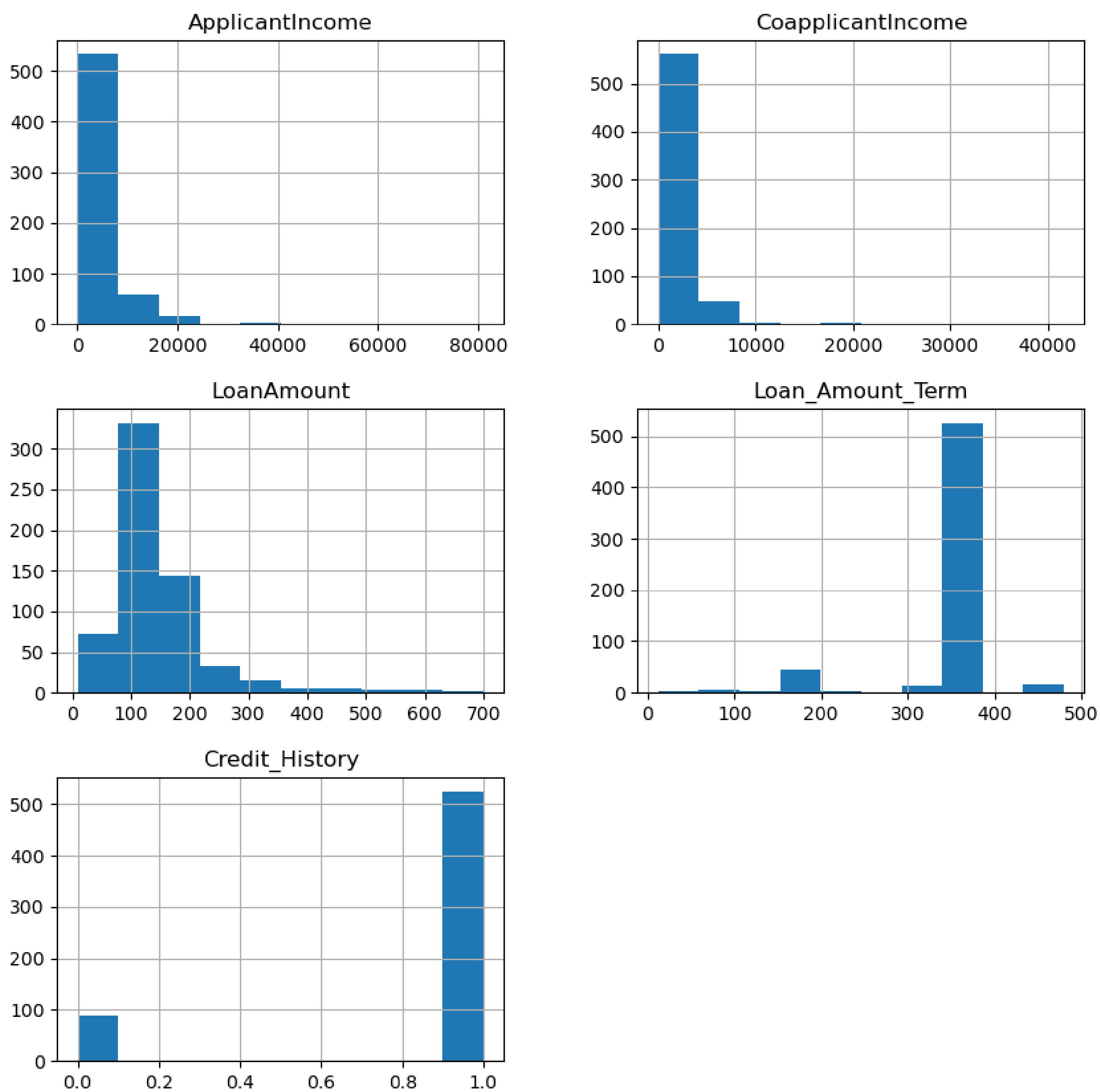
```
plt.figure(figsize=(10,5))
plt.title('property area',fontsize=15)
sns.countplot(df['Property_Area'])
```

```
<AxesSubplot:title={'center':'property area'}, xlabel='Property_Area',
ylabel='count'>
```



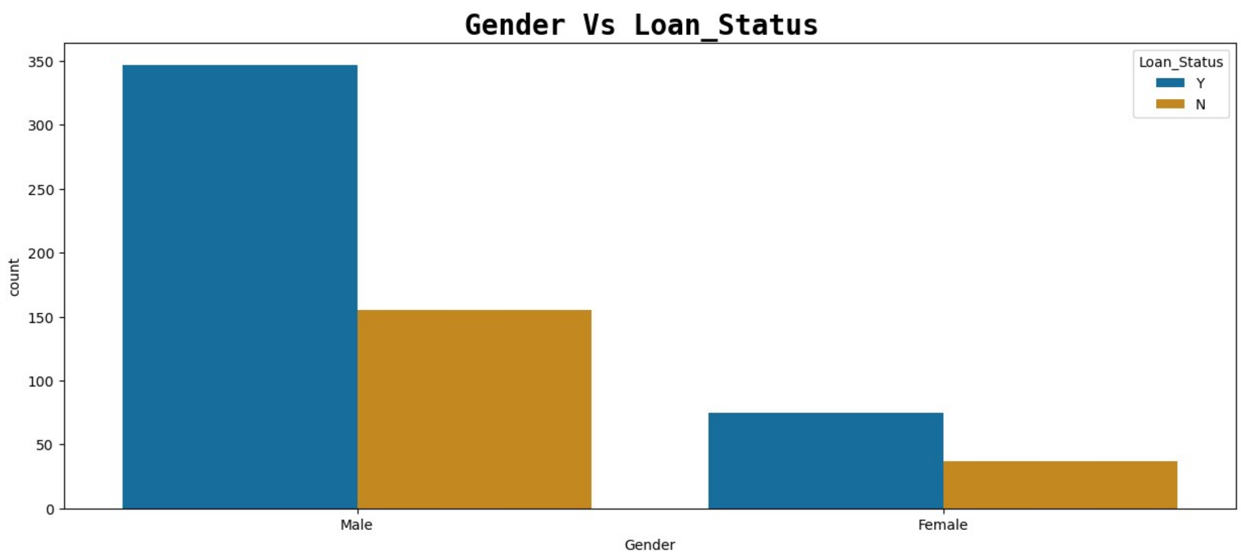
More than 200 people belongs to Semiurban area, arond 200 people belongs to urban area and around 170-180 people belongs to Rural area.

```
df.hist(figsize=(10,10))

array([[<AxesSubplot:title={'center':'ApplicantIncome'}>,
        <AxesSubplot:title={'center':'CoapplicantIncome'}>],
       [<AxesSubplot:title={'center':'LoanAmount'}>,
        <AxesSubplot:title={'center':'Loan_Amount_Term'}>],
       [<AxesSubplot:title={'center':'Credit_History'}>,
<AxesSubplot:>]],
      dtype=object)
```



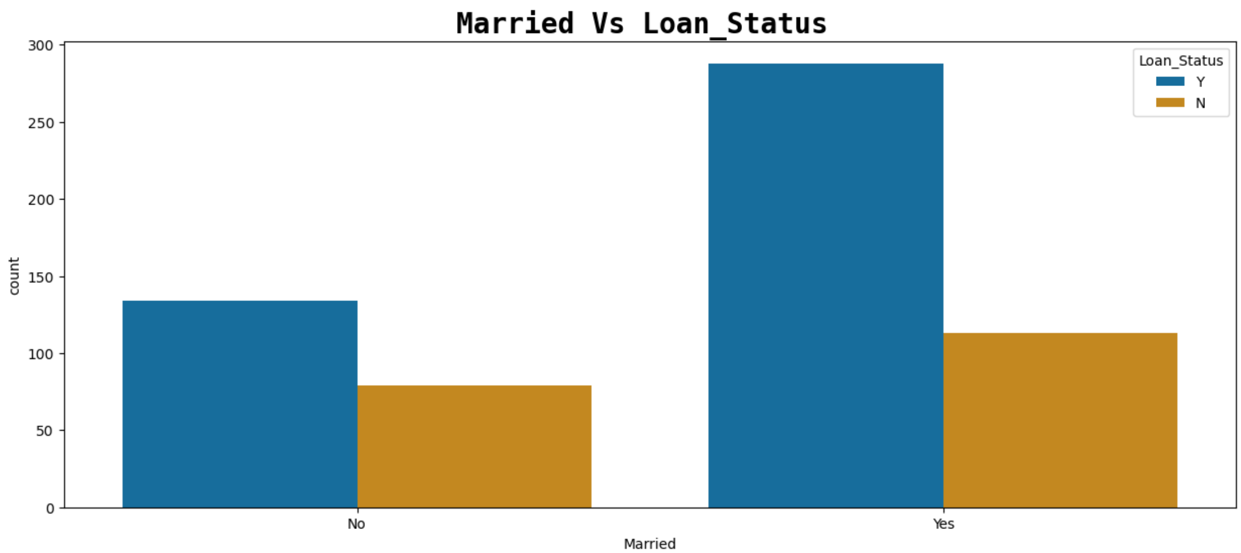
Bi-variate Analysis

```
# Creating a function
def relation_target(df,col):
    plt.figure(figsize=(15,6))
    plt.title(col+' Vs Loan_Status ',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
    sns.countplot(x =col, hue
="Loan_Status",palette='colorblind' ,data = df)
    plt.show()

relation_target(df,'Gender')
```



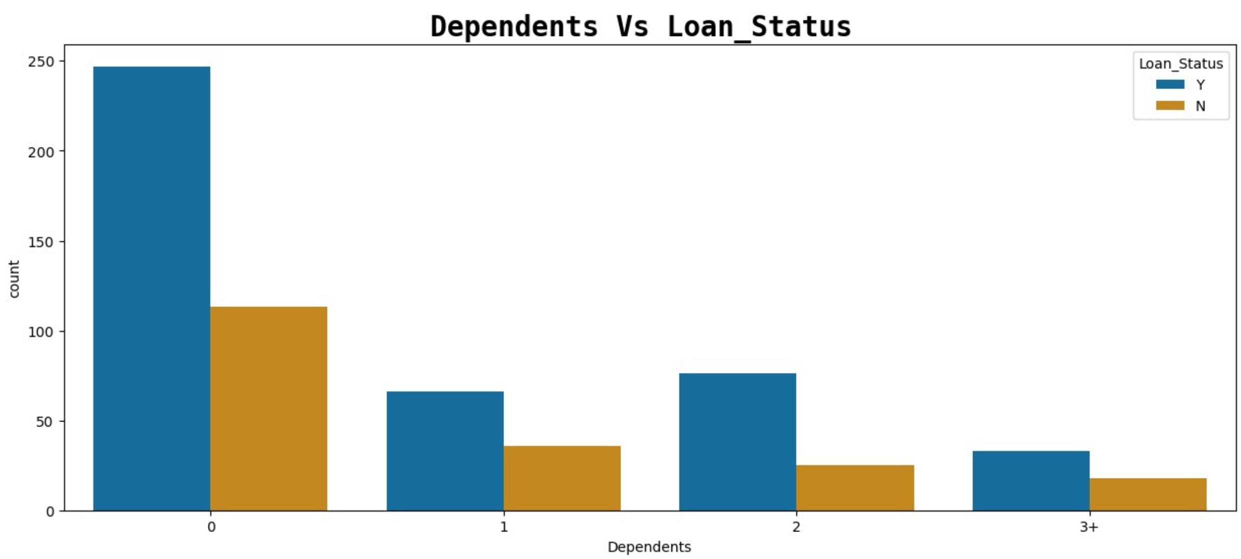
We could see that Mostly Males sanctioned for loan as compaired to Females.

```
relation_target(df,'Married')
```



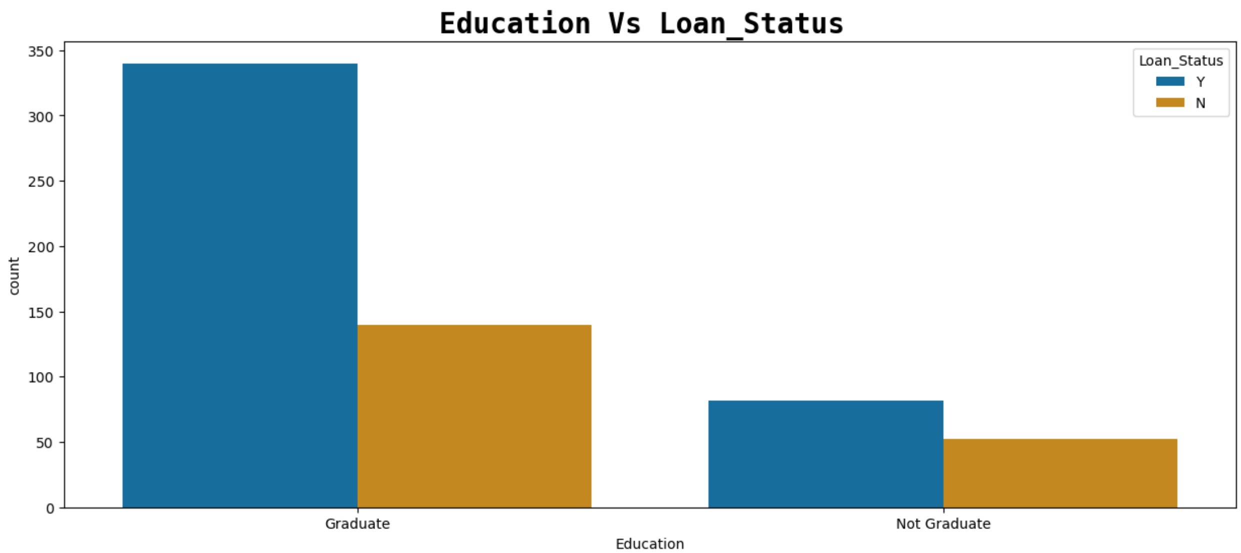
Around 300 applicants are married whose loans are approved as compared to the applicants who are not married but their loans were approved

```
relation_target(df,'Dependents')
```



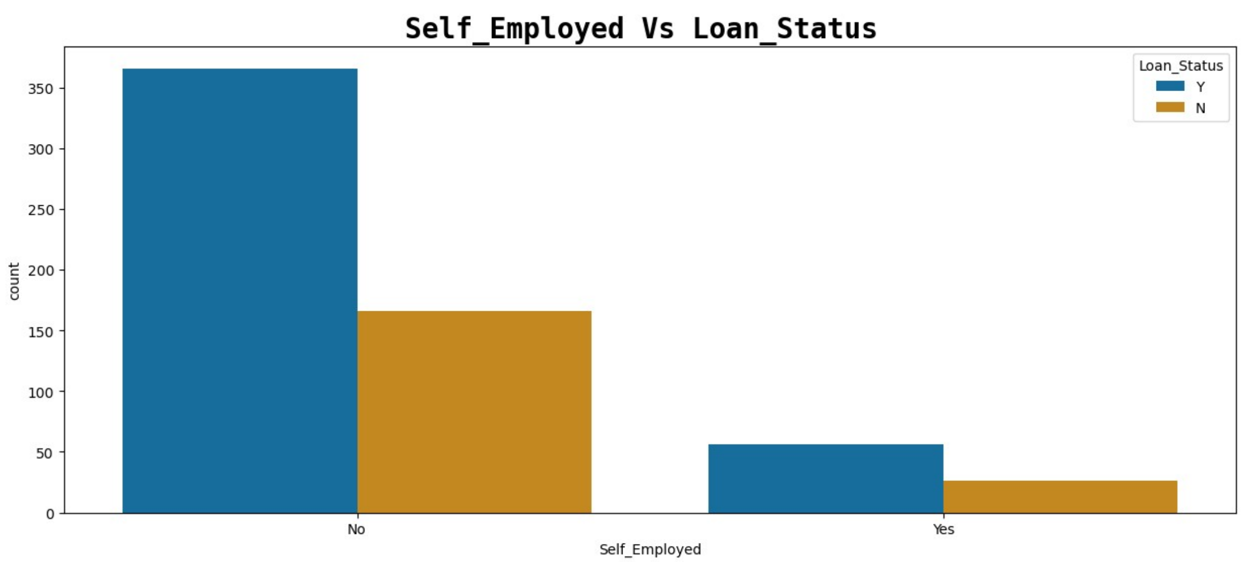
Majority of the applicants whose loans are approved have no or 0 dependency & the minimun loan approved to those who has higher number of dependents.

```
relation_target(df,'Education')
```



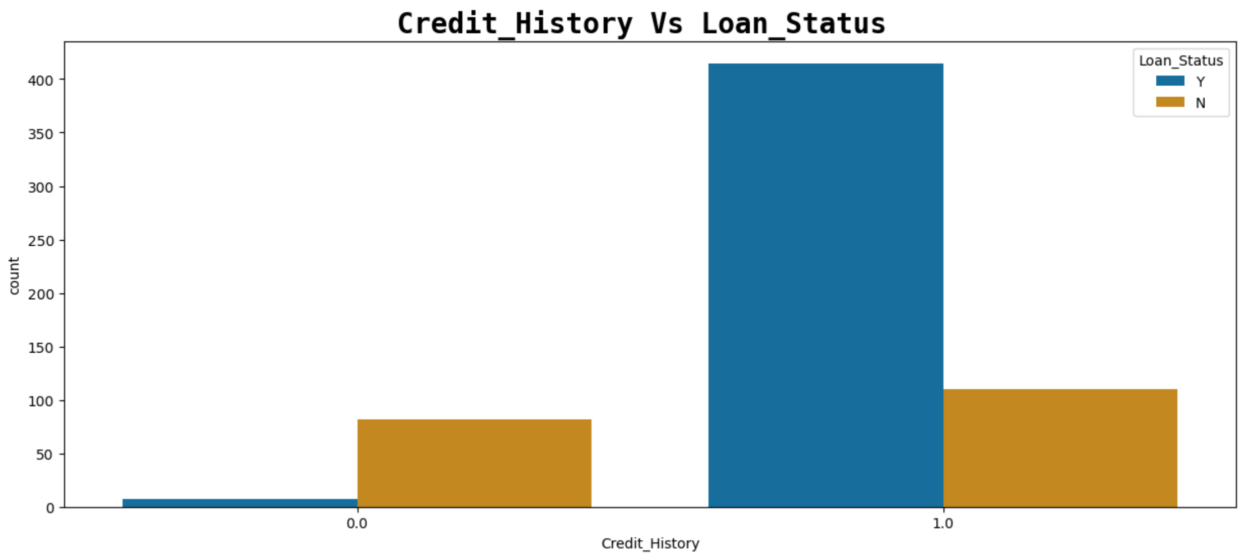
The count of graduates whose loans are approved is high as compared to the non graduates having approved loans

```
relation_target(df,'Self_Employed')
```



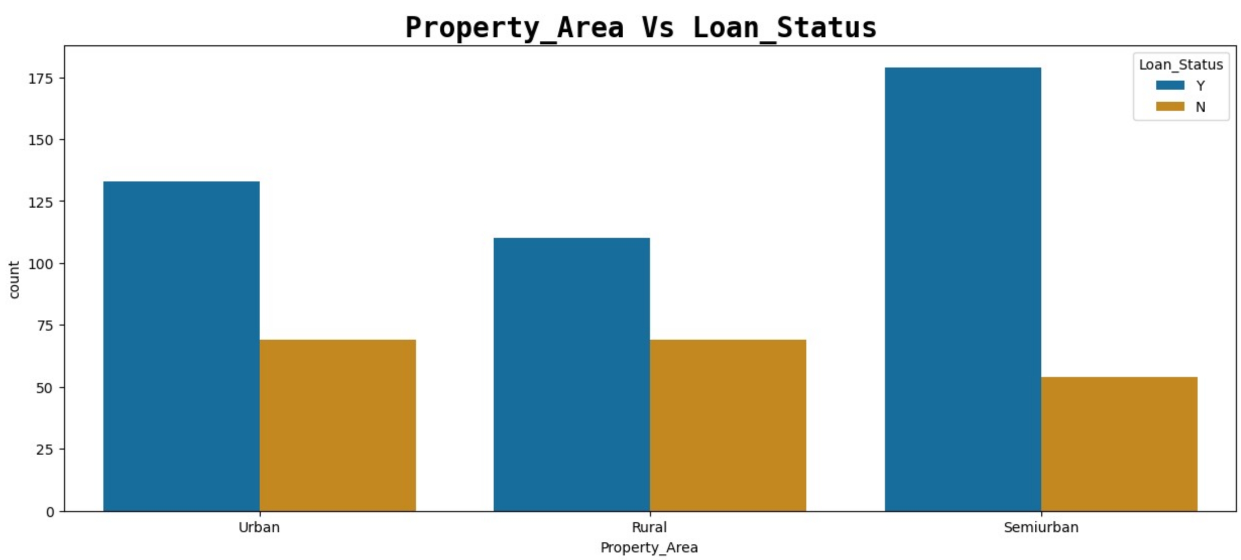
The percentage of self-employed applicants having approved loans is around 15% of the non self employed applicants having approved loans.

```
relation_target(df,'Credit_History')
```



People who has credit history 1 has the highest loan approval as compared to 0 credit history. People Who has zero credit score mostly they are denied to grant loan.

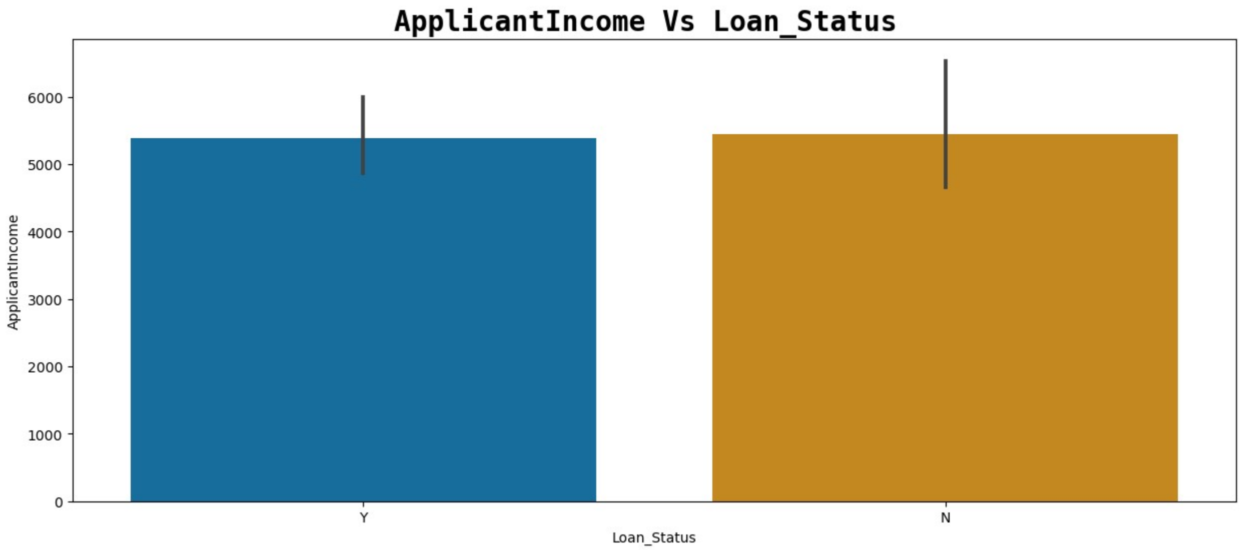
```
relation_target(df,'Property_Area')
```



The max. no. of applicants whose loans are approved belongs to or having property in semi-urban area.

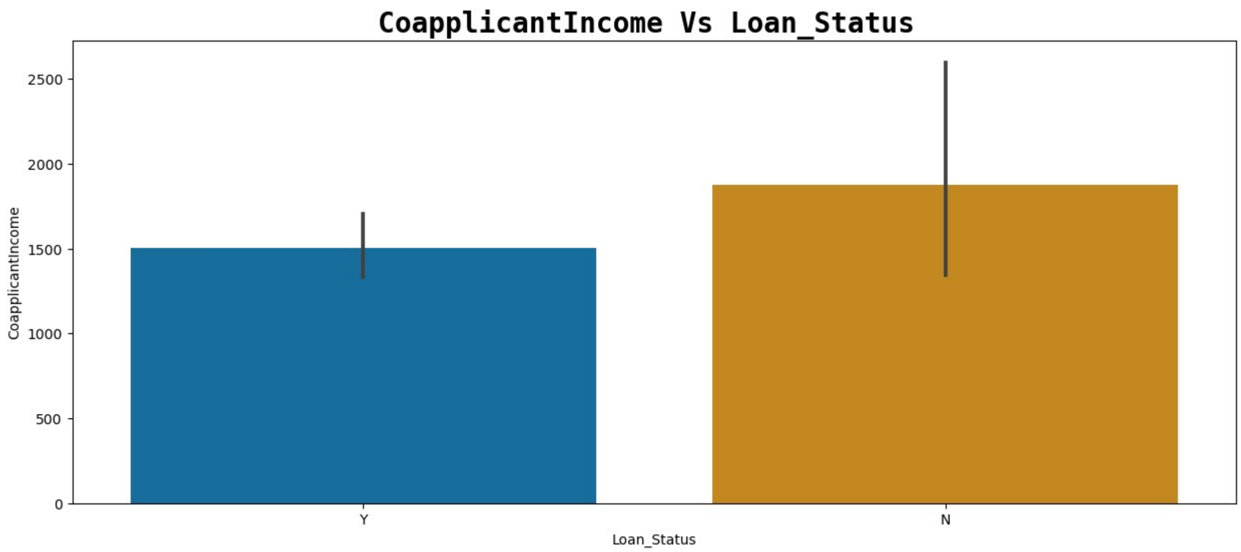
```
def barplot_target(df,col):
    plt.figure(figsize=(15,6))
    plt.title(col+' Vs Loan_Status ',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
    sns.barplot(y =col, x="Loan_Status",palette='colorblind' ,data =
df)
    plt.show()
```

```python
barplot_target(df,'ApplicantIncome')
```



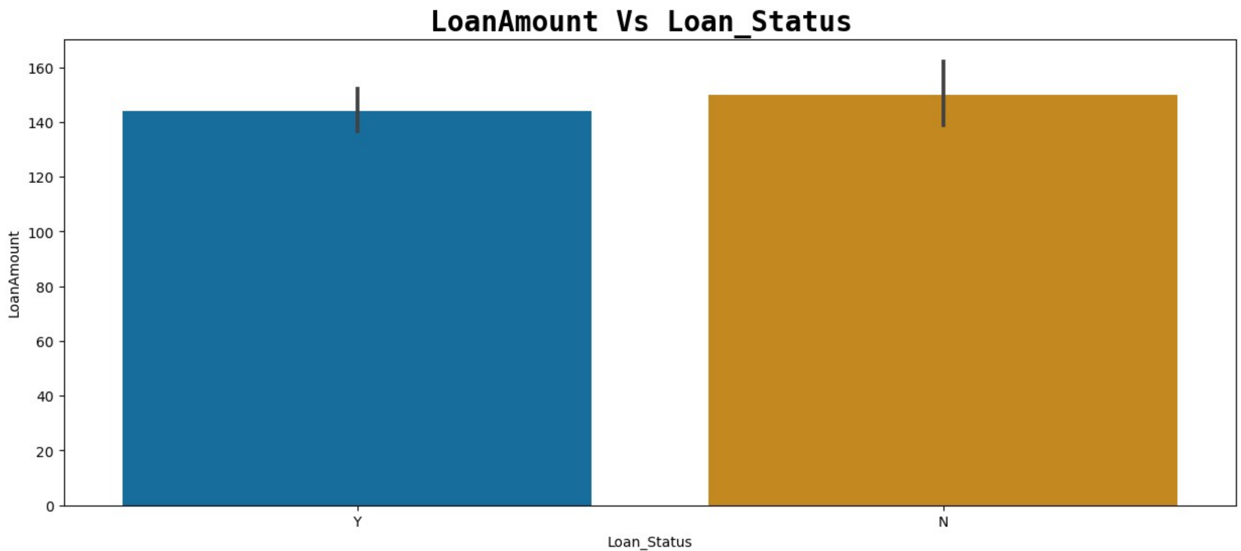
There is almost similar income of people who sanction loans/ denied. Applicant income has no significance to decide whether loan will approve or not.

```python
barplot_target(df,'CoapplicantIncome')
```



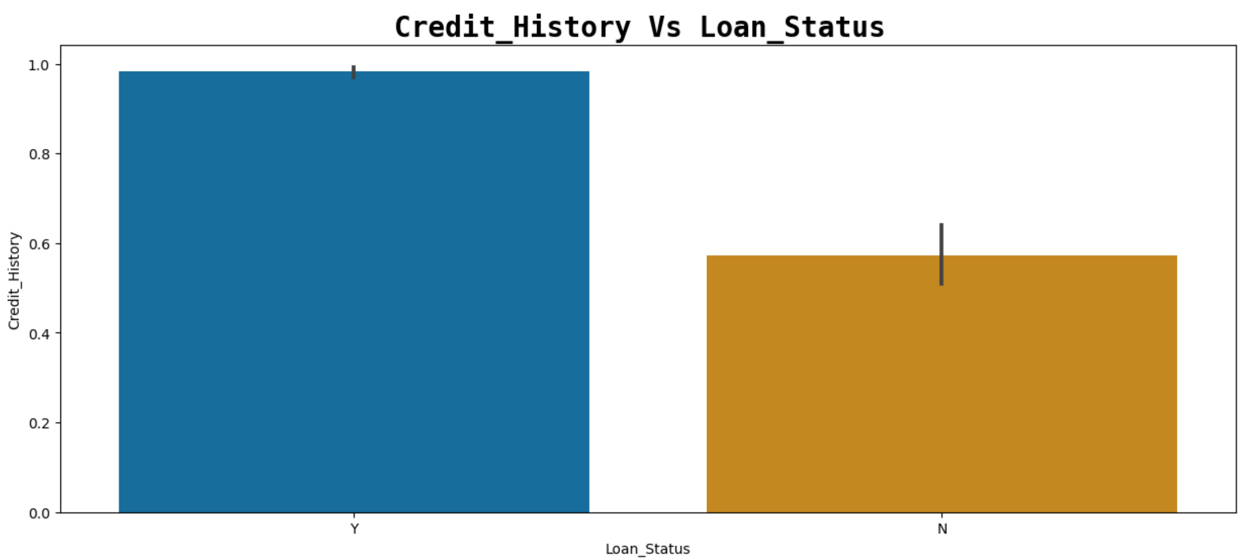
We can observe that, if co applicant income is higher than 1500, there are chances of denial to loan.

```python
barplot_target(df,'LoanAmount')
```



There is almost similar trend regarding Loan Amount. There is no relation between Loan Amount and Loan Status.

```
barplot_target(df,'Credit_History')
```

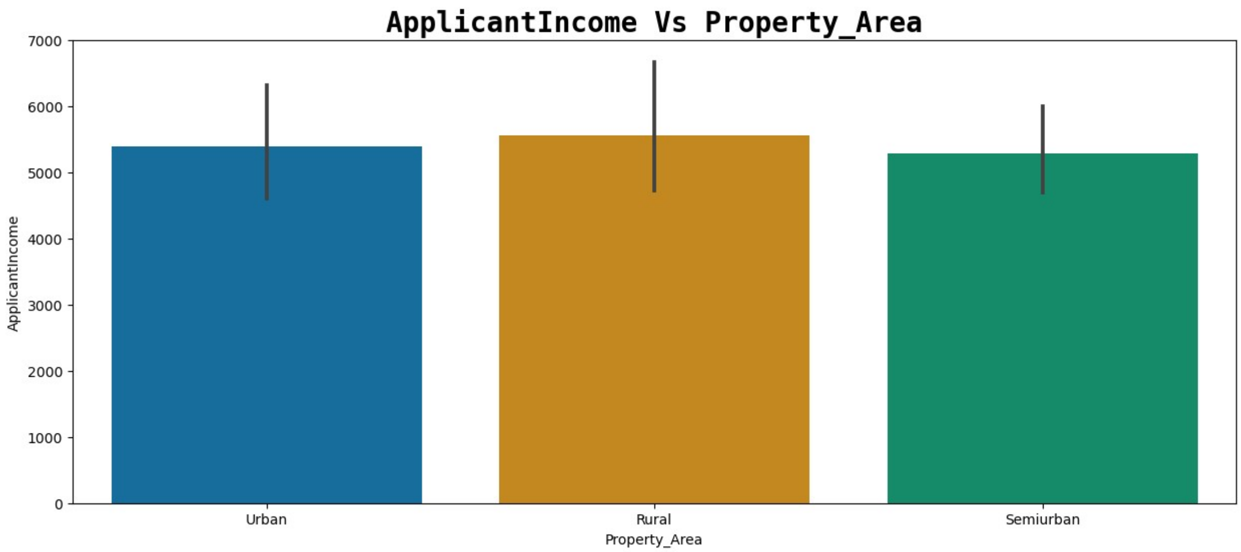


As earlier we can see that a person who has credit history one has highest loan approval rate

Relation With Applicant Income and Other Attributes

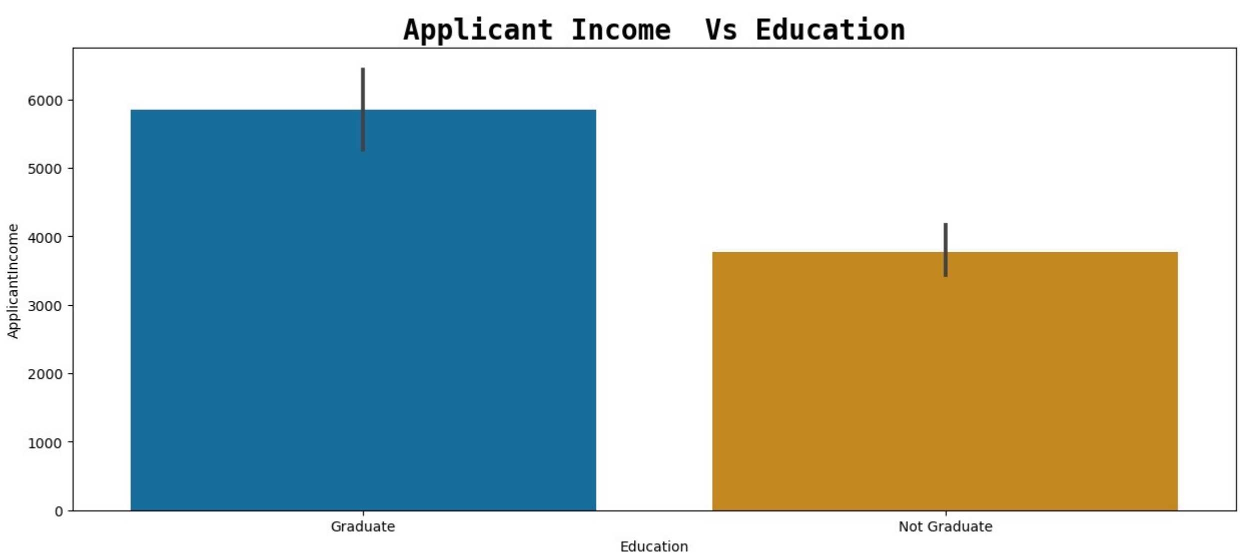
```
plt.figure(figsize=(15,6))
plt.title('ApplicantIncome Vs Property_Area',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
```

```
sns.barplot(y ='ApplicantIncome',
x="Property_Area",palette='colorblind' ,data = df)
plt.show()
```



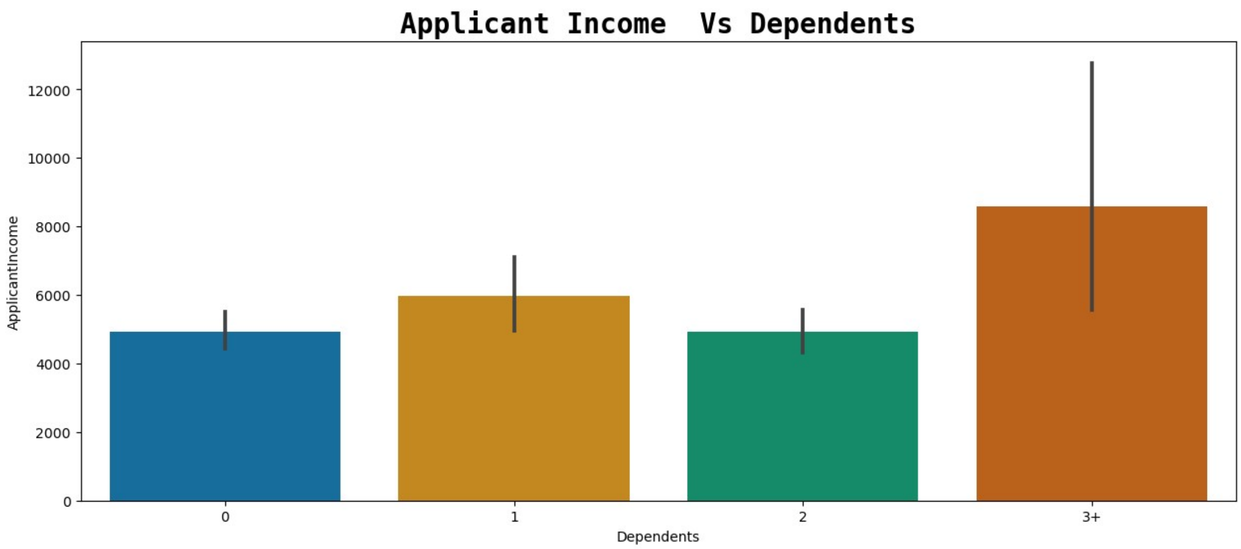
There is almost similar income status of applicants belong from different regions.

```
plt.figure(figsize=(15,6))
plt.title('Applicant Income  Vs Education',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
sns.barplot(y ='ApplicantIncome',
x="Education",palette='colorblind' ,data = df)
plt.show()
```



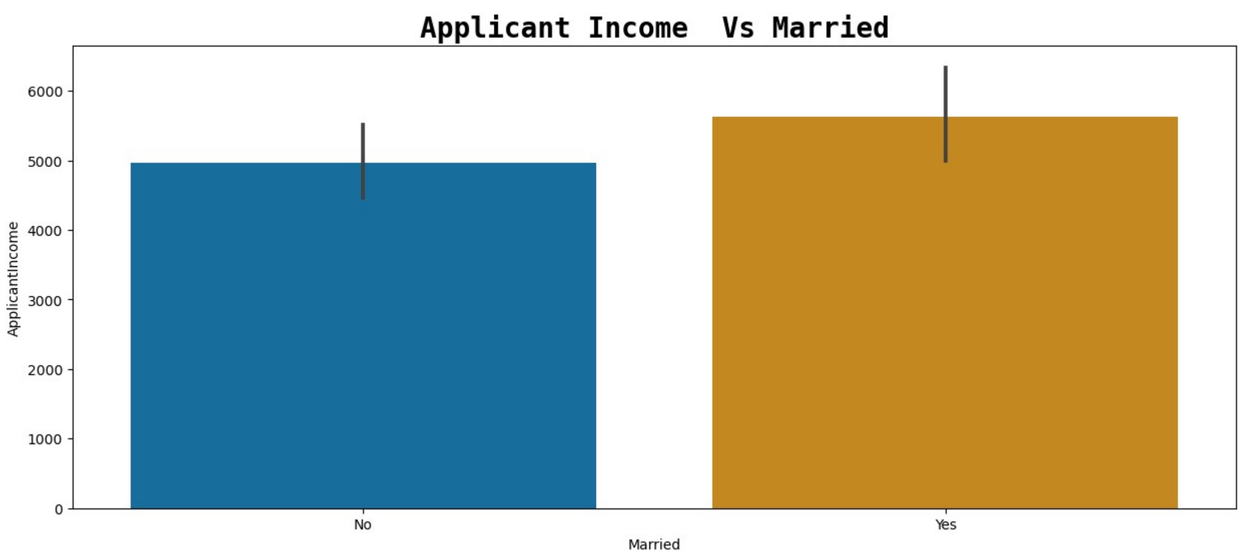
Graduate Applicant's income is higher than non Graduate Applicants.

```
plt.figure(figsize=(15,6))
plt.title('Applicant Income  Vs Dependents',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
sns.barplot(y ='ApplicantIncome',
x="Dependents",palette='colorblind' ,data = df)
plt.show()
```



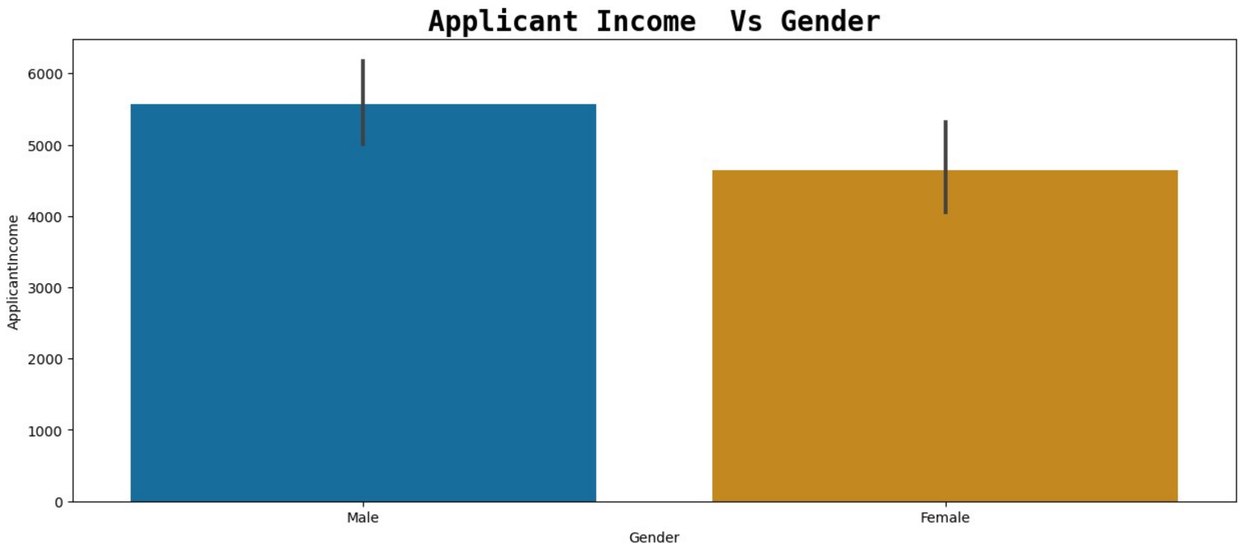
The Applicant who has maximum number of depenents has higher income (8000+).

```
plt.figure(figsize=(15,6))
plt.title('Applicant Income  Vs Married',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
sns.barplot(y ='ApplicantIncome',
x="Married",palette='colorblind' ,data = df)
plt.show()
```



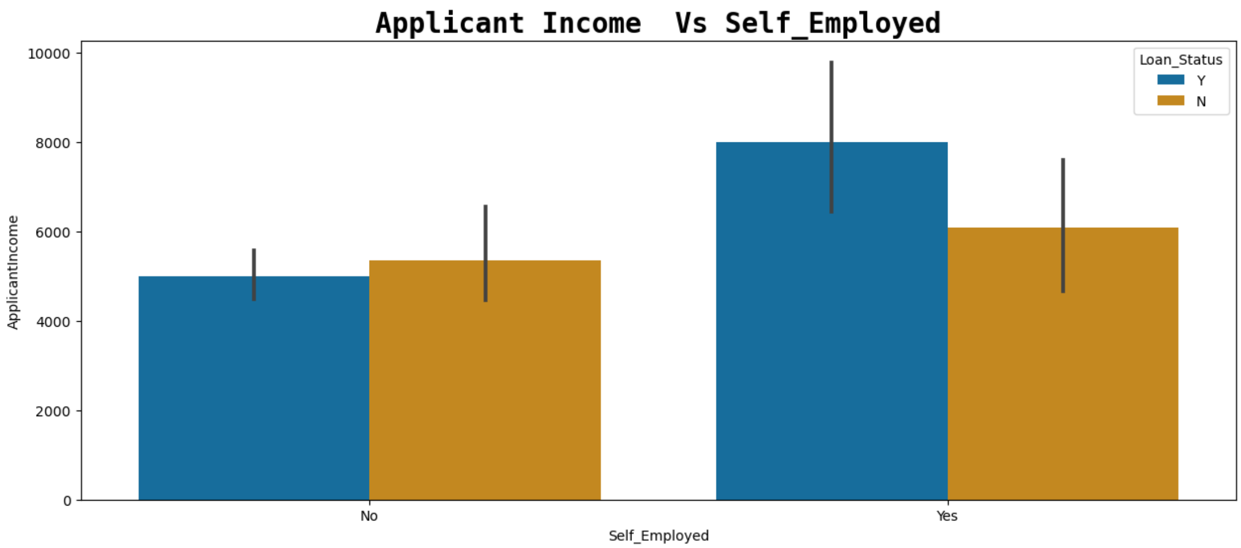
The Applicant who are married has higher income as compared to unmarried applicants.

```
plt.figure(figsize=(15,6))
plt.title('Applicant Income  Vs Gender',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
sns.barplot(y ='ApplicantIncome',
x="Gender",palette='colorblind' ,data = df)
plt.show()
```



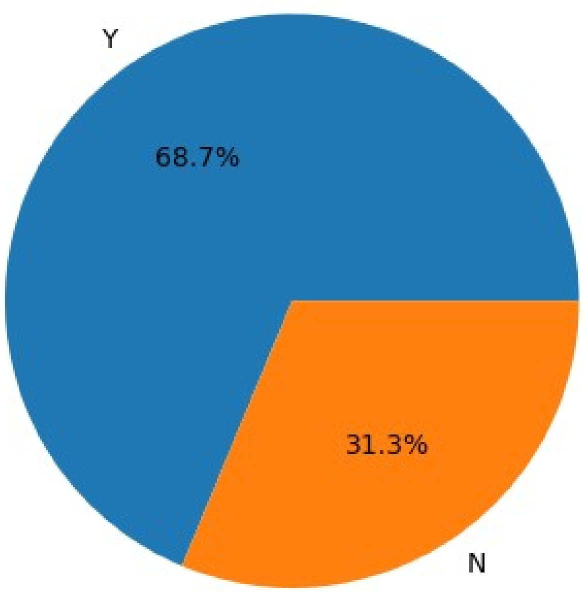
Male applicant's income is higher than the female applicants.

```
plt.figure(figsize=(15,6))
plt.title('Applicant Income  Vs Self_Employed',fontdict={'fontname':
'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
sns.barplot(y ='ApplicantIncome',
x="Self_Employed",hue='Loan_Status',palette='colorblind' ,data = df)
plt.show()
```



We could see that the person who are self employed are earning well and their loan approval rate is also high as compared to non-self employed.

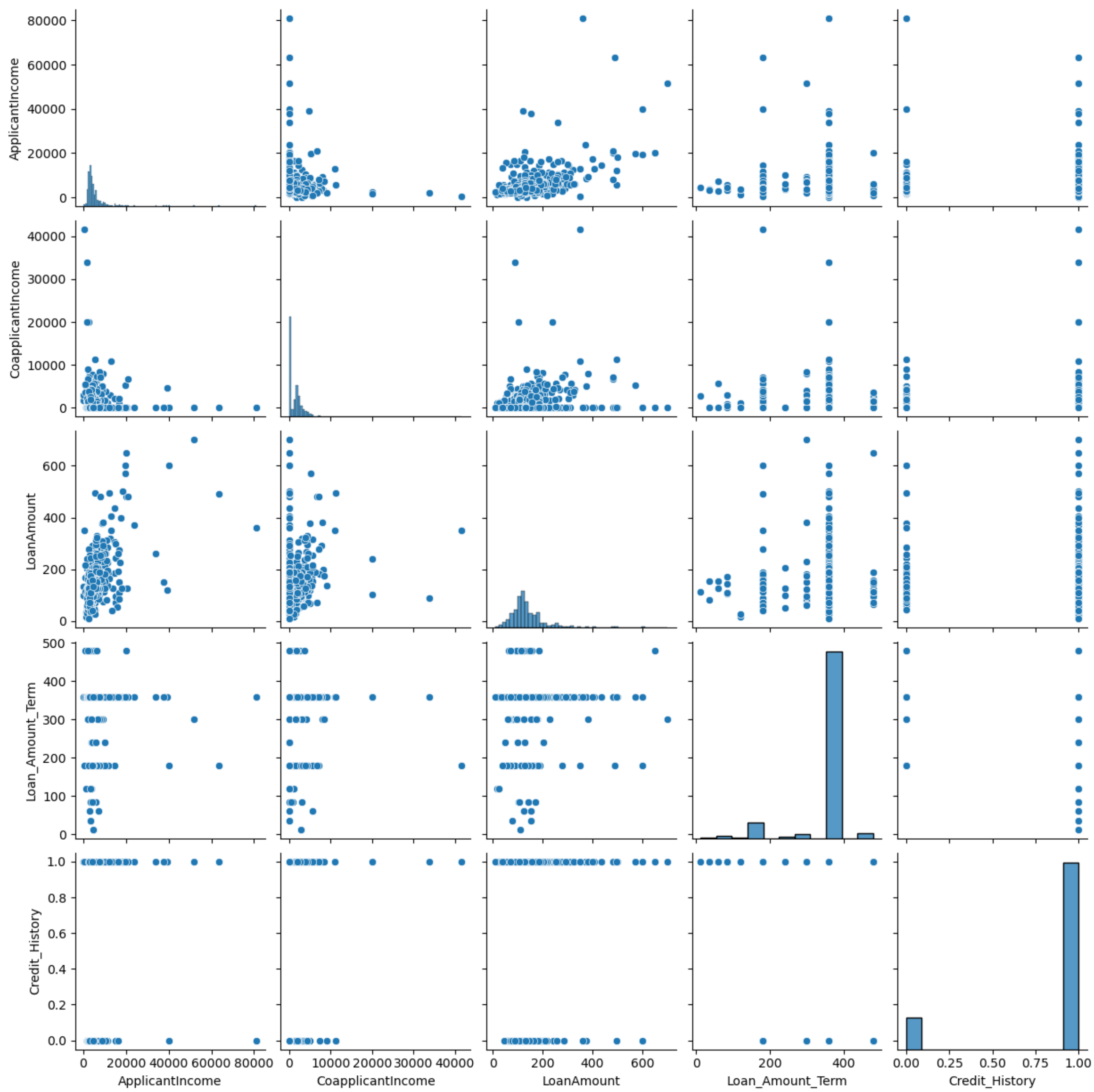
```
# checking data imbalancing
temp = df['Loan_Status'].value_counts()
plt.pie(temp.values,
        labels=temp.index,
        autopct='%1.1f%%')
plt.show()
```



Here we have an imbalanced dataset. We will have to balance it before training any model on this data. so we do it later

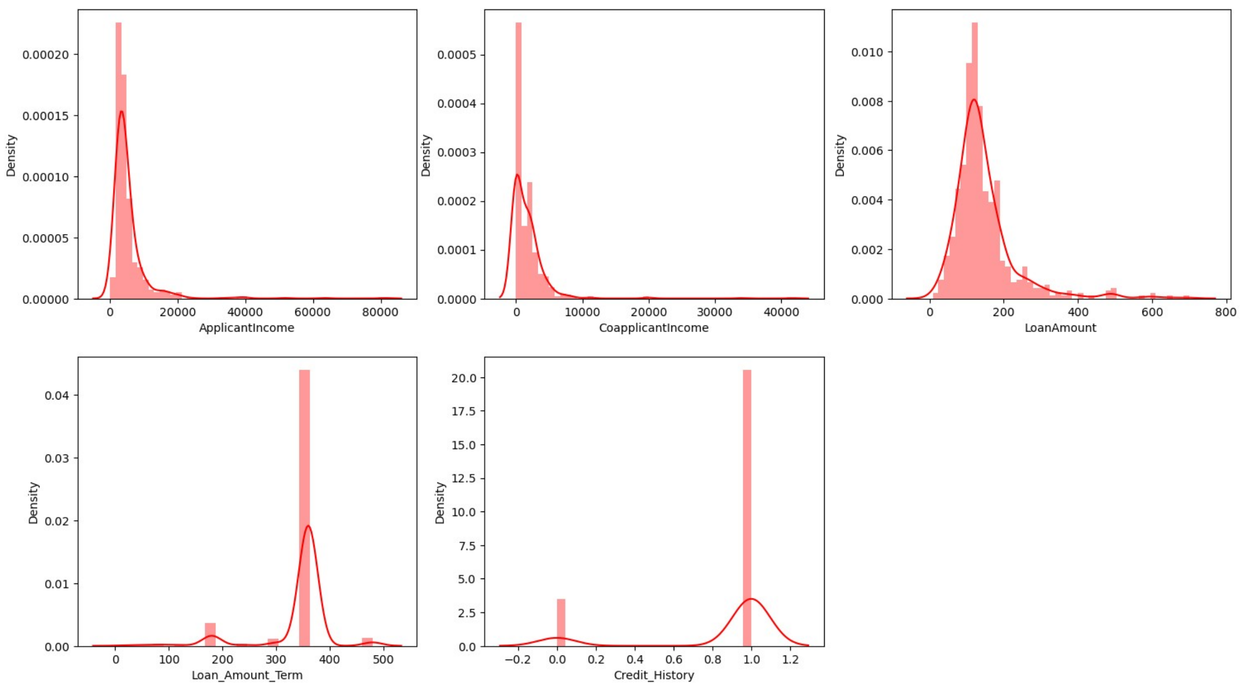
```
# Plotting a pair plot
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x152bffc62b0>
```



Distribution

```
plt.figure(figsize=(18,10))
plot=1
for col in num_df:
    if plot<=6:
        plt.subplot(2,3,plot)
        sns.distplot(df[col],color='red')
        plt.xlabel(col)
        plot=plot+1
plt.show()
```



: We can see that applicants income, Co-applicants income, Loan Amount are right skewed.

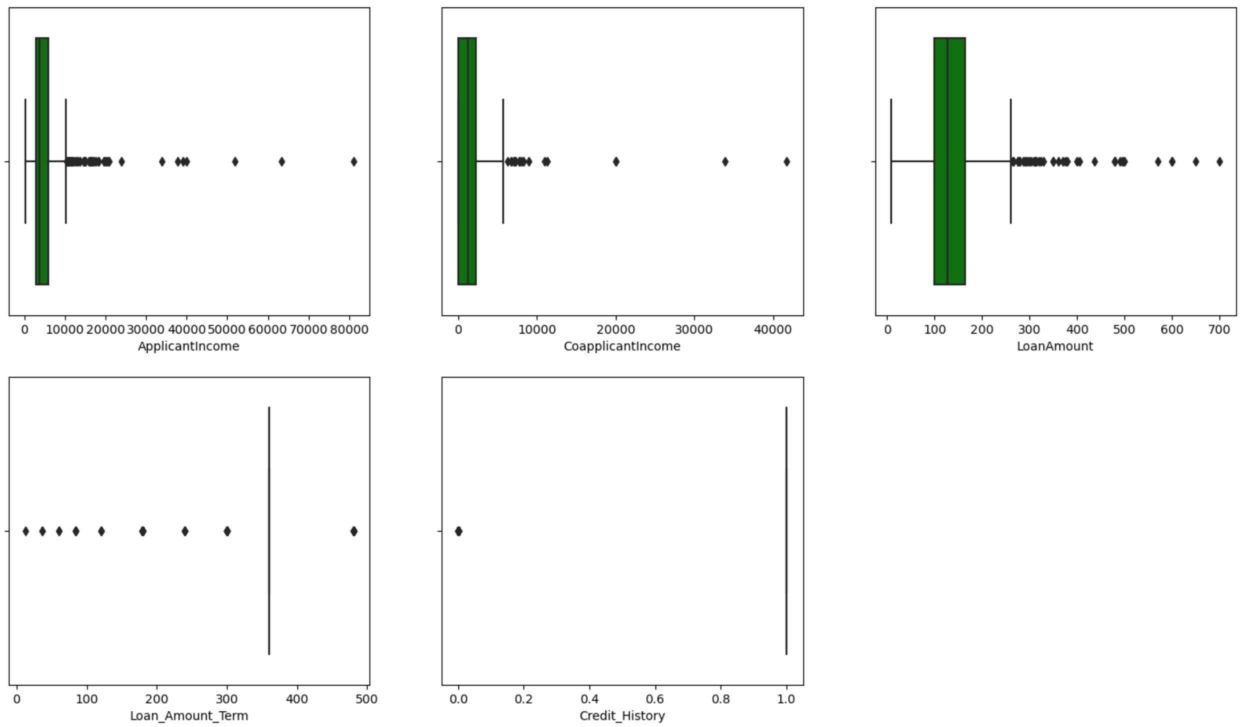
: Loan Amount Term has majority values of 360 months.

: Credit history has only two values (0 or 1). In which majority values are One.

Outliers Detection

```
plt.figure(figsize=(18,10))
plot=1
for col in num_df:
    if plot<=6:
        plt.subplot(2,3,plot)
        sns.boxplot(df[col],color='green')
        plt.xlabel(col)
```

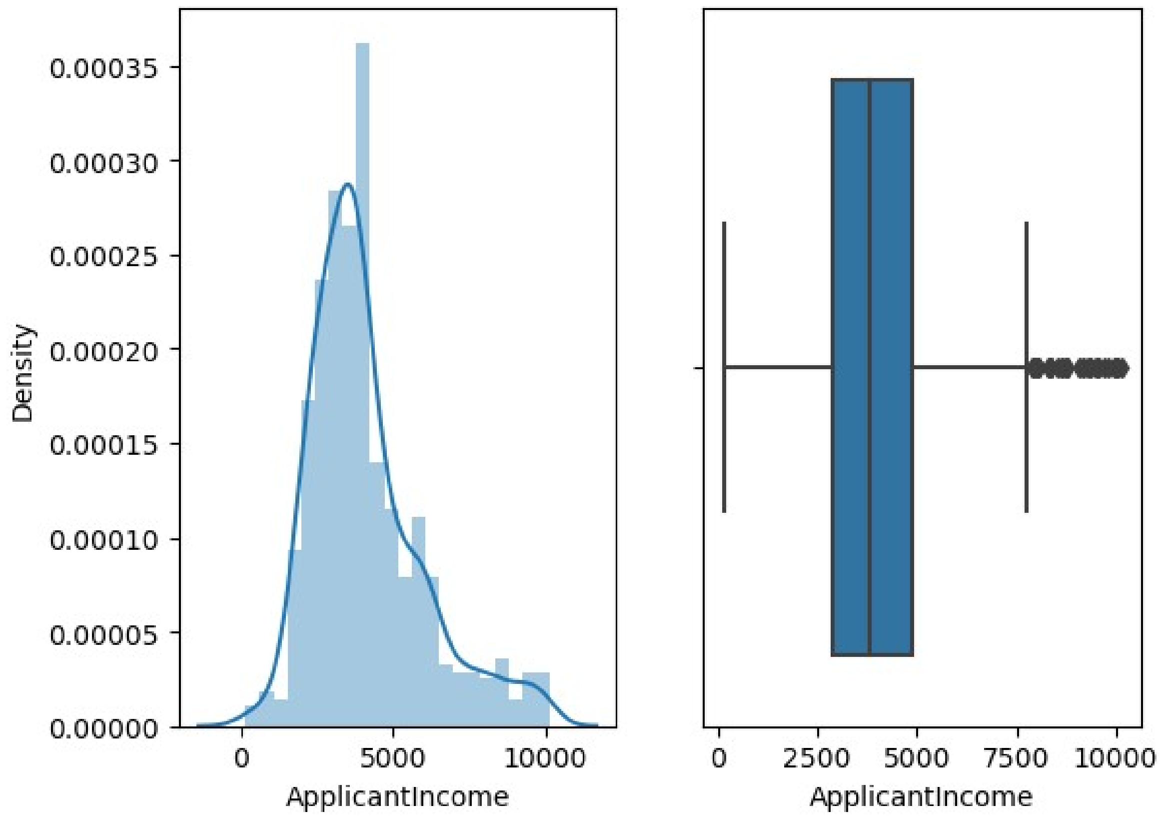
```
        plot=plot+1
plt.show()
```



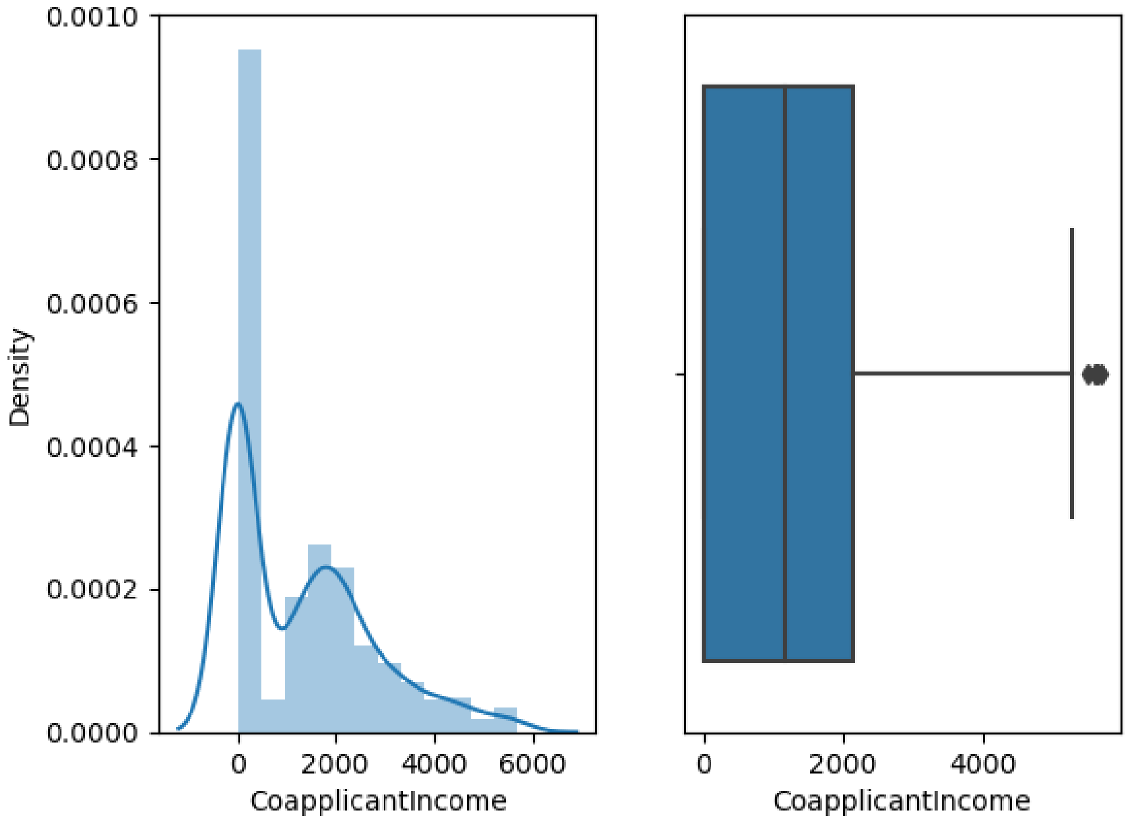
Outliers are present in Appilcants Income, Coapplicants Income and Loan Amounts.

Outliers Treatment

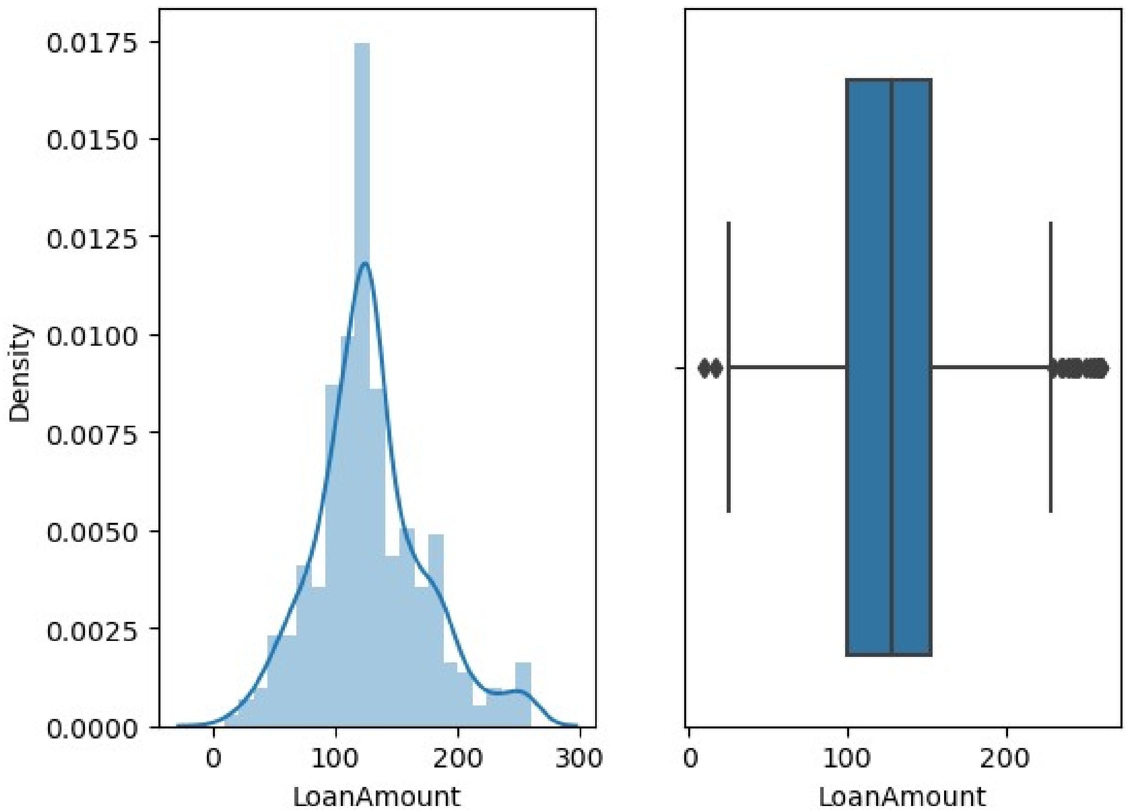
```
## when data is normally distributed.
def replace_outlier(df,col):
    IQR=df[col].quantile(.75)-df[col].quantile(.25)
    lower_limit=df[col].quantile(.25)-(1.5*IQR)
    upper_limit=df[col].quantile(.75)+(1.5*IQR)
    non_outlier=np.where((df[col]<lower_limit )|
(df[col]>upper_limit),df[col].median(),df[col])
    df[col]=non_outlier
    plt.subplot(1,2,1)
    sns.distplot(df[col])
    plt.subplot(1,2,2)
    sns.boxplot(df[col])

replace_outlier(df,'ApplicantIncome')
```




```
replace_outlier(df,'CoapplicantIncome')
```




```
replace_outlier(df,'LoanAmount')
```



We have sucesfully replace our outliers from Applicant income,Co applicant Income & Loan Amount.

Skewness

```
df_1=df.copy()
```

```
df_1.skew()
```

```
ApplicantIncome       1.149106
CoapplicantIncome     0.936471
LoanAmount            0.498333
Loan_Amount_Term     -2.402112
Credit_History       -2.021971
dtype: float64
```

```
df_1['ApplicantIncome']=np.sqrt(df_1['ApplicantIncome'])
```

```
df_1['CoapplicantIncome']=np.sqrt(df_1['CoapplicantIncome'])
```

```
df_1['LoanAmount']=np.sqrt(df_1['LoanAmount'])
```

```
df_1.skew()
```

```
ApplicantIncome      0.438048
CoapplicantIncome    0.152060
LoanAmount          -0.242054
Loan_Amount_Term    -2.402112
Credit_History      -2.021971
dtype: float64
```

We have removed skewness to its possible extent.

Label Encoding

```
# converting categorical column into numeric using label encoding
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for col in obj_df:
    df_1[col]=le.fit_transform(df_1[col])

df_1.head()

   Gender  Married  Dependents  Education  Self_Employed
ApplicantIncome  \
0       1        0           0          0              0
76.478755
1       1        1           1          0              0
67.697858
2       1        1           0          0              1
54.772256
3       1        1           0          1              0
50.823223
4       1        0           0          0              0
77.459667

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0           0.000000   11.313708             360.0             1.0
1          38.832976   11.313708             360.0             1.0
2           0.000000    8.124038             360.0             1.0
3          48.559242   10.954451             360.0             1.0
4           0.000000   11.874342             360.0             1.0

   Property_Area  Loan_Status
0              2            1
1              0            0
2              2            1
3              2            1
4              2            1
```

Splitting Data into Input and Output Variable

```
x = df_1.drop(['Loan_Status'],axis=1)
y = df_1['Loan_Status']

from sklearn.model_selection import train_test_split

x_train, x_val,y_train, y_val = train_test_split(x, y, test_size=0.2,
random_state=0)

from imblearn.over_sampling import RandomOverSampler

# As the data was highly imbalanced we will balance it by adding
repetitive rows of minority class.
ros = RandomOverSampler(sampling_strategy='minority',
                        random_state=0)
x, y = ros.fit_resample(x_train, y_train)

x_train.shape, x.shape
```

```
((491, 11), (664, 11))
```

```
x
```

```
     Gender  Married  Dependents  Education  Self_Employed
ApplicantIncome  \
0         1        1           0          0              0
54.387499
1         1        0           1          0              0
61.745445
2         1        1           0          0              0
62.833112
3         0        0           0          0              0
61.749494
4         1        1           2          0              0
68.614867
..      ...      ...         ...        ...            ...
...
659       1        1           2          0              0
61.644140
660       1        1           2          0              1
40.000000
661       1        1           0          1              1
65.909028
662       1        0           0          0              0
47.296934
663       1        1           1          1              0
63.639610

     CoapplicantIncome  LoanAmount  Loan_Amount_Term
```

```
Credit_History  \
0            53.851648   11.445523             360.0             1.0

1             0.000000   14.000000             360.0             1.0

2            41.629317   12.206556             360.0             0.0

3             0.000000   10.770330             180.0             1.0

4            37.242449   12.247449             360.0             1.0

..                 ...         ...               ...             ...

659          60.000000   14.696938             360.0             0.0

660          34.474628   15.459625             360.0             1.0

661          27.129320    9.327379             360.0             1.0

662           0.000000    7.937254             480.0             0.0

663          72.814834   11.747340             360.0             1.0


     Property_Area
0                1
1                1
2                0
3                2
4                1
..             ...
659              2
660              2
661              1
662              1
663              0

[664 rows x 11 columns]

y

0      1
1      0
2      0
3      1
4      1
      ..
659    0
660    0
661    0
662    0
```

```
663    0
Name: Loan_Status, Length: 664, dtype: int32
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
x_scaled=ss.fit_transform(x)
x=pd.DataFrame(x_scaled,columns=x.columns)
x
```

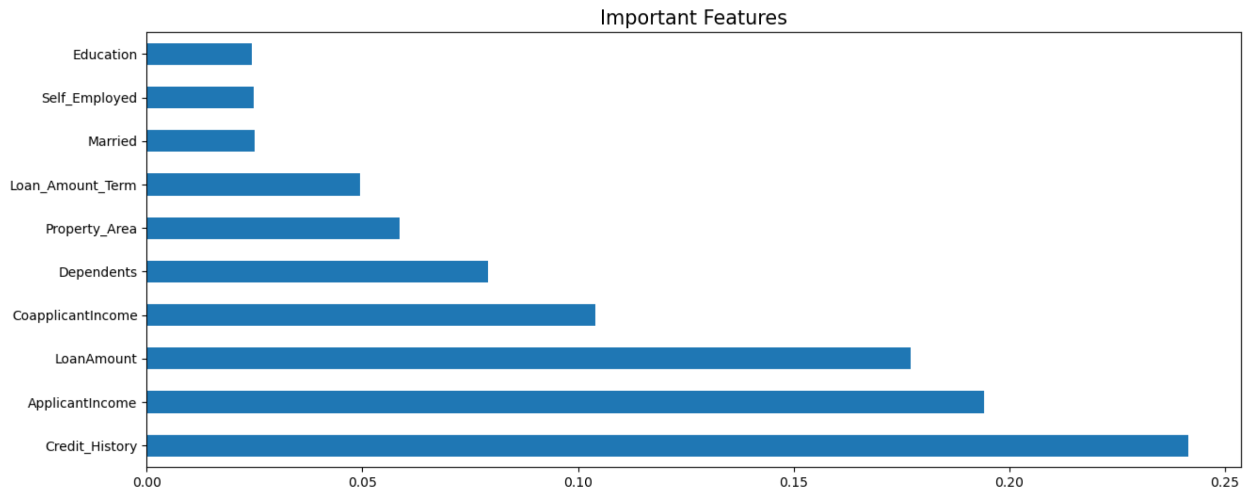
```
       Gender   Married  Dependents  Education  Self_Employed  \
0    0.452859  0.720729   -0.758604  -0.544862      -0.398514   
1    0.452859 -1.387483    0.232957  -0.544862      -0.398514   
2    0.452859  0.720729   -0.758604  -0.544862      -0.398514   
3   -2.208191 -1.387483   -0.758604  -0.544862      -0.398514   
4    0.452859  0.720729    1.224519  -0.544862      -0.398514   
..        ...       ...         ...        ...            ...   
659  0.452859  0.720729    1.224519  -0.544862      -0.398514   
660  0.452859  0.720729    1.224519  -0.544862       2.509323   
661  0.452859  0.720729   -0.758604   1.835326       2.509323   
662  0.452859 -1.387483   -0.758604  -0.544862      -0.398514   
663  0.452859  0.720729    0.232957   1.835326      -0.398514   

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  
\
0          -0.595073           1.213757    0.166210          0.251113   

1          -0.052819          -0.992105    1.413565          0.251113   

2           0.027338           0.713108    0.537823          0.251113   

3          -0.052521          -0.992105   -0.163488         -2.524789   

4           0.453432           0.533414    0.557791          0.251113   

..               ...                ...         ...               ...   

659        -0.060285           1.465605    1.753881          0.251113   

660        -1.655378           0.420039    2.126302          0.251113   

661         0.254021           0.119162   -0.868083          0.251113   

662        -1.117621          -0.992105   -1.546883          2.101715   

663         0.086774           1.990524    0.313588          0.251113   
```

```
     Credit_History  Property_Area
0          0.533229      -0.028248
1          0.533229      -0.028248
2         -1.875368      -1.278688
3          0.533229       1.222192
4          0.533229      -0.028248
..              ...            ...
659       -1.875368       1.222192
660        0.533229       1.222192
661        0.533229      -0.028248
662       -1.875368      -0.028248
663        0.533229      -1.278688

[664 rows x 11 columns]
```

Standardization doesn't have any fixed minimum or maximum value. Here, the values of all the columns are scaled in such a way that they all have a mean equal to 0 and standard deviation equal to 1. This scaling technique works well with outliers. Thus, this technique is preferred if outliers are present in the dataset.

Feature Importance

```
from sklearn.ensemble import ExtraTreesClassifier
extra=ExtraTreesClassifier()
extra.fit(x,y)

ExtraTreesClassifier()

print(extra.feature_importances_)

[0.02191379 0.02512831 0.07907252 0.02428871 0.02478742 0.19410193
 0.10402099 0.17709329 0.04943947 0.24159802 0.05855553]

plt.figure(figsize=(15,6))
plt.title('Important Features',fontsize=15)
feat_importance=pd.Series(extra.feature_importances_,index=x.columns)
feat_importance.nlargest(10).plot(kind='barh')
plt.show()
```



Model Building

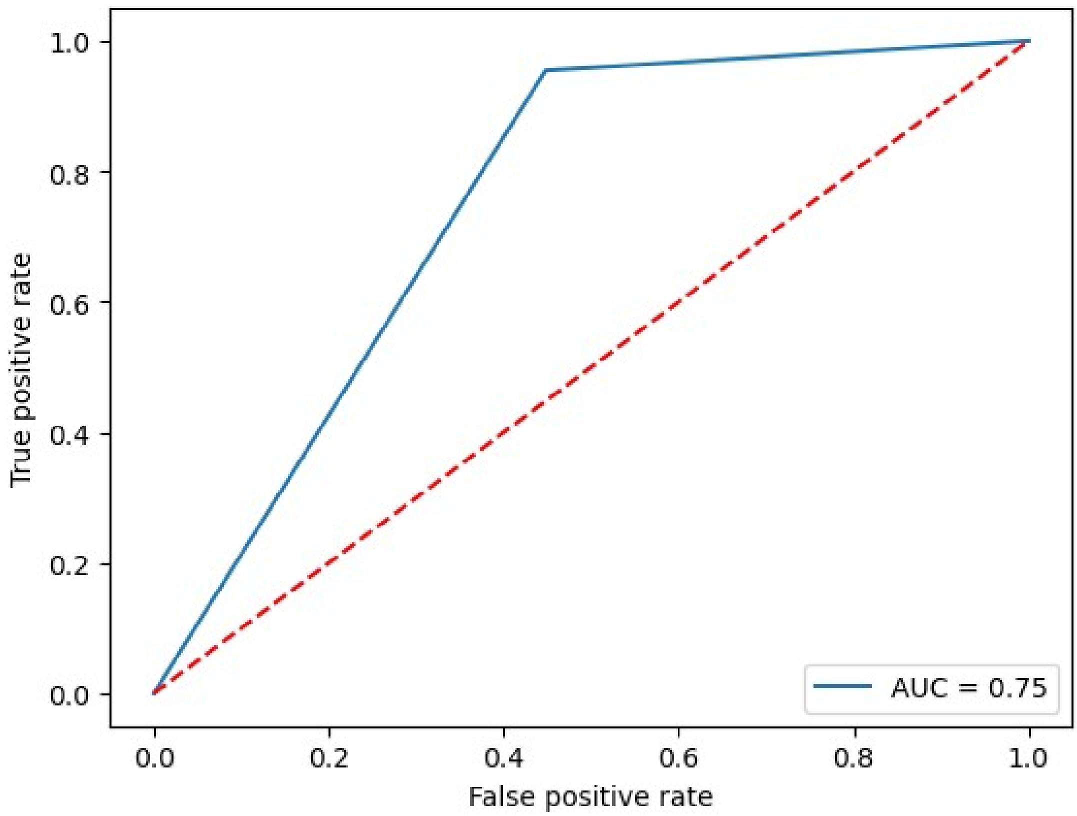
Importing Packages For Classification Algoritham

```
from sklearn.linear_model import LogisticRegression
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
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import
train_test_split,GridSearchCV,cross_val_score
from sklearn.metrics import
accuracy_score,classification_report,confusion_matrix,roc_auc_score,f1
_score,roc_curve,auc

def max_accuracy_score(clf,x,y):
    max_accuracy=0
    for i in range(42,100):

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.20,rando
m_state=0,stratify=y)
        clf.fit(x_train,y_train)
        pred=clf.predict(x_test)
        accuracy_check=accuracy_score(y_test,pred)
        if accuracy_check>max_accuracy:
            max_accuracy=accuracy_check
```

```
            final_r=i
    print('max accuracy score corresponding
to',final_r,'is',max_accuracy)
    print('\n')
    print('cross validation
score',cross_val_score(clf,x,y,scoring='accuracy').mean())
    print('\n')
    print('Standard
Deviation',cross_val_score(clf,x,y,scoring='accuracy').std())
    print('\n')
    print('F1 score',f1_score(y_test,pred))
    print('\n')
    print('Training accuracy',clf.score(x_train,y_train))
    print('\n')
    print('Test Accuracy',clf.score(x_test,y_test))
    print('\n')
    print('Confusion Matrix',confusion_matrix(y_test,pred))
    print('\n')
    print('Classification Report',classification_report(y_test,pred))
    print('\n')
    print('Roc_auc Score',roc_auc_score(y_test,pred))
    false_positive_rate, true_positive_rate, thresholds =
roc_curve(y_test,pred)
    roc_auc = auc( false_positive_rate, true_positive_rate)
    plt.plot(false_positive_rate, true_positive_rate,label = "AUC =
%0.2f"% roc_auc)
    plt.plot([0,1],[0,1],'r--')
    plt.legend(loc = 'lower right')
    plt.ylabel("True positive rate")
    plt.xlabel("False positive rate")
    print("\n\n")
    return final_r

## Logistic Regression
lg=LogisticRegression()
max_accuracy_score(lg,x,y)
```

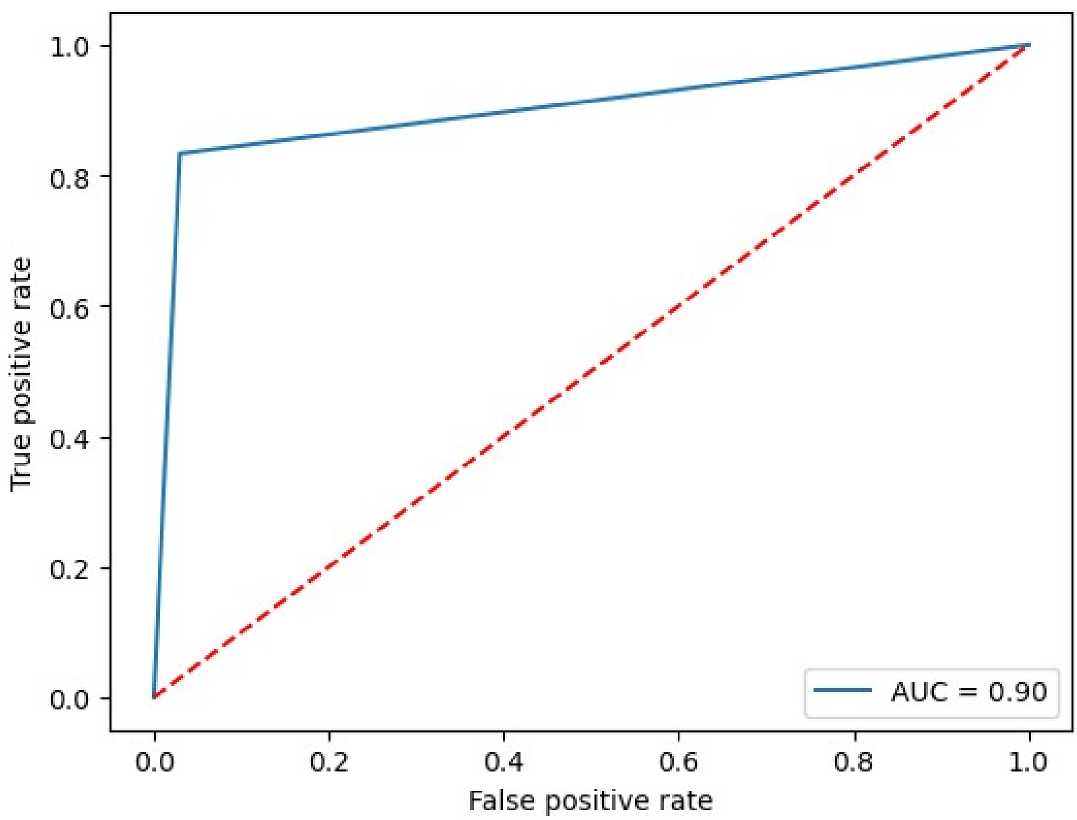
```
max accuracy score corresponding to 42 is 0.7518796992481203


cross validation score 0.7002961950330372


Standard Deviation 0.02099742331813525


F1 score 0.7924528301886793


Training accuracy 0.704331450094162
```

```
Test Accuracy 0.7518796992481203


Confusion Matrix [[37 30]
 [ 3 63]]


Classification Report               precision    recall  f1-score   support

           0       0.93      0.55      0.69        67
           1       0.68      0.95      0.79        66

    accuracy                           0.75       133
   macro avg       0.80      0.75      0.74       133
weighted avg       0.80      0.75      0.74       133



Roc_auc Score 0.7533921302578019




42
```



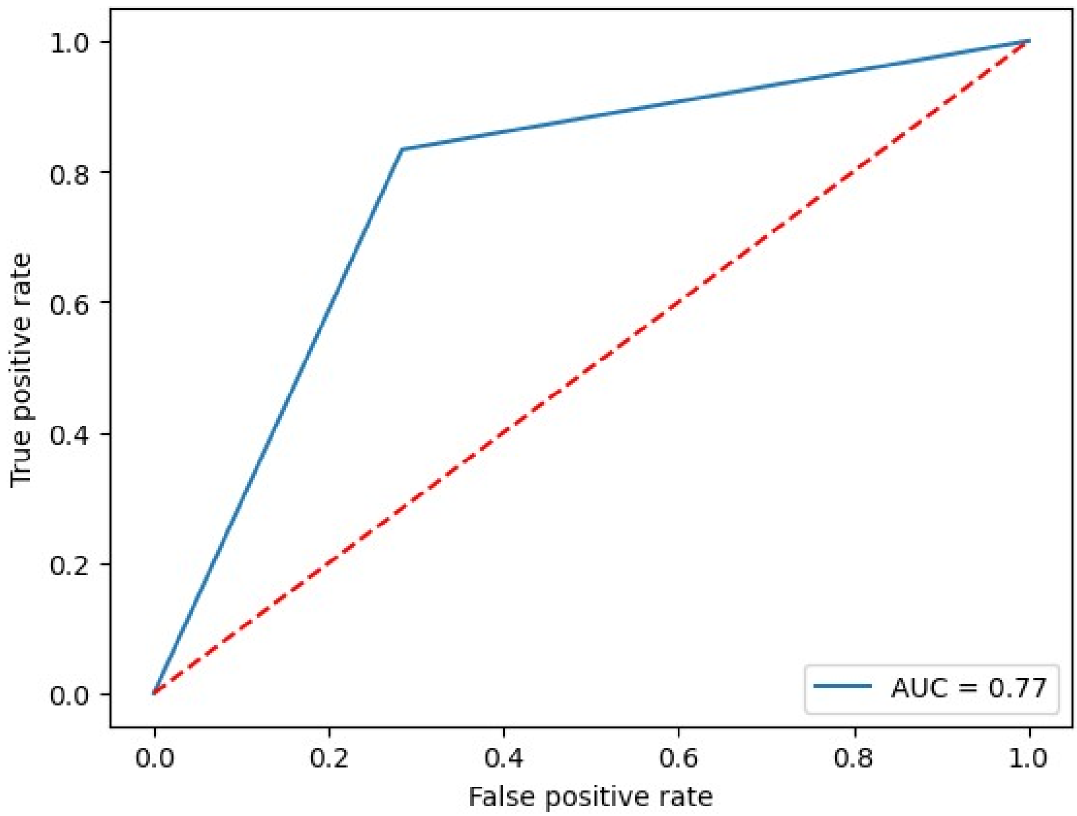

```
## DEcision Tree
dt=DecisionTreeClassifier()
max_accuracy_score(dt,x,y)

max accuracy score corresponding to 42 is 0.9097744360902256


cross validation score 0.8419685577580314


Standard Deviation 0.03704708629443282


F1 score 0.8943089430894309


Training accuracy 1.0


Test Accuracy 0.9022556390977443


Confusion Matrix [[65  2]
 [11 55]]
```

```
Classification Report               precision    recall  f1-score   support

           0       0.86      0.97      0.91        67
           1       0.96      0.83      0.89        66

    accuracy                           0.90       133
   macro avg       0.91      0.90      0.90       133
weighted avg       0.91      0.90      0.90       133



Roc_auc Score 0.9017412935323385



42
```




```
## KNn
knn=KNeighborsClassifier()
max_accuracy_score(knn,x,y)

max accuracy score corresponding to 42 is 0.7744360902255639
```

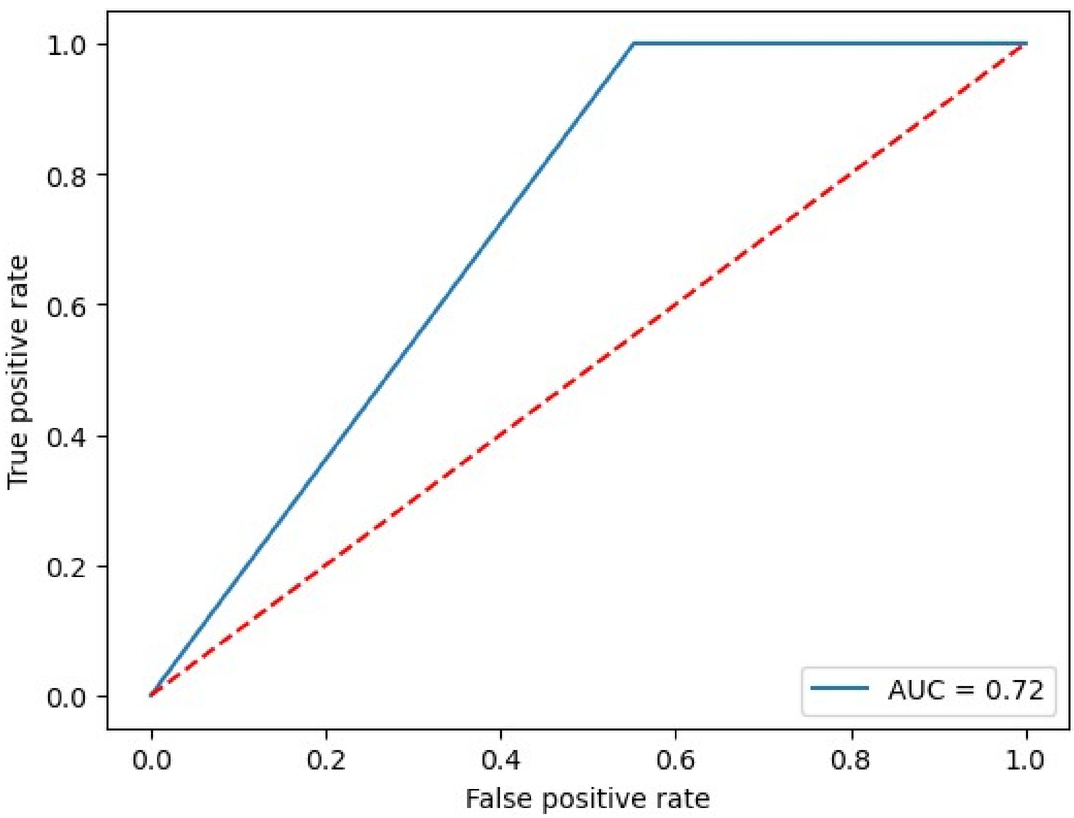
```
cross validation score 0.6672248803827752


Standard Deviation 0.023246852730769926


F1 score 0.7857142857142858


Training accuracy 0.768361581920904


Test Accuracy 0.7744360902255639


Confusion Matrix [[48 19]
 [11 55]]


Classification Report               precision    recall  f1-score
support

           0       0.81      0.72      0.76        67
           1       0.74      0.83      0.79        66

    accuracy                           0.77       133
   macro avg       0.78      0.77      0.77       133
weighted avg       0.78      0.77      0.77       133



Roc_auc Score 0.7748756218905474
```




```
##Naive Bayes
gnb=GaussianNB()
max_accuracy_score(gnb,x,y)
```

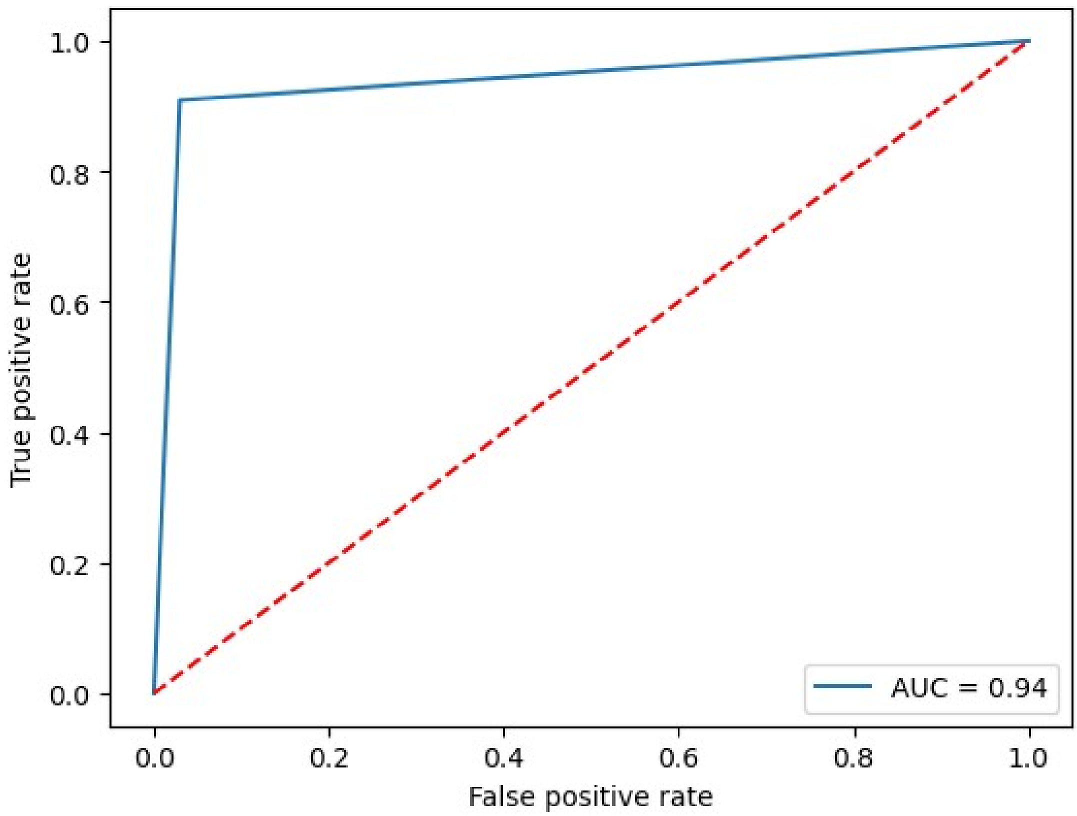
```
max accuracy score corresponding to 42 is 0.7218045112781954


cross validation score 0.7032695374800638


Standard Deviation 0.0402982757829823


F1 score 0.7810650887573964


Training accuracy 0.7024482109227872


Test Accuracy 0.7218045112781954


Confusion Matrix [[30 37]
 [ 0 66]]
```

```
Classification Report               precision    recall  f1-score   support

           0       1.00      0.45      0.62        67
           1       0.64      1.00      0.78        66

    accuracy                           0.72       133
   macro avg       0.82      0.72      0.70       133
weighted avg       0.82      0.72      0.70       133



Roc_auc Score 0.7238805970149254



42
```




```
#Random forest
rf=RandomForestClassifier()
max_accuracy_score(rf,x,y)

max accuracy score corresponding to 64 is 0.9548872180451128
```

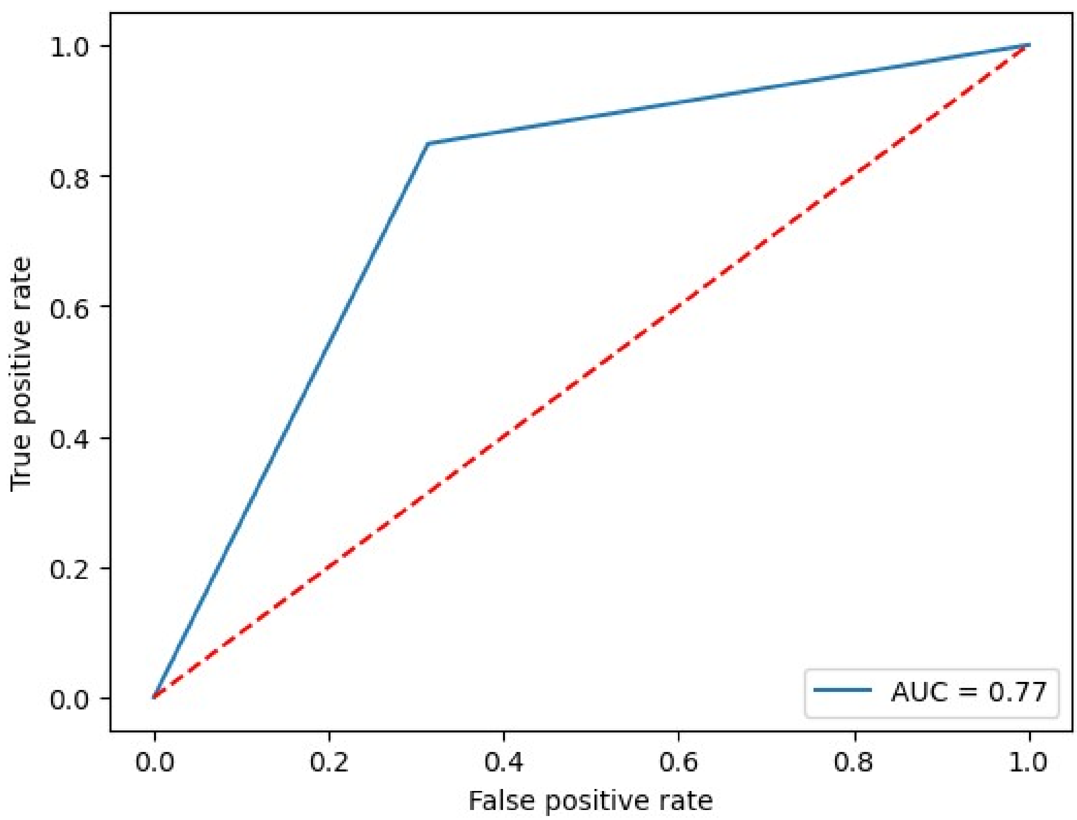
```
cross validation score 0.9021758942811575


Standard Deviation 0.0371680336995404


F1 score 0.9374999999999999


Training accuracy 1.0


Test Accuracy 0.9398496240601504


Confusion Matrix [[65  2]
 [ 6 60]]


Classification Report               precision    recall  f1-score
support

           0       0.92      0.97      0.94        67
           1       0.97      0.91      0.94        66

    accuracy                           0.94       133
   macro avg       0.94      0.94      0.94       133
weighted avg       0.94      0.94      0.94       133



Roc_auc Score 0.9396200814111263
```




```
## adaboost
Adb=AdaBoostClassifier()
max_accuracy_score(Adb,x,y)
```

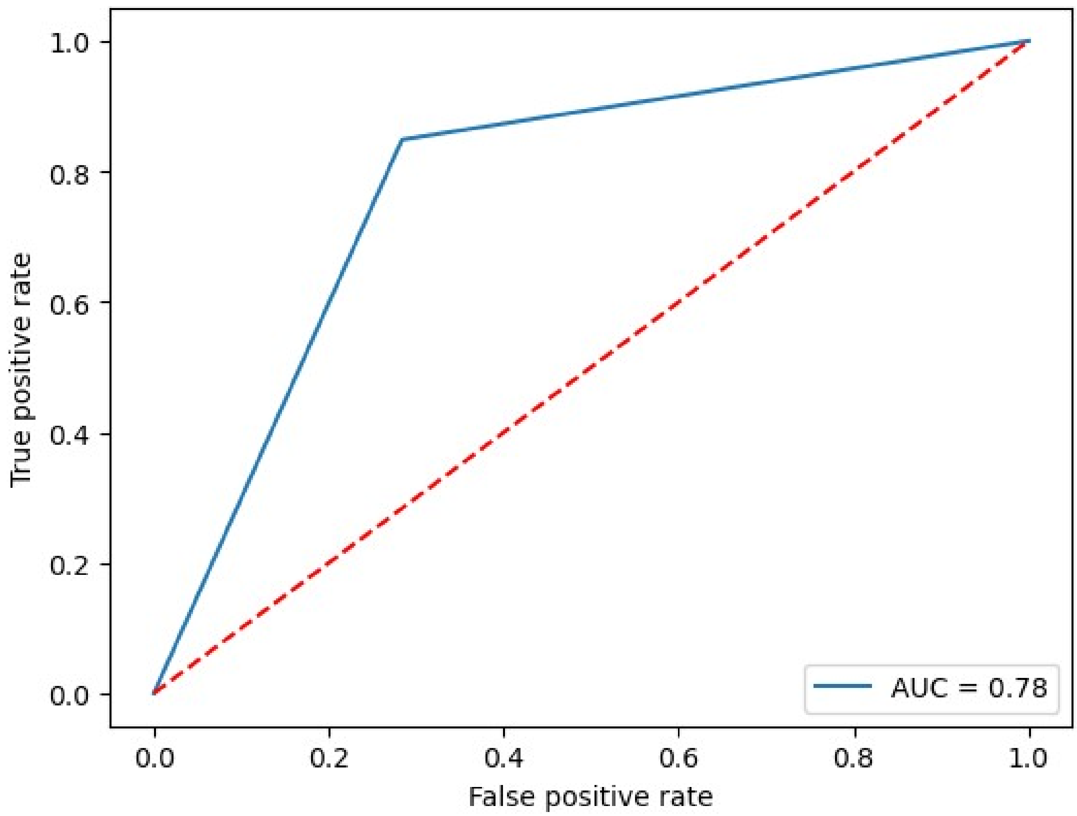
```
max accuracy score corresponding to 42 is 0.7669172932330827


cross validation score 0.722818409660515


Standard Deviation 0.027507760706141932


F1 score 0.7832167832167832


Training accuracy 0.8342749529190208


Test Accuracy 0.7669172932330827


Confusion Matrix [[46 21]
 [10 56]]
```

```
Classification Report                precision    recall  f1-score   support

           0       0.82      0.69      0.75        67
           1       0.73      0.85      0.78        66

    accuracy                           0.77       133
   macro avg       0.77      0.77      0.77       133
weighted avg       0.77      0.77      0.77       133



Roc_auc Score 0.7675260063319764



42
```




```
## Gardient Boost
gb=GradientBoostingClassifier()
max_accuracy_score(gb,x,y)

max accuracy score corresponding to 42 is 0.7819548872180451
```

```
cross validation score 0.7801321485532011


Standard Deviation 0.022624238885104613


F1 score 0.7943262411347518


Training accuracy 0.8983050847457628


Test Accuracy 0.7819548872180451


Confusion Matrix [[48 19]
 [10 56]]


Classification Report               precision    recall  f1-score
support

           0       0.83      0.72      0.77        67
           1       0.75      0.85      0.79        66

    accuracy                           0.78       133
   macro avg       0.79      0.78      0.78       133
weighted avg       0.79      0.78      0.78       133



Roc_auc Score 0.7824513794663049
```




```
best_model=pd.DataFrame({'Model':
['LogisticRegression','DecisionTreeClassifier','KNN','GaussianNB','Ran
domForestClassifier','AdaBoostClassifier','GradientBoostingClassifier'
],
                         'Accuracy Score':
[0.75,0.90,0.77,0.72,0.95,0.76,0.78],
                         'F1_Score':
[0.70,0.84,0.66,0.73,0.90,0.72,0.78],
                         'Cross_validation':
[0.79,0.89,0.78,0.78,0.93,0.78,0.79]})
best_model

                        Model  Accuracy Score  F1_Score
Cross_validation
0          LogisticRegression            0.75      0.70
0.79
1      DecisionTreeClassifier            0.90      0.84
0.89
2                         KNN            0.77      0.66
0.78
3                  GaussianNB            0.72      0.73
0.78
4      RandomForestClassifier            0.95      0.90
0.93
```

```
5          AdaBoostClassifier            0.76      0.72
0.78
6  GradientBoostingClassifier            0.78      0.78
0.79
```

conclusion:

Based on above graph, It is clear that Random Forest is Most generalised model among all because it has highest accuracy and the difference between Accuracy Score and cross validation score is miminum. So this would be our best model to predict the loan approval status.