# Loan Approval Prediction

## Import Modules

In [1]:
```python
#Importing Required Modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')

print("Modules Imported Successfully!")
```

```
Modules Imported Successfully!
```

In [2]:
```python
#Importing Modules As Required
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier

print("Success!")
```

```
Success!
```

In [3]:
```python
#Loading Dataset
df = pd.read_csv('Loan_Train.csv')

print("Dataset Loaded Successfully!")
```

```
Dataset Loaded Successfully!
```

In [4]:
```python
#Checking the Shape of Dataset
df.shape
```

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

- There are **614 Rows** and **13 Columns** in our dataset.

In [5]:
```python
#Checking Column Names
df.columns
```

Out[5]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [6]:
```python
#First 5 rows of data
df.head()
```

Out[6]:

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | NaN | 360.0 |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.0 | 360.0 |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.0 | 360.0 |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.0 | 360.0 |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.0 | 360.0 |

In [7]:
```python
#Datatypes of features
df.info()
```

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

In [8]:
```python
#Statistical information about data
df.describe()
```

Out[8]:

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

In [9]:
```python
#Checking unique values in each feature
df.apply(lambda x: len(x.unique()))
```

Out[9]:
```
Loan_ID              614
Gender                 3
Married                3
Dependents             5
Education              2
Self_Employed          3
ApplicantIncome      505
CoapplicantIncome    287
LoanAmount           204
Loan_Amount_Term      11
Credit_History         3
Property_Area          3
Loan_Status            2
dtype: int64
```

In [10]:
```python
#Datatypes of features
df.info()
```

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

In [11]:
```python
#Checking null values in data, if any
df.isnull().sum()
```

Out[11]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [12]:
```python
#Handling Null Values with different strae
df['Gender'] = df['Gender'].fillna('Male')
df['Married'] = df['Married'].fillna('Yes')
df['Dependents'] = df['Dependents'].fillna(0)
df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].mean())
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].median())
df['Self_Employed'] = df['Self_Employed'].fillna('No')
df['Credit_History'] = df['Credit_History'].fillna(0)
```

In [13]:
```python
#Rechecking for null values
df.isnull().sum()
```

Out[13]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

In [14]:
```python
#Loan_ID as index and then dropping it
df.index = df['Loan_ID']
df = df.drop(columns='Loan_ID', axis=1)
df.head()
```

Out[14]:

| Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term |
|---|---|---|---|---|---|---|---|---|---|
| LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | 146.412162 | 360.0 |
| LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.000000 | 360.0 |
| LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.000000 | 360.0 |
| LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.000000 | 360.0 |
| LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.000000 | 360.0 |

In [15]:
```python
#Checking for Duplicate Rows
df.duplicated().sum()
```

Out[15]:
```
0
```

In [16]:
```python
#Checking data before moving to EDA
df.head()
```

Out[16]:

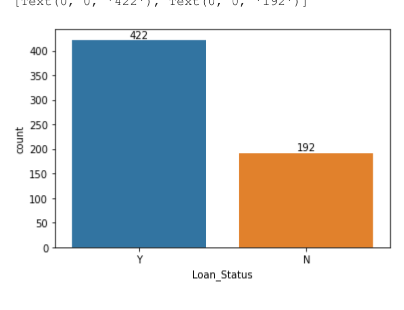
| Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term |
|---|---|---|---|---|---|---|---|---|---|
| LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | 146.412162 | 360.0 |
| LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.000000 | 360.0 |
| LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.000000 | 360.0 |
| LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.000000 | 360.0 |
| LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.000000 | 360.0 |

## Exploratory Data Analysis

### Loan Status

In [17]:
```python
#Countplot for Loan Status
ax = sns.countplot(x='Loan_Status', data=df)
ax.bar_label(ax.containers[0])
```

Out[17]:
```
[Text(0, 0, '422'), Text(0, 0, '192')]
```

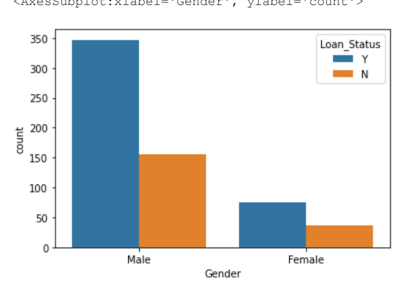



- Nearly **68%** loans gets approved.

### Gender

In [18]:
```python
#Countplot for loans on the basis of gender
sns.countplot(x=df['Gender'], data=df, hue='Loan_Status')
```

Out[18]:
```
&lt;AxesSubplot:xlabel='Gender', ylabel='count'&gt;
```

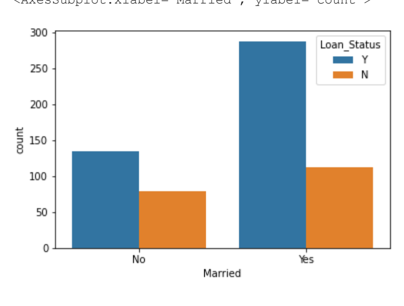



- **There are more Men than Women. (Approx. 3x)**

### Married

In [19]:
```python
#Countplot for loans on the basis of marital status
sns.countplot(x=df['Married'], data=df, hue='Loan_Status')
```

Out[19]:
```
&lt;AxesSubplot:xlabel='Married', ylabel='count'&gt;
```

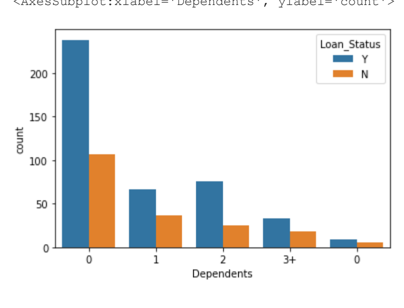



- **2/3rd of the population in the dataset is Married and Married applicants are more likely to be granted loans.**

### Dependents

In [20]:
```python
#Countplot for loans on the basis of Dependents
sns.countplot(x=df['Dependents'], data=df, hue='Loan_Status')
```

Out[20]:
```
&lt;AxesSubplot:xlabel='Dependents', ylabel='count'&gt;
```

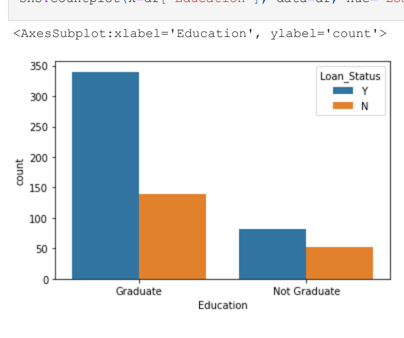



- **Majority of the population have 0 dependents and are also likely to accepted for loan.**

### Education

In [21]:
```python
#Countplot for loans on the basis of Education
sns.countplot(x=df['Education'], data=df, hue='Loan_Status')
```

Out[21]:
```
&lt;AxesSubplot:xlabel='Education', ylabel='count'&gt;
```

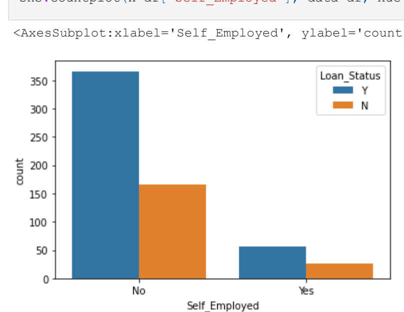



- **Nearly 5/6th population is graduate and are more likey to be approved for loan**

### Self Employed

In [22]:
```python
#Countplot for loans on the basis of Employment
sns.countplot(x=df['Self_Employed'], data=df, hue='Loan_Status')
```

Out[22]:
```
&lt;AxesSubplot:xlabel='Self_Employed', ylabel='count'&gt;
```

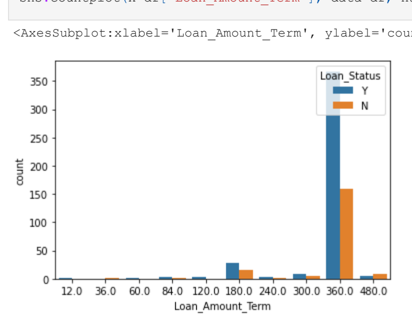



- **5/6th of the population is not self-employed.**

### Loan Amount Term

In [23]:
```python
#Countplot for loans on the basis of Term
sns.countplot(x=df['Loan_Amount_Term'], data=df, hue='Loan_Status')
```

Out[23]:
```
&lt;AxesSubplot:xlabel='Loan_Amount_Term', ylabel='count'&gt;
```

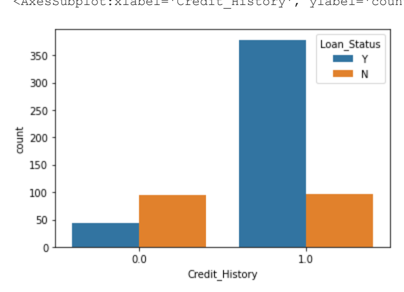



- **Majority of the loans are taken for 360 Months.(30 Years)**

### Credit History

In [24]:
```python
#Countplot for the loans on the basis of Credit History
sns.countplot(x=df['Credit_History'], data=df, hue='Loan_Status')
```

Out[24]:
```
&lt;AxesSubplot:xlabel='Credit_History', ylabel='count'&gt;
```




- **Applicants with credit history are more likely to be approved.**

### Property Area

In [25]:
```python
#Countplot for loans on the basis of Area
sns.countplot(x=df['Property_Area'], data=df, hue='Loan_Status')
```

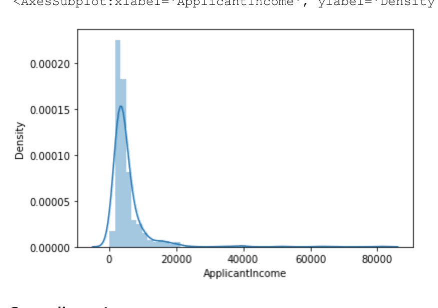
Out[25]:
```
&lt;AxesSubplot:xlabel='Property_Area', ylabel='count'&gt;
```


- **More applicants from Semi-urban and also more likely to be granted loans**

### Applicant Income

In [26]:
```python
#Histogram for Applicant Income
sns.distplot(df['ApplicantIncome'])
```

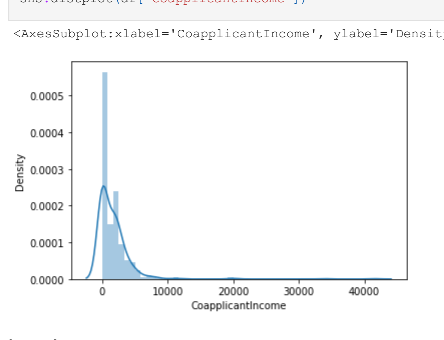
Out[26]:
```
&lt;AxesSubplot:xlabel='ApplicantIncome', ylabel='Density'&gt;
```




### Coapplicant Income

In [27]:
```python
#Histogram for Coapplicant Income
sns.distplot(df['CoapplicantIncome'])
```

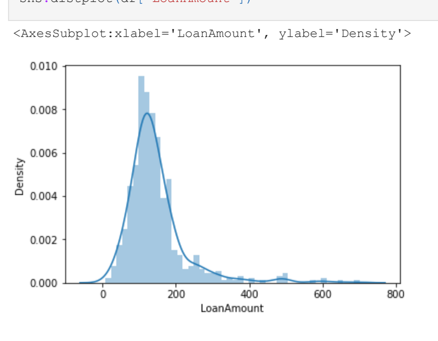
Out[27]:
```
&lt;AxesSubplot:xlabel='CoapplicantIncome', ylabel='Density'&gt;
```




### Loan Amount

In [28]:
```python
#Histogram for Loan Amount
sns.distplot(df['LoanAmount'])
```

Out[28]:
```
&lt;AxesSubplot:xlabel='LoanAmount', ylabel='Density'&gt;
```




- **Other than the skewedness of numerical data, there is nothing much to correlate the data in numerical features.**

## Preprocessing

In [29]:
```python
#Encoding categorical values to numerical
df = pd.get_dummies(df, drop_first=True)
```

In [30]:
```python
#Splitting the data into Feature and Target Variable
X = df.drop(columns = 'Loan_Status_Y')
y = df['Loan_Status_Y']
```

In [31]:
```python
#Splitting the data in Training and Test set
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,stratify =y,random_state =42)
```

## Training the models

### Logistic Regression

In [32]:
```python
LR = LogisticRegression()
LR.fit(X_train,y_train)
```

Out[32]:
```
LogisticRegression()
```

In [33]:
```python
y_pred = LR.predict(X_test)
```

In [34]:
```python
acc_LR = accuracy_score(y_test,y_pred)
f1_LR = f1_score(y_test,y_pred)

print("Accuracy: ", acc_LR)
print("F1 Score: ", f1_LR)
```

```
Accuracy:  0.8048780487804879
F1 Score:  0.8666666666666667
```

### Gaussian Naive Bayes

In [35]:
```python
GNB = GaussianNB()
GNB.fit(X_train,y_train)
```

Out[35]:
```
GaussianNB()
```

In [36]:
```python
y_pred = GNB.predict(X_test)
```

In [37]:
```python
acc_GNB = accuracy_score(y_test,y_pred)
f1_GNB = f1_score(y_test,y_pred)

print("Accuracy: ", acc_GNB)
print("F1 Score: ", f1_GNB)
```

```
Accuracy:  0.7642276422764228
F1 Score:  0.8432432432432432
```

### Decision Tree

In [38]:
```python
DT = DecisionTreeClassifier()
DT.fit(X_train,y_train)
```

Out[38]:
```
DecisionTreeClassifier()
```

In [39]:
```python
y_pred = DT.predict(X_test)
```

In [40]:
```python
acc_DT = accuracy_score(y_test,y_pred)
f1_DT = f1_score(y_test,y_pred)

print("Accuracy: ", acc_DT)
print("F1 Score: ", f1_DT)
```

```
Accuracy:  0.6829268292682927
F1 Score:  0.7636363636363637
```

### Random Forest

In [41]:
```python
RF = RandomForestClassifier()
RF.fit(X_train,y_train)
```

Out[41]:
```
RandomForestClassifier()
```

In [42]:
```python
y_pred = RF.predict(X_test)
```

In [43]:
```python
acc_RF = accuracy_score(y_test,y_pred)
f1_RF = f1_score(y_test,y_pred)

print("Accuracy: ", acc_RF)
print("F1 Score: ", f1_RF)
```

```
Accuracy:  0.7804878048780488
F1 Score:  0.8439306358381502
```

### Support Vecotr Machine

In [44]:
```python
SVM = SVC()
SVM.fit(X_train,y_train)
```

Out[44]:
```
SVC()
```

In [45]:
```python
y_pred = SVM.predict(X_test)
```

In [46]:
```python
acc_SVM = accuracy_score(y_test,y_pred)
f1_SVM = f1_score(y_test,y_pred)

print("Accuracy: ", acc_SVM)
print("F1 Score: ", f1_SVM)
```

```
Accuracy:  0.6910569105691057
F1 Score:  0.8173076923076924
```

### K-Nearest Neighbors

In [47]:
```python
KNN = KNeighborsClassifier()
KNN.fit(X_train,y_train)
```

Out[47]:
```
KNeighborsClassifier()
```

In [48]:
```python
y_pred = KNN.predict(X_test)
```

In [49]:
```python
acc_KNN = accuracy_score(y_test,y_pred)
f1_KNN = f1_score(y_test,y_pred)

print("Accuracy: ", acc_KNN)
print("F1 Score: ", f1_KNN)
```

```
Accuracy:  0.6504065040650406
F1 Score:  0.7624309392265194
```

### XGBoost

In [50]:
```python
XGB = XGBClassifier(eval_metric='mlogloss')
XGB.fit(X_train, y_train)
```

Out[50]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='mlogloss',
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=4,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

In [51]:
```python
y_pred = XGB.predict(X_test)
```

In [52]:
```python
acc_XGB = accuracy_score(y_test,y_pred)
f1_XGB = f1_score(y_test,y_pred)

print("Accuracy: ", acc_XGB)
print("F1 Score: ", f1_XGB)
```

```
Accuracy:  0.7317073170731707
F1 Score:  0.8070175438596492
```

### Light GBM

In [53]:
```python
LGBM = LGBMClassifier()
LGBM.fit(X_train, y_train)
```

Out[53]:
```
LGBMClassifier()
```

In [54]:
```python
y_pred = LGBM.predict(X_test)
```

In [55]:
```python
acc_LGBM = accuracy_score(y_test,y_pred)
f1_LGBM = f1_score(y_test,y_pred)

print("Accuracy: ", acc_LGBM)
print("F1 Score: ", f1_LGBM)
```

```
Accuracy:  0.7479674796747967
F1 Score:  0.8208092485549133
```

## Evaluation

### Accuracy Scores

In [56]:
```python
models = pd.DataFrame({
    'Model': ['Logistic Regression', 'Naive Bayes', 'Decision Tree', 'Random Forest', 'Support Vector Machines'
              'K - Nearest Neighbors', 'XGBoost Classifier', 'Light Gradient Boosting Machine'],
    'Score': [acc_LR, acc_GNB, acc_DT, acc_RF, acc_SVM, acc_KNN, acc_XGB, acc_LGBM]})

models.sort_values(by='Score', ascending=False)
```

Out[56]:

| | Model | Score |
|---|---|---|
| 0 | Logistic Regression | 0.804878 |
| 3 | Random Forest | 0.780488 |
| 1 | Naive Bayes | 0.764228 |
| 7 | Light Gradient Boosting Machine | 0.747967 |
| 6 | XGBoost Classifier | 0.731707 |
| 4 | Support Vector Machines | 0.691057 |
| 2 | Decision Tree | 0.682927 |
| 5 | K - Nearest Neighbors | 0.650407 |

### F1 Scores

In [57]:
```python
models = pd.DataFrame({
    'Model': ['Logistic Regression', 'Naive Bayes', 'Decision Tree', 'Random Forest', 'Support Vector Machines'
              'K - Nearest Neighbors', 'XGBoost Classifier', 'Light Gradient Boosting Machine'],
    'Score': [f1_LR, f1_GNB, f1_DT, f1_RF, f1_SVM, f1_KNN, f1_XGB, f1_LGBM]})

models.sort_values(by='Score', ascending=False)
```

Out[57]:

| | Model | Score |
|---|---|---|
| 0 | Logistic Regression | 0.866667 |
| 3 | Random Forest | 0.843931 |
| 1 | Naive Bayes | 0.843243 |
| 7 | Light Gradient Boosting Machine | 0.820809 |
| 4 | Support Vector Machines | 0.817308 |
| 6 | XGBoost Classifier | 0.807018 |
| 2 | Decision Tree | 0.763636 |
| 5 | K - Nearest Neighbors | 0.762431 |

### Confusion Matrix

In [58]:
```python
#Confusion Matrix using Logistic Regression
y_pred = LR.predict(X_test)
cnf = confusion_matrix(y_test, y_pred)
cnf
```

Out[58]:
```
array([[21, 17],
       [ 7, 78]], dtype=int64)
```

In [59]:
```python
print("Plotting Confusion Matrix on Test Data")
sns.heatmap(pd.DataFrame(cnf), annot=True, cmap='YlGnBu')
```

```
Plotting Confusion Matrix on Test Data
&lt;AxesSubplot:&gt;
```

Out[59]: