Loan Application Status Prediction

Importing necessary Libraries

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

Importing the dataset

In [2]:
```
# reading the csv file from dataset
df = pd.read_csv('loan_application.csv')
df
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapp
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	
...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	
610	LP002979	Male	Yes	3+	Graduate	No	4106	
611	LP002983	Male	Yes	1	Graduate	No	8072	
612	LP002984	Male	Yes	2	Graduate	No	7583	
613	LP002990	Female	No	0	Graduate	Yes	4583	

614 rows × 13 columns

- The dataset contains both numerical and categorical columns .
- This dataset includes details of applicants who have applied for loan. The dataset inclueds details like credit history, loan amount, their income, dependents etc.
- Here "Loan_Status" is our target variable which has two classes 'yes' and 'no' . So it will be termed as Classification provlem

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

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplic
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	

- This is the top 5 rows o fthe data set.

EDA

In [4]:
```
# checking the dimension of dataset
df.shape
```

Out[4]:
```
(614, 13)
```

- The dataset contains 614 rows and 13 comumns which inclues both categoricla and numerical data .
- Also out of 13 columns 12 are features and remaining 1 is our target variable .

In [5]:
```
# checking the type of dataset
df.dtypes
```

Out[5]:
```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

- The dataset contains object , integer and float type of data.

Since we have object data type so will take care of them by using appropriate encoding methods.

In [6]:
```python
# checking for categorical columns
categorical_col=[]
for i in df.dtypes.index:
    if df.dtypes[i]=='object':
        categorical_col.append(i)
print(categorical_col)
```

```
['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
'Property_Area', 'Loan_Status']
```

- These are the categorical columns in the given dataset.

In [7]:
```python
# now checking for numerical columns
numerical_col=[]
for i in df.dtypes.index:
    if df.dtypes[i]!='object':
        numerical_col.append(i)
print(numerical_col)
```

```
['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'C
redit_History']
```

- These are the numerical columns present in the dataset .

The columns 'Loan_Amount_Term' and 'Credit_History' have categories in integer data type so they aslo comes under categorical type.

In [8]:
```python
# to get good overview of the 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
```

- This gives the information about the dataset which inclues indexing type, column type, no-null values and memory usage.

Here we can observe the missing values in some columns will treat them later.

In [9]:
```
# checking number of unique values in each columns
df.nunique()
```

Out[9]:
```
Loan_ID              614
Gender                 2
Married                2
Dependents             4
Education              2
Self_Employed          2
ApplicantIncome      505
CoapplicantIncome    287
LoanAmount           203
Loan_Amount_Term      10
Credit_History         2
Property_Area          3
Loan_Status            2
dtype: int64
```

- These are the unique values present in the columns

Let's check the list of value counts in each columns to find if there are any unexpected or corrupted entries in the dataset.

In [10]:
```python
# checking the value counts of each columns
for i in df.columns:
    print(df[i].value_counts())
    print('************************************************************')
```

```
LP002933    1
LP002158    1
LP001634    1
LP001926    1
LP002863    1
           ..
LP002862    1
LP001020    1
LP002403    1
LP002101    1
LP001894    1
Name: Loan_ID, Length: 614, dtype: int64
************************************************************
Male      489
Female    112
Name: Gender, dtype: int64
************************************************************
Yes    398
No     213
Name: Married, dtype: int64
************************************************************
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
************************************************************
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
************************************************************
No     500
Yes     82
Name: Self_Employed, dtype: int64
************************************************************
2500    9
4583    6
2600    6
6000    6
5000    5
       ..
5818    1
5819    1
5821    1
2750    1
3691    1
Name: ApplicantIncome, Length: 505, dtype: int64
************************************************************
0.0       273
1666.0      5
2083.0      5
2500.0      5
1750.0      3
         ...
7166.0      1
2138.0      1
2166.0      1
```

```
3541.0      1
3021.0      1
Name: CoapplicantIncome, Length: 287, dtype: int64
************************************************************
120.0    20
110.0    17
100.0    15
187.0    12
160.0    12
         ..
570.0     1
300.0     1
376.0     1
117.0     1
311.0     1
Name: LoanAmount, Length: 203, dtype: int64
************************************************************
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
************************************************************
1.0    475
0.0     89
Name: Credit_History, dtype: int64
************************************************************
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
************************************************************
Y    422
N    192
Name: Loan_Status, dtype: int64
************************************************************
```

- These are the list of value counts present in each columns.

The column Loan_ID is the unique ID given to the applicants also it has no significant in the prediction so let's drop this column

In [11]:
```
# removing unwanted column
df.drop("Loan_ID", axis=1,inplace=True)
```

In [12]:
```python
# checking null values in the dataframe
df.isnull().sum()
```

Out[12]:
```
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
```

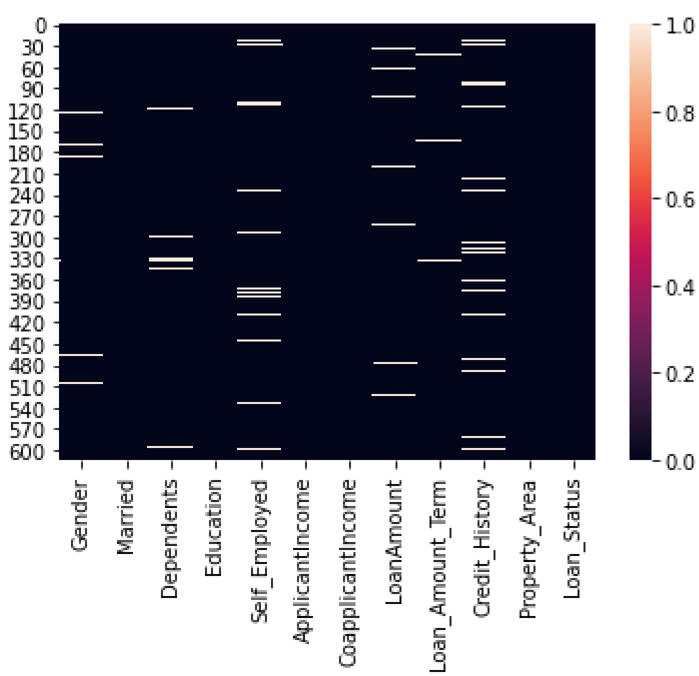
We can observe the missing values in the columns

- Gender
- Married
- Dependents-Self-Employed
- LoanAmount
- Loan-Amount-Term
- Credit-History

We fill them using imputation technique

In [13]:
```python
# let's visualize the null values clearly
sns.heatmap(df.isnull())
```

Out[13]:
```
<AxesSubplot:>
```



- The white lines in the heat map represent the missing values in the dataset

In [14]:
```
df.skew()
```

Out[14]:
```
ApplicantIncome      6.539513
CoapplicantIncome    7.491531
LoanAmount           2.677552
Loan_Amount_Term    -2.362414
Credit_History      -1.882361
dtype: float64
```

Treating null values using imputation technique

There are both categorical and numerical columns which have missing values, so will fill them by using appropriate methods.

- The features Gender, Married, Dependents, Self_Employed, Loan_Amount_Term and Credit_History are seems to be categorical so will fill the missing values using their mode values.

In [15]:
```
# let's check the mode of the categorical columns to fill the null values

print("The mode of Gender  is:",df['Gender'].mode())        # we will fill the
print("The mode of Married  is:",df['Married'].mode())
print("The mode of Dependents  is:",df['Dependents'].mode())
print("The mode of Self_Employed  is:",df['Self_Employed'].mode())
print("The mode of Credit_History  is:",df['Credit_History'].mode())
print("The mode of Loan_Amount_Term  is:",df['Loan_Amount_Term'].mode())
```

```
The mode of Gender  is: 0    Male
dtype: object
The mode of Married  is: 0    Yes
dtype: object
The mode of Dependents  is: 0    0
dtype: object
The mode of Self_Employed  is: 0    No
dtype: object
The mode of Credit_History  is: 0    1.0
dtype: float64
The mode of Loan_Amount_Term  is: 0    360.0
dtype: float64
```

- These are modes of the categorical columns which contains null values.

These are the values which are highly repeated in the columns.

The missing values will be replaced by their respective mode values.

In [16]:
```
# Filling the missing values in Gender by its mode Male
df["Gender"] = df["Gender"].fillna(df["Gender"].mode()[0])

# Filling the missing values in Married by its mode Yes
df["Married"] = df["Married"].fillna(df["Married"].mode()[0])

# Filling the missing values in Dependents by its mode 0
df["Dependents"] = df["Dependents"].fillna(df["Dependents"].mode()[0])

# Filling the missing values in Self_Employed by its mode No
df["Self_Employed"] = df["Self_Employed"].fillna(df["Self_Employed"].mode()[0])

# Filling the missing values in Credit_History  by its mode  No
df["Credit_History"] = df["Credit_History"].fillna(df["Credit_History"].mode()[

# Filling the missing values in Loan_Amount_Term  by its mode 360
df["Loan_Amount_Term"] = df["Loan_Amount_Term"].fillna(df["Loan_Amount_Term"].m
```

- So here we have filled the missing values in the categorical columns using mode method.

let's check the null values now.

In [17]:
```
df.isnull().sum()
```

Out[17]:
```
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term      0
Credit_History        0
Property_Area         0
Loan_Status           0
dtype: int64
```

- Here LoanAmount is continuous in nature also has skewness which means it has outliers, so will fill the null values using median method.

Now let's fill the null values in numerical columns

In [18]:
```
# let's check the median values of the numerical columns
print("The median of LoanAmount is:", df["LoanAmount"].median())
```

```
The median of LoanAmount is: 128.0
```

The median values of LoanAmount is 128.0 let's fill the null values using median method.

In [19]:
```
df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].median())
```

We have filled the null values in all the coluns. let's check it

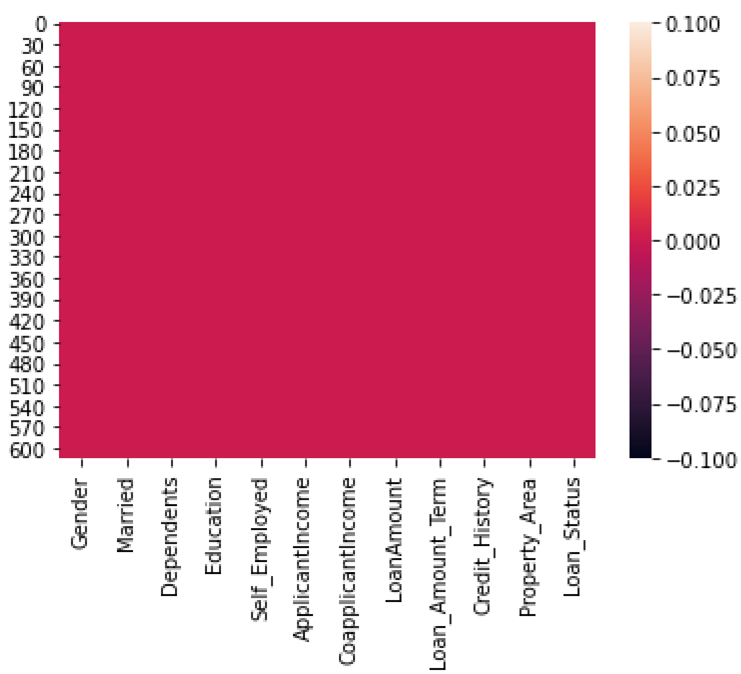
In [20]:
```
df.isnull().sum()
```

Out[20]:
```
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
```

Now our data is free from null values and is cleaned.

In [21]:
```
# let's visualize the null values clearly
sns.heatmap(df.isnull())
```

Out[21]: <AxesSubplot:>



So it is clear that there are no missing values anymore.

In [22]:
```python
df.columns
```

Out[22]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

These are the columns present in the dataset.

In [23]:
```python
# checking the uniqueness of primary_fuel
df['Loan_Status'].unique()
```

Out[23]:
```
array(['Y', 'N'], dtype=object)
```

These are the unique values present in the target column

In [24]:
```python
# checking the list of counts in target columns
df['Loan_Status'].value_counts()
```

Out[24]:
```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

- We have 2 counts in Loan_Status namely 'Y' and 'N'. Here 'Y' stands for 'Yes' that is the loan of the applicant is approved and 'N' stands for 'No' that is the loan of the applicant is not approved.
- Here loan approved has high counts than loan not approved.

In [25]:
```python
# checking wheather the dataset contains any space
df.loc[df['Loan_Status']==" "]
```

Out[25]:

Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome

It seems that there are no spaces in the dataset.

Description of DataSet

In [26]:
```
# Statistical summary of dataset
df.describe()
```

Out[26]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	145.752443	342.410423	0.855049
std	6109.041673	2926.248369	84.107233	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	128.000000	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

This gives the statistical information of the dataset

- The summary of this dataset looks perfect since there is no negative/invalid vlaues present it gives the summary of nunerical data.

From the above description we can observe the following things :

- The counts of all the columns are same which means there are no null values present in the dataset.
- The mean value is greater than the median(50%) in ApplicatIncome, CoapplicantIncome, LoanAmount, which means they are skewed to right.
- The median is greater than the mean in Loan_Amount_Term and Credit_History which means they are skewed to left.
- There is a huge difference between mean and the standard deviation.
- In Summarizing the data we can infer that there is a huge difference in max and 75% percentile means there are huge outliers present in the dataset .

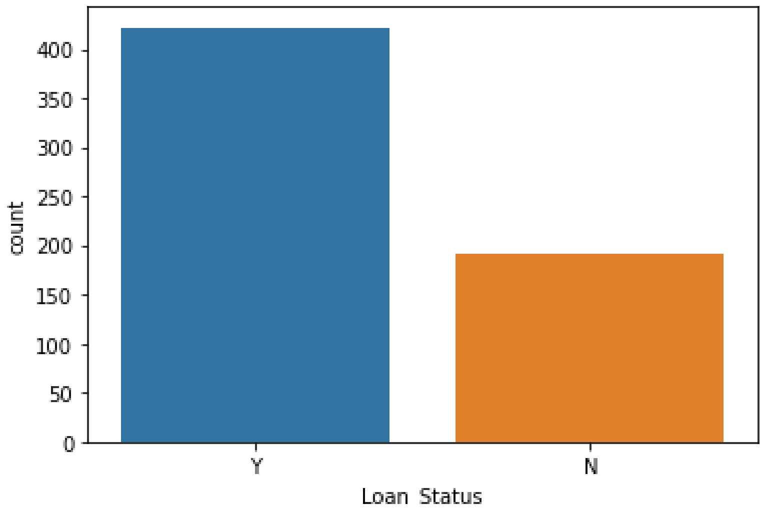
We will remove these outliers using ZSCORE or IQR method in later part.

Data Visualization

Univariate Analysis

In [27]:
```
# visualizing the loan approval status
print(df['Loan_Status'].value_counts())
sns.countplot(df['Loan_Status'])
plt.show()
```

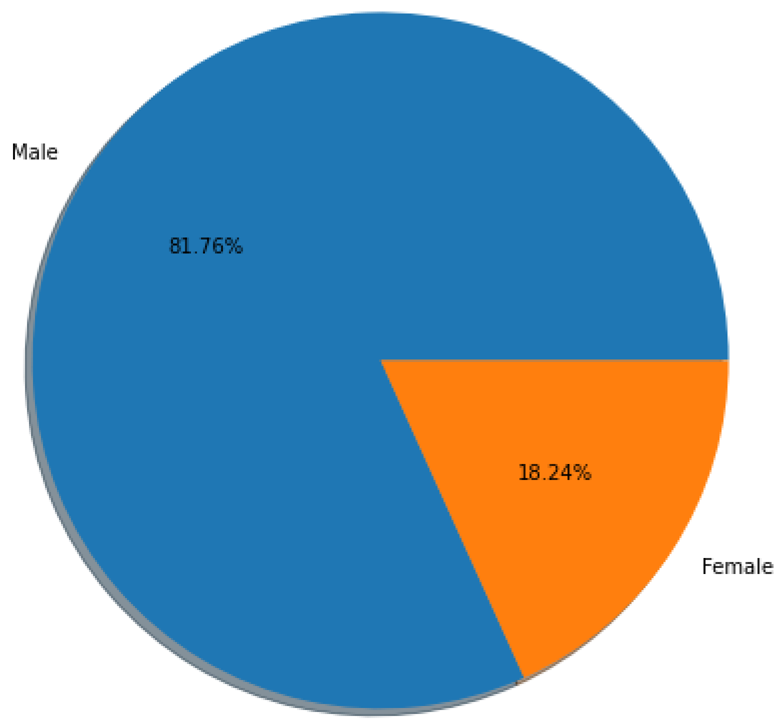
```
Y    422
N    192
Name: Loan_Status, dtype: int64
```



- The count of 'Y' is maximum compare to 'N' that means total 422 applicants get their loan approved and only 192 applicants gets dinied due to some reason.
- We can also notice the class imbalancing issue here, So we can use oversampling method just to increase the instances of minority class.

In [28]:
```
# Visualize the count of applicants Gender
print(df['Gender'].value_counts())
labels='Male','Female'
fig, ax = plt.subplots(figsize=(10,8))
ax.pie(df['Gender'].value_counts(), labels=labels, autopct='%1.2f%%', shadow=Tr
plt.show()
```

```
Male      502
Female    112
Name: Gender, dtype: int64
```

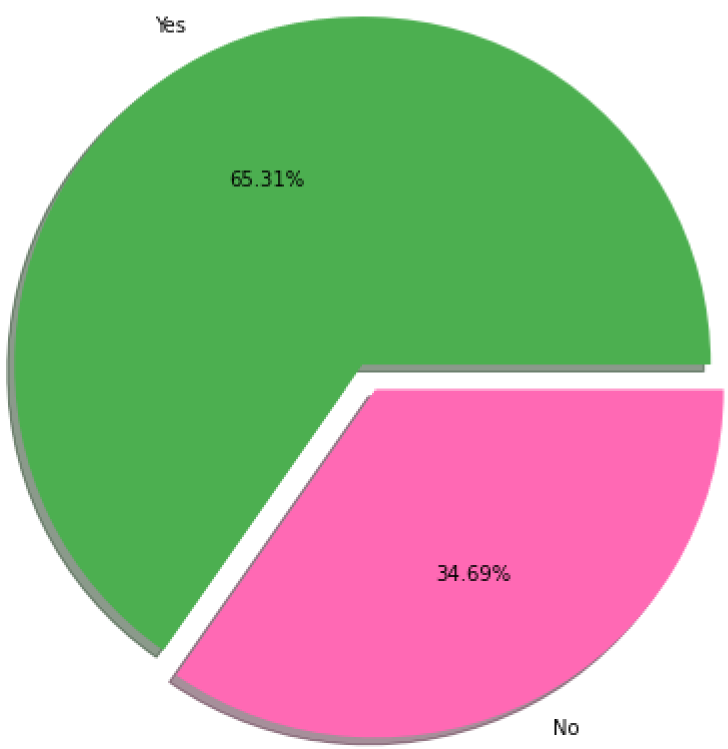


There are more number of Male applicants applying for loan than Female applicants.

There are about 81% of the Male candidates and only 18% of Female candidates are applying for the loan.

In [29]:
```
# Visualize the count of marital status of the applicants
print(df['Married'].value_counts())
labels='Yes','No'
colors = ['#4CAF50', 'hotpink']
fig, ax = plt.subplots(figsize=(10,8))
ax.pie(df['Married'].value_counts(), labels=labels, autopct='%1.2f%%', shadow=T
plt.show()
```

```
Yes    401
No     213
Name: Married, dtype: int64
```

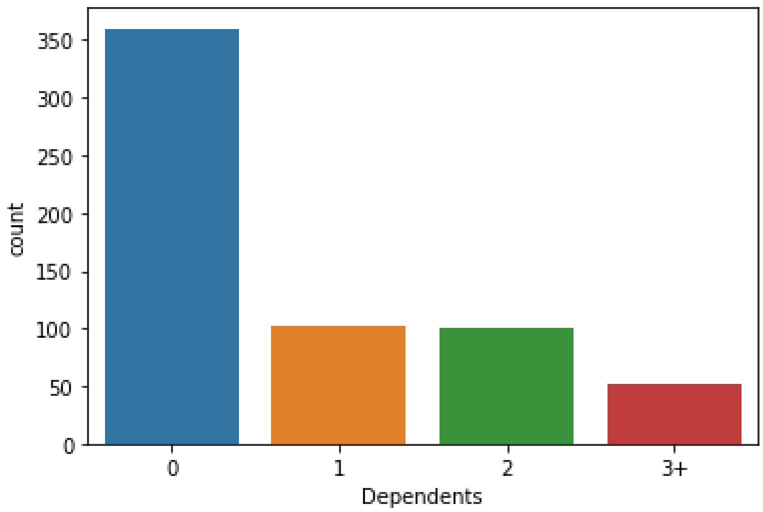


The numbeer of Married applicants who are applying for loan is higher than Unmarried applicants.

- There are about 65% of the applicants who got married and about 34% of the applicants are singles

In [30]:
```
# Visualize the count of Dependents
print(df['Dependents'].value_counts())
sns.countplot(df['Dependents'])
plt.show()
```

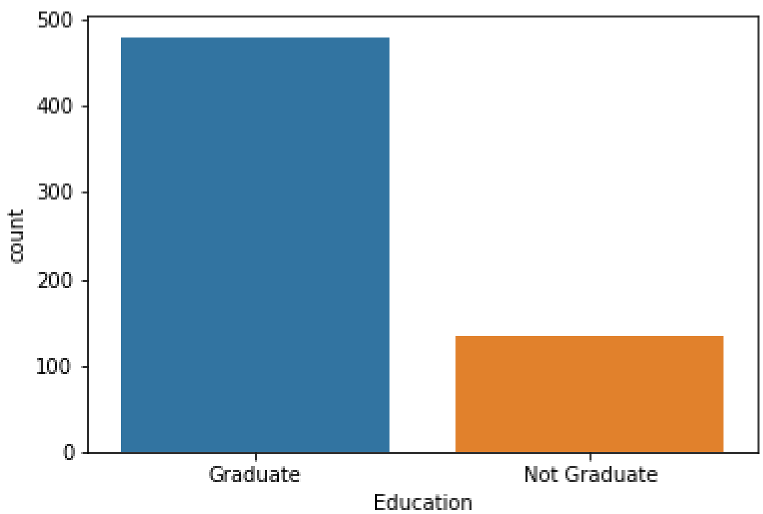
```
0     360
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```



The applicants who have 0 dependents have high counts and the applicants having more than 3 dependents counts are very less.

In [31]:
```
# visualizing the count of Education of the applicants

print(df['Education'].value_counts())
sns.countplot(df['Education'])
plt.show()
```

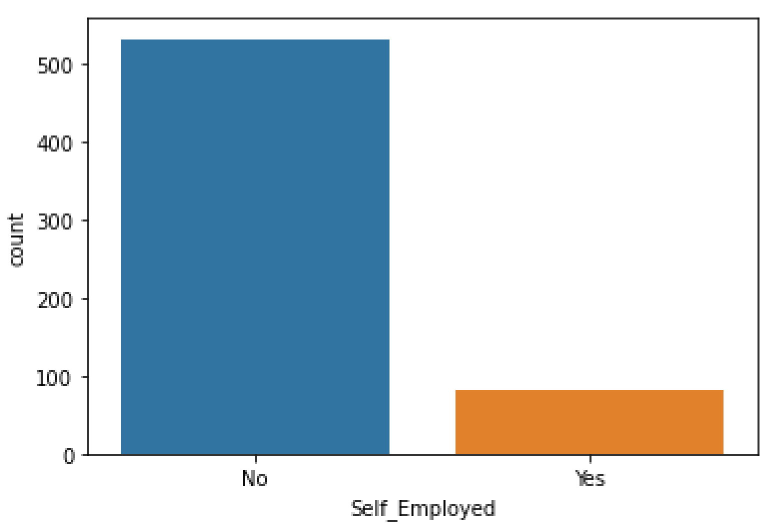
```
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```



- The count of Graduate applicants is high in counts means the maximum number of Graduated applicants are applying for the loan.

In [32]:
```
# visualizing the count of Self_Employed applicants

print(df['Self_Employed'].value_counts())
sns.countplot(df['Self_Employed'])
plt.show()
```

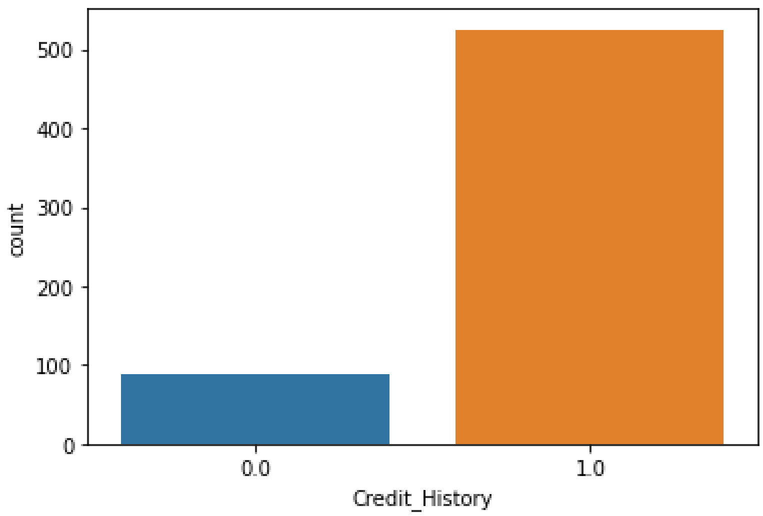
```
No     532
Yes     82
Name: Self_Employed, dtype: int64
```



- Most of the applicants or not self employed that means they might working in the public sectors and only 82 applicants are self employed and running their own business.

In [33]:
```
# visualizing the count of Credit_History of the applicants

print(df['Credit_History'].value_counts())
sns.countplot(df['Credit_History'])
plt.show()
```

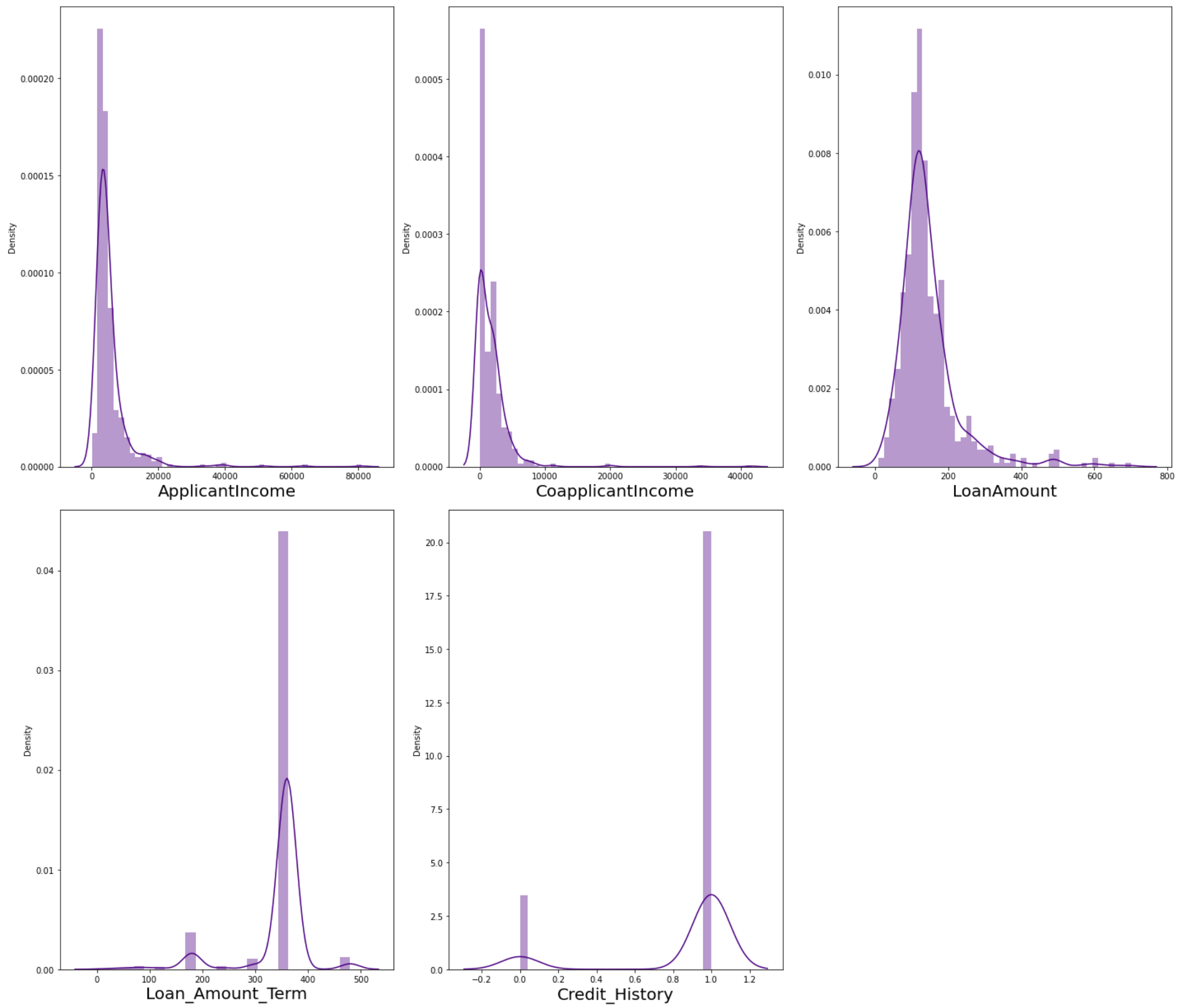
```
1.0    525
0.0     89
Name: Credit_History, dtype: int64
```



- Most of the applicants who have credit history 1 are high in numbers

Distribution of Skewness

In [34]:
```python
# checking how the data has been distributed in each column

plt.figure(figsize=(20,25),facecolor='White')
plotnumber=1
for column in numerical_col:
    if plotnumber<=9:
        ax=plt.subplot(3,3,plotnumber)
        sns.distplot(df[column],color='indigo')
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.tight_layout()
```



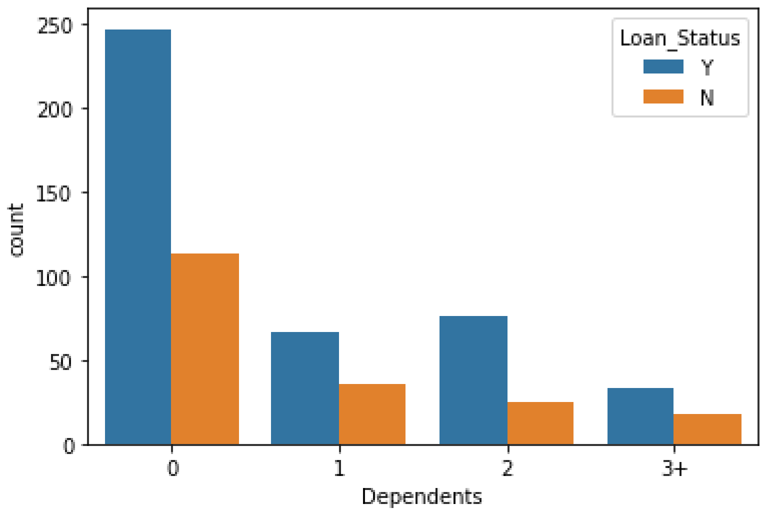
From above distribution plot we can observe :

- The data is not normally distributed in any of the columns.
- The mean value is greater than the median in ApplicatIncome, CoapplicantIncome, LoanAmount and ToalIncome which means they are skewed to right.
- The median is greater than the mean in Loan_Amount_Term and Credit_History columns which means they are skewed to left.

We will remove these skewness usnin appropriate method in the later part.

Bivariate Analysis

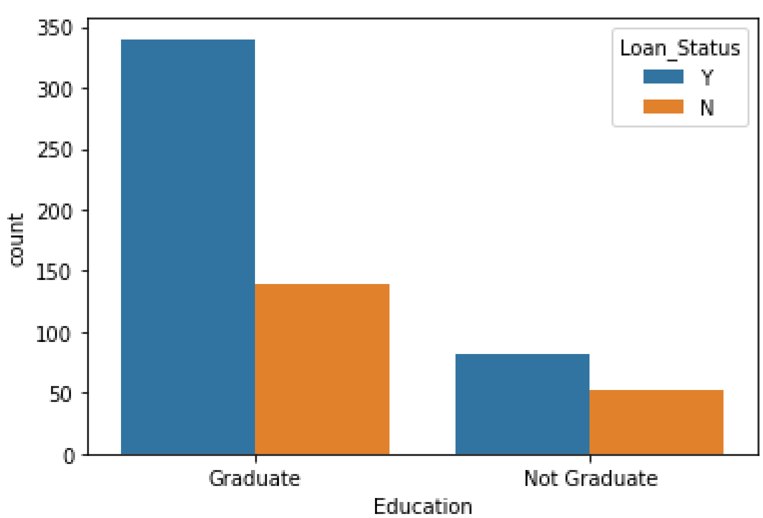
In [35]:
```
# visualizing count  of Dependents of the applicants on the basis of Loan Statu
sns.countplot(df['Dependents'],hue=df['Loan_Status'])
plt.show()
```



- The counts of 0 dependents is high which means most of the applicants have no dependents . Having dependents means having commitments. The 3+ dependents means more than 3 applicants have dependents.
- The applicants who have dependents 0 are more likely to get their loan approved.

In [36]:
```
# visualizing count  of Education of the applicants
print(df['Education'].value_counts())
sns.countplot(df['Education'],hue=df['Loan_Status'])
plt.show()
```

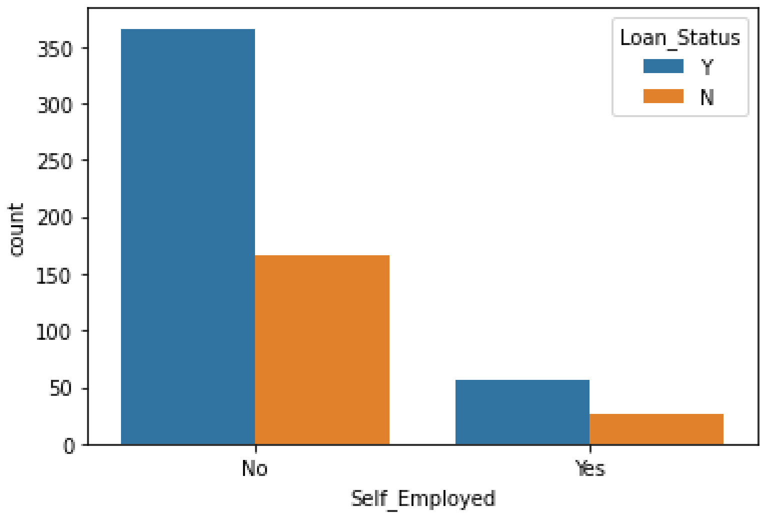
```
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```



- Most of the applicants who are applying for loan are graduated and only few are not graduated. Also the applicants who are graduated have tendency of getting loans than who are not.

In [37]:
```python
# visualizing whether the applicants are Self_Employed or not
print(df['Self_Employed'].value_counts())
sns.countplot(df['Self_Employed'],hue=df['Loan_Status'])
plt.show()
```

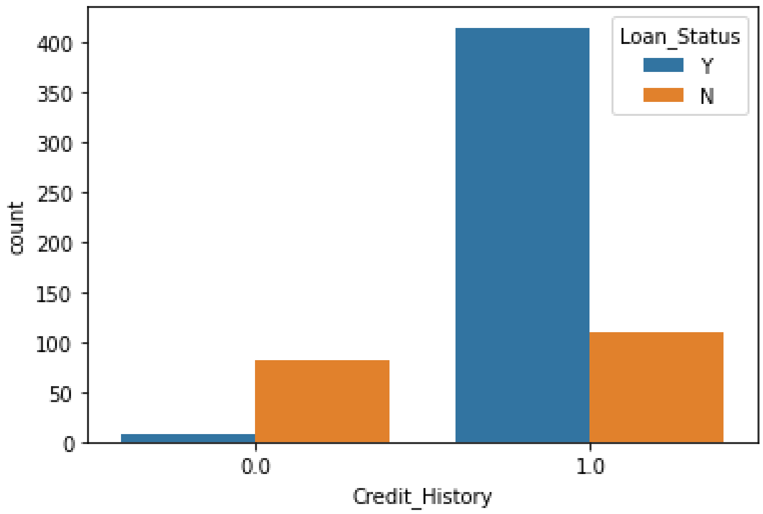
```
No     532
Yes     82
Name: Self_Employed, dtype: int64
```



- Most of the applicants are not Self_Employed means they are working in public sectors and only few of the applicants are Self_Employed
- The applicants who are not self employed have the tendancy of getting their loans than self employed applicants.

In [38]:
```python
# visualizing the count of the Credit_History of the applicants
print(df['Credit_History'].value_counts())
sns.countplot(df['Credit_History'],hue=df['Loan_Status'])
plt.show()
```

```
1.0    525
0.0     89
Name: Credit_History, dtype: int64
```



- The Credit_History gives the information of the applicants who took in the past have cleared or not. Here we can notice the applicants who have credit history 1 have high counts which means most of the applicants have cleared their past loan only few of them have to clear the loan.
- The applicants who have credit history 1 have got their loan approval which means they have cleared their past loans.

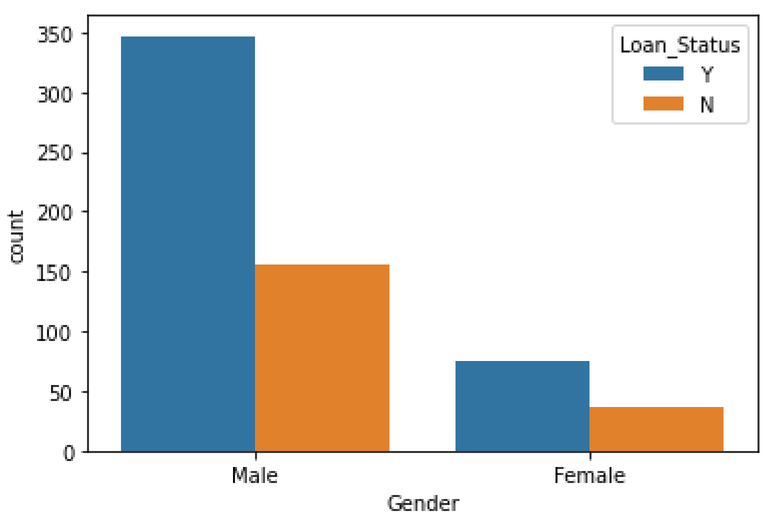
In [39]:
```
# visualizing Property_Area of th eapplicants
print(df['Property_Area'].value_counts())
sns.countplot(df['Property_Area'],hue=df['Loan_Status'],palette='husl')
plt.show()
```

```
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```

Most of the applicants from the Semiurban are applying for loan followed by Urban area. Also they have more chance of getting their loan approval.

In [40]:
```
# visualizing Gender of  the applicants
print(df['Gender'].value_counts())
sns.countplot(df['Gender'],hue=df['Loan_Status'])
plt.show()
```

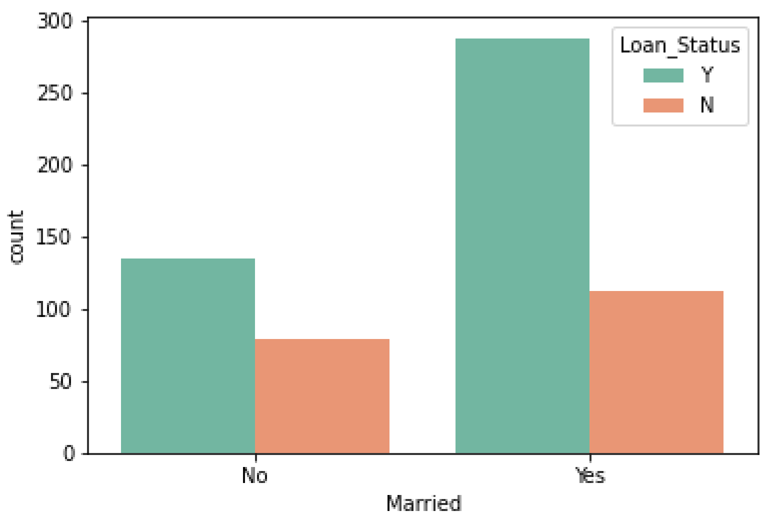
```
Male      502
Female    112
Name: Gender, dtype: int64
```



- The male applicnats who have applied for the loan have got approved compared to the female applicants

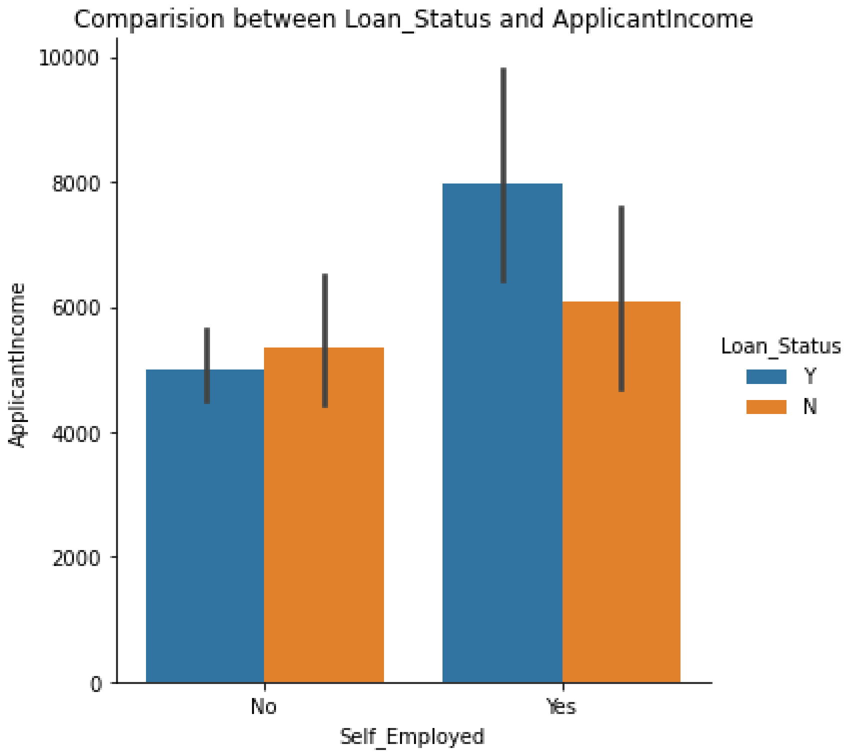
In [41]:
```
# visualizing Married status of the applicants
print(df['Married'].value_counts())
sns.countplot(df['Married'],hue=df['Loan_Status'],palette="Set2")
plt.show()
```

```
Yes    401
No     213
Name: Married, dtype: int64
```



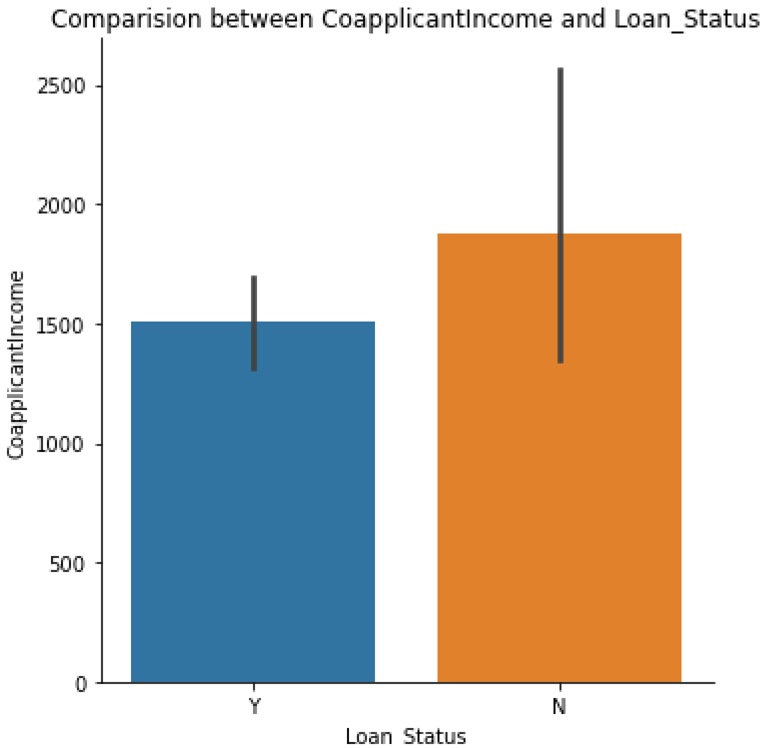
- There are more number of Male applicants who are applying for loan than compared to Female applicants. Also more Male candidates loans got approved compared to Female.

In [42]:
```
# checking relation between Self_Employed and ApplicantIncome
sns.catplot(x='Self_Employed',y='ApplicantIncome',data=df,kind='bar',hue='Loan_
plt.title("Comparision between Loan_Status and ApplicantIncome")
plt.show()
```



- The applicants whose loan got approved have average income and have their own business means they are self employed

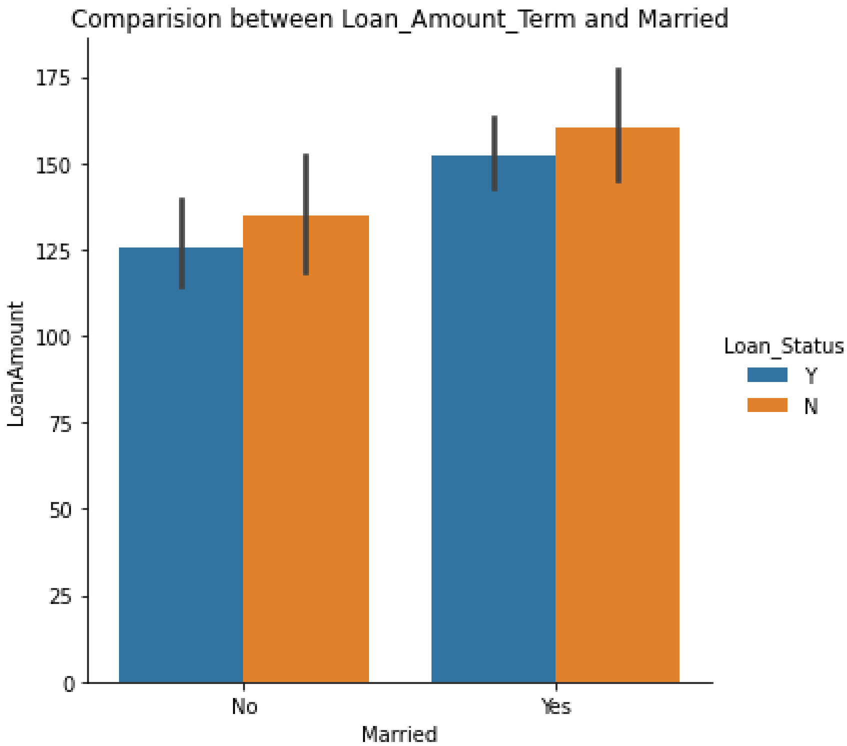
In [43]:
```
# checking relation between Loan_Status and CoapplicantIncome
sns.catplot(x='Loan_Status',y="CoapplicantIncome",data=df,kind='bar')
plt.title("Comparision between CoapplicantIncome and Loan_Status")
plt.show()
```



- The coapplicants who got loan have average income

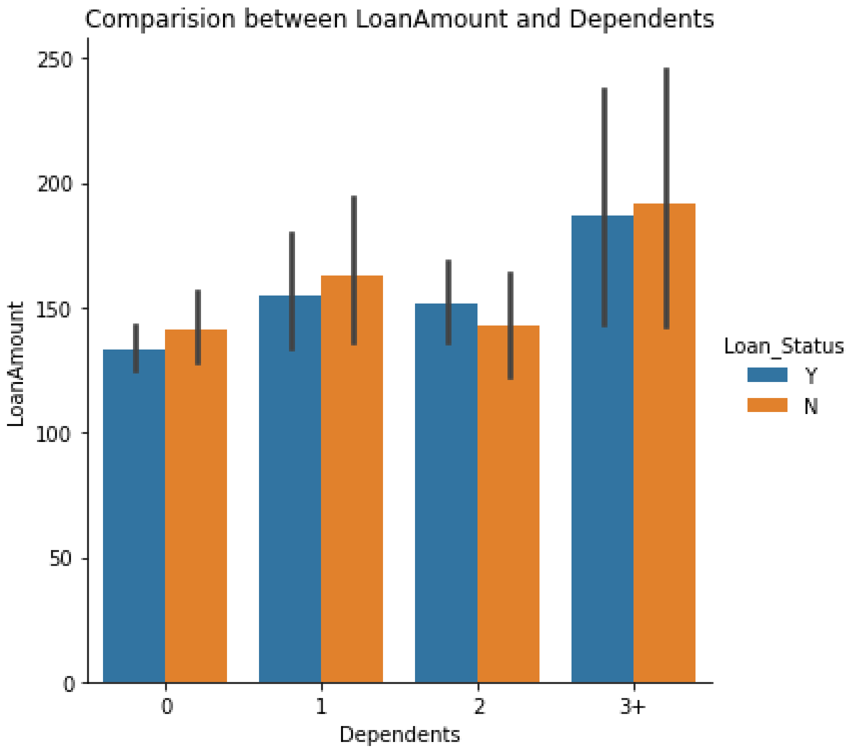
In [44]:

```
# checking relation between LoanAmount and Married on the basis of target
sns.catplot(x='Married',y="LoanAmount",data=df,kind='bar',hue="Loan_Status")
plt.title("Comparision between Loan_Amount_Term and Married")
plt.show()
```



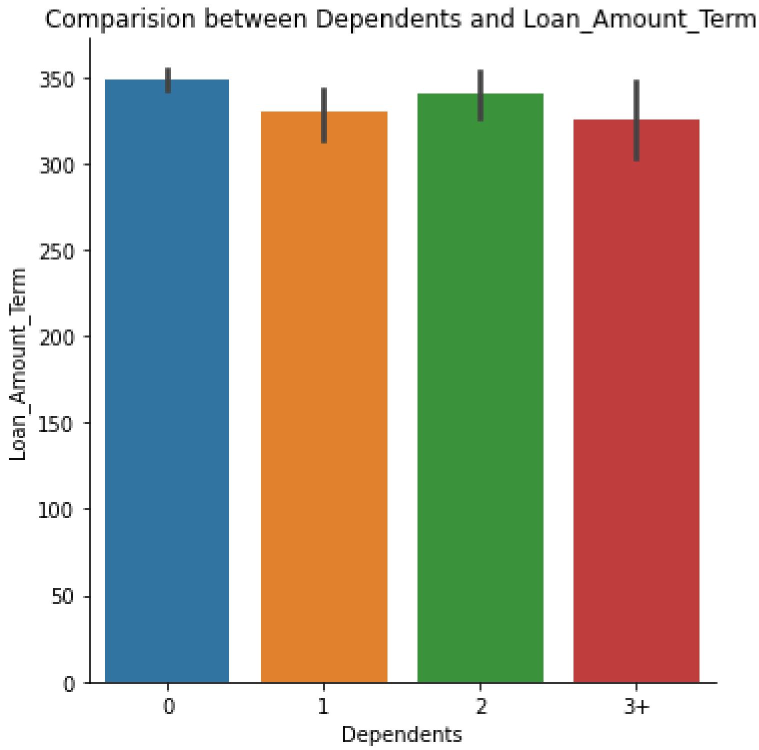
- The applicant who got married and have average loan amount have more tendency to getting loan

In [45]:
```
# checking relation between Loan_Amount and Dependents on the basis of target
sns.catplot(x='Dependents',y="LoanAmount",data=df,kind='bar',hue='Loan_Status')
plt.title("Comparision between LoanAmount and Dependents")
plt.show()
```



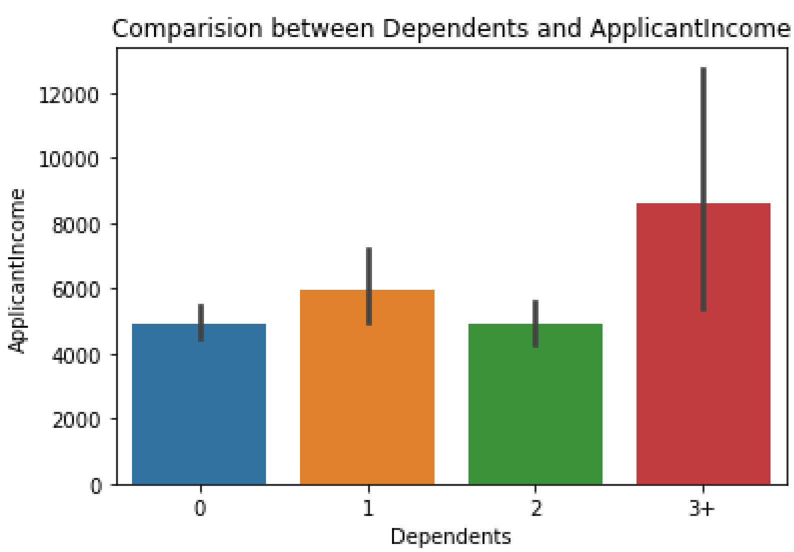
- The applicants who have more than 3 dependents with average loan amount have got their loan approved.

In [46]:
```
# checking relation between Loan_Amount_Term and Dependents
sns.catplot(x='Dependents',y="Loan_Amount_Term",data=df,kind='bar')
plt.title("Comparision between Dependents and Loan_Amount_Term")
plt.show()
```



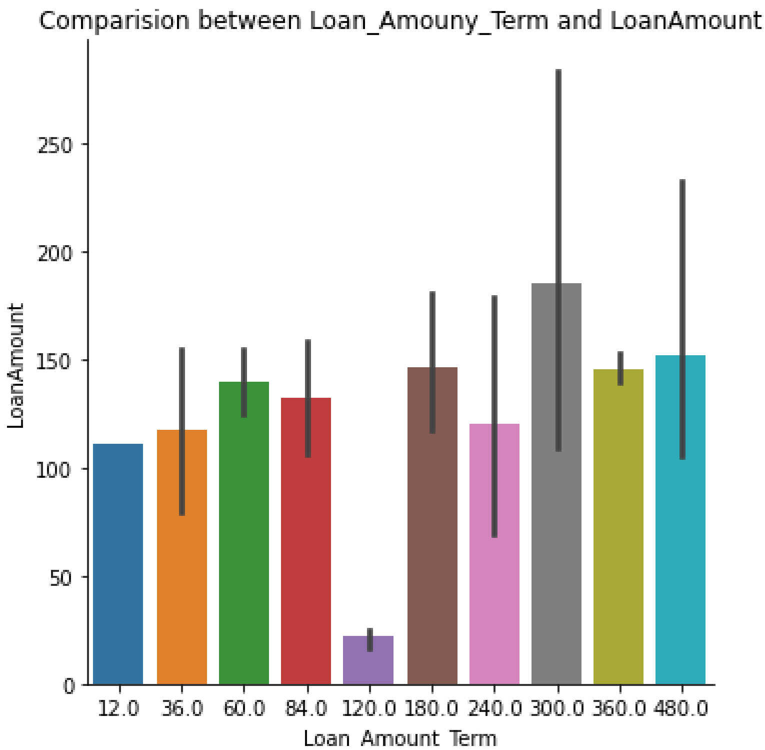
- The applicants 0 dependents have high Loan amount term followed by the dependents 2

In [47]:
```
# let's check the applicant income as per Dependents
sns.barplot(x='Dependents',y="ApplicantIncome",data=df)
plt.title("Comparision between Dependents and ApplicantIncome")
plt.show()
```



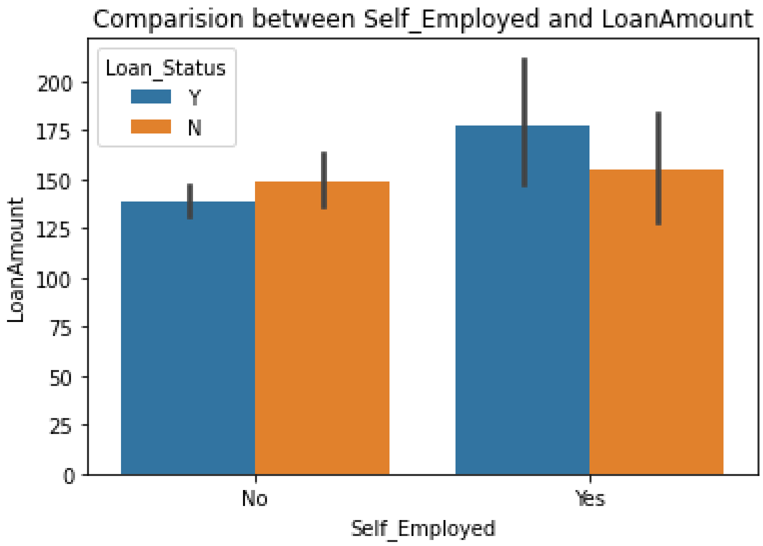
- The applicants dependents more than 3 has high average income and dependents with 2 has less income

In [48]:
```
# comparing Loan_Amount_Term and LoanAmount
sns.catplot(x='Loan_Amount_Term',y="LoanAmount",data=df,kind='bar')
plt.title("Comparision between Loan_Amouny_Term and LoanAmount")
plt.show()
```



- The loan amount term 300.0 is high with loan amount compared to others

In [49]:
```
# let's compare the loan amount with self employed
sns.barplot(x="Self_Employed",y="LoanAmount",data=df,hue='Loan_Status')
plt.title("Comparision between Self_Employed and LoanAmount")
plt.show()
```

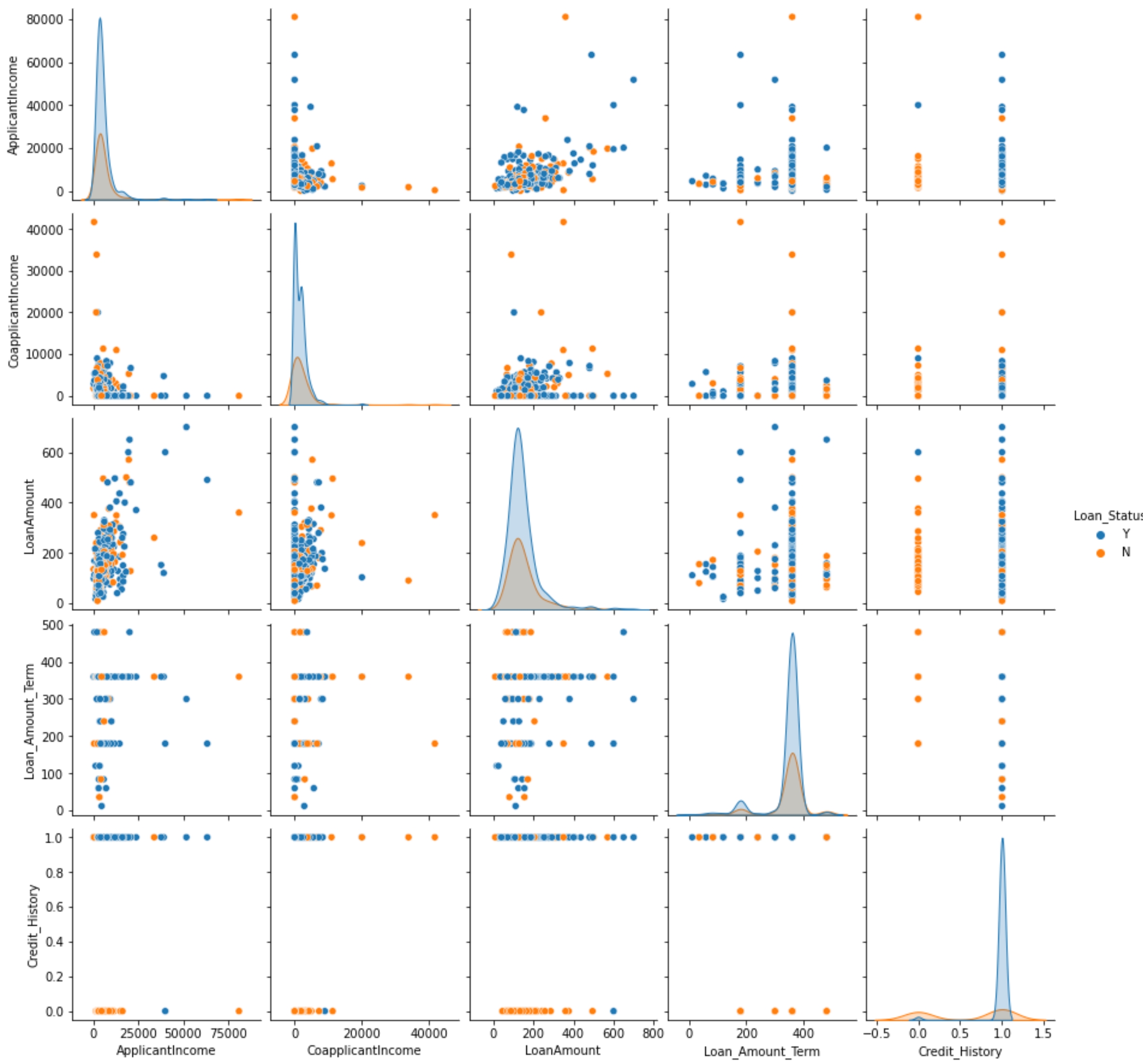


- The average loan amount demanded by the self employed is more compare to the other also the loan approval for self employes applicants with average loan amount is high compare to the applicants who are not self employed

Multivariate Analysis

In [50]:
```
# checking the pairwise relation in the dataset
sns.pairplot(df,hue="Loan_Status")
```

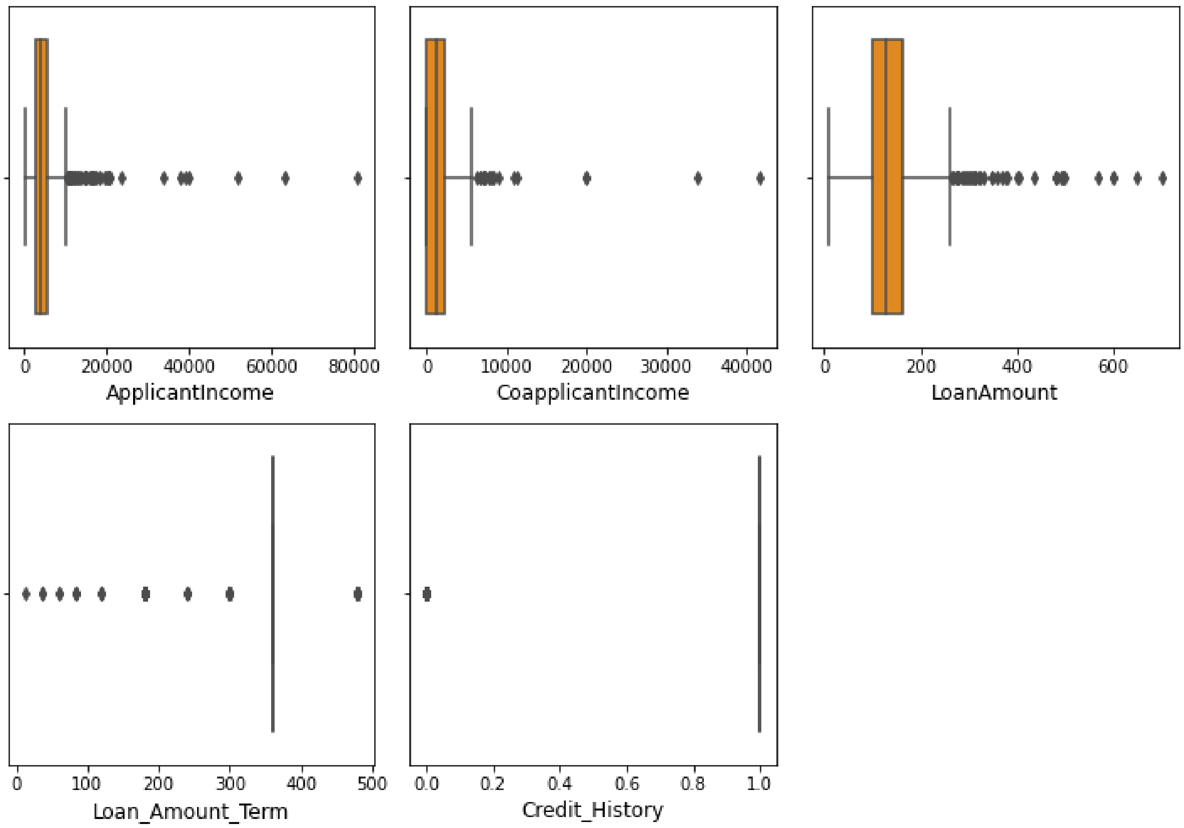
Out[50]: <seaborn.axisgrid.PairGrid at 0x20c88c36dc0>



- This pair plot gives the pairwise relation between the columns which is plotted on the basis of target variable "Loan_Status". Here we can ovserve the relation between the features and label.
- We can observe the linear relationship between ApplicatIncome and LoanAmount, CoapplicantIncome and LoanAmount, ApplicantIncome and TotalIncome.
- We can also observe the correlation in some columns also there are outliers present in some of the columns.

Identifying the outliers

In [51]:
```
plt.figure(figsize=(10,10),facecolor='white')
plotnumber=1
for column in numerical_col:
    if plotnumber<=9:
        ax=plt.subplot(3,3,plotnumber)
        sns.boxplot(df[column],color='darkorange')
        plt.xlabel(column,fontsize=12)
    plotnumber+=1
plt.tight_layout()
```



- We can observe the outliers present in all the columns . But the columns Credit History has only 2 unique values so no need to remove outliers in this column.

Let's remove outliers in remaining columns them using ZSCORE Method.

Removing Outliers

In [52]:
```
df.columns
```

Out[52]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

1. ZSCORE METHOD

In [53]:
```
# numerical columns containing outliers
features = df[['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_

#using zscore method to remove outliers
from scipy.stats import zscore

z=np.abs(zscore(features))
z
```

Out[53]:
```
array([[0.07299082, 0.55448733, 0.21124125, 0.2732313 ],
       [0.13441195, 0.03873155, 0.21124125, 0.2732313 ],
       [0.39374734, 0.55448733, 0.94899647, 0.2732313 ],
       ...,
       [0.43717437, 0.47240418, 1.27616847, 0.2732313 ],
       [0.35706382, 0.55448733, 0.49081614, 0.2732313 ],
       [0.13441195, 0.55448733, 0.15174486, 0.2732313 ]])
```

- Now we have removed the outliers, let's check the dataloss by creating new dataframe

In [54]:
```
new_df = df[(z<3).all(axis=1)]
new_df
```

Out[54]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncom
0	Male	No	0	Graduate	No	5849	0
1	Male	Yes	1	Graduate	No	4583	1508
2	Male	Yes	0	Graduate	Yes	3000	0
3	Male	Yes	0	Not Graduate	No	2583	2358
4	Male	No	0	Graduate	No	6000	0
...	...	...	...	...	...	...	
609	Female	No	0	Graduate	No	2900	0
610	Male	Yes	3+	Graduate	No	4106	0
611	Male	Yes	1	Graduate	No	8072	240
612	Male	Yes	2	Graduate	No	7583	0
613	Female	No	0	Graduate	Yes	4583	0

577 rows × 12 columns

- This is the new dataframe after removing the outliers . Here we have removed the outliers whose zscore is less than 3

In [55]:
```
# Shape of original dataset
df.shape
```

Out[55]:
```
(614, 12)
```

- Before removing the outliers we had 614 rows and 12 columns in our dataset.

In [56]:
```
# Shape of new dataframe
new_df.shape
```

Out[56]:
```
(577, 12)
```

- After removing the outliers we have 577 rows and 12 columns

In [57]:
```
# checking the data loss
data_loss = (614-577)/614*100
data_loss
```

Out[57]:
```
6.026058631921824
```

So here we haveremoved outliers using zscore method and we are losing only 6% data.

- Let's remove the outliers and check data loss using IQR method.

2. IQR METHOD

In [58]:
```
Q1 = features.quantile(0.25)

Q3 = features.quantile(0.75)

IQR = Q3-Q1

df1 = df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]
```

In [59]:
```
df1.shape
```

Out[59]:
```
(459, 12)
```

Using IQR method the dataframe has 459 rows and 12 columns.

In [60]:
```
# let's check the dataloss
data_loss = (614-459)/614*100
data_loss
```

Out[60]:
```
25.2442996742671
```

using IQR method we are losing 25% of data. So considering zscore method.

Checking the skewness

In [61]:
```
new_df.skew()
```

Out[61]:
```
ApplicantIncome       2.148522
CoapplicantIncome     1.350517
LoanAmount            1.151525
Loan_Amount_Term     -2.098806
Credit_History       -1.976043
dtype: float64
```

- The skewness present in all the above columns. Here the columns Credit_History and Loan_Amount_Term have categorical data of integer type so no need to remove skewness in these columns

Removing Skewness using yeo-johnson method

In [62]:
```
skew = ['ApplicantIncome','CoapplicantIncome','LoanAmount']

from sklearn.preprocessing import PowerTransformer

scaler = PowerTransformer(method='yeo-johnson')
'''
parameters:
method = 'box-cox' or 'yeo-johnson'
'''
```

Out[62]:
```
"\nparameters:\nmethod = 'box-cox' or 'yeo-johnson'\n"
```

In [63]:
```
new_df[skew] = scaler.fit_transform(new_df[skew].values)
new_df[skew].head()
```

Out[63]:

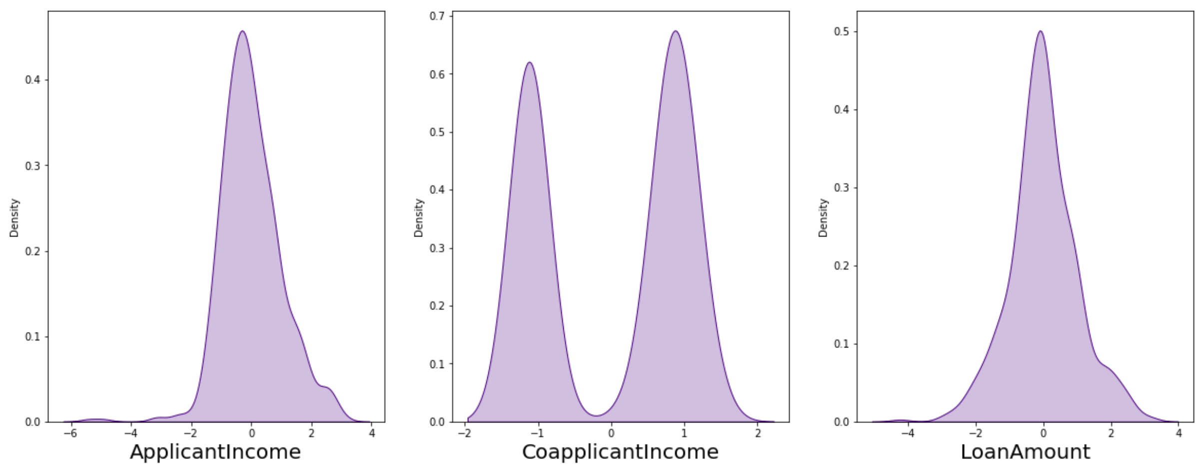
	ApplicantIncome	CoapplicantIncome	LoanAmount
0	0.681780	-1.122446	0.000771
1	0.234783	0.744117	0.000771
2	-0.527201	-1.122446	-1.437336
3	-0.791972	0.895786	-0.153545
4	0.728848	-1.122446	0.238260

In [64]:
```
# checking skewness after using yeo-johnson method
new_df.skew()
```

Out[64]:
```
ApplicantIncome       0.027981
CoapplicantIncome    -0.191876
LoanAmount            0.048425
Loan_Amount_Term     -2.098806
Credit_History       -1.976043
dtype: float64
```

- So here we have removed the skewness using yeo-hohnson method . The skewness has been removed in all the numerical integer type columns.

In [65]:
```
# after removing skewness let's check how the data has been distributed in each

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

for column in new_df[skew]:
    if plotnumber<=9:
        ax = plt.subplot(3,3,plotnumber)
        sns.distplot(new_df[column],color='indigo',kde_kws={"shade": True},hist
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.show()
```



- The data is almost normal also we have removed the skewness that we can notice in the above distplot.

Encoding the categorical columns using Label Encoding

In [66]:
```
categorical_col = ['Gender','Married','Dependents','Education','Self_Employed',
```

In [67]:
```
from sklearn.preprocessing import LabelEncoder
LE=LabelEncoder()
new_df[categorical_col]= new_df[categorical_col].apply(LE.fit_transform)
```

- Encoding the categorical columns using label encoder

In [68]:
```
new_df[categorical_col]
```

Out[68]:

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

577 rows × 7 columns

- The categorical columns have been converted into numerical columns by using label encoding.

Correlation between the target variable and independent variables using HEAT map

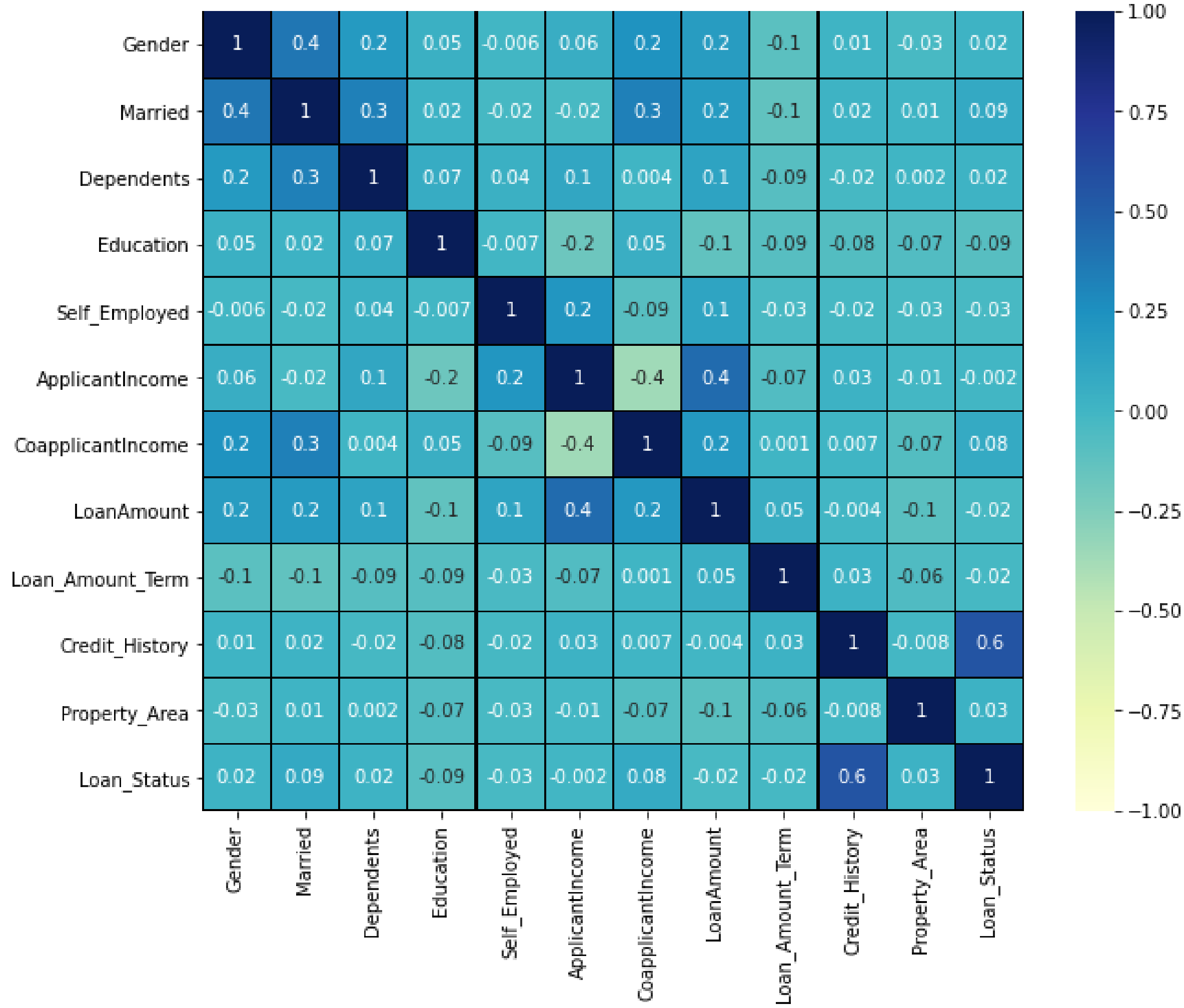
In [69]:
```python
cor = new_df.corr()
cor
```

Out[69]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncom
Gender	1.000000	0.378997	0.188162	0.045696	-0.006207	0.05859
Married	0.378997	1.000000	0.329900	0.024817	-0.015779	-0.02478
Dependents	0.188162	0.329900	1.000000	0.069814	0.044543	0.10599
Education	0.045696	0.024817	0.069814	1.000000	-0.007139	-0.17607
Self_Employed	-0.006207	-0.015779	0.044543	-0.007139	1.000000	0.21226
ApplicantIncome	0.058590	-0.024783	0.105994	-0.176074	0.212260	1.00000
CoapplicantIncome	0.234551	0.335820	0.004109	0.049739	-0.087338	-0.36094
LoanAmount	0.172146	0.181878	0.131772	-0.128715	0.117218	0.43215
Loan_Amount_Term	-0.104983	-0.127348	-0.087389	-0.090523	-0.032914	-0.06942
Credit_History	0.013172	0.019308	-0.020288	-0.075217	-0.016390	0.02882
Property_Area	-0.026340	0.010595	0.002327	-0.068596	-0.028253	-0.01136
Loan_Status	0.017408	0.089026	0.017872	-0.092658	-0.026525	-0.00248

- This gives the correlation between the dependent and independent variables. We can visualize this by plotting heat map.

In [70]:
```
# visualizing the correlation matrix by plotting heat map.
plt.figure(figsize=(10,8))
sns.heatmap(new_df.corr(),linewidths=.1,vmin=-1, vmax=1, fmt='.1g', annot = Tru
plt.yticks(rotation=0);
```



This heatmap shows the correlation matrix by visualizing the data. We can observe the relation between one feature to other.

This heatmap contains both positive and negative correlation.

- The target column Loan_Status is highly positively correlated with the feature Credit_History.
- The other features have very less correlation with the target column.
- Also we can notice there is no multicolinearity issue in the features. Features have moderate level of correlation with each other.
- ApplicantIncome and Gender is very less correlated with the target.
- Dark shades are highly correlated and light shades are very less correlated.

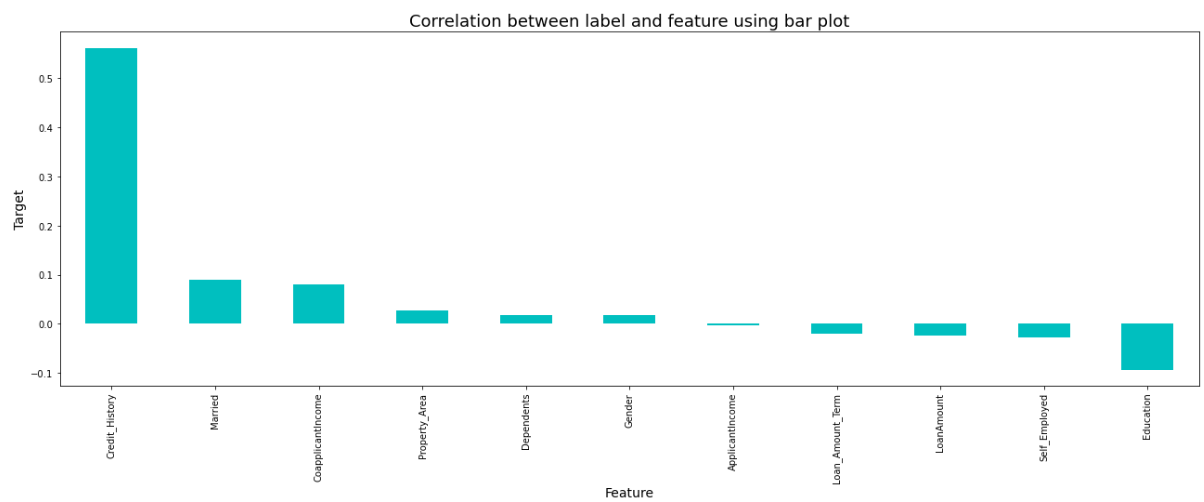
In [71]:
```python
cor['Loan_Status'].sort_values(ascending=False)
```

Out[71]:
```
Loan_Status          1.000000
Credit_History       0.560936
Married              0.089026
CoapplicantIncome    0.079344
Property_Area        0.026507
Dependents           0.017872
Gender               0.017408
ApplicantIncome     -0.002484
Loan_Amount_Term    -0.020291
LoanAmount          -0.023609
Self_Employed       -0.026525
Education           -0.092658
Name: Loan_Status, dtype: float64
```

- Here we can see the positive and negative correlation of target and features.

Visualizing the correlation between label and features using bar plot

In [72]:
```python
plt.figure(figsize=(22,7))
new_df.corr()['Loan_Status'].sort_values(ascending=False).drop(['Loan_Status'])
plt.xlabel('Feature',fontsize=14)
plt.ylabel('Target',fontsize=14)
plt.title("Correlation between label and feature using bar plot", fontsize=18)
plt.show()
```



Here the columns ApplicantIncome has very less correlation with the target . So we can drop this column if necessary

Separating the features and label variables into x and y

In [73]:
```
x = new_df.drop("Loan_Status", axis=1)
y = new_df["Loan_Status"]
```

- We have seperated both dependent and independent variables.

In [74]:
```
x.shape
```

Out[74]:
```
(577, 11)
```

In [75]:
```
y.shape
```

Out[75]:
```
(577,)
```

- Here are the dimension of x and y

Feature Scaling using Standard Scalarization

In [76]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x = pd.DataFrame(scaler.fit_transform(x), columns=x.columns)
x
```

Out[76]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIn
0	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.681780	-1.1:
1	0.477137	0.733939	0.282353	-0.541961	-0.380580	0.234783	0.7
2	0.477137	0.733939	-0.723313	-0.541961	2.627567	-0.527201	-1.1:
3	0.477137	0.733939	-0.723313	1.845150	-0.380580	-0.791972	0.8
4	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.728848	-1.1:
...	...	...	...	...	...	...	
572	-2.095835	-1.362511	-0.723313	-0.541961	-0.380580	-0.587375	-1.1:
573	0.477137	0.733939	2.293686	-0.541961	-0.380580	0.035386	-1.1:
574	0.477137	0.733939	0.282353	-0.541961	-0.380580	1.281658	0.1
575	0.477137	0.733939	1.288020	-0.541961	-0.380580	1.164426	-1.1:
576	-2.095835	-1.362511	-0.723313	-0.541961	2.627567	0.234783	-1.1:

577 rows × 11 columns

- We have scaled the data using standard scalarization method to overcome with the issue of data biasness.

In [77]:
```
y.value_counts()
```

Out[77]:
```
1    398
0    179
Name: Loan_Status, dtype: int64
```

- Here we can notice the class imbalancing issue so let's use SMOTE to balance the data

Oversampling

In [78]:
```
from imblearn.over_sampling import SMOTE
SM = SMOTE()
x, y = SM.fit_resample(x,y)
```

In [79]:
```
y.value_counts()
```

Out[79]:
```
1    398
0    398
Name: Loan_Status, dtype: int64
```

- The data is balance now, Since the highest count of the target is 398 . So the data is balance by oversampling all the classes to the count 398

In [80]:
```
new_df.head()
```

Out[80]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	1	0	0	0	0	0.681780	-1.122446
1	1	1	1	0	0	0.234783	0.744117
2	1	1	0	0	1	-0.527201	-1.122446
3	1	1	0	1	0	-0.791972	0.895786
4	1	0	0	0	0	0.728848	-1.122446

- We have done with the preprocessing and data cleaning . Now let's move to build the model

Modeling

Finding best random state

In [81]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
maxAccu=0
maxRS=0
for i in range(1,200):
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.30, random_
    RFC = RandomForestClassifier()
    RFC.fit(x_train,y_train)
    pred = RFC.predict(x_test)
    acc=accuracy_score(y_test,pred)
    if acc>maxAccu:
        maxAccu=acc
        maxRS=i
print("Best accuracy is ",maxAccu," on Random_state ",maxRS)
```

```
Best accuracy is  0.8870292887029289  on Random_state  113
```

- The best accuracy is 89.12 on the Random state 46

Creating train_test_split

```
In [82]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.30,random_state=m
```

- We have created a new train test split using Random State.

Classification Algorithm

```
In [83]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.linear_model import LogisticRegression
         from sklearn.svm import SVC
         from sklearn.neighbors import KNeighborsClassifier as KNN
         from sklearn.ensemble import GradientBoostingClassifier, AdaBoostClassifier
         from sklearn.naive_bayes import GaussianNB
         from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
```

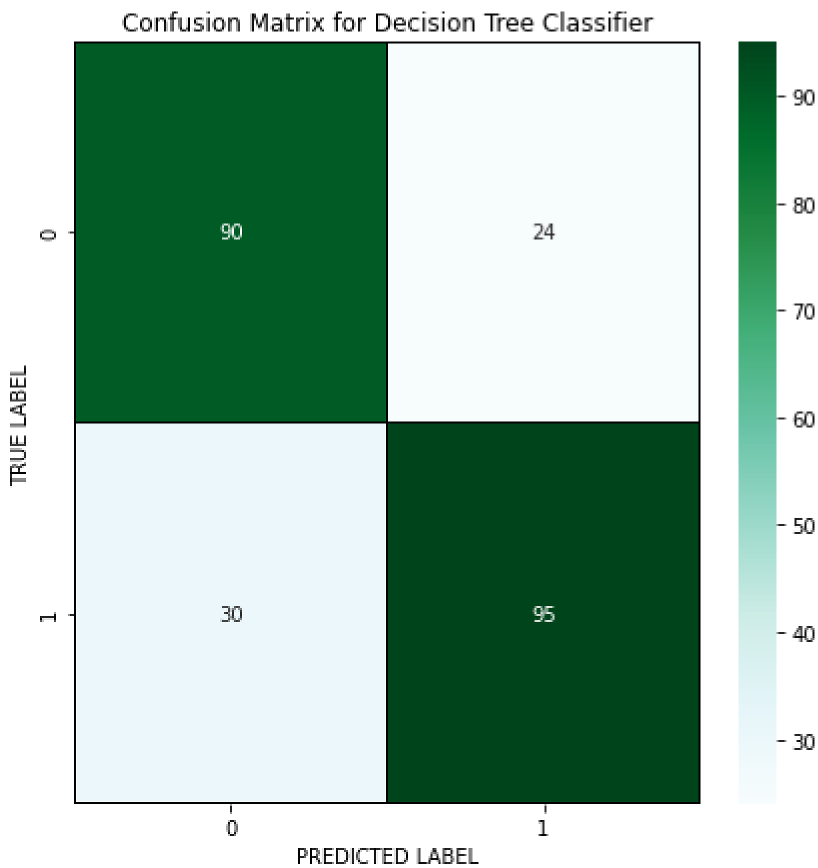
Decision Tree Classifier

```
In [84]: DTC = DecisionTreeClassifier()
         DTC.fit(x_train,y_train)

         # prediction
         predDTC = DTC.predict(x_test)

         print(accuracy_score(y_test, predDTC))
         print(confusion_matrix(y_test, predDTC))
         print(classification_report(y_test, predDTC))
```

```
0.7740585774058577
[[90 24]
 [30 95]]
              precision    recall  f1-score   support

           0       0.75      0.79      0.77       114
           1       0.80      0.76      0.78       125

    accuracy                           0.77       239
   macro avg       0.77      0.77      0.77       239
weighted avg       0.78      0.77      0.77       239
```

- The accuracy using DTC is 77%

In [85]:
```
# let's plot confusion matrix for DTC
cm = confusion_matrix(y_test,predDTC)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for Decision Tree Classifier")
plt.show()
```



- This is the confusion matrix for Decision Tree Classifier where we can observe the true positive rate, true negative rate and false negative rate and is ploted predicted value against true values.

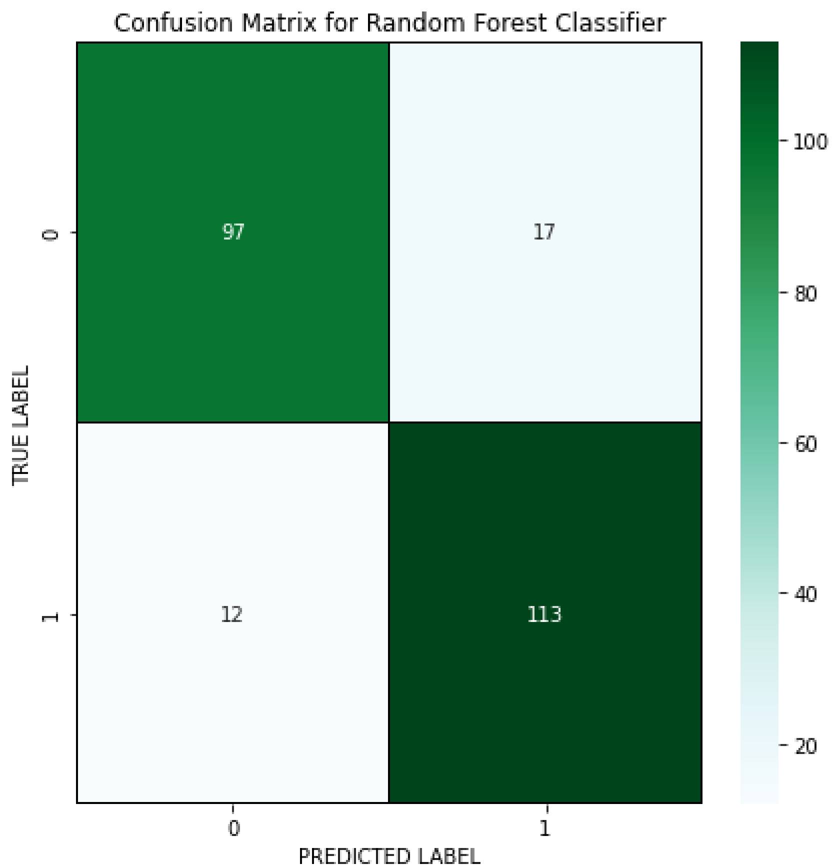
Random Forest Classifier

In [86]:
```python
RFC = RandomForestClassifier()
RFC.fit(x_train,y_train)

# prediction
predRFC = RFC.predict(x_test)

print(accuracy_score(y_test, predRFC))
print(confusion_matrix(y_test, predRFC))
print(classification_report(y_test, predRFC))
```

```
0.8786610878661087
[[ 97  17]
 [ 12 113]]
              precision    recall  f1-score   support

           0       0.89      0.85      0.87       114
           1       0.87      0.90      0.89       125

    accuracy                           0.88       239
   macro avg       0.88      0.88      0.88       239
weighted avg       0.88      0.88      0.88       239
```

- The accuracy using RFC is 87%

In [87]:
```
# let's plot confusion matrix for RFC
cm = confusion_matrix(y_test,predRFC)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for Random Forest Classifier")
plt.show()
```



- This is the confusion matrix for Random Forest Classifier where we can observe the true positive rate, false positive rate, true negative rate and false negative rate and is ploted predicted value against True values.

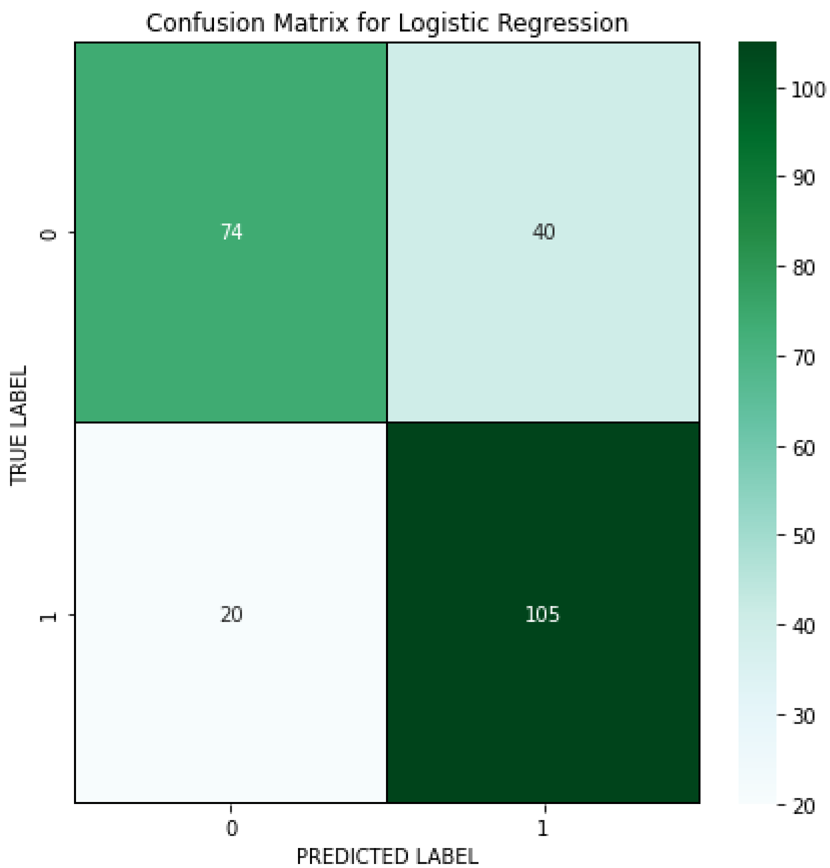
Logistic Regression

In [88]:
```
LR = LogisticRegression()
LR.fit(x_train,y_train)

# prediction
predLR = LR.predict(x_test)

print(accuracy_score(y_test, predLR))
print(confusion_matrix(y_test, predLR))
print(classification_report(y_test, predLR))
```

```
0.7489539748953975
[[ 74  40]
 [ 20 105]]
              precision    recall  f1-score   support

           0       0.79      0.65      0.71       114
           1       0.72      0.84      0.78       125

    accuracy                           0.75       239
   macro avg       0.76      0.74      0.74       239
weighted avg       0.75      0.75      0.75       239
```

- The accuracy using LR is 74%

In [89]:
```python
# let's plot confusion matrix for LR
cm = confusion_matrix(y_test,predLR)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for Logistic Regression")
plt.show()
```



- This is the confusion matrix for Logistic Regression classifier where we can observe the true positive rate, false positive rate, ture negative rate and false negative rate and is ploted prdicted value against true values.

Support Vector Classifier

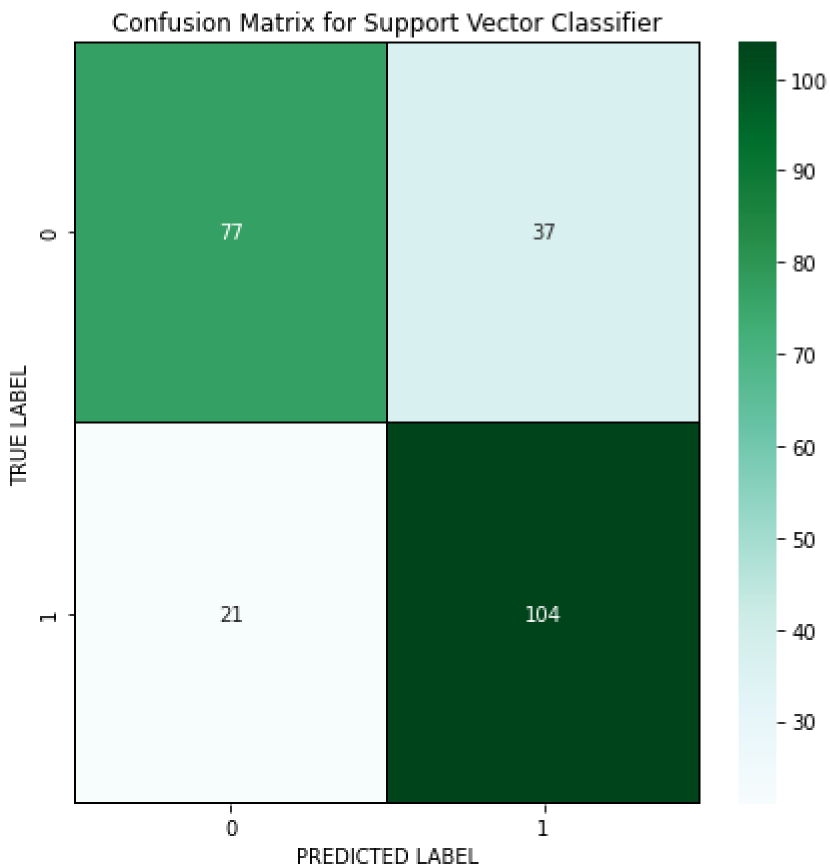
In [90]:

```
svc = SVC()
svc.fit(x_train,y_train)

# prediction
predsvc = svc.predict(x_test)

print(accuracy_score(y_test, predsvc))
print(confusion_matrix(y_test, predsvc))
print(classification_report(y_test, predsvc))
```

```
0.7573221757322176
[[ 77  37]
 [ 21 104]]
              precision    recall  f1-score   support

           0       0.79      0.68      0.73       114
           1       0.74      0.83      0.78       125

    accuracy                           0.76       239
   macro avg       0.76      0.75      0.75       239
weighted avg       0.76      0.76      0.76       239
```

- The accuracy using svc is 75%

In [91]:
```
# let's plot confusion matrix for SVC
cm = confusion_matrix(y_test,predsvc)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for Support Vector Classifier")
plt.show()
```



This is the confusion matrix for Support Vector classifier where we can observe the true positive rate, false positive rate, ture negative rate and false negative rate and is ploted prdicted value against true values.

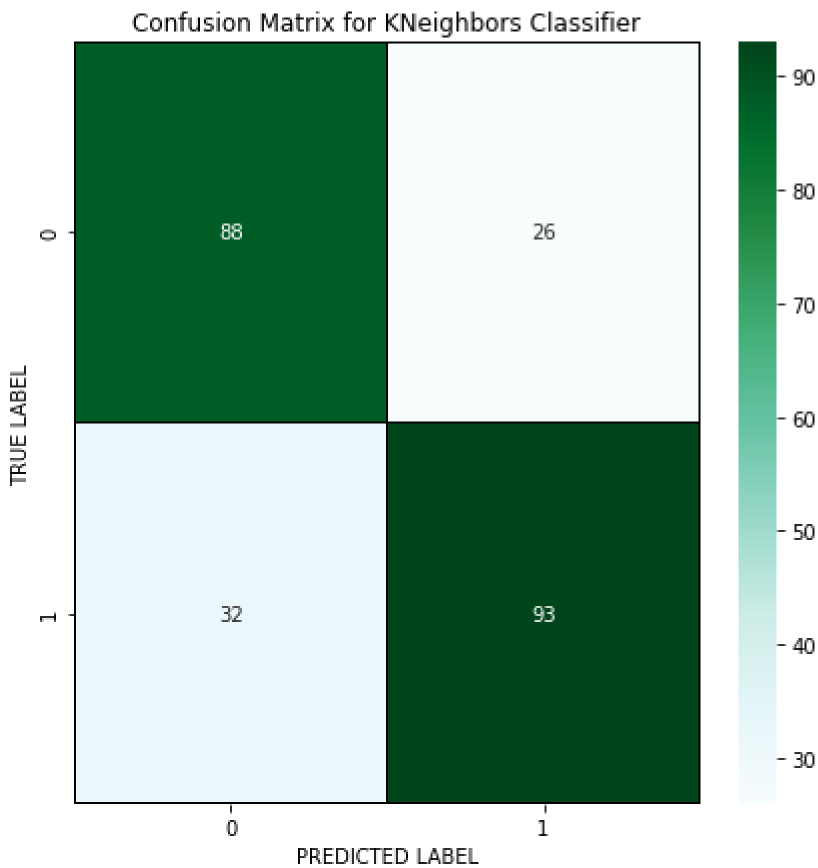
KNeighbors Classifier

In [92]:
```
knn = KNN()
knn.fit(x_train,y_train)

# prediction
predknn = knn.predict(x_test)

print(accuracy_score(y_test, predknn))
print(confusion_matrix(y_test, predknn))
print(classification_report(y_test, predknn))
```

```
0.7573221757322176
[[88 26]
 [32 93]]
              precision    recall  f1-score   support

           0       0.73      0.77      0.75       114
           1       0.78      0.74      0.76       125

    accuracy                           0.76       239
   macro avg       0.76      0.76      0.76       239
weighted avg       0.76      0.76      0.76       239
```

- The accuracy using KNN is 75%

In [93]:
```
# let's plot confusion matrix for KNN
cm = confusion_matrix(y_test,predknn)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for KNeighbors Classifier")
plt.show()
```



This is the confusion matrix for KNeighbors classifier where we can observe the true positive rate, false positive rate, ture negative rate and false negative rate and is ploted prdicted value against true values.

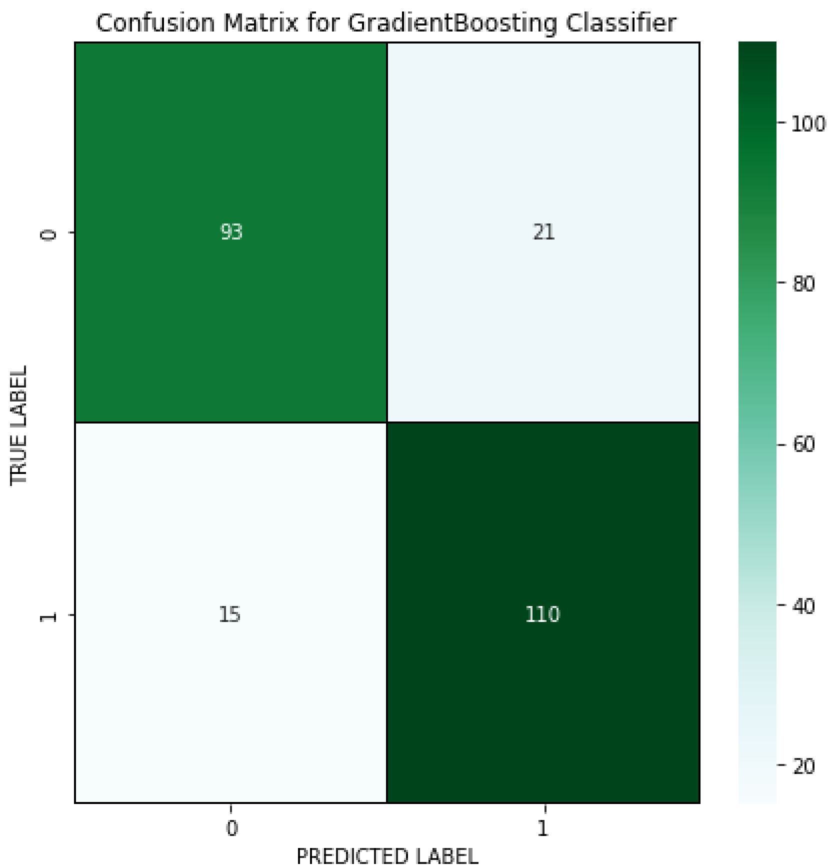
Gradient Boosting Classifier

In [94]:
```python
GB = GradientBoostingClassifier()
GB.fit(x_train,y_train)

# prediction
predGB = GB.predict(x_test)

print(accuracy_score(y_test, predGB))
print(confusion_matrix(y_test, predGB))
print(classification_report(y_test, predGB))
```

```
0.8493723849372385
[[ 93  21]
 [ 15 110]]
              precision    recall  f1-score   support

           0       0.86      0.82      0.84       114
           1       0.84      0.88      0.86       125

    accuracy                           0.85       239
   macro avg       0.85      0.85      0.85       239
weighted avg       0.85      0.85      0.85       239
```

- The accuracy using GB is 84%

In [120]:
```
# let's plot confusion matrix for GB
cm = confusion_matrix(y_test,predGB)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for GradientBoosting Classifier")
plt.show()
```



This is the confusion matrix for Gradient Boosting classifier where we can observe the true positive rate, false positive rate, ture negative rate and false negative rate and is ploted prdicted value against true values.

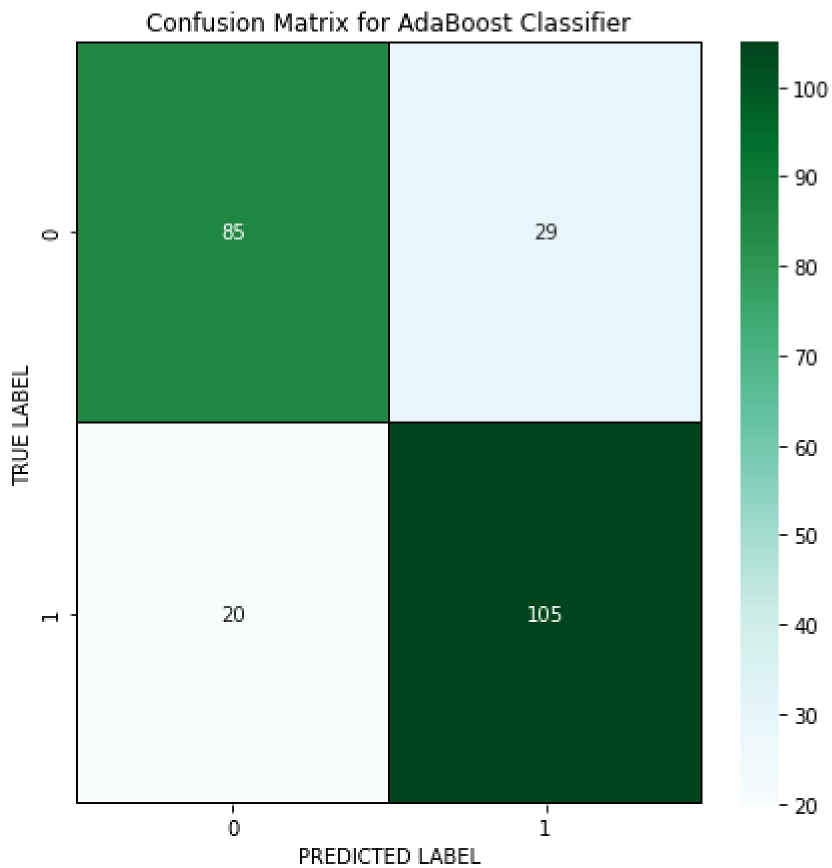
AdaBoost Classifier

In [96]:
```
ABC = AdaBoostClassifier()
ABC.fit(x_train,y_train)

# prediction
predABC = ABC.predict(x_test)

print(accuracy_score(y_test, predABC))
print(confusion_matrix(y_test, predABC))
print(classification_report(y_test, predABC))
```

```
0.7949790794979079
[[ 85  29]
 [ 20 105]]
              precision    recall  f1-score   support

           0       0.81      0.75      0.78       114
           1       0.78      0.84      0.81       125

    accuracy                           0.79       239
   macro avg       0.80      0.79      0.79       239
weighted avg       0.80      0.79      0.79       239
```

- The accuracy using AdaBoost Classifier is 79%

In [97]:
```
# let's plot confusion matrix for ABC
cm = confusion_matrix(y_test,predABC)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for AdaBoost Classifier")
plt.show()
```



This is the confusion matrix for Ada Boost classifier where we can observe the true positive rate, false positive rate, ture negative rate and false negative rate and is ploted prdicted value against true values.

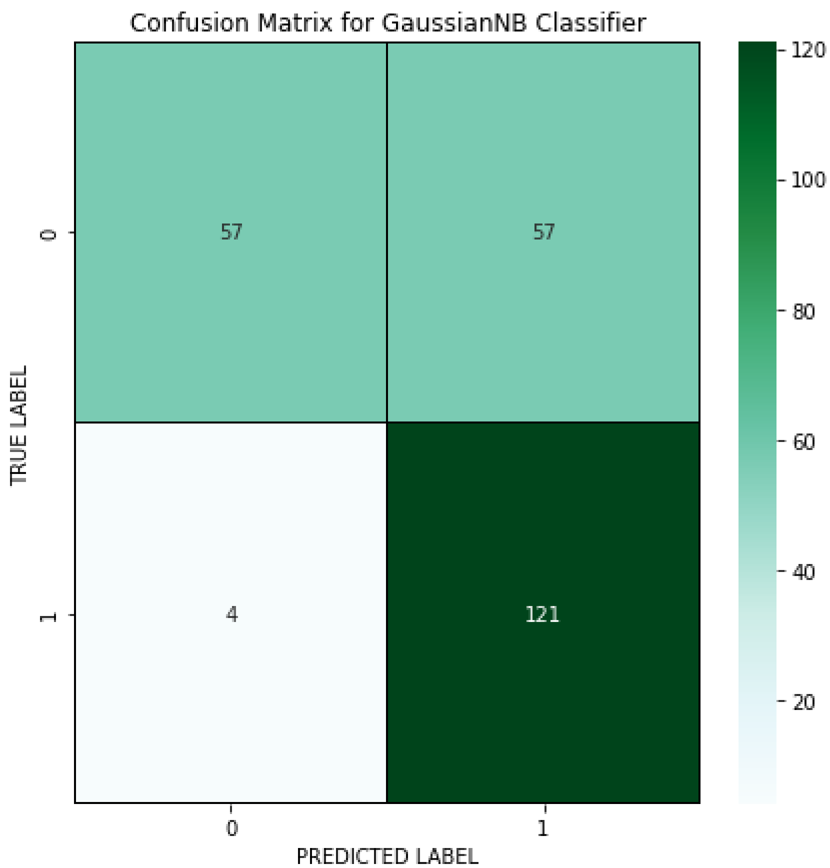
GaussianNB Classifier

In [98]:
```python
NB = GaussianNB()
NB.fit(x_train,y_train)

# prediction
predNB = NB.predict(x_test)

print(accuracy_score(y_test, predNB))
print(confusion_matrix(y_test, predNB))
print(classification_report(y_test, predNB))
```

```
0.7447698744769874
[[ 57  57]
 [  4 121]]
              precision    recall  f1-score   support

           0       0.93      0.50      0.65       114
           1       0.68      0.97      0.80       125

    accuracy                           0.74       239
   macro avg       0.81      0.73      0.73       239
weighted avg       0.80      0.74      0.73       239
```

- The accuracy using NB is 74%

In [99]:
```python
# let's plot confusion matrix for NB
cm = confusion_matrix(y_test,predNB)

x_axis_labels = ["0","1"]
y_axis_labels = ["0","1"]

f , ax = plt.subplots(figsize=(7,7))
sns.heatmap(cm, annot = True, linewidths=.2, linecolor='black', fmt = ".0f", ax

plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title("Confusion Matrix for GaussianNB Classifier")
plt.show()
```



This is the confusion matrix for GaussianNB classifier where we can observe the true positive rate, false positive rate, ture negative rate and false negative rate and is ploted prdicted value against true values.

Checking the Cross Validation Score

In [100]:
```python
from sklearn.model_selection import cross_val_score
```

In [101]:
```
# cv score for Decision Tree Classifier
print(cross_val_score(DTC ,x,y,cv=5).mean())
```

```
0.7676179245283018
```

In [102]:
```
# cv score for Random Forest Classifier
print(cross_val_score(RFC ,x,y,cv=5).mean())
```

```
0.8367924528301888
```

In [103]:
```
# cv score for Logistic Regression
print(cross_val_score(LR ,x,y,cv=5).mean())
```

```
0.7097798742138365
```

In [104]:
```
# cv score for Support Vector Classifier
print(cross_val_score(svc ,x,y,cv=5).mean())
```

```
0.7160849056603773
```

In [105]:
```
# cv score for KNN Classifier
print(cross_val_score(knn ,x,y,cv=5).mean())
```

```
0.7399842767295597
```

In [106]:
```
# cv score for Gradient Boosting Classifier
print(cross_val_score(GB ,x,y,cv=5).mean())
```

```
0.790314465408805
```

In [107]:
```
# cv score for Ada Boost Classifier
print(cross_val_score(ABC ,x,y,cv=5).mean())
```

```
0.752617924528302
```

In [108]:
```
# cv score for GaussianNB Classifier
print(cross_val_score(NB ,x,y,cv=5).mean())
```

```
0.7110849056603773
```

- Above are the cross validation score for the models.

From the difference between the accuracy score and the cross validation score we can conclude that KNeighbors Classifier as our best fitting model which is giving very less difference compare to other models

Hyper Parameter Tuning

In [109]:
```
from sklearn.model_selection import GridSearchCV
```

In [110]:
```
# KNeighbors Classifier

parameters = {'n_neighbors':[2,3,4,5,6],
              'algorithm':['auto','ball_tree','kd_tree','brute'],
              'leaf_size':[10,20,30,40,50],
              'weights':['uniform','distance'],
              'p':[1,2,3,4,5]}
```

- These are the parameters for KNN Classifier

In [111]:
```
GCV=GridSearchCV(KNN(),parameters,cv=5)
```

Running GridSearchCV for KNN

In [112]:
```
GCV.fit(x_train,y_train)
```

Out[112]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brut
e'],
                         'leaf_size': [10, 20, 30, 40, 50],
                         'n_neighbors': [2, 3, 4, 5, 6], 'p': [1, 2, 3, 4,
5],
                         'weights': ['uniform', 'distance']})
```

In [113]:
```
GCV.best_params_
```

Out[113]:
```
{'algorithm': 'auto',
 'leaf_size': 10,
 'n_neighbors': 2,
 'p': 1,
 'weights': 'distance'}
```

- These are the best parameters values that we have got for KNN Classifier

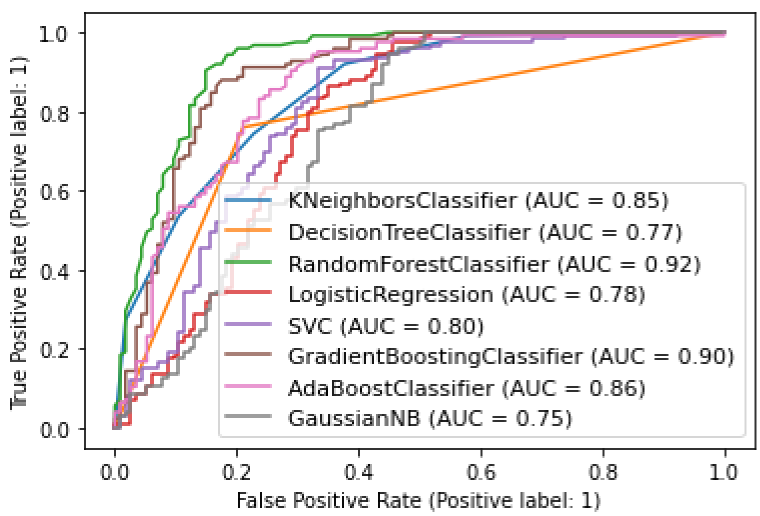
In [114]:
```
Loan = KNN(algorithm='auto', leaf_size=10, n_neighbors=4, weights='distance',p=
Loan.fit(x_train,y_train)
pred = Loan.predict(x_test)
acc=accuracy_score(y_test,pred)
print(acc*100)
```

```
80.3347280334728
```

- The accuracy of best model increased by 5% after tuning and giving 83.26% which is very good.

Plotting ROC and compare AUC for all the models used

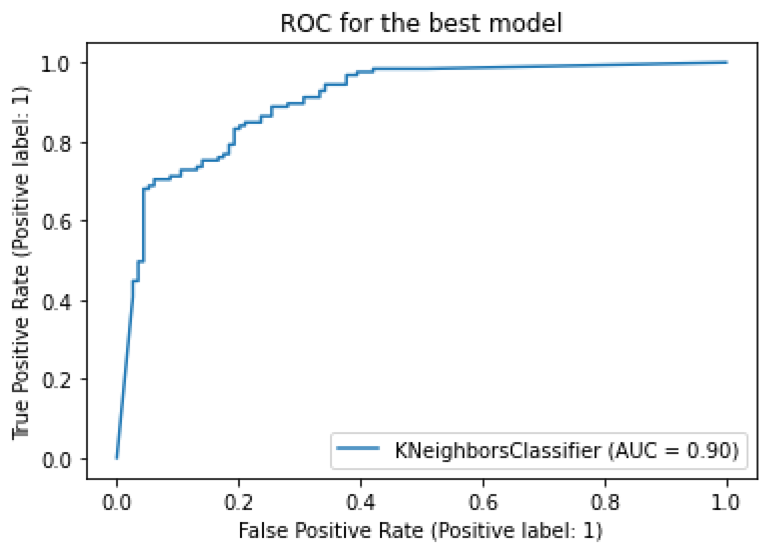
In [115]:
```
from sklearn import datasets
from sklearn import metrics
from sklearn import model_selection
from sklearn.metrics import plot_roc_curve

disp = plot_roc_curve(knn,x_test,y_test)
plot_roc_curve(DTC , x_test, y_test, ax=disp.ax_)      # ax_=Axes with confusio
plot_roc_curve(RFC , x_test, y_test, ax=disp.ax_)
plot_roc_curve(LR , x_test, y_test, ax=disp.ax_)
plot_roc_curve(svc , x_test, y_test, ax=disp.ax_)
plot_roc_curve(GB , x_test, y_test, ax=disp.ax_)
plot_roc_curve(ABC , x_test, y_test, ax=disp.ax_)
plot_roc_curve(NB , x_test, y_test, ax=disp.ax_)

plt.legend(prop={'size':11}, loc='lower right')
plt.show()
```



- This is the AUC-ROC curve for the models that we have used and is plotted False positive rate against True positive rate.

Plotting ROC and compare AUC for the best model KNeighbors Classifier

In [116]:
```
plot_roc_curve(Loan, x_test, y_test)
plt.title("ROC for the best model")
plt.show()
```



- This is the ROC curve for the best model KNN and AUC for KNN is 91%

Saving the Model

In [117]:
```
import joblib
joblib.dump(Loan,"Loan_Application_Status.pkl")
```

Out[117]:
```
['Loan_Application_Status.pkl']
```

- We have saved our model using joblib library

Predicting the saved model

In [118]:

```python
# let's load the saved model and get the prediction

# Loading the saved model
model=joblib.load("Loan_Application_Status.pkl")

# Prediction
prediction = model.predict(x_test)
prediction
```

Out[118]:

```
array([1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0,
       1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0,
       1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1,
       1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1,
       0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0])
```

- These are the predicted loan approval status of the applicants

In [119]:

```python
pd.DataFrame([model.predict(x_test)[:],y_test[:]],index=["Predicted","Original"
```

Out[119]:

	Predicted	Original
0	1	1
1	0	0
2	1	1
3	1	1
4	1	1
...	...	...
234	0	0
235	1	1
236	1	1
237	1	1
238	0	1

239 rows × 2 columns

- We can observe both original and predicted values are same.

That means the loan approval status for both predicted and original are same.

In [ ]:

In [ ]:

In [ ]:

In [ ]: