In [1]:

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

In [2]:

```
df1=pd.read_csv('test.csv')
df2=pd.read_csv('train.csv')
```

In [3]:

```
df=df1.append(df2)
```

In [4]:

```
df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapp
0	LP001015	Male	Yes	0	Graduate	No	5720	
1	LP001022	Male	Yes	1	Graduate	No	3076	
2	LP001031	Male	Yes	2	Graduate	No	5000	
3	LP001035	Male	Yes	2	Graduate	No	2340	
4	LP001051	Male	No	0	Not Graduate	No	3276	

In [5]:

```
df.shape
```

Out[5]:

```
(981, 13)
```

In [6]:

```
df.describe()
```

Out[6]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	981.000000	981.000000	954.000000	961.000000	902.000000
mean	5179.795107	1601.916330	142.511530	342.201873	0.835920
std	5695.104533	2718.772806	77.421743	65.100602	0.370553
min	0.000000	0.000000	9.000000	6.000000	0.000000
25%	2875.000000	0.000000	100.000000	360.000000	1.000000
50%	3800.000000	1110.000000	126.000000	360.000000	1.000000
75%	5516.000000	2365.000000	162.000000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 981 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            981 non-null    object 
 1   Gender             957 non-null    object 
 2   Married            978 non-null    object 
 3   Dependents         956 non-null    object 
 4   Education          981 non-null    object 
 5   Self_Employed      926 non-null    object 
 6   ApplicantIncome    981 non-null    int64  
 7   CoapplicantIncome  981 non-null    float64
 8   LoanAmount         954 non-null    float64
 9   Loan_Amount_Term   961 non-null    float64
 10  Credit_History     902 non-null    float64
 11  Property_Area      981 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 107.3+ KB
```

In [8]:

```
df.isnull().sum()
```

Out[8]:

```
Loan_ID                0
Gender                24
Married                3
Dependents            25
Education              0
Self_Employed         55
ApplicantIncome        0
CoapplicantIncome      0
LoanAmount            27
Loan_Amount_Term      20
Credit_History        79
Property_Area          0
Loan_Status          367
dtype: int64
```

In [9]:

```
df.isnull().sum()/len(df)*100
```

Out[9]:

```
Loan_ID               0.000000
Gender                2.446483
Married               0.305810
Dependents            2.548420
Education             0.000000
Self_Employed         5.606524
ApplicantIncome       0.000000
CoapplicantIncome     0.000000
LoanAmount            2.752294
Loan_Amount_Term      2.038736
Credit_History        8.053007
Property_Area         0.000000
Loan_Status          37.410805
dtype: float64
```

In [10]:

```
mode_sf_emp=df['Self_Employed'].mode()
```

In [11]:

```
mode_sf_emp
```

Out[11]:

```
0    No
Name: Self_Employed, dtype: object
```

In [12]:

```
df['Self_Employed']=df['Self_Employed'].fillna(method='ffill')
```

In [13]:

```
mode_ln_st=df['Loan_Status'].mode()
mode_ln_st
```

Out[13]:

```
0    Y
Name: Loan_Status, dtype: object
```

In [14]:

```
df['Loan_Status']=df['Loan_Status'].fillna(method='ffill')
```

In [15]:

```
median_cr=df['Credit_History'].median()
median_cr
```

Out[15]:

```
1.0
```

In [16]:

```
df['Credit_History']=df['Credit_History'].fillna(median_cr)
```

In [17]:

```
df.isnull().sum()/len(df)*100
```

Out[17]:

```
Loan_ID               0.000000
Gender                2.446483
Married               0.305810
Dependents            2.548420
Education             0.000000
Self_Employed         0.000000
ApplicantIncome       0.000000
CoapplicantIncome     0.000000
LoanAmount            2.752294
Loan_Amount_Term      2.038736
Credit_History        0.000000
Property_Area         0.000000
Loan_Status          37.410805
dtype: float64
```

In [18]:

```
df.dropna(inplace=True)
```

In [19]:

```
df.isnull().sum()
```

Out[19]:

```
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 [20]:

```
#Numerical_col
num_col=df.select_dtypes(include=['int64','float64']).columns
num_col
```

Out[20]:

```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History'],
      dtype='object')
```

In [21]:

```
#Categorical_col
cat_col=df.select_dtypes(include=['O']).columns
cat_col
```

Out[21]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [22]:

```
df.drop('Dependents',axis=1,inplace=True)
```

In [23]:

```
df.head(10)
```

Out[23]:

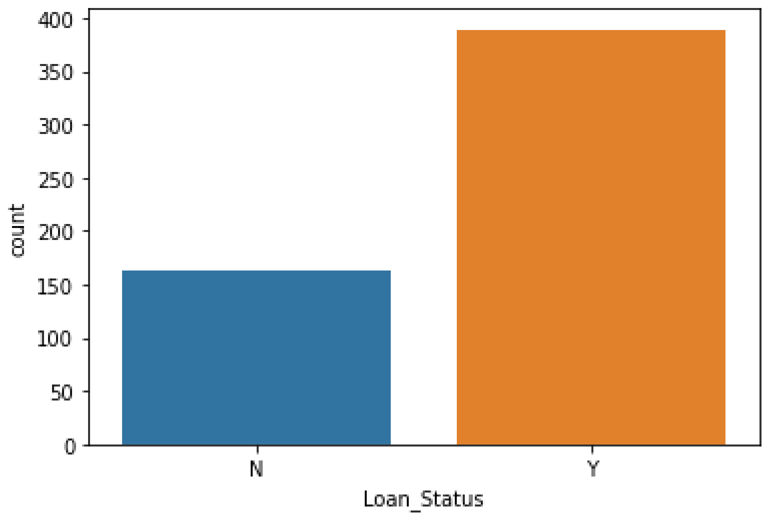
	Loan_ID	Gender	Married	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
1	LP001003	Male	Yes	Graduate	No	4583	1508.(
2	LP001005	Male	Yes	Graduate	Yes	3000	0.(
3	LP001006	Male	Yes	Not Graduate	No	2583	2358.(
4	LP001008	Male	No	Graduate	No	6000	0.(
5	LP001011	Male	Yes	Graduate	Yes	5417	4196.(
6	LP001013	Male	Yes	Not Graduate	No	2333	1516.(
7	LP001014	Male	Yes	Graduate	No	3036	2504.(
8	LP001018	Male	Yes	Graduate	No	4006	1526.(
9	LP001020	Male	Yes	Graduate	No	12841	10968.(
10	LP001024	Male	Yes	Graduate	No	3200	700.(

In [24]:

```
sns.countplot(df['Loan_Status'])
```

Out[24]:

<AxesSubplot:xlabel='Loan_Status', ylabel='count'>

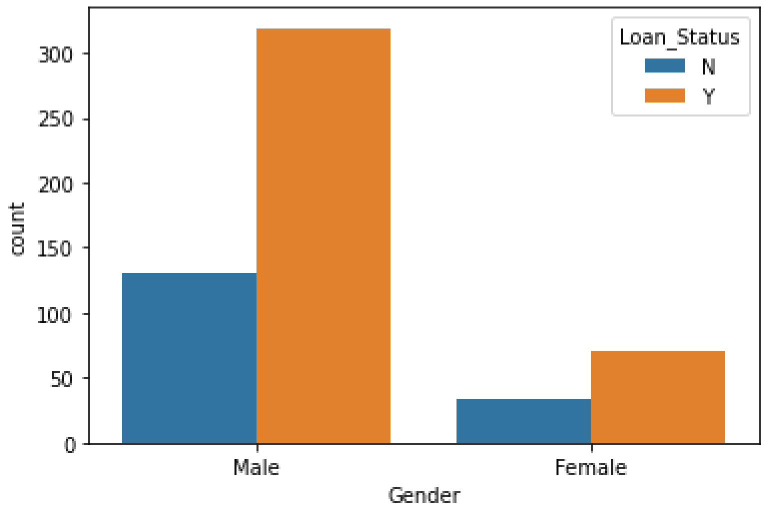


In [25]:

```
sns.countplot(df['Gender'],hue=df['Loan_Status'])
```

Out[25]:

<AxesSubplot:xlabel='Gender', ylabel='count'>

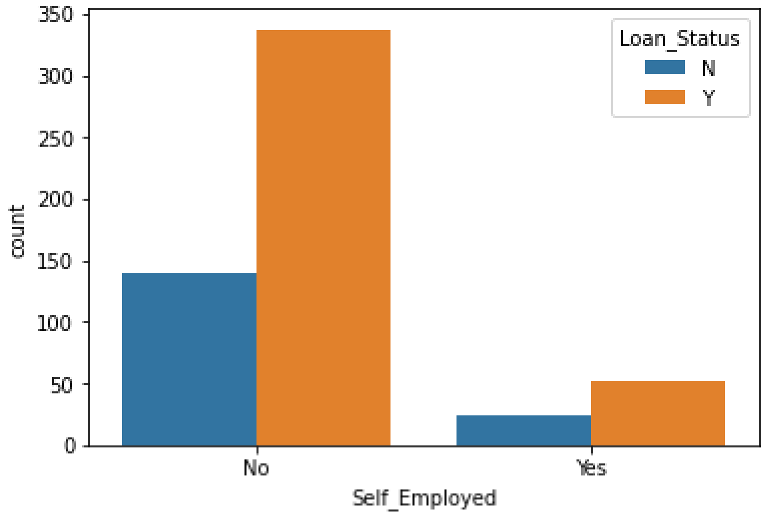


In [26]:

```
sns.countplot(df['Self_Employed'],hue=df['Loan_Status'])
```

Out[26]:

<AxesSubplot:xlabel='Self_Employed', ylabel='count'>

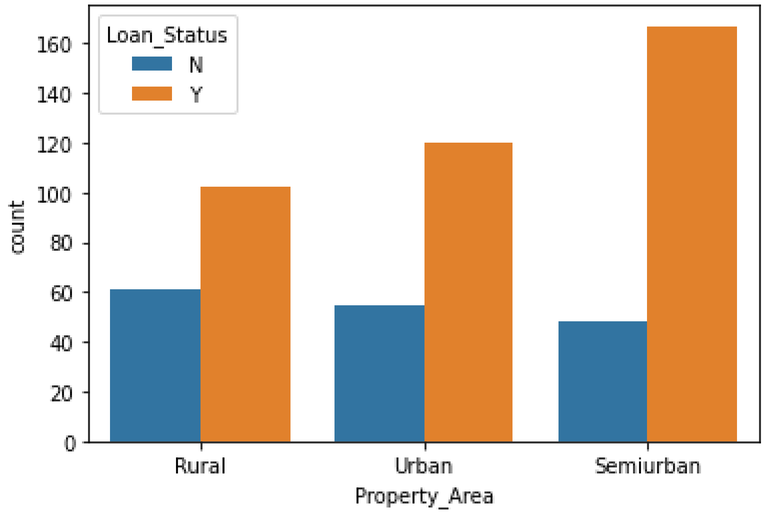


In [27]:

```
sns.countplot(df['Property_Area'],hue=df['Loan_Status'])
```

Out[27]:

```
<AxesSubplot:xlabel='Property_Area', ylabel='count'>
```

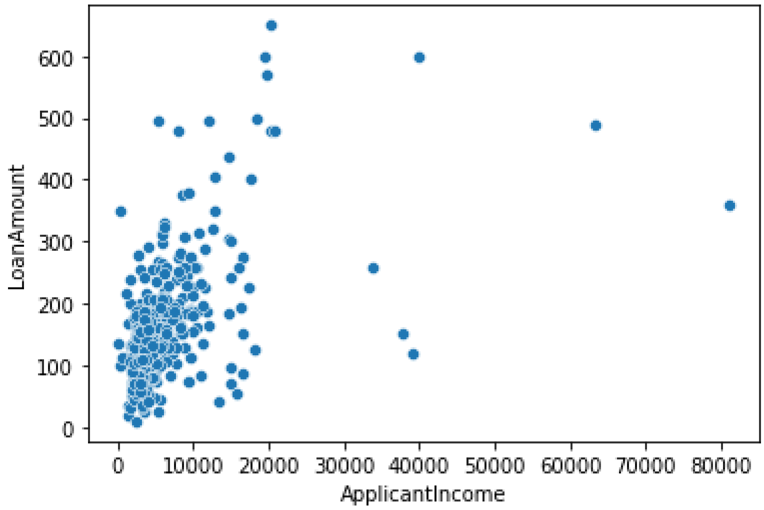


In [28]:

```
sns.scatterplot(df['ApplicantIncome'],df['LoanAmount'])
```

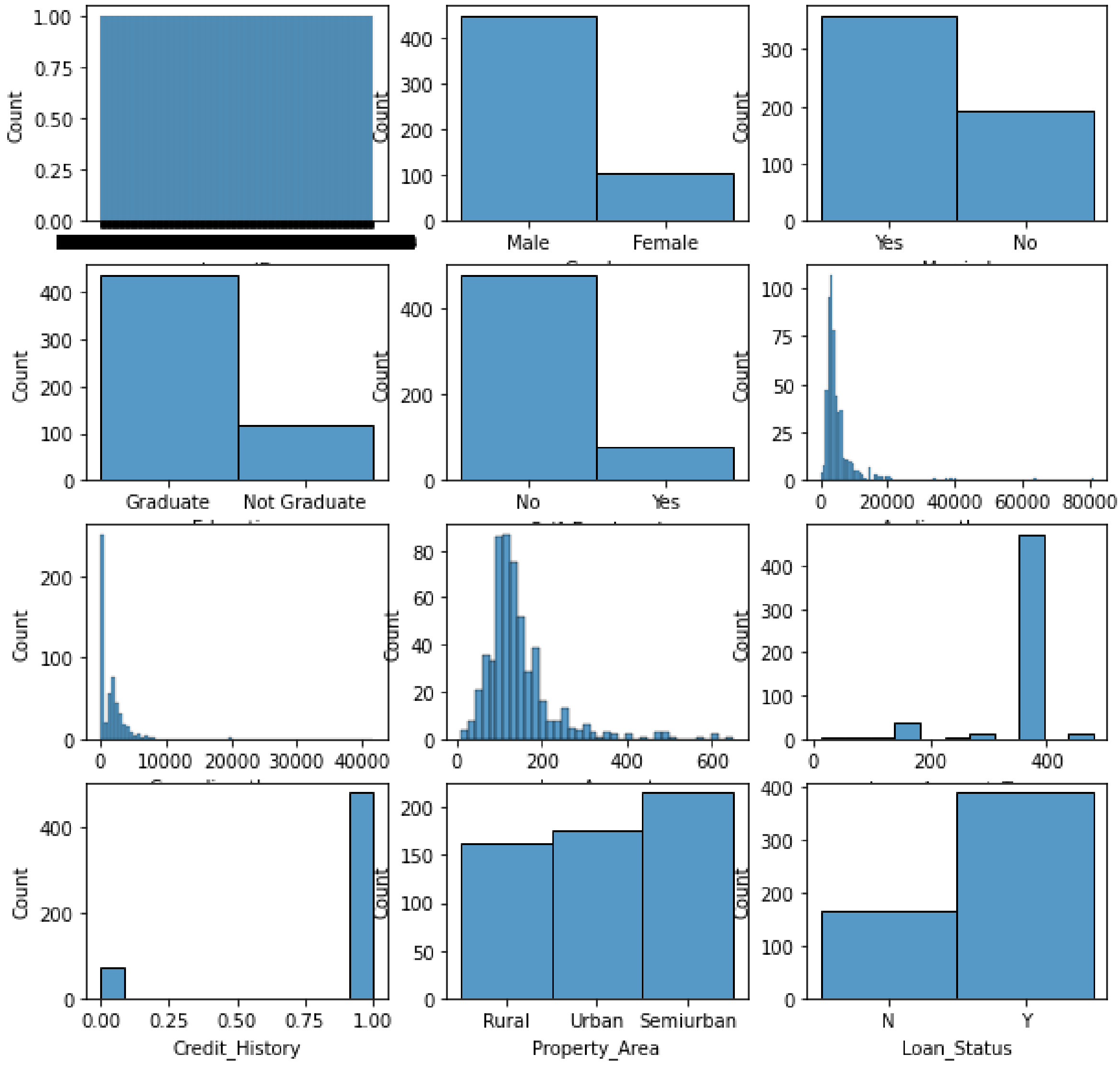
Out[28]:

```
<AxesSubplot:xlabel='ApplicantIncome', ylabel='LoanAmount'>
```



In [29]:

```
plt.figure(figsize=(10,10))
count=1
for i in df:
    plt.subplot(4,3,count)
    sns.histplot(x=df[i],data=df)
    count+=1
```

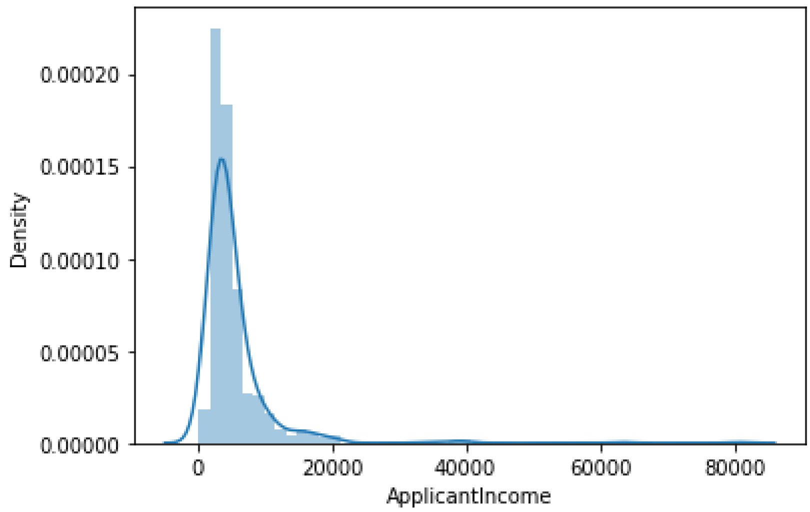


In [30]:

```
sns.distplot(df['ApplicantIncome'])
```

Out[30]:

<AxesSubplot:xlabel='ApplicantIncome', ylabel='Density'>

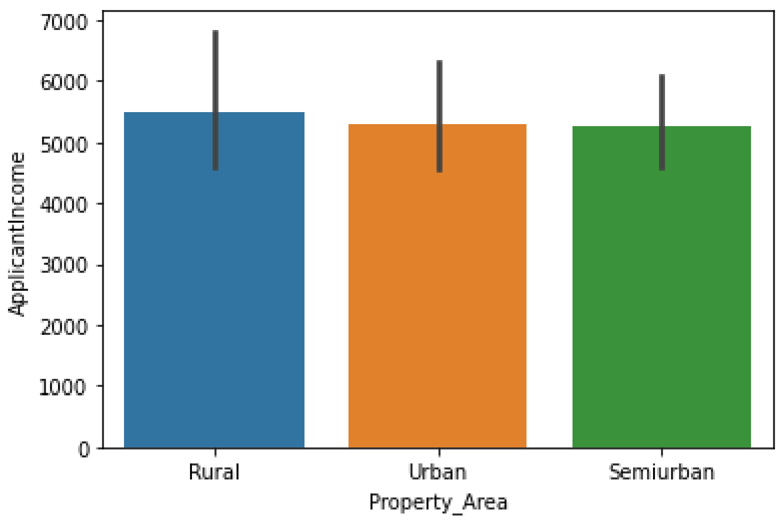


In [31]:

```
sns.barplot(df['Property_Area'],df['ApplicantIncome'])
```

Out[31]:

<AxesSubplot:xlabel='Property_Area', ylabel='ApplicantIncome'>

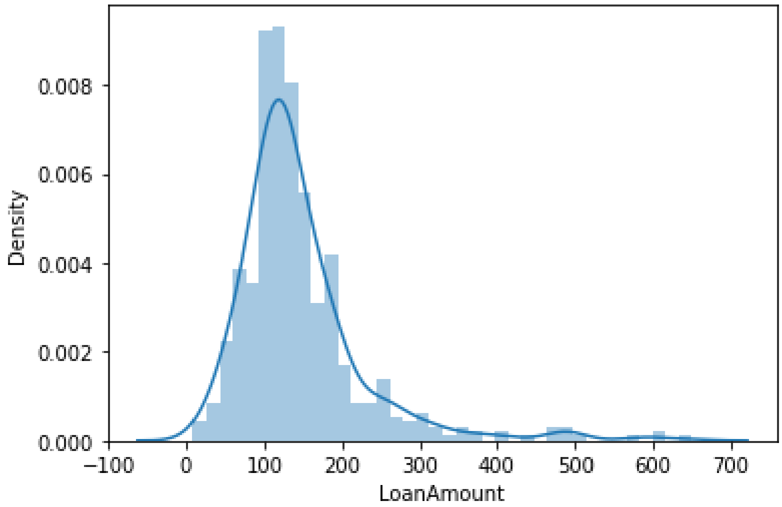


In [32]:

```
sns.distplot(df['LoanAmount'])
```

Out[32]:

<AxesSubplot:xlabel='LoanAmount', ylabel='Density'>

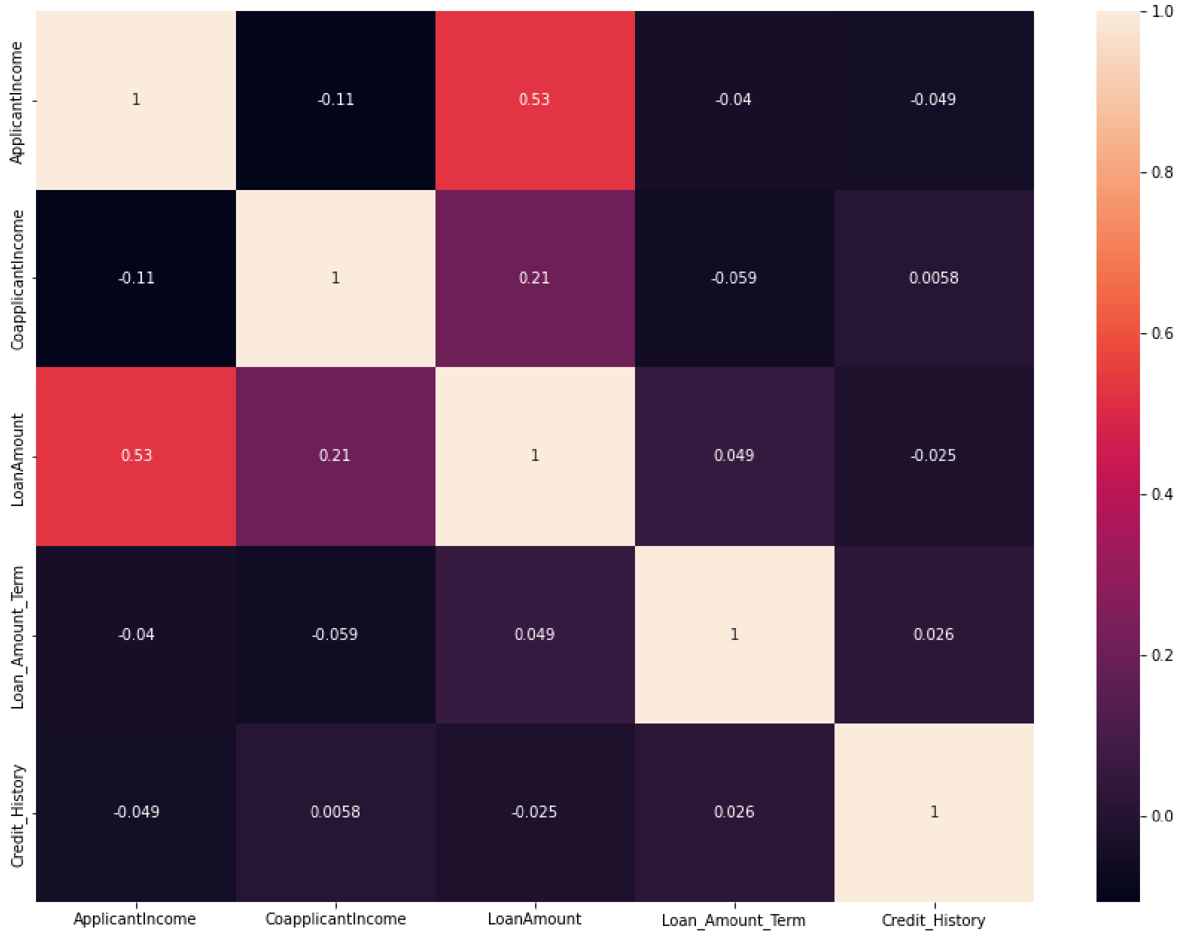


In [33]:

```
plt.figure(figsize=(15,11))
sns.heatmap(df.corr(),annot=True)
```

Out[33]:

```
<AxesSubplot:>
```



LabelEncoder

In [34]:

```
from sklearn.preprocessing import LabelEncoder
```

In [35]:

```
le=LabelEncoder()
```

In [36]:

```
cat_col=df.select_dtypes(include='O').columns
cat_col
```

Out[36]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Education', 'Self_Employed',
       'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [37]:

```
for i in cat_col:
    df[i]=le.fit_transform(df[i])
```

In [38]:

```
df.head()
```

Out[38]:

	Loan_ID	Gender	Married	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
1	0	1	1	0	0	4583	1508.0
2	1	1	1	0	1	3000	0.0
3	2	1	1	1	0	2583	2358.0
4	3	1	0	0	0	6000	0.0
5	4	1	1	0	1	5417	4196.0

In [39]:

```
x=df.drop('Loan_Status',axis=1)
x
```

Out[39]:

	Loan_ID	Gender	Married	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
1	0	1	1	0	0	4583	1508.(
2	1	1	1	0	1	3000	0.(
3	2	1	1	1	0	2583	2358.(
4	3	1	0	0	0	6000	0.(
5	4	1	1	0	1	5417	4196.(
...	...	...	...	...	...	...	..
609	548	0	0	0	0	2900	0.(
610	549	1	1	0	0	4106	0.(
611	550	1	1	0	0	8072	240.(
612	551	1	1	0	0	7583	0.(
613	552	0	0	0	1	4583	0.(

553 rows × 11 columns

In [40]:

```
y=df['Loan_Status']
y
```

Out[40]:

```
1      0
2      1
3      1
4      1
5      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 553, dtype: int32
```

train_test_split

In [41]:

```
from sklearn.model_selection import train_test_split
```

In [42]:

```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=1)
```

In [43]:

```
X_train.shape
```

Out[43]:

```
(442, 11)
```

In [44]:

```
X_test.shape
```

Out[44]:

```
(111, 11)
```

In [45]:

```
y_train.shape
```

Out[45]:

```
(442,)
```

In [46]:

```
y_test.shape
```

Out[46]:

```
(111,)
```

LogisticRegression

In [47]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
```

In [48]:

```
def my_model(clf):
    clf.fit(X_train,y_train)
    y_train_pred=clf.predict(X_train)
    y_test_pred=clf.predict(X_test)
    print('Train Data')
    print(classification_report(y_train,y_train_pred))
    print('Test Data')
    print(classification_report(y_test,y_test_pred))
```

In [49]:

```
lr=LogisticRegression()
```

In [50]:

```
my_model(lr)
```

```
Train Data
              precision    recall  f1-score   support

           0       0.85      0.38      0.53       133
           1       0.79      0.97      0.87       309

    accuracy                           0.79       442
   macro avg       0.82      0.68      0.70       442
weighted avg       0.80      0.79      0.77       442

Test Data
              precision    recall  f1-score   support

           0       0.62      0.42      0.50        31
           1       0.80      0.90      0.85        80

    accuracy                           0.77       111
   macro avg       0.71      0.66      0.67       111
weighted avg       0.75      0.77      0.75       111
```

DecisionTreeClassifier

In [51]:

```
from sklearn.tree import DecisionTreeClassifier
```

In [52]:

```
dt=DecisionTreeClassifier()
```

In [53]:

```
dt
```

Out[53]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [54]:

```
my_model(dt)
```

```
Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       133
           1       1.00      1.00      1.00       309

    accuracy                           1.00       442
   macro avg       1.00      1.00      1.00       442
weighted avg       1.00      1.00      1.00       442

Test Data
              precision    recall  f1-score   support

           0       0.49      0.55      0.52        31
           1       0.82      0.78      0.79        80

    accuracy                           0.71       111
   macro avg       0.65      0.66      0.66       111
weighted avg       0.72      0.71      0.72       111
```

In [55]:

```
from sklearn.model_selection import RandomizedSearchCV
```

In [56]:

```
param_grid={
    'criterion':['gini','entropy'],
    'class_weight':[None,'balanced'],
    'max_depth':np.arange(2,50),
    'min_samples_split':np.arange(2,50,2),
    'min_samples_leaf':np.arange(2,50)
}
```

In [57]:

```
1 dt_rcv=RandomizedSearchCV(dt,param_distributions=param_grid,n_iter=10,scoring='f1',n_jo
```

In [58]:

```
1 dt_rcv.fit(X_train,y_train)
```

Out[58]:

```
▸ RandomizedSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

In [59]:

```
1 dt_rcv.best_params_
```

Out[59]:

```
{'min_samples_split': 12,
 'min_samples_leaf': 41,
 'max_depth': 29,
 'criterion': 'entropy',
 'class_weight': None}
```

In [60]:

```
1 dt1=DecisionTreeClassifier(criterion='gini',class_weight='balanced',max_depth=39,min_sa
```

In [61]:

```
1 my_model(dt1)
```

```
Train Data
              precision    recall  f1-score   support

           0       0.65      0.89      0.75       133
           1       0.94      0.79      0.86       309

    accuracy                           0.82       442
   macro avg       0.80      0.84      0.81       442
weighted avg       0.85      0.82      0.83       442

Test Data
              precision    recall  f1-score   support

           0       0.42      0.71      0.53        31
           1       0.85      0.62      0.72        80

    accuracy                           0.65       111
   macro avg       0.64      0.67      0.62       111
weighted avg       0.73      0.65      0.67       111
```

RandomForestClassifier

In [62]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [63]:

```
rf=RandomForestClassifier()
```

In [64]:

```
my_model(rf)
```

```
Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       133
           1       1.00      1.00      1.00       309

    accuracy                           1.00       442
   macro avg       1.00      1.00      1.00       442
weighted avg       1.00      1.00      1.00       442

Test Data
              precision    recall  f1-score   support

           0       0.71      0.55      0.62        31
           1       0.84      0.91      0.87        80

    accuracy                           0.81       111
   macro avg       0.77      0.73      0.75       111
weighted avg       0.80      0.81      0.80       111
```

In [65]:

```
rf_rcv=RandomizedSearchCV(rf,param_distributions=param_grid,n_iter=10,scoring='f1',n_jo
```

In [66]:

```
rf_rcv.fit(X_train,y_train)
```

Out[66]:

```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

In [67]:

```
rf_rcv.best_params_
```

Out[67]:

```
{'min_samples_split': 38,
 'min_samples_leaf': 3,
 'max_depth': 27,
 'criterion': 'gini',
 'class_weight': None}
```

In [68]:

```
rf1=RandomForestClassifier(criterion='gini',class_weight='balanced',max_depth=31,min_sa
```

In [69]:

```
my_model(rf1)
```

```
Train Data
              precision    recall  f1-score   support

           0       0.62      0.69      0.65       133
           1       0.86      0.82      0.84       309

    accuracy                           0.78       442
   macro avg       0.74      0.75      0.74       442
weighted avg       0.79      0.78      0.78       442

Test Data
              precision    recall  f1-score   support

           0       0.45      0.68      0.54        31
           1       0.84      0.68      0.75        80

    accuracy                           0.68       111
   macro avg       0.65      0.68      0.64       111
weighted avg       0.73      0.68      0.69       111
```

AdaBoostClassifier

In [70]:

```
from sklearn.ensemble import AdaBoostClassifier
```

In [71]:

```
adb=AdaBoostClassifier(n_estimators=450)
```

In [72]:

```
my_model(adb)
```

```
Train Data
              precision    recall  f1-score   support

           0       0.95      0.80      0.87       133
           1       0.92      0.98      0.95       309

    accuracy                           0.93       442
   macro avg       0.93      0.89      0.91       442
weighted avg       0.93      0.93      0.93       442

Test Data
              precision    recall  f1-score   support

           0       0.62      0.65      0.63        31
           1       0.86      0.85      0.86        80

    accuracy                           0.79       111
   macro avg       0.74      0.75      0.75       111
weighted avg       0.79      0.79      0.79       111
```

In [73]:

```
param_grid_ada={
    'learning_rate':[0.1,0.01,1,2,3],
    'n_estimators':[50,100,150]
}
```

In [76]:

```
adb_rcv=RandomizedSearchCV(adb,param_distributions=param_grid_ada,n_iter=10,scoring='f1
```

In [77]:

```
adb_rcv.fit(X_train,y_train)
```

Out[77]:

```
▸ RandomizedSearchCV
▸ estimator: AdaBoostClassifier
    ▸ AdaBoostClassifier
```

In [78]:

```
adb_rcv.best_params_
```

Out[78]:

```
{'n_estimators': 50, 'learning_rate': 0.01}
```

In [81]:

```
adb1=AdaBoostClassifier(n_estimators=50,learning_rate=1)
```

In [82]:

```
my_model(adb1)
```

```
Train Data
              precision    recall  f1-score   support

           0       0.89      0.57      0.70       133
           1       0.84      0.97      0.90       309

    accuracy                           0.85       442
   macro avg       0.87      0.77      0.80       442
weighted avg       0.86      0.85      0.84       442

Test Data
              precision    recall  f1-score   support

           0       0.70      0.61      0.66        31
           1       0.86      0.90      0.88        80

    accuracy                           0.82       111
   macro avg       0.78      0.76      0.77       111
weighted avg       0.81      0.82      0.82       111
```

Best Prediction is given by AdaBoost Classifier model. ¶

In [ ]:

```

```