Loan Eligibility Prediction

Importing Libraries

In [1]:
```
# Importing Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import copy
from sklearn import preprocessing
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import CategoricalNB
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import accuracy_score
```

Loading Dataset

In [2]:
```
# loading dataset

df = pd.read_csv("train.csv")
validation_df = pd.read_csv("validation.csv")
```

Exploratory Data Analysis (EDA)

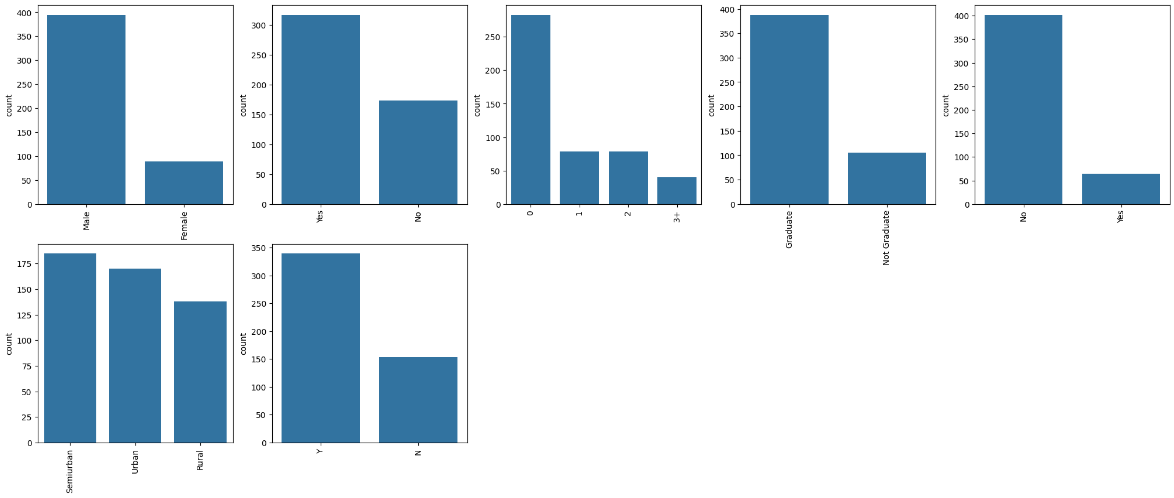
In [3]:
```
######################## Exploratory Data Analysis ######################

print("Shape of the train dataset is: ", df.shape) # dataset has 493 rows
print("\nTop 5 rows in the train dataset are: \n\n",df.head(5)) # display
print("\nColumns in the train dataset are: \n\n",df.columns) # display al
print("\nDatatypes of the columns in the train dataset are: \n\n",df.dtyp

print("\nTotal Columns in the train dataset is: ",len(df.columns))

print("\nTotal Categorical variables in the train dataset is: ",len(df.dt

print(len(np.unique(df['Loan_ID']))==len(df)) # True

# Loan_ID column has all unique values and not null values
```

```
Shape of the train dataset is:  (493, 13)

Top 5 rows in the train dataset are:

       Loan_ID Gender Married Dependents     Education Self_Employed  \
0  ID001002XY   Male      No          0      Graduate            No
1  ID001003XY   Male     Yes          1      Graduate            No
2  ID001005XY   Male     Yes          0      Graduate           Yes
3  ID001006XY   Male     Yes          0  Not Graduate            No
4  ID001008XY   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

Columns in the train dataset are:

 Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
t',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Statu
s'],
      dtype='object')

Datatypes of the columns in the train dataset are:

 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

Total Columns in the train dataset is:  13

Total Categorical variables in the train dataset is:  8
True
```

In [4]:

```python
# visualize all the unique values of categorical variables

categorical = (df.dtypes == 'object')
categorical_cols = list(categorical[categorical].index)
```

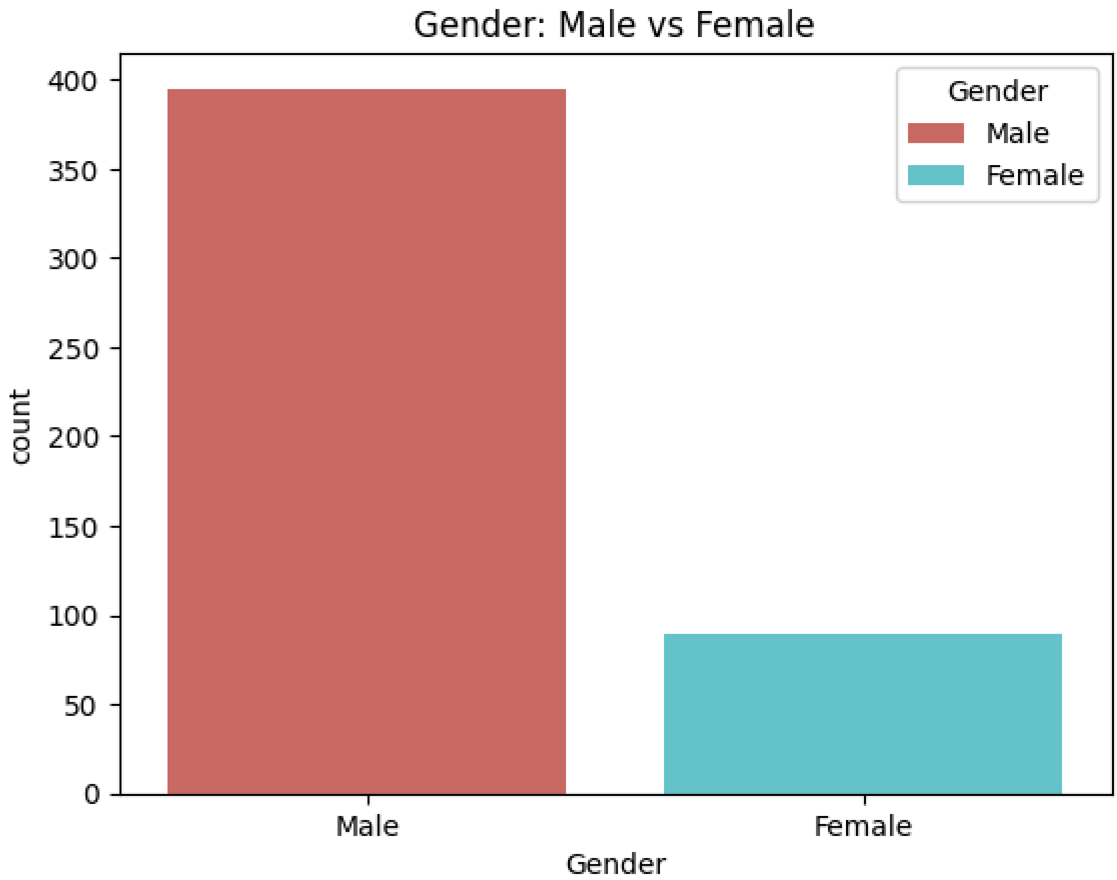
```
categorical_cols.remove('Loan_ID')
plt.figure(figsize=(25,52))
index = 1

for col in categorical_cols:
    y = df[col].value_counts()
    plt.subplot(10,5,index)
    plt.xticks(rotation=90)
    sns.barplot(x=list(y.index), y=y)
    index +=1
plt.savefig('figures//combined.png', bbox_inches='tight')
```



In [5]:

```
# Exploring each categorical variable

# 1. Gender
df['Gender'].unique()
print(df.Gender.value_counts(dropna=False))
print("Percentage of Male:", len(df[df['Gender']=='Male'])/len(df.Gender)
print("Percentage of Female:", len(df[df['Gender']=='Female'])/len(df.Gen
sns.countplot(x="Gender", data=df,hue='Gender', palette="hls")
plt.title("Gender: Male vs Female")
plt.savefig('figures//Gender.png', bbox_inches='tight')
plt.show()
# Males are significantly higher than Feamles
```

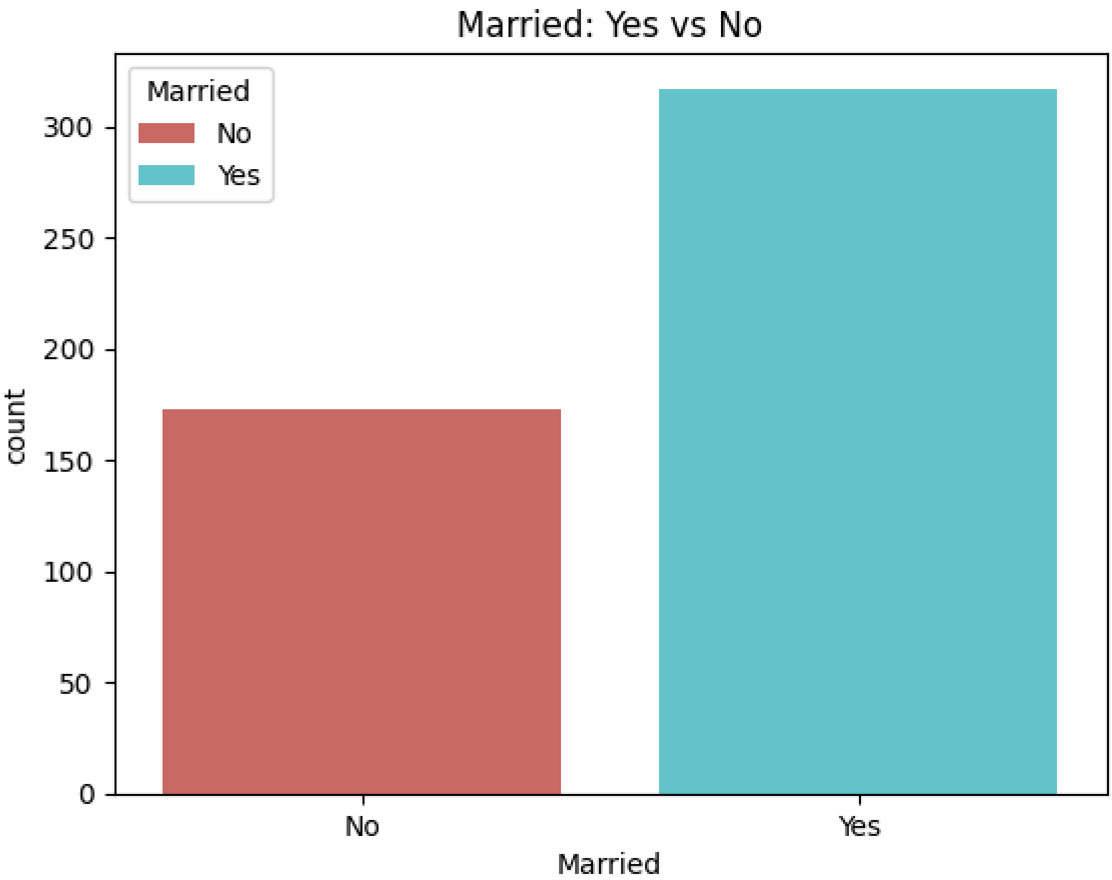
```
Gender
Male      395
Female     89
NaN         9
Name: count, dtype: int64
Percentage of Male: 80.12170385395537
Percentage of Female: 18.052738336713997
```



In [6]:

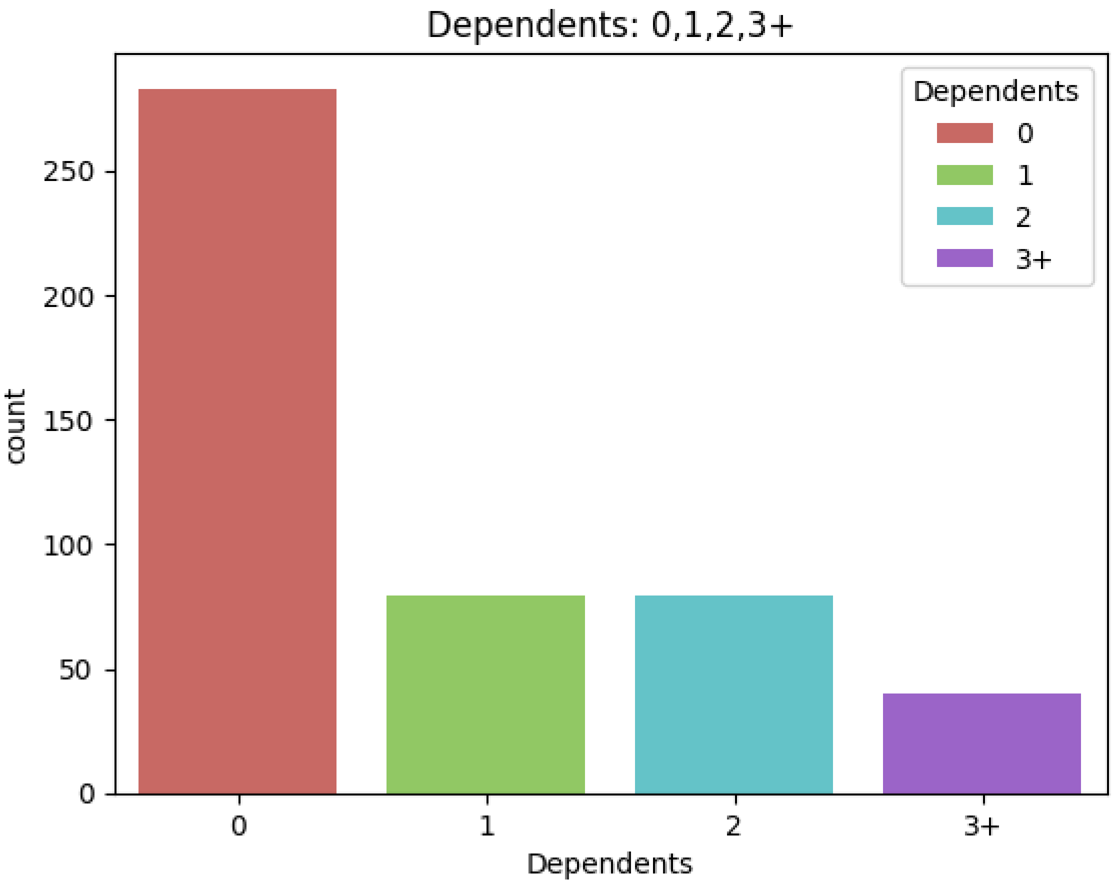
```
#2. Married

print(df['Married'].unique())
print(df.Married.value_counts(dropna=False))
print("Percentage of Yes:", len(df[df['Married']=='Yes'])/len(df.Married)
print("Percentage of No:", len(df[df['Married']=='No'])/len(df.Married)*1
sns.countplot(x="Married", data=df,hue='Married', palette="hls")
plt.title("Married: Yes vs No")
plt.savefig('figures//Married.png', bbox_inches='tight')
plt.show()

# Married are significantly higher than Non-Married
```

```
['No' 'Yes' nan]
Married
Yes    317
No     173
NaN      3
Name: count, dtype: int64
Percentage of Yes: 64.3002028397566
Percentage of No: 35.09127789046653
```



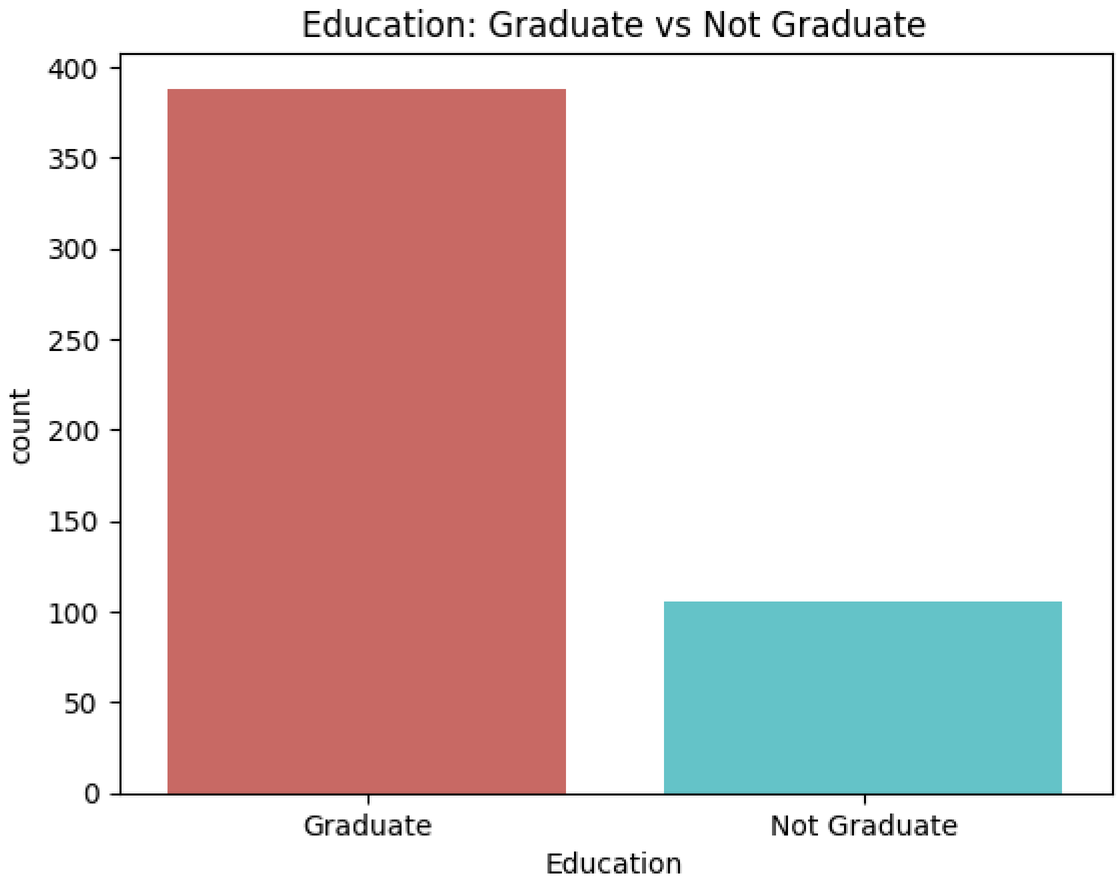
In [7]:
```
# 3. Dependents

print(df['Dependents'].unique())
print(df.Dependents.value_counts(dropna=False))
print("Percentage of 0:", len(df[df['Dependents']=='0'])/len(df.Dependent
print("Percentage of 1:", len(df[df['Dependents']=='1'])/len(df.Dependent
print("Percentage of 2:", len(df[df['Dependents']=='2'])/len(df.Dependent
print("Percentage of 3+:", len(df[df['Dependents']=='3+'])/len(df.Depende
sns.countplot(x="Dependents", data=df,hue='Dependents', palette="hls")
plt.title("Dependents: 0,1,2,3+")
plt.savefig('figures//Dependents.png', bbox_inches='tight')
plt.show()

# Applicants which don't have dependents are significantly higher than ap
# that have 1,2 and 3 or more than 3 dependents
```

```
['0' '1' '2' '3+' nan]
Dependents
0      283
1       79
2       79
3+      40
NaN     12
Name: count, dtype: int64
Percentage of 0: 57.40365111561866
Percentage of 1: 16.024340770791078
Percentage of 2: 16.024340770791078
Percentage of 3+: 8.113590263691684
```



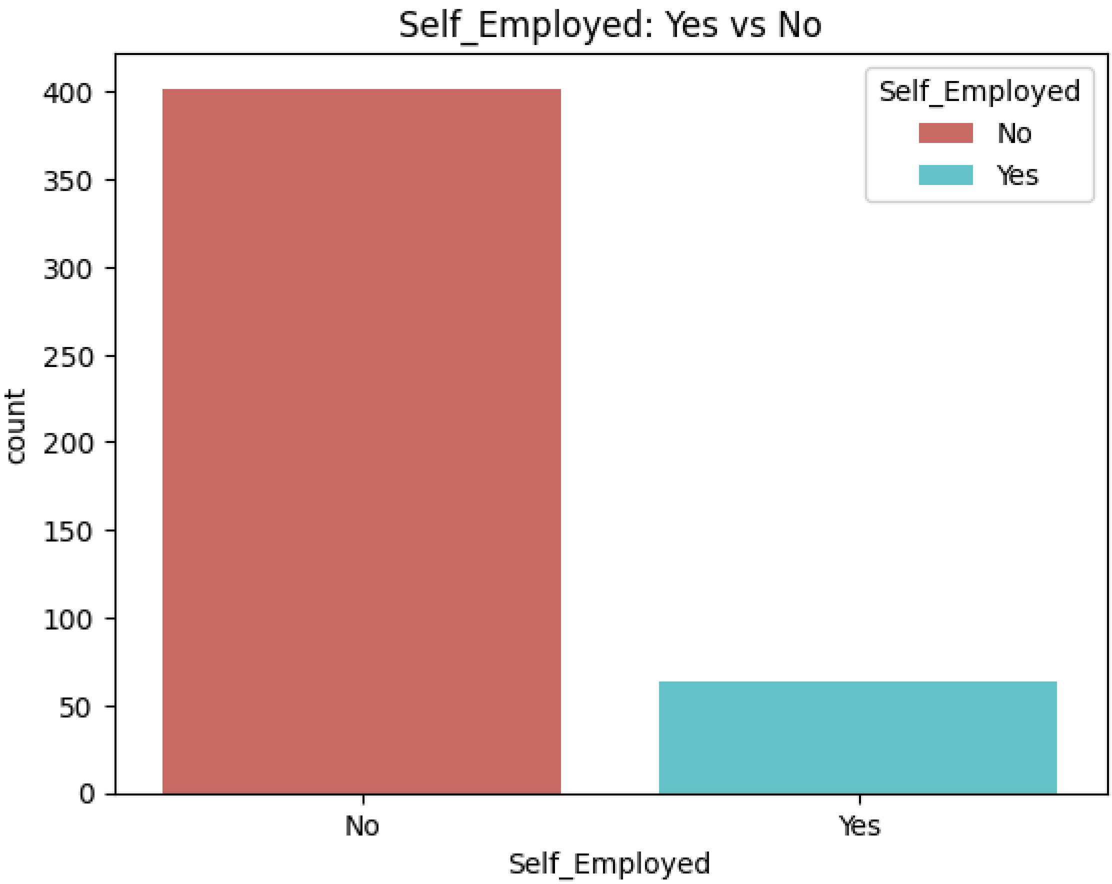
In [8]:
```
# 4.  Education

print(df['Education'].unique())
print(df.Education.value_counts(dropna=False))
print("Percentage of Graduate:", len(df[df['Education']=='Graduate'])/len
print("Percentage of Not Graduate:", len(df[df['Education']=='Not Graduat
sns.countplot(x="Education", data=df,hue='Education', palette="hls")
plt.title("Education: Graduate vs Not Graduate")
plt.savefig('figures//Education.png', bbox_inches='tight')
plt.show()

# Graduate applicants are significantly higher than non-graduate applican
```

```
['Graduate' 'Not Graduate']
Education
Graduate        388
Not Graduate    105
Name: count, dtype: int64
Percentage of Graduate: 78.70182555780933
Percentage of Not Graduate: 21.29817444219067
```



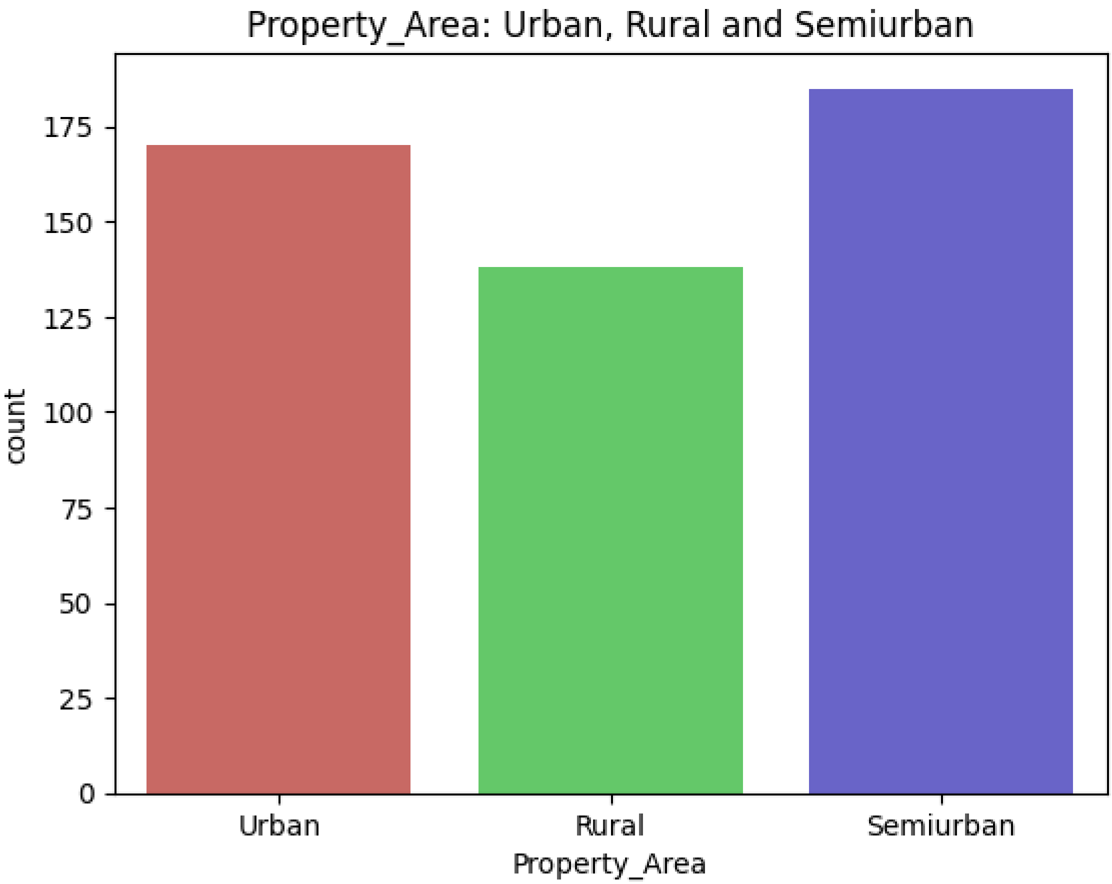
In [9]:
```
# 5. Self_Employed

print(df['Self_Employed'].unique())
print(df.Self_Employed.value_counts(dropna=False))
print("Percentage of Yes:", len(df[df['Self_Employed']=='Yes'])/len(df.Se
print("Percentage of No:", len(df[df['Self_Employed']=='No'])/len(df.Self
sns.countplot(x="Self_Employed", data=df,hue='Self_Employed', palette="hl
plt.title("Self_Employed: Yes vs No")
plt.savefig('figures//Self_Employed.png', bbox_inches='tight')
plt.show()

# non-self_employed are significantly higher than applicants who are self
```

```
['No' 'Yes' nan]
Self_Employed
No     402
Yes     64
NaN     27
Name: count, dtype: int64
Percentage of Yes: 12.981744421906694
Percentage of No: 81.54158215010142
```



In [10]:
```
# 6. Property_Area

print(df['Property_Area'].unique())
print(df.Property_Area.value_counts(dropna=False))
print("Percentage of Urban:", len(df[df['Property_Area']=='Urban'])/len(d
print("Percentage of Rural:", len(df[df['Property_Area']=='Rural'])/len(d
print("Percentage of Semiurban:", len(df[df['Property_Area']=='Semiurban'
sns.countplot(x="Property_Area", data=df,hue='Property_Area', palette="hl
plt.title("Property_Area: Urban, Rural and Semiurban")
plt.savefig('figures//Property_Area.png', bbox_inches='tight')
plt.show()

# All 3 categories or Urban, Rural and Semiurban are almost in equal prop
```

```
['Urban' 'Rural' 'Semiurban']
Property_Area
Semiurban    185
Urban        170
Rural        138
Name: count, dtype: int64
Percentage of Urban: 34.48275862068966
Percentage of Rural: 27.99188640973631
Percentage of Semiurban: 37.52535496957404
```



In [11]:
```
#  Exploring Numerical variables

# 7. Credit_History

print(df['Credit_History'].unique())
print(df.Credit_History.value_counts(dropna=False))
print("Percentage of 1:", len(df[df['Credit_History']==1.0])/len(df.Credi
print("Percentage of 0:", len(df[df['Credit_History']==0.0])/len(df.Credi
sns.countplot(x="Credit_History", data=df,hue='Credit_History', palette="
plt.title("Credit_History: 1 vs 0")
plt.savefig('figures//Credit_History.png', bbox_inches='tight')
plt.show()

# Applicants those have credit history are significantly higher than appl
# those don't have credit history
```

```
[ 1.  0. nan]
Credit_History
1.0    383
0.0     70
NaN     40
Name: count, dtype: int64
Percentage of 1: 77.68762677484787
Percentage of 0: 14.198782961460447
```

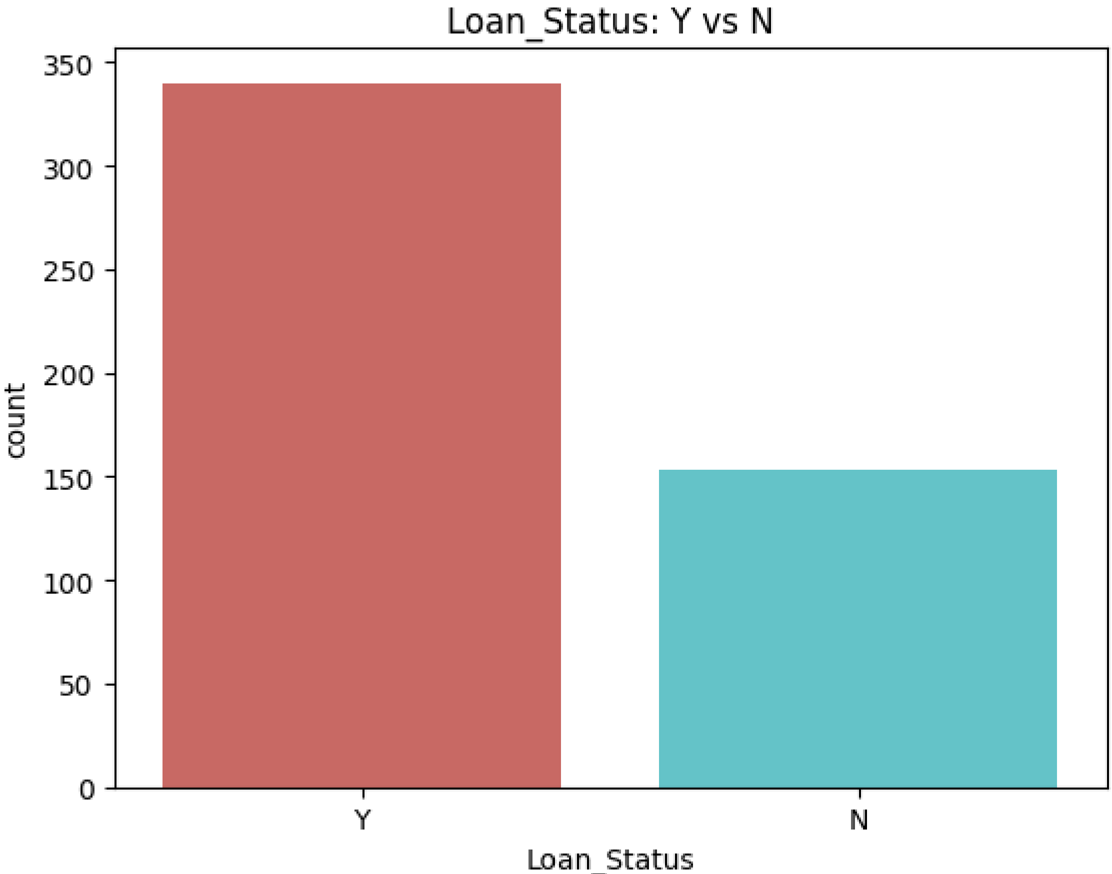
In [12]:
```
#  8. ApplicantIncome

print(df['Loan_Amount_Term'].unique())
print(df.Loan_Amount_Term.value_counts(dropna=False))

# Number of applicants those have loan amount term as 360 are significant
```

```
[360. 120. 240.  nan 180.  60. 300. 480.  36.  84.]
Loan_Amount_Term
360.0    410
180.0     35
NaN       14
300.0     12
480.0     12
120.0      3
240.0      3
60.0       2
36.0       1
84.0       1
Name: count, dtype: int64
```

In [13]:
```
# 9. Loan_Status

print(df['Loan_Status'].unique())
print(df.Loan_Status.value_counts(dropna=False))
print("Percentage of Y:", len(df[df['Loan_Status']=='Y'])/len(df.Loan_Sta
print("Percentage of N:", len(df[df['Loan_Status']=='N'])/len(df.Loan_Sta
sns.countplot(x="Loan_Status", data=df,hue='Loan_Status', palette="hls")
plt.title("Loan_Status: Y vs N")
plt.savefig('figures//Loan_Status.png', bbox_inches='tight')
plt.show()
```

```
# Applicants those are eligible for loan are significantly higher than th
# who are not eligible
```

```
['Y' 'N']
Loan_Status
Y    340
N    153
Name: count, dtype: int64
Percentage of Y: 68.96551724137932
Percentage of N: 31.03448275862069
```



In [14]:

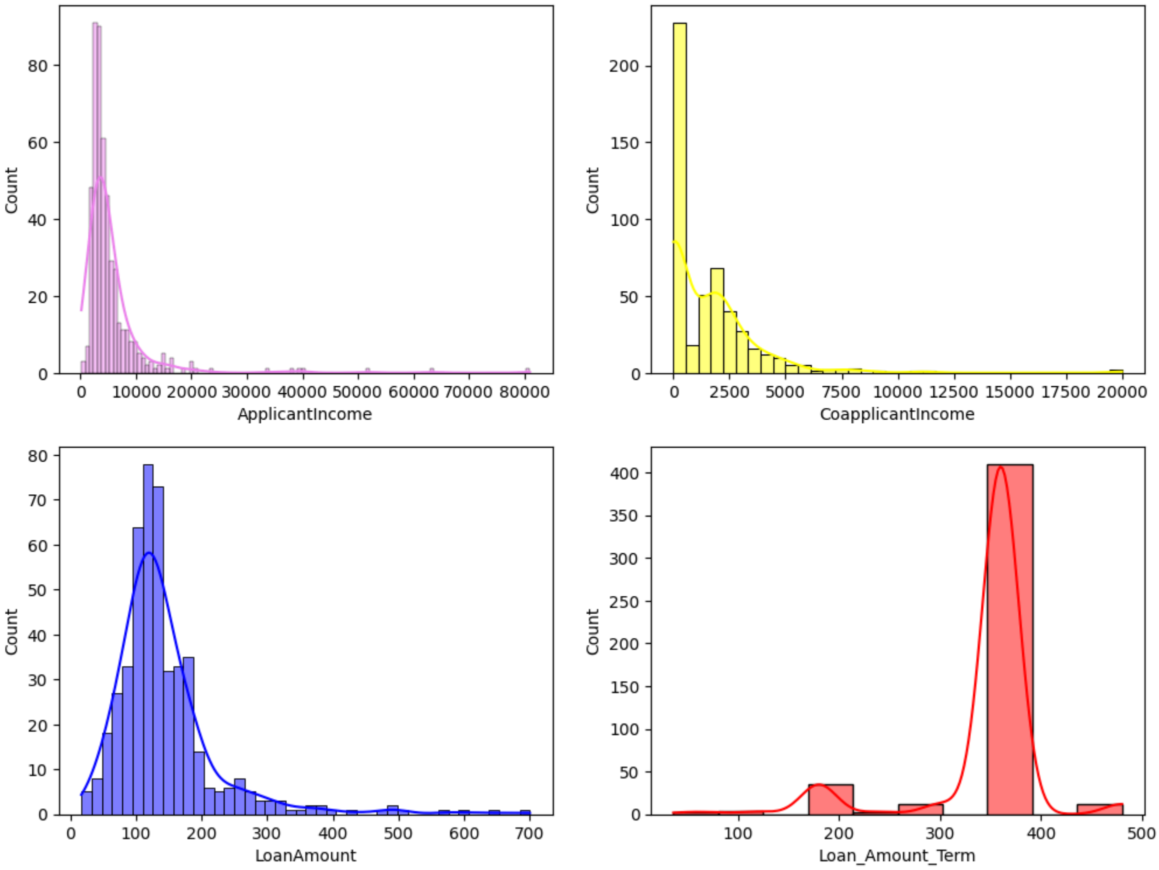
```
# Other Numerical variables

print(df[['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
count	493.000000	493.000000	475.000000	479.000000
mean	5489.316430	1503.267586	144.098947	343.590814
std	6536.512594	2142.152671	82.724115	61.334118
min	150.000000	0.000000	17.000000	36.000000
25%	2873.000000	0.000000	100.000000	360.000000
50%	3858.000000	1125.000000	127.000000	360.000000
75%	5746.000000	2253.000000	161.000000	360.000000
max	81000.000000	20000.000000	700.000000	480.000000

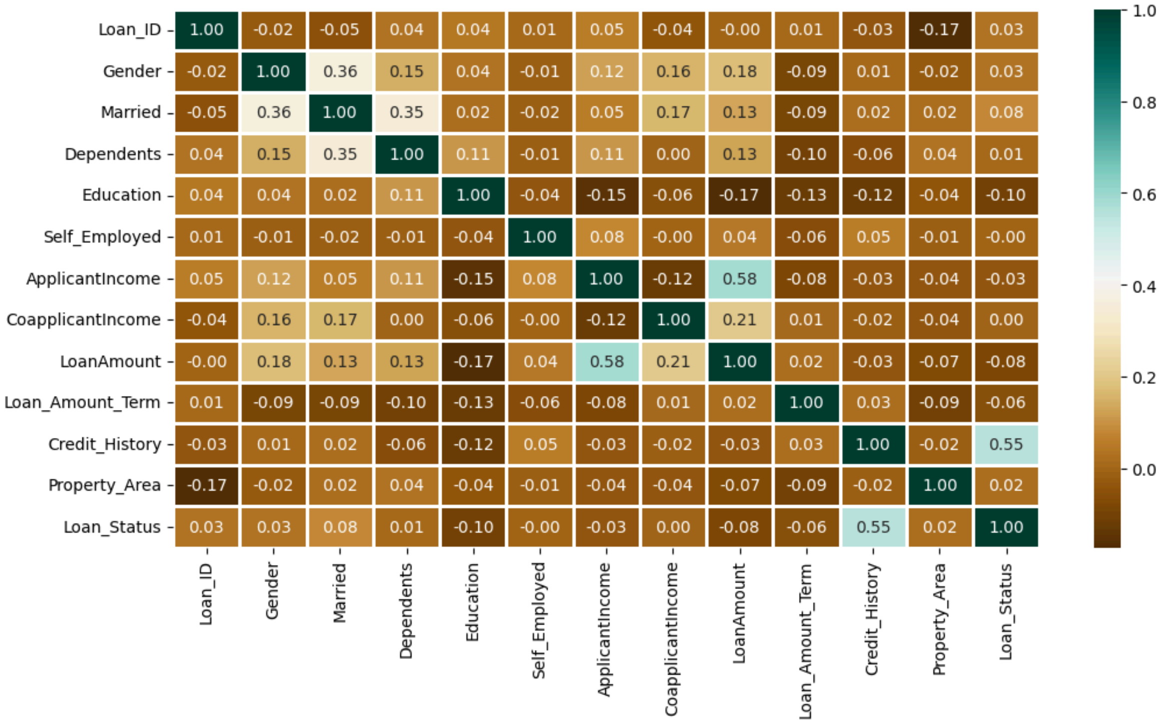
In [15]:

```
# Histograms

fig, axs = plt.subplots(2, 2, figsize=(12, 9))

sns.histplot(data=df, x="ApplicantIncome", kde=True, ax=axs[0, 0], color=
sns.histplot(data=df, x="CoapplicantIncome", kde=True, ax=axs[0, 1], colo
sns.histplot(data=df, x="LoanAmount", kde=True, ax=axs[1, 0], color='blue
sns.histplot(data=df, x="Loan_Amount_Term", kde=True, ax=axs[1, 1], color
plt.savefig('figures//NumVar_Hist.png', bbox_inches='tight')
```

```
# Here, ApplicantIncome, CoapplicantIncome are positive skewed and has ou
# Loan_Amount_Term feature has a outlier and negative skewed.
```



In [16]:
```
# Finding Correlation
df1=copy.copy(df)
label_encoder = preprocessing.LabelEncoder()
cat = (df1.dtypes == 'object')
for i in list(cat[cat].index):
    df1[i] = label_encoder.fit_transform(df1[i])

plt.figure(figsize=(12,6))

sns.heatmap(df1.corr(),cmap='BrBG',fmt='.2f', linewidths=2,annot=True)
plt.savefig('figures//Correlation.png', bbox_inches='tight')
# symmetric correlation matrix and loan_status is highly correlated with
# Gender/Dependents and Married are somewhat correlated
# LoanAmount and ApplicantIncome is correlated

# Loan_ID is very less correlated with other variables and the target var
# it is used for the primary key, we can drop it.
```



Data Preprocessing

In [17]:
```
############################ Data Preprocessing  ########################

print(df.isnull().sum())
print("#################################################")
print(validation_df.isnull().sum())

## Removing unnecessary variable

# Loan_ID is very less correlated with other variables and the target var
# and it is used as a primary key, so, we can drop it.


df = df.drop(['Loan_ID'], axis = 1)
validation_df = validation_df.drop(['Loan_ID'], axis = 1)
```

```
Loan_ID              0
Gender               9
Married              3
Dependents          12
Education            0
Self_Employed       27
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount          18
Loan_Amount_Term    14
Credit_History      40
Property_Area        0
Loan_Status          0
dtype: int64
##################################################
Loan_ID              0
Gender               4
Married              0
Dependents           3
Education            0
Self_Employed        5
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           4
Loan_Amount_Term     0
Credit_History      10
Property_Area        0
dtype: int64
```

In [18]:
```
## make the same datatypes

validation_df["CoapplicantIncome"] = validation_df["CoapplicantIncome"].a
validation_df["Loan_Amount_Term"] = validation_df["Loan_Amount_Term"].ast

## Imputing the missing values

# For missing valued categorical variables, we will use "mode".

df['Gender'].fillna(df['Gender'].mode()[0],inplace=True)
df['Married'].fillna(df['Married'].mode()[0],inplace=True)
df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0],inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],inplace=Tr
# Though Credit_History and Loan_Amount_Term is a numberical variable but
# its values are in particular class like 0 and 1 and 360,180 etc and it

# For missing valued numerical variables, we will use "mean".


df['LoanAmount'].fillna(df['LoanAmount'].mean(),inplace=True)

#######

validation_df['Gender'].fillna(validation_df['Gender'].mode()[0],inplace=
validation_df['Married'].fillna(validation_df['Married'].mode()[0],inplac
validation_df['Dependents'].fillna(validation_df['Dependents'].mode()[0],
validation_df['Self_Employed'].fillna(validation_df['Self_Employed'].mode
validation_df['Credit_History'].fillna(validation_df['Credit_History'].mo
validation_df['Loan_Amount_Term'].fillna(validation_df['Loan_Amount_Term'
```

```
# Though Credit_History and Loan_Amount_Term is a numberical variable but
# its values are in particular class like 0 and 1 and 360,180 etc and it

# For missing valued numerical variables, we will use "mean".


validation_df['LoanAmount'].fillna(validation_df['LoanAmount'].mean(),inp
```

```
/tmp/ipykernel_36101/2255197945.py:10: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Gender'].fillna(df['Gender'].mode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:11: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Married'].fillna(df['Married'].mode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:12: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:13: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Self_Employed'].fillna(df['Self_Employed'].mode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:14: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
```

```
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:15: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],inplace=T
rue)
/tmp/ipykernel_36101/2255197945.py:22: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['LoanAmount'].fillna(df['LoanAmount'].mean(),inplace=True)
/tmp/ipykernel_36101/2255197945.py:26: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['Gender'].fillna(validation_df['Gender'].mode()[0],inplace
=True)
/tmp/ipykernel_36101/2255197945.py:27: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['Married'].fillna(validation_df['Married'].mode()[0],inpla
ce=True)
```

```
/tmp/ipykernel_36101/2255197945.py:28: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['Dependents'].fillna(validation_df['Dependents'].mode()
[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:29: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['Self_Employed'].fillna(validation_df['Self_Employed'].mod
e()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:30: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['Credit_History'].fillna(validation_df['Credit_History'].m
ode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:31: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['Loan_Amount_Term'].fillna(validation_df['Loan_Amount_Ter
m'].mode()[0],inplace=True)
/tmp/ipykernel_36101/2255197945.py:38: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment using
an inplace method.
The behavior will change in pandas 3.0. This inplace method will never wor
```

```
k because the intermediate object on which we are setting values always be
haves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  validation_df['LoanAmount'].fillna(validation_df['LoanAmount'].mean(),in
place=True)
```

In [19]:
```
## Label Encoding (One-hot Encoding)

df = pd.get_dummies(df)

# removing unwanted columns
df = df.drop(['Gender_Female', 'Married_No', 'Education_Not Graduate',
              'Self_Employed_No', 'Loan_Status_N'], axis = 1)

# Rename the columns
df.rename(columns={'Gender_Male': 'Gender', 'Married_Yes': 'Married',
       'Education_Graduate': 'Education', 'Self_Employed_Yes': 'Self_Empl
       'Loan_Status_Y': 'Loan_Status'}, inplace=True)
#df.replace({False: 0, True: 1}, inplace=True)
print("\nColumns are:\n\n",df.columns)

df["Gender"] = df["Gender"].astype(int)
df["Married"] = df["Married"].astype(int)
df["Dependents_0"] = df["Dependents_0"].astype(int)
df["Dependents_1"] = df["Dependents_1"].astype(int)
df["Dependents_2"] = df["Dependents_2"].astype(int)
df["Dependents_3+"] = df["Dependents_3+"].astype(int)
df["Education"] = df["Education"].astype(int)
df["Self_Employed"] = df["Self_Employed"].astype(int)
df["Property_Area_Rural"] = df["Property_Area_Rural"].astype(int)
df["Property_Area_Semiurban"] = df["Property_Area_Semiurban"].astype(int)
df["Property_Area_Urban"] = df["Property_Area_Urban"].astype(int)
df["Loan_Status"] = df["Loan_Status"].astype(int)

#########

validation_df = pd.get_dummies(validation_df)

# removing unwanted columns
validation_df = validation_df.drop(['Gender_Female', 'Married_No', 'Educa
              'Self_Employed_No'], axis = 1)

# Rename the columns
validation_df.rename(columns={'Gender_Male': 'Gender', 'Married_Yes': 'Ma
       'Education_Graduate': 'Education', 'Self_Employed_Yes': 'Self_Empl
#df.replace({False: 0, True: 1}, inplace=True)
print("\nColumns are:\n\n",validation_df.columns)

validation_df["Gender"] = validation_df["Gender"].astype(int)
validation_df["Married"] = validation_df["Married"].astype(int)
validation_df["Dependents_0"] = validation_df["Dependents_0"].astype(int)
validation_df["Dependents_1"] = validation_df["Dependents_1"].astype(int)
validation_df["Dependents_2"] = validation_df["Dependents_2"].astype(int)
validation_df["Dependents_3+"] = validation_df["Dependents_3+"].astype(in
validation_df["Education"] = validation_df["Education"].astype(int)
```

```
validation_df["Self_Employed"] = validation_df["Self_Employed"].astype(in
validation_df["Property_Area_Rural"] = validation_df["Property_Area_Rural
validation_df["Property_Area_Semiurban"] = validation_df["Property_Area_S
validation_df["Property_Area_Urban"] = validation_df["Property_Area_Urban
```

```
Columns are:

 Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Gender', 'Married',
       'Dependents_0', 'Dependents_1', 'Dependents_2', 'Dependents_3+',
       'Education', 'Self_Employed', 'Property_Area_Rural',
       'Property_Area_Semiurban', 'Property_Area_Urban', 'Loan_Status'],
      dtype='object')

Columns are:

 Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Gender', 'Married',
       'Dependents_0', 'Dependents_1', 'Dependents_2', 'Dependents_3+',
       'Education', 'Self_Employed', 'Property_Area_Rural',
       'Property_Area_Semiurban', 'Property_Area_Urban'],
      dtype='object')
```

In [20]:

```
print("\n number of rows in dataset before outlier removal:",len(df))
# ## Removing Outliers by using boxplots

Q1 = df.quantile(0.25) # 25 percentile
Q3 = df.quantile(0.75) # 75 percentile
IQR = Q3 - Q1 # Interquartile range

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

print("\n number of rows in dataset after outlier removal:",len(df))
```

```
 number of rows in dataset before outlier removal: 493

 number of rows in dataset after outlier removal: 114
```

In [21]:

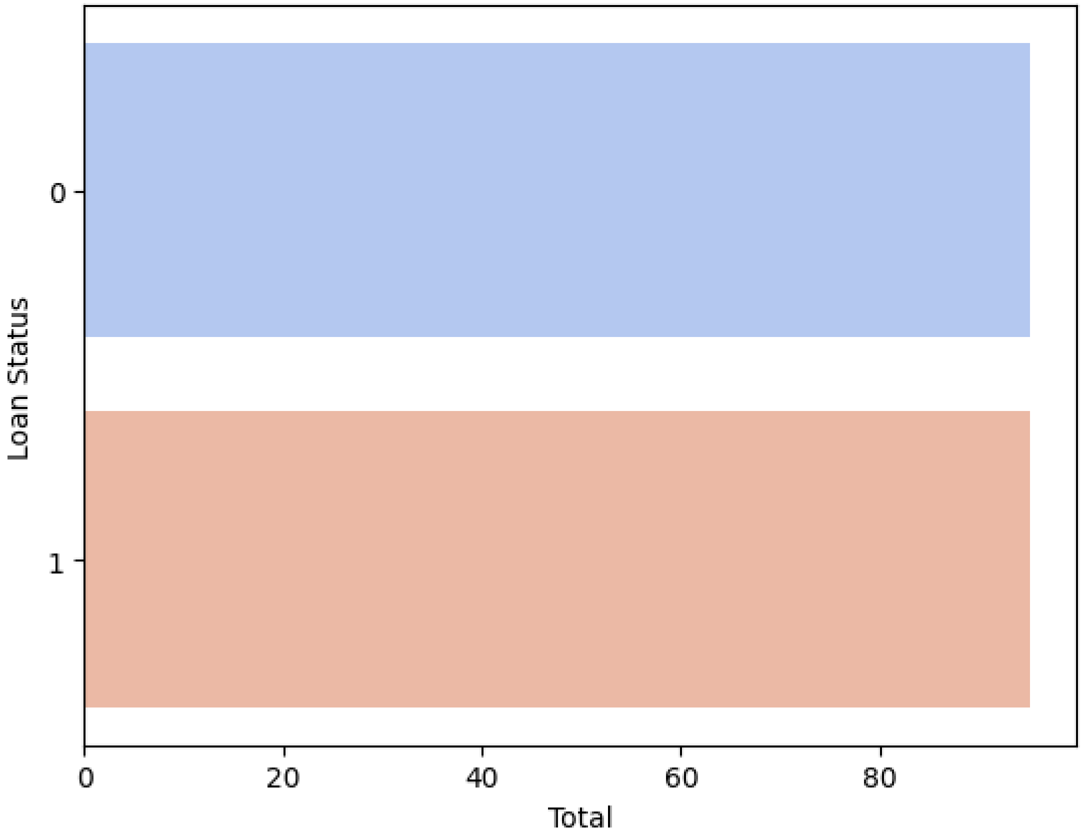
```
# ApplicantIncome, CoapplicantIncome, and LoanAmount are positively skewe
# So, we will use square root transformation to normalized the distributi

df.ApplicantIncome = np.sqrt(df.ApplicantIncome)
df.CoapplicantIncome = np.sqrt(df.CoapplicantIncome)
df.LoanAmount = np.sqrt(df.LoanAmount)
validation_df.ApplicantIncome = np.sqrt(validation_df.ApplicantIncome)
validation_df.CoapplicantIncome = np.sqrt(validation_df.CoapplicantIncome
validation_df.LoanAmount = np.sqrt(validation_df.LoanAmount)
```

In [22]:

```
## Splitting into dependent and independent features

X = df.drop(["Loan_Status"], axis=1)
y = df["Loan_Status"]

## Data Imbalanced resolution

# As we have seen initially that Loan_Status column is imbalanced for cla
# so we use oversampling using SMOTE to avoid the overfitting problem

X, y = SMOTE().fit_resample(X, y)
```

```
# check whether classes are baanced or not
sns.countplot(y=y, data=df, palette="coolwarm")
plt.ylabel('Loan Status')
plt.xlabel('Total')
plt.savefig('figures//Balanced_Loan_Status.png', bbox_inches='tight')
plt.show()
```

```
/tmp/ipykernel_36101/4180333104.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for
the same effect.

  sns.countplot(y=y, data=df, palette="coolwarm")
```



In [23]:
```
## Data Normalization


X = MinMaxScaler().fit_transform(X)

## Train-Test Split

# we make the 80% for training set and 20% for the validation set

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2
```

Build and fit the Model and Evaluate the results

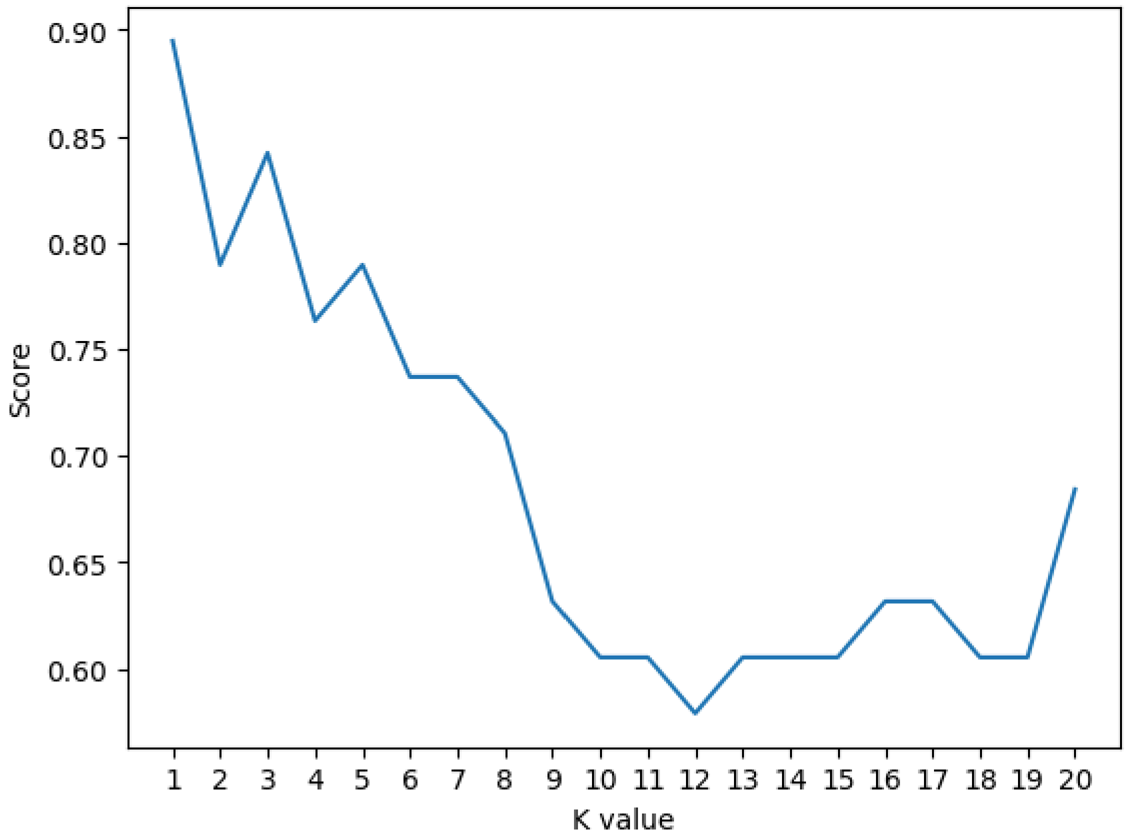
In [24]:
```
##############################  Models  ##################################

# 1. Logistic Regression

LogR_clf = LogisticRegression(solver='saga', max_iter=500, random_state=1
```

```
LogR_clf.fit(X_train, y_train)

y_pred = LogR_clf.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

LogR_Acc = accuracy_score(y_pred,y_test)
print('Logistic Regression accuracy:',LogR_Acc*100)
```

```
              precision    recall  f1-score   support

           0       0.47      0.57      0.52        14
           1       0.71      0.62      0.67        24

    accuracy                           0.61        38
   macro avg       0.59      0.60      0.59        38
weighted avg       0.62      0.61      0.61        38

[[ 8  6]
 [ 9 15]]
Logistic Regression accuracy: 60.526315789473685
```

In [25]:

```
# 2. KNN

score_list = []
for i in range(1,21):
    KNN_clf = KNeighborsClassifier(n_neighbors = i)
    KNN_clf.fit(X_train, y_train)
    score_list.append(KNN_clf.score(X_test, y_test))

plt.plot(range(1,21), score_list)
plt.xticks(np.arange(1,21,1))
plt.xlabel("K value")
plt.ylabel("Score")
plt.savefig('figures//KNN.png', bbox_inches='tight')
plt.show()
KNN_Acc = max(score_list)
print("KNN best accuracy: ",KNN_Acc*100)
```




```
KNN best accuracy:  89.47368421052632
```

In [26]:
```
# 3. SVM

SVC_clf = SVC(kernel='rbf', max_iter=500)
SVC_clf.fit(X_train, y_train)

y_pred = SVC_clf.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

SVC_Acc = accuracy_score(y_pred,y_test)
print('SVC accuracy: ',SVC_Acc*100)
```

```
              precision    recall  f1-score   support

           0       0.47      0.57      0.52        14
           1       0.71      0.62      0.67        24

    accuracy                           0.61        38
   macro avg       0.59      0.60      0.59        38
weighted avg       0.62      0.61      0.61        38

[[ 8  6]
 [ 9 15]]
SVC accuracy:  60.526315789473685
```

In [27]:
```
# 4. Naive Bayes

# 4.1 Categorical NB

NB_clf1 = CategoricalNB()
NB_clf1.fit(X_train, y_train)
```

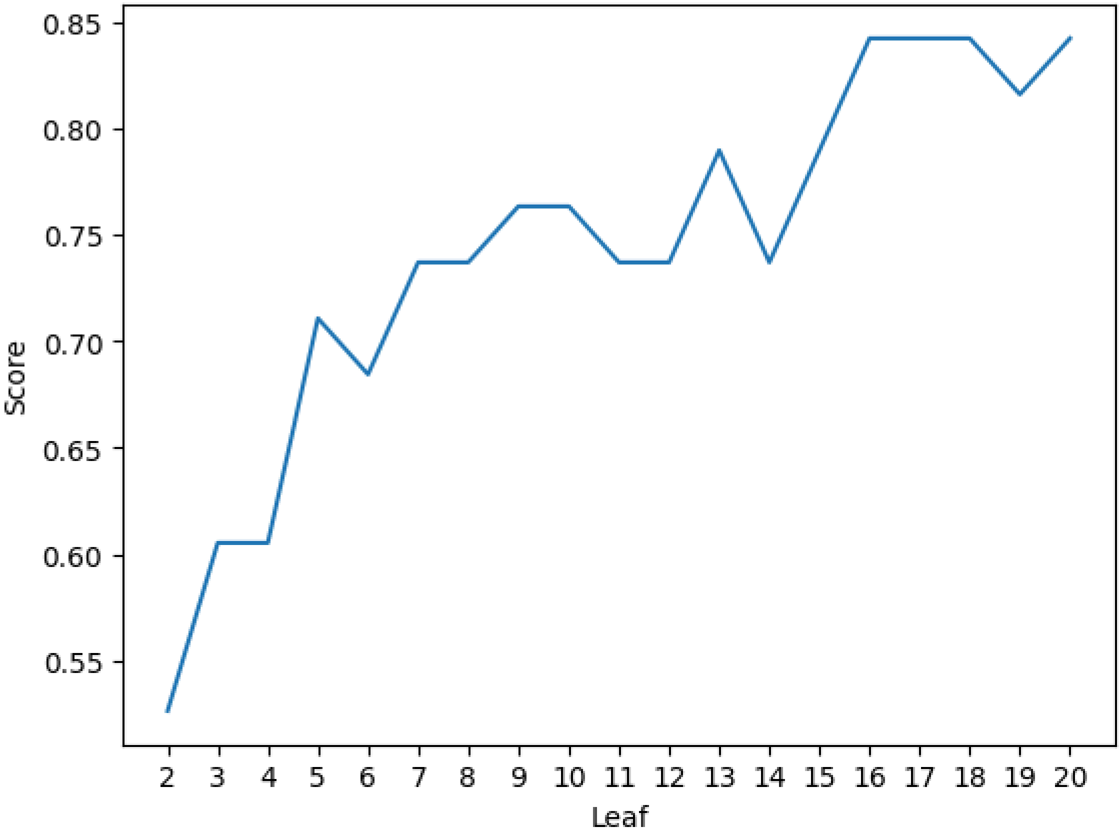
```
y_pred = NB_clf1.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

NB_Acc1 = accuracy_score(y_pred,y_test)
print('Categorical Naive Bayes accuracy: ',NB_Acc1*100)

# 4.2 Gaussian NB

NB_clf2 = GaussianNB()
NB_clf2.fit(X_train, y_train)

y_pred = NB_clf2.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

NB_Acc2 = accuracy_score(y_pred,y_test)
print('Gaussian Naive Bayes accuracy: ',NB_Acc2*100)
```

```
              precision    recall  f1-score   support

           0       0.52      0.86      0.65        14
           1       0.87      0.54      0.67        24

    accuracy                           0.66        38
   macro avg       0.69      0.70      0.66        38
weighted avg       0.74      0.66      0.66        38

[[12  2]
 [11 13]]
Categorical Naive Bayes accuracy:  65.78947368421053
              precision    recall  f1-score   support

           0       0.48      0.86      0.62        14
           1       0.85      0.46      0.59        24

    accuracy                           0.61        38
   macro avg       0.66      0.66      0.60        38
weighted avg       0.71      0.61      0.60        38

[[12  2]
 [13 11]]
Gaussian Naive Bayes accuracy:  60.526315789473685
```

In [28]:

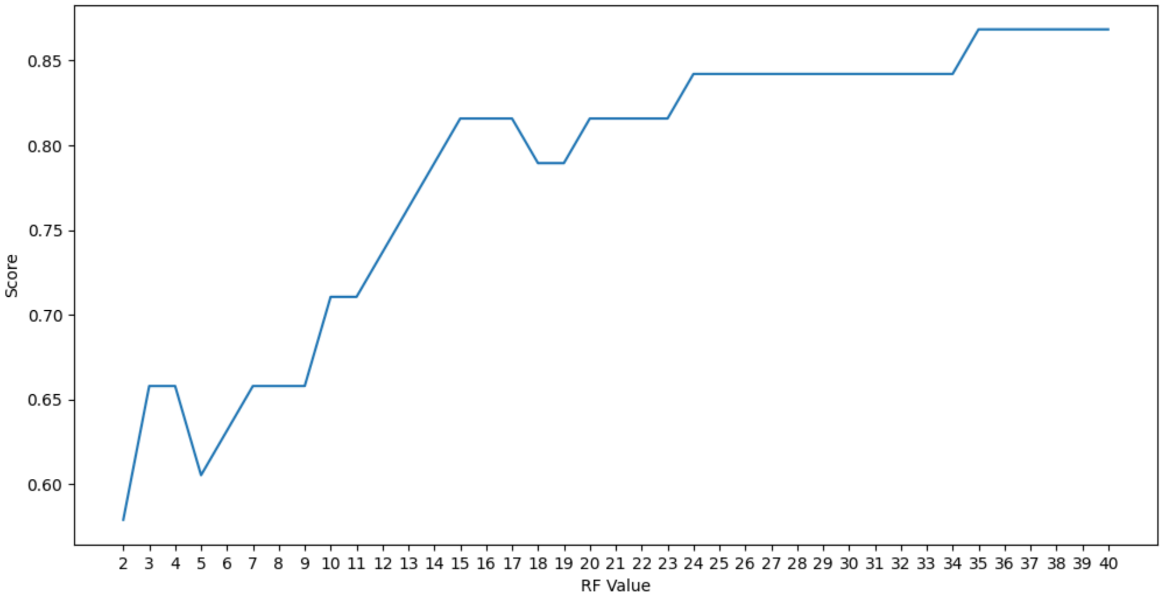
```
# 5. Decision Tree

score_list= []
for i in range(2,21):
    DT_clf = DecisionTreeClassifier(max_leaf_nodes=i)
    DT_clf.fit(X_train, y_train)
    score_list.append(DT_clf.score(X_test, y_test))

plt.plot(range(2,21), score_list)
plt.xticks(np.arange(2,21,1))
plt.xlabel("Leaf")
plt.ylabel("Score")
plt.savefig('figures//Decision_Tree.png', bbox_inches='tight')
plt.show()
```

```
DT_Acc = max(score_list)
print("Decision Tree Accuracy: ",DT_Acc*100)
```




```
Decision Tree Accuracy:  84.21052631578947
```

In [29]:
```
# 6. Random Forest

score_list = []
for i in range(2,41):
    RF_clf = RandomForestClassifier(n_estimators = 1000, random_state = 1
    RF_clf.fit(X_train, y_train)
    score_list.append(RF_clf.score(X_test, y_test))

plt.figure(figsize=(12,6))
plt.plot(range(2,41), score_list)
plt.xticks(np.arange(2,41,1))
plt.xlabel("RF Value")
plt.ylabel("Score")
plt.savefig('figures//Random_Forest.png', bbox_inches='tight')
plt.show()
RF_Acc = max(score_list)
print("Random Forest Accuracy: ",RF_Acc*100)
```




```
Random Forest Accuracy:  86.8421052631579
```

In [30]:

```
# 7. Gradient Boosting

params_GB={'n_estimators':[100,200,300,400,500],
       'max_depth':[1,2,3,4,5],
       'subsample':[0.5,1],
       'max_leaf_nodes':[2,5,10,20,30,40,50]}

GB = RandomizedSearchCV(GradientBoostingClassifier(), params_GB, cv=20)
GB.fit(X_train, y_train)

print(GB.best_estimator_)
print(GB.best_score_)
print(GB.best_params_)
print(GB.best_index_)

GB_clf = GradientBoostingClassifier(subsample=0.2, n_estimators=200, max_
GB_clf.fit(X_train, y_train)

y_pred = GB_clf.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

GB_Acc = accuracy_score(y_pred,y_test)
print('Gradient Boosting accuracy: ',GB_Acc*100)
```

```
GradientBoostingClassifier(max_leaf_nodes=50, n_estimators=200, subsample=
0.5)
0.85
{'subsample': 0.5, 'n_estimators': 200, 'max_leaf_nodes': 50, 'max_depth':
3}
0
              precision    recall  f1-score   support

           0       0.79      0.79      0.79        14
           1       0.88      0.88      0.88        24

    accuracy                           0.84        38
   macro avg       0.83      0.83      0.83        38
weighted avg       0.84      0.84      0.84        38

[[11  3]
 [ 3 21]]
Gradient Boosting accuracy:  84.21052631578947
```

In [31]:

```
## Model Comparison

compare = pd.DataFrame({'Model': ['Logistic Regression', 'KNN',
                                  'SVM', 'Categorical NB',
                                  'Gaussian NB', 'Decision Tree',
                                  'Random Forest', 'Gradient Boost'],
                        'Accuracy': [LogR_Acc*100, KNN_Acc*100, SVC_Acc*1
                                     NB_Acc1*100, NB_Acc2*100, DT_Acc*100
                                     RF_Acc*100, GB_Acc*100]})
compare.sort_values(by='Accuracy', ascending=False)
```

Out[31]:

	Model	Accuracy
1	KNN	89.473684
6	Random Forest	86.842105
5	Decision Tree	84.210526
7	Gradient Boost	84.210526
3	Categorical NB	65.789474
0	Logistic Regression	60.526316
2	SVM	60.526316
4	Gaussian NB	60.526316

Prediction

In [32]:

```
# Prediction using Random Forest
X_val=validation_df.values
y_pred = RF_clf.predict(X_val)
val_df = pd.read_csv("validation.csv")
val_df['Predicted_Value']=y_pred
val_df.to_csv("result.csv",index=False)
```

In [ ]: