Importing Data-Set

In [1]:

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

Loading Data

In [2]:

```
train=pd.read_csv("train.csv")
test=pd.read_csv("test.csv")
```

In [3]:

```
train.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Te
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	36
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	36
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	36
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	36
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	36

In [4]:

```
test.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Te
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	36
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	36
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	36
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	36
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	36

In [5]:

```
train.shape
```

Out[5]:

```
(614, 13)
```

In [6]:

```
test.shape
```

Out[6]:

```
(367, 12)
```

In [7]:

```
#dropping the Loan_ID column
train.drop(['Loan_ID'],axis=1,inplace=True)
```

In [8]:

```
#dropping the Loan_ID colum
test.drop(['Loan_ID'],axis=1,inplace=True)
```

Observations

In [9]:

```
categorical_features_train = (train.select_dtypes(include=['object']).columns)
categorical_features_train
```

Out[9]:

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

In [10]:

```
continous_features_train = (train.select_dtypes(exclude=['object']).columns)
continous_features_train
```

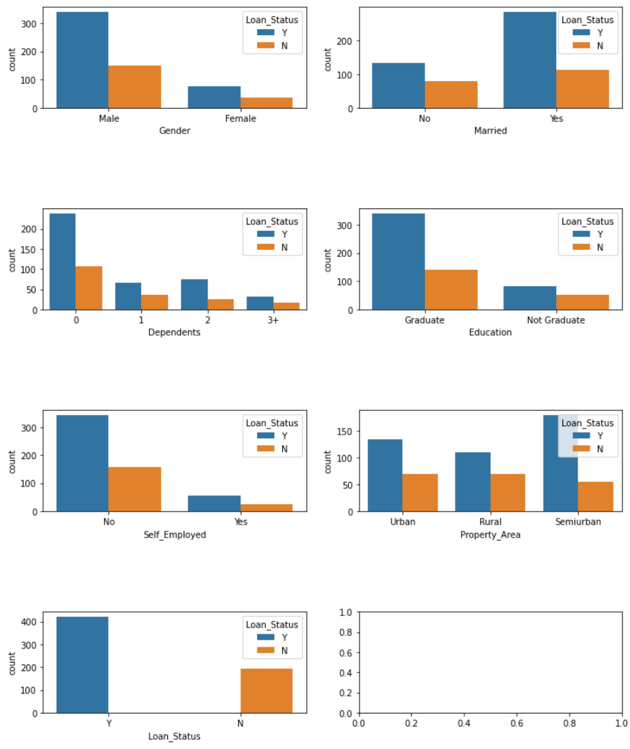
Out[10]:

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

For Categorical Features

In [11]:

```
fig,axes = plt.subplots(4,2,figsize=(12,15))
for idx,cat_col in enumerate(categorical_features_train):
    row,col = idx//2,idx%2
    sns.countplot(x=cat_col,data=train,hue='Loan_Status',ax=axes[row,col])
plt.subplots_adjust(hspace=1)
```



Plots above convey following things about the dataset:

1)Loan Approval Status: About 2/3rd of applicants have been granted loan.

2)Sex: There are more Men than Women (approx. 3x)

3)Martial Status: 2/3rd of the population in the dataset is Marred; Married applicants are more likely to be granted loans.

4)Dependents: Majority of the population have zero dependents and are also likely to accepted for loan.

5)Education: About 5/6th of the population is Graduate and graduates have higher propotion of loan approval

6)Employment: 5/6th of population is not self employed.

7)Property Area: More applicants from Semi-urban and also likely to be granted loans.

8)Applicant with credit history are far more likely to be accepted.

9)Loan Amount Term: Majority of the loans taken are for 360 Months (30 years).

Feature Engineering

In [12]:

```
train.dtypes
```

Out[12]:

```
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
```

In [13]:

```
test.dtypes
```

Out[13]:

```
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome      int64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
dtype: object
```

In [14]:

```
train.isnull().sum()
```

Out[14]:

```
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 [15]:

```
test.isnull().sum()
```

Out[15]:

```
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

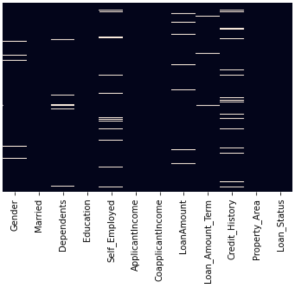
Checking null values

In [16]:

```
sns.heatmap(train.isnull(),yticklabels=False,cbar=False)
```

Out[16]:

```
<AxesSubplot:>
```



In [17]:

```
print("Train Data Categorical Objects")
print()
categorical_features_train = (train.select_dtypes(include=['object']).columns)
for categorical_features_train in train:
    if(train[categorical_features_train].isnull().sum()>0):
        print(categorical_features_train,"=",train[categorical_features_train].isnull().sum())
```

```
Train Data Categorical Objects

Gender = 13
Married = 3
Dependents = 15
Self_Employed = 32
LoanAmount = 22
Loan_Amount_Term = 14
Credit_History = 50
```

In [18]:

```
print("Test-Data Categorical Objects")
print()
categorical_features_test = (test.select_dtypes(include=['object']).columns)
for categorical_features_test in test:
    if(test[categorical_features_test].isnull().sum()>0):
        print(categorical_features_test,"=",test[categorical_features_test].isnull().sum())
```

```
Test-Data Categorical Objects

Gender = 11
Dependents = 10
Self_Employed = 23
LoanAmount = 5
Loan_Amount_Term = 6
Credit_History = 29
```

In [19]:

```
#filling all the continuous variables
train.fillna(train.mean(),inplace=True)
```

In [20]:

```
#filling all the categorical variables
train['Gender']=train['Gender'].fillna(train['Gender'].mode()[0])
train['Married']=train['Married'].fillna(train['Married'].mode()[0])
train['Dependents']=train['Dependents'].fillna(train['Dependents'].mode()[0])
train['Self_Employed']=train['Self_Employed'].fillna(train['Self_Employed'].mode()[0])
train['LoanAmount']=train['LoanAmount'].fillna(train['LoanAmount'].mode()[0])
train['Loan_Amount_Term']=train['Loan_Amount_Term'].fillna(train['Loan_Amount_Term'].mode()[0])
train['Credit_History']=train['Credit_History'].fillna(train['Credit_History'].mode()[0])
```

In [21]:

```
#test data-set
test.fillna(test.mean(),inplace=True)
test['Gender']=test['Gender'].fillna(test['Gender'].mode()[0])
test['Married']=test['Married'].fillna(test['Married'].mode()[0])
test['Dependents']=test['Dependents'].fillna(test['Dependents'].mode()[0])
test['Self_Employed']=test['Self_Employed'].fillna(test['Self_Employed'].mode()[0])
test['LoanAmount']=test['LoanAmount'].fillna(test['LoanAmount'].mode()[0])
test['Loan_Amount_Term']=test['Loan_Amount_Term'].fillna(test['Loan_Amount_Term'].mode()[0])
test['Credit_History']=test['Credit_History'].fillna(test['Credit_History'].mode()[0])
```

In [22]:

```
print("For Train Data-Set")
print()
for categorical_features_train in train:
    if(train[categorical_features_train].isnull().sum()>0):
        print(categorical_features_train,"=",train[categorical_features_train].isnull().sum())
    else:
        print("No Null Values")
        break
```

```
For Train Data-Set

No Null Values
```

In [23]:

```
print("For Test Data-Set")
print()
for categorical_features_test in test:
    if(test[categorical_features_test].isnull().sum()>0):
        print(categorical_features_test,"=",test[categorical_features_test].isnull().sum())
    else:
        print("No Null Values")
        break
```

```
For Test Data-Set

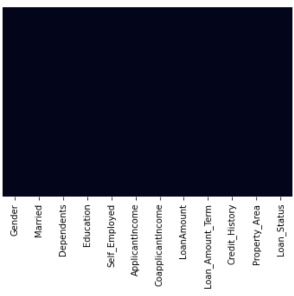
No Null Values
```

In [24]:

```
#In the below graph the white colour represent the null values
#we can see that Alley , poolIOC conitans more null vaules
sns.heatmap(train.isnull(),yticklabels=False,cbar=False)
```

Out[24]:

```
<AxesSubplot:>
```



In [25]:

```
train.isnull().sum()
```

Out[25]:

```
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
```

Handling Outliers

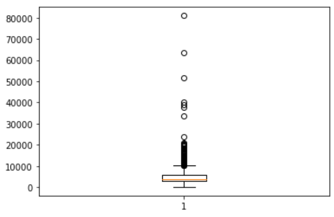
1. Naivye Bayes Classifier--- Not Sensitive To Outliers
2. SVM-------- Not Sensitive To Outliers
3. Linear Regression---------- Sensitive To Outliers
4. Logistic Regression------- Sensitive To Outliers
5. Decision Tree Regressor or Classifier---- Not Sensitive
6. Ensemble(RF,XGboost,GB)------- Not Sensitive
7. KNN-------------------------- Not Sensitive
8. Kmeans----------------------- Sensitive
9. Hierarichal------------------ Sensitive
10. PCA------------------------- Sensitive
11. Neural Networks------------- Sensitive

In [26]:

```
#ApplicantIncome-int64
plt.boxplot(train['ApplicantIncome'])
```

Out[26]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1788259e088>,
  <matplotlib.lines.Line2D at 0x178825b6fc8>],
 'caps': [<matplotlib.lines.Line2D at 0x178825bcfc8>,
  <matplotlib.lines.Line2D at 0x178825c0b48>],
 'boxes': [<matplotlib.lines.Line2D at 0x178825b6f08>],
 'medians': [<matplotlib.lines.Line2D at 0x178825c0b88>],
 'fliers': [<matplotlib.lines.Line2D at 0x178825ca688>],
 'means': []}
```

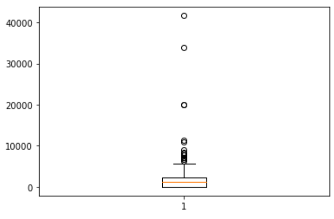


In [27]:

```
plt.boxplot(train['CoapplicantIncome'])
```

Out[27]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x178822b0a08>,
  <matplotlib.lines.Line2D at 0x17882341588>],
 'caps': [<matplotlib.lines.Line2D at 0x178822f0888>,
  <matplotlib.lines.Line2D at 0x17882360f08>],
 'boxes': [<matplotlib.lines.Line2D at 0x178823279c8>],
 'medians': [<matplotlib.lines.Line2D at 0x17882355f48>],
 'fliers': [<matplotlib.lines.Line2D at 0x1788246df48>],
 'means': []}
```

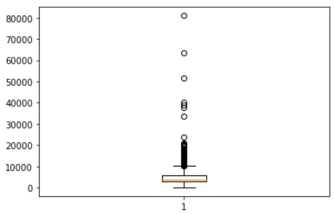


In [28]:

```
#LoanAmount           float64
plt.boxplot(train['ApplicantIncome'])
```

Out[28]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x178826526c8>,
  <matplotlib.lines.Line2D at 0x17882672e88>],
 'caps': [<matplotlib.lines.Line2D at 0x17882672dc8>,
  <matplotlib.lines.Line2D at 0x17882672fc8>],
 'boxes': [<matplotlib.lines.Line2D at 0x17882672208>],
 'medians': [<matplotlib.lines.Line2D at 0x17882678b88>],
 'fliers': [<matplotlib.lines.Line2D at 0x17882678d88>],
 'means': []}
```

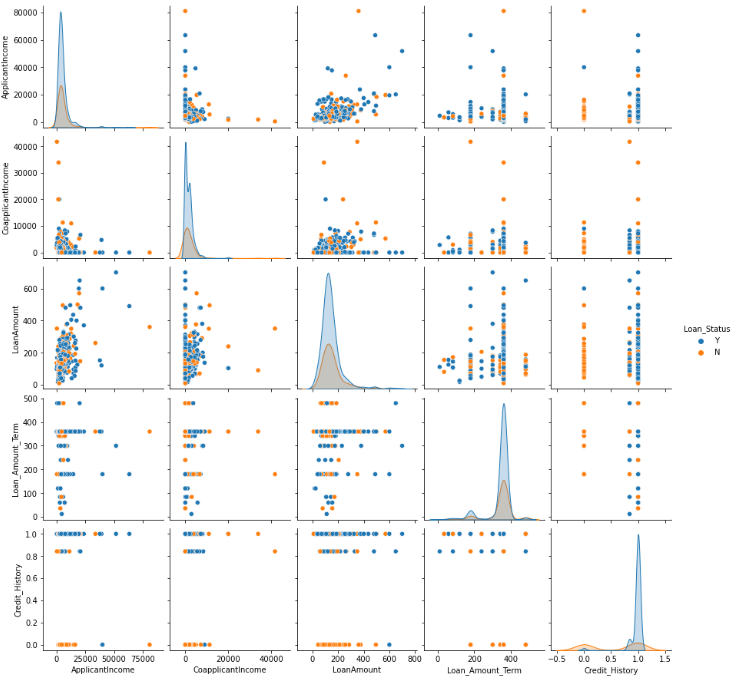


Pairplot

- Plot pairwise relationships in a dataset. It is also possible to show a subset of variables or plot different variables on the rows and columns.

In [29]:
```
sns.pairplot(train,hue='Loan_Status')
```

Out[29]:
```
<seaborn.axisgrid.PairGrid at 0x178826a7e08>
```



By observing the above graphs we can say that there is a more overlapping betwen the 2 features .. so it's not better to use the logistic regression here it's better to use KNN

In [30]:
```
##combining the train and test data-set
train_copy=train.copy()
test_copy=test.copy()
traintest=pd.concat([train,test],axis=0)
traintest.shape
```

Out[30]:
```
(981, 12)
```

In [31]:
```
traintest.head()
```

Out[31]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_
0	Male	No	0	Graduate	No	5849	0.0	146.412162	360.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128.000000	360.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66.000000	360.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120.000000	360.0	
4	Male	No	0	Graduate	No	6000	0.0	141.000000	360.0	

Handling Categorical Variables

In [32]:
```
for i in traintest.select_dtypes(include=['object']).columns:
    print(i,"=",len(traintest[i].unique()))
```

```
Gender = 2
Married = 2
Dependents = 4
Education = 2
Self_Employed = 2
Property_Area = 3
Loan_Status = 3
```

In [33]:
```
traintest_copy=traintest.copy()
traintest = pd.get_dummies(traintest,drop_first=True)
```

In [34]:
```
traintest.isnull().sum()
```

Out[34]:
```
ApplicantIncome            0
CoapplicantIncome          0
LoanAmount                 0
Loan_Amount_Term           0
Credit_History             0
Gender_Male                0
Married_Yes                0
Dependents_1               0
Dependents_2               0
Dependents_3+              0
Education_Not Graduate     0
Self_Employed_Yes          0
Property_Area_Semiurban    0
Property_Area_Urban        0
Loan_Status_Y              0
dtype: int64
```

In [35]:
```
traintest.shape
```

Out[35]:
```
(981, 15)
```

In [36]:
```
traintest.head()
```

Out[36]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Depend
0	5849	0.0	146.412162	360.0	1.0	1	0	0	
1	4583	1508.0	128.000000	360.0	1.0	1	1	1	
2	3000	0.0	66.000000	360.0	1.0	1	1	0	
3	2583	2358.0	120.000000	360.0	1.0	1	1	0	
4	6000	0.0	141.000000	360.0	1.0	1	0	0	

In [37]:
```
train.head()
```

Out[37]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_
0	Male	No	0	Graduate	No	5849	0.0	146.412162	360.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128.000000	360.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66.000000	360.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120.000000	360.0	
4	Male	No	0	Graduate	No	6000	0.0	141.000000	360.0	

In [38]:
```
traintest.dtypes
```

Out[38]:
```
ApplicantIncome              int64
CoapplicantIncome          float64
LoanAmount                 float64
Loan_Amount_Term           float64
Credit_History             float64
Gender_Male                  uint8
Married_Yes                  uint8
Dependents_1                 uint8
Dependents_2                 uint8
Dependents_3+                uint8
Education_Not Graduate       uint8
Self_Employed_Yes            uint8
Property_Area_Semiurban      uint8
Property_Area_Urban          uint8
Loan_Status_Y                uint8
dtype: object
```

In [39]:
```
train.isnull().sum()
```

Out[39]:
```
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 [40]:
```
#Splitting the data set
train=traintest.iloc[:614]
test=traintest.iloc[614:,:]
```

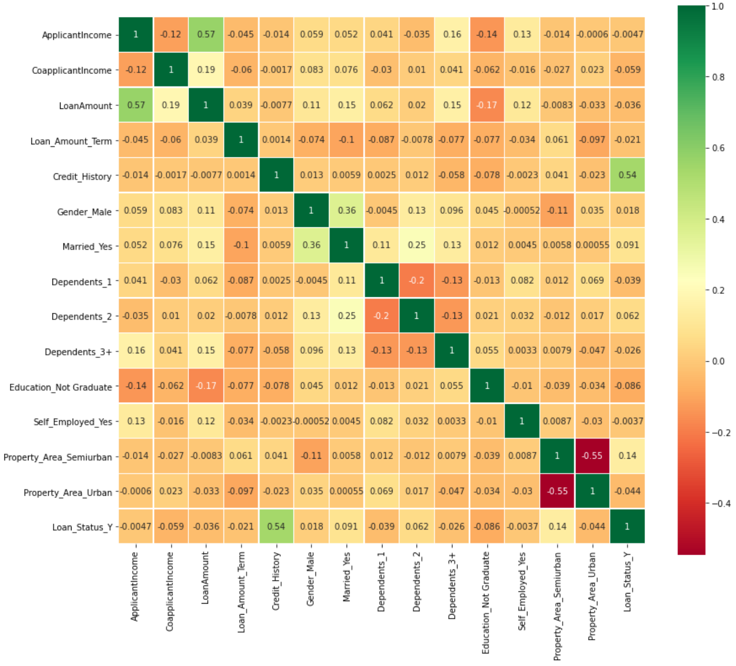
In [41]:
```
(train.shape),(test.shape)
```

Out[41]:
```
((614, 15), (367, 15))
```

In [42]:
```
#checking co-realtion
colormap = plt.cm.RdBu
plt.figure(figsize=(14,12))
plt.title('Pearson Correlation of Features', y=1.05, size=15)
sns.heatmap(train.astype(float).corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap='RdYlGn', linecolor='white', annot=True)
```

Out[42]:
```
<AxesSubplot:title={'center':'Pearson Correlation of Features'}>
```

Pearson Correlation of Features



	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Dependents_2	Dependents_3+	Education_Not Graduate	Self_Employed_Yes	Property_Area_Semiurban	Property_Area_Urban	Loan_Status_Y
ApplicantIncome	1	-0.12	0.57	-0.045	-0.014	0.059	0.052	0.041	-0.035	0.16	-0.14	0.13	-0.014	-0.0006	-0.0047
CoapplicantIncome	-0.12	1	0.19	-0.06	-0.0017	0.083	0.076	-0.03	0.01	0.041	-0.062	-0.016	-0.027	0.023	-0.059
LoanAmount	0.57	0.19	1	0.039	-0.0077	0.11	0.15	0.062	0.02	0.15	-0.17	0.12	-0.0083	-0.033	-0.036
Loan_Amount_Term	-0.045	-0.06	0.039	1	0.0014	-0.074	-0.1	-0.087	-0.0078	-0.077	-0.077	-0.034	0.061	-0.097	-0.021
Credit_History	-0.014	-0.0017	-0.0077	0.0014	1	0.013	0.0059	0.0025	0.012	-0.058	-0.078	-0.0023	0.041	-0.023	0.54
Gender_Male	0.059	0.083	0.11	-0.074	0.013	1	0.36	-0.0045	0.13	0.096	0.045	-0.00052	-0.11	0.035	0.018
Married_Yes	0.052	0.076	0.15	-0.1	0.0059	0.36	1	0.11	0.25	0.13	0.012	0.0045	0.0058	0.00055	0.091
Dependents_1	0.041	-0.03	0.062	-0.087	0.0025	-0.0045	0.11	1	-0.2	-0.13	-0.013	0.082	0.012	0.069	-0.039
Dependents_2	-0.035	0.01	0.02	-0.0078	0.012	0.13	0.25	-0.2	1	-0.13	0.021	0.032	-0.012	0.017	0.062
Dependents_3+	0.16	0.041	0.15	-0.077	-0.058	0.096	0.13	-0.13	-0.13	1	0.055	0.0033	0.0079	-0.047	-0.026
Education_Not Graduate	-0.14	-0.062	-0.17	-0.077	-0.078	0.045	0.012	-0.013	0.021	0.055	1	-0.01	-0.039	-0.034	-0.086
Self_Employed_Yes	0.13	-0.016	0.12	-0.034	-0.0023	-0.00052	0.0045	0.082	0.032	0.0033	-0.01	1	0.0087	-0.03	-0.0037
Property_Area_Semiurban	-0.014	-0.027	-0.0083	0.061	0.041	-0.11	0.0058	0.012	-0.012	0.0079	-0.039	0.0087	1	-0.55	0.14
Property_Area_Urban	-0.0006	0.023	-0.033	-0.097	-0.023	0.035	0.00055	0.069	0.017	-0.047	-0.034	-0.03	-0.55	1	-0.044
Loan_Status_Y	-0.0047	-0.059	-0.036	-0.021	0.54	0.018	0.091	-0.039	0.062	-0.026	-0.086	-0.0037	0.14	-0.044	1

In [43]:
```
train.head()
```

Out[43]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Depenc
0	5849	0.0	146.412162	360.0	1.0	1	0	0	
1	4583	1508.0	128.000000	360.0	1.0	1	1	1	
2	3000	0.0	66.000000	360.0	1.0	1	1	0	
3	2583	2358.0	120.000000	360.0	1.0	1	1	0	
4	6000	0.0	141.000000	360.0	1.0	1	0	0	

In [44]:
```
train.isnull().sum()
```

Out[44]:
```
ApplicantIncome            0
CoapplicantIncome          0
LoanAmount                 0
Loan_Amount_Term           0
Credit_History             0
Gender_Male                0
Married_Yes                0
Dependents_1               0
Dependents_2               0
Dependents_3+              0
Education_Not Graduate     0
Self_Employed_Yes          0
Property_Area_Semiurban    0
Property_Area_Urban        0
Loan_Status_Y              0
dtype: int64
```

In [45]:
```
test.drop(['Loan_Status_Y'],axis=1,inplace=True)
```

In [46]:
```
X = train.drop(columns='Loan_Status_Y')
y = train['Loan_Status_Y']
```

Using CV

In [47]:
```
from sklearn.model_selection import cross_val_score
def cv(model,cv=10):
    cvx= np.sqrt(cross_val_score(model, X, y, scoring="accuracy", cv=10))
    return(cvx)
```

Logistic Regression

In [48]:
```
from sklearn.linear_model import LogisticRegression
log_classifier=LogisticRegression()
print("Train Accuracy =",cv(log_classifier, cv=10).mean())
```

```
Train Accuracy = 0.8921531795435378
```

In [49]:
```
log_classifier.fit(X,y)
pred=log_classifier.predict(test)
print("Test Accuracy =",pred.mean())
```

```
Test Accuracy = 0.8337874659400545
```

K-Nearest Neighbours

In [50]:
```
from sklearn.neighbors import KNeighborsClassifier
k=KNeighborsClassifier(n_neighbors=18)
print("Train Accuracy =",cv(k).mean())
```

```
Train Accuracy = 0.8200728048786399
```

In [51]:
```
k.fit(X,y)
knn_pred=k.predict(test)
print("Test Accuracy =",knn_pred.mean())
```

```
Test Accuracy = 0.9237057220708447
```

Decision Trees

In [52]:
```
from sklearn.tree import DecisionTreeClassifier
tree_classifier = DecisionTreeClassifier(random_state=0,max_depth=3)
cv(tree_classifier,cv=10).mean()
```

Out[52]:
```
0.897765640443222
```

In [53]:
```
tree_classifier.fit(X,y)
tree_pred=tree_classifier.predict(test)
tree_pred.mean()
```

Out[53]:
```
0.8283378746594006
```

Random Forest

In [54]:
```
from sklearn.ensemble import RandomForestClassifier
random_classifier = RandomForestClassifier(n_estimators=40,max_depth=3)
print("Train Accuracy =",cv(random_classifier, cv=10).mean())
```

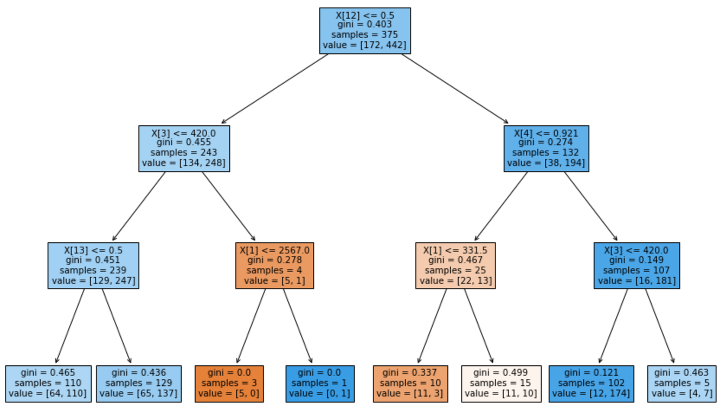
```
Train Accuracy = 0.8986679952802561
```

In [55]:
```
random_classifier.fit(X,y)
random_pred=random_classifier.predict(test)
print("Test Accuracy =",random_pred.mean())
```

```
Test Accuracy = 0.8392370572207084
```

In [56]:
```
from sklearn import tree
plt.figure(figsize=(15,10))
tree.plot_tree(random_classifier.estimators_[10-1],filled=True)
```

Out[56]:
```
[Text(418.5, 475.65000000000003, 'X[12] <= 0.5\ngini = 0.403\nsamples = 375\nvalue = [172, 442]'),
 Text(209.25, 339.75, 'X[3] <= 420.0\ngini = 0.455\nsamples = 243\nvalue = [134, 248]'),
 Text(104.625, 203.85000000000002, 'X[13] <= 0.5\ngini = 0.451\nsamples = 239\nvalue = [129, 247]'),
 Text(52.3125, 67.94999999999999, 'gini = 0.465\nsamples = 110\nvalue = [64, 110]'),
 Text(156.9375, 67.94999999999999, 'gini = 0.436\nsamples = 129\nvalue = [65, 137]'),
 Text(313.875, 203.85000000000002, 'X[1] <= 2567.0\ngini = 0.278\nsamples = 4\nvalue = [5, 1]'),
 Text(261.5625, 67.94999999999999, 'gini = 0.0\nsamples = 3\nvalue = [5, 0]'),
 Text(366.1875, 67.94999999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(627.75, 339.75, 'X[4] <= 0.921\ngini = 0.274\nsamples = 132\nvalue = [38, 194]'),
 Text(523.125, 203.85000000000002, 'X[1] <= 331.5\ngini = 0.467\nsamples = 25\nvalue = [22, 13]'),
 Text(470.8125, 67.94999999999999, 'gini = 0.337\nsamples = 10\nvalue = [11, 3]'),
 Text(575.4375, 67.94999999999999, 'gini = 0.499\nsamples = 15\nvalue = [11, 10]'),
 Text(732.375, 203.85000000000002, 'X[3] <= 420.0\ngini = 0.149\nsamples = 107\nvalue = [16, 181]'),
 Text(680.0625, 67.94999999999999, 'gini = 0.121\nsamples = 102\nvalue = [12, 174]'),
 Text(784.6875, 67.94999999999999, 'gini = 0.463\nsamples = 5\nvalue = [4, 7]')]
```



SVM

In [57]:
```
from sklearn.svm import SVC
svm_classifier =SVC()
print("Train Accuracy =",cv(svm_classifier, cv=10).mean())
```
```
Train Accuracy = 0.8290343746340472
```

In [58]:
```
svm_classifier.fit(X,y)
svm_pred=svm_classifier.predict(test)
print("Test Accuracy =",svm_pred.mean())
```
```
Test Accuracy = 1.0
```

AdaBoost

In [59]:
```
from sklearn.ensemble import AdaBoostClassifier
ada_classifier=AdaBoostClassifier(learning_rate=0.5)
cv(ada_classifier,cv=10).mean()
```
Out[59]:
```
0.8940568173117258
```

In [60]:
```
ada_classifier.fit(X,y)
ada_pred=ada_classifier.predict(test)
ada_pred.mean()
```
Out[60]:
```
0.8147138964577657
```

Gradient Boost

In [61]:
```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier(n_estimators=50, max_features=2)
cv(gb,cv=10).mean()
```
Out[61]:
```
0.8931462739836444
```

In [62]:
```
gb.fit(X,y)
gb_pred=gb.predict(test)
gb_pred.mean()
```
Out[62]:
```
0.8310626702997275
```

Using Tensorflow

In [63]:
```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from keras import regularizers
import pandas as pd
```
```
Using TensorFlow backend.
```

In [64]:
```
import tensorflow as tf
```

In [65]:
```
train1=pd.read_csv("train.csv")
```

In [66]:
```
train1.head()
```
Out[66]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Te
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	36
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	36
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	36
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	36
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	36

In [67]:
```
train1.isnull().sum()
```
Out[67]:
```
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
```

Handling Categorical Features

In [68]:
```
from sklearn.preprocessing import LabelEncoder
train1.iloc[:,0] = LabelEncoder().fit_transform(train1.iloc[:,0].astype('str'))
train1.iloc[:,1] = LabelEncoder().fit_transform(train1.iloc[:,1].astype('str'))
train1.iloc[:,2] = LabelEncoder().fit_transform(train1.iloc[:,2].astype('str'))
train1.iloc[:,3] = LabelEncoder().fit_transform(train1.iloc[:,3].astype('str'))
train1.iloc[:,4] = LabelEncoder().fit_transform(train1.iloc[:,4].astype('str'))
train1.iloc[:,5] = LabelEncoder().fit_transform(train1.iloc[:,5].astype('str'))
train1.iloc[:,11] = LabelEncoder().fit_transform(train1.iloc[:,11].astype('str'))
train1.iloc[:,12] = LabelEncoder().fit_transform(train1.iloc[:,12].astype('str'))
```

In [69]:
```
train1.shape
```
Out[69]:
```
(614, 13)
```

In [70]:
```
train1.head()
```
Out[70]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Terr
0	0	1	0	0	0	0	5849	0.0	NaN	360.
1	1	1	1	1	0	0	4583	1508.0	128.0	360.
2	2	1	1	0	0	1	3000	0.0	66.0	360.
3	3	1	1	0	1	0	2583	2358.0	120.0	360.
4	4	1	0	0	0	0	6000	0.0	141.0	360.

In [71]:
```
train1.shape
```
Out[71]:
```
(614, 13)
```

In [72]:
```
train1.isnull().sum()
```
Out[72]:
```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [73]:
```
import numpy as np
train1['LoanAmount'].replace(np.NaN, train1['LoanAmount'].mean())
train1['Loan_Amount_Term'].replace(np.NaN, train1['Loan_Amount_Term'].mean())
```
Out[73]:
```
0      360.0
1      360.0
2      360.0
3      360.0
4      360.0
       ...
609    360.0
610    180.0
611    360.0
612    360.0
613    360.0
Name: Loan_Amount_Term, Length: 614, dtype: float64
```

In [74]:
```
train1= train1.dropna()
train1.isnull().sum()
```
Out[74]:
```
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 [75]:
```
dataset=train1.values
pd.DataFrame(dataset)
```
Out[75]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	1.0	1.0	1.0	1.0	0.0	0.0	4583.0	1508.0	128.0	360.0	1.0	0.0	0.0
1	2.0	1.0	1.0	0.0	0.0	1.0	3000.0	0.0	66.0	360.0	1.0	2.0	1.0
2	3.0	1.0	1.0	0.0	1.0	0.0	2583.0	2358.0	120.0	360.0	1.0	2.0	1.0
3	4.0	1.0	0.0	0.0	0.0	0.0	6000.0	0.0	141.0	360.0	1.0	2.0	1.0
4	5.0	1.0	1.0	2.0	0.0	1.0	5417.0	4196.0	267.0	360.0	1.0	2.0	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
524	609.0	0.0	0.0	0.0	0.0	0.0	2900.0	0.0	71.0	360.0	1.0	0.0	1.0
525	610.0	1.0	1.0	3.0	0.0	0.0	4106.0	0.0	40.0	180.0	1.0	0.0	1.0
526	611.0	1.0	1.0	1.0	0.0	0.0	8072.0	240.0	253.0	360.0	1.0	2.0	1.0
527	612.0	1.0	1.0	2.0	0.0	0.0	7583.0	0.0	187.0	360.0	1.0	2.0	1.0
528	613.0	0.0	0.0	0.0	0.0	1.0	4583.0	0.0	133.0	360.0	0.0	1.0	0.0

529 rows × 13 columns

Scaling Features

In [76]:

```
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
X_scale = min_max_scaler.fit_transform(X)
pd.DataFrame(X_scale)
```

Out[76]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	0.070489	0.000000	0.198860	0.743590	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
1	0.054830	0.036192	0.172214	0.743590	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.035250	0.000000	0.082489	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
3	0.030093	0.056592	0.160637	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0
4	0.072356	0.000000	0.191027	0.743590	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
609	0.034014	0.000000	0.089725	0.743590	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
610	0.048930	0.000000	0.044863	0.358974	1.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
611	0.097984	0.005760	0.353111	0.743590	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0
612	0.091936	0.000000	0.257598	0.743590	1.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0
613	0.054830	0.000000	0.179450	0.743590	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0

614 rows × 14 columns

Splitting Our Data

In [77]:

```
from sklearn.model_selection import train_test_split
X_train, X_val_and_test, Y_train, Y_val_and_test = train_test_split(X_scale, y, test_size=0.3)
```

In [78]:

```
pd.DataFrame(X_train)
```

Out[78]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	0.253766	0.000000	0.198860	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.041707	0.000000	0.104197	0.358974	1.0	1.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0
2	0.096265	0.000000	0.384949	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
3	0.061422	0.034824	0.225760	0.743590	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
4	0.068237	0.064007	0.247467	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
424	0.037304	0.049536	0.137482	0.743590	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
425	0.023055	0.046296	0.094067	0.743590	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
426	0.020656	0.042456	0.124457	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
427	0.056710	0.000000	0.186686	0.743590	1.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0
428	0.046592	0.000000	0.166425	0.743590	1.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0

429 rows × 14 columns

In [79]:

```
x_val, X_test, y_val, Y_test = train_test_split(X_val_and_test, Y_val_and_test, test_size=0.5)
```

In [80]:

```
print(X_train.shape, X_test.shape, x_val.shape, Y_train.shape, Y_test.shape, y_val.shape)
```

```
(429, 14) (93, 14) (92, 14) (429,) (93,) (92,)
```

In [81]:

```
#the word dense is used to define a layer of connected neurons here we use 3 layers and input_shape refers t
#inputs we are using


model = Sequential([
    Dense(32, activation='relu', input_shape=(14,)),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid'),
])
```

In [82]:

```
model.compile(optimizer='sgd',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

In [83]:

```
hist=model.fit(X_train,Y_train,
          batch_size = 32, epochs = 100,
        validation_data = (x_val,y_val))
```

```
Train on 429 samples, validate on 92 samples
Epoch 1/100
429/429 [==============================] - 0s 579us/step - loss: 0.7406 - accuracy: 0.3263 - val_loss: 0.721
9 - val_accuracy: 0.3696
Epoch 2/100
429/429 [==============================] - 0s 78us/step - loss: 0.6994 - accuracy: 0.4755 - val_loss: 0.6837
- val_accuracy: 0.5109
Epoch 3/100
429/429 [==============================] - 0s 76us/step - loss: 0.6691 - accuracy: 0.6760 - val_loss: 0.6581
- val_accuracy: 0.7174
Epoch 4/100
429/429 [==============================] - 0s 82us/step - loss: 0.6493 - accuracy: 0.6830 - val_loss: 0.6404
- val_accuracy: 0.6848
Epoch 5/100
429/429 [==============================] - 0s 77us/step - loss: 0.6354 - accuracy: 0.6807 - val_loss: 0.6272
- val_accuracy: 0.6848
Epoch 6/100
429/429 [==============================] - 0s 79us/step - loss: 0.6251 - accuracy: 0.6783 - val_loss: 0.6180
- val_accuracy: 0.6739
Epoch 7/100
429/429 [==============================] - 0s 79us/step - loss: 0.6181 - accuracy: 0.6783 - val_loss: 0.6113
- val_accuracy: 0.6739
Epoch 8/100
429/429 [==============================] - 0s 78us/step - loss: 0.6124 - accuracy: 0.6783 - val_loss: 0.6053
- val_accuracy: 0.6739
Epoch 9/100
429/429 [==============================] - 0s 86us/step - loss: 0.6078 - accuracy: 0.6783 - val_loss: 0.6010
- val_accuracy: 0.6739
Epoch 10/100
429/429 [==============================] - 0s 84us/step - loss: 0.6042 - accuracy: 0.6783 - val_loss: 0.5979
- val_accuracy: 0.6739
Epoch 11/100
429/429 [==============================] - 0s 83us/step - loss: 0.6014 - accuracy: 0.6783 - val_loss: 0.5951
- val_accuracy: 0.6739
Epoch 12/100
429/429 [==============================] - 0s 84us/step - loss: 0.5988 - accuracy: 0.6783 - val_loss: 0.5929
- val_accuracy: 0.6739
Epoch 13/100
429/429 [==============================] - 0s 83us/step - loss: 0.5969 - accuracy: 0.6783 - val_loss: 0.5912
- val_accuracy: 0.6739
Epoch 14/100
429/429 [==============================] - 0s 84us/step - loss: 0.5950 - accuracy: 0.6783 - val_loss: 0.5896
- val_accuracy: 0.6739
Epoch 15/100
429/429 [==============================] - 0s 84us/step - loss: 0.5932 - accuracy: 0.6783 - val_loss: 0.5877
- val_accuracy: 0.6739
Epoch 16/100
429/429 [==============================] - 0s 84us/step - loss: 0.5916 - accuracy: 0.6783 - val_loss: 0.5861
- val_accuracy: 0.6739
Epoch 17/100
429/429 [==============================] - 0s 79us/step - loss: 0.5896 - accuracy: 0.6783 - val_loss: 0.5847
- val_accuracy: 0.6739
Epoch 18/100
429/429 [==============================] - 0s 77us/step - loss: 0.5881 - accuracy: 0.6783 - val_loss: 0.5832
- val_accuracy: 0.6739
Epoch 19/100
429/429 [==============================] - 0s 77us/step - loss: 0.5867 - accuracy: 0.6783 - val_loss: 0.5815
- val_accuracy: 0.6739
Epoch 20/100
429/429 [==============================] - 0s 81us/step - loss: 0.5852 - accuracy: 0.6783 - val_loss: 0.5802
- val_accuracy: 0.6739
Epoch 21/100
429/429 [==============================] - 0s 82us/step - loss: 0.5836 - accuracy: 0.6783 - val_loss: 0.5787
- val_accuracy: 0.6739
Epoch 22/100
429/429 [==============================] - 0s 77us/step - loss: 0.5822 - accuracy: 0.6783 - val_loss: 0.5772
- val_accuracy: 0.6739
Epoch 23/100
429/429 [==============================] - 0s 79us/step - loss: 0.5806 - accuracy: 0.6783 - val_loss: 0.5759
- val_accuracy: 0.6739
Epoch 24/100
429/429 [==============================] - 0s 74us/step - loss: 0.5791 - accuracy: 0.6783 - val_loss: 0.5743
- val_accuracy: 0.6739
Epoch 25/100
429/429 [==============================] - 0s 81us/step - loss: 0.5774 - accuracy: 0.6783 - val_loss: 0.5728
- val_accuracy: 0.6848
Epoch 26/100
429/429 [==============================] - 0s 77us/step - loss: 0.5761 - accuracy: 0.6783 - val_loss: 0.5714
- val_accuracy: 0.6848
Epoch 27/100
429/429 [==============================] - 0s 79us/step - loss: 0.5743 - accuracy: 0.6783 - val_loss: 0.5700
- val_accuracy: 0.6848
Epoch 28/100
429/429 [==============================] - 0s 81us/step - loss: 0.5727 - accuracy: 0.6783 - val_loss: 0.5685
- val_accuracy: 0.6848
Epoch 29/100
429/429 [==============================] - 0s 75us/step - loss: 0.5712 - accuracy: 0.6807 - val_loss: 0.5671
- val_accuracy: 0.6848
Epoch 30/100
429/429 [==============================] - 0s 79us/step - loss: 0.5696 - accuracy: 0.6807 - val_loss: 0.5658
- val_accuracy: 0.6848
Epoch 31/100
429/429 [==============================] - 0s 79us/step - loss: 0.5679 - accuracy: 0.6807 - val_loss: 0.5643
- val_accuracy: 0.6848
Epoch 32/100
429/429 [==============================] - 0s 84us/step - loss: 0.5664 - accuracy: 0.6807 - val_loss: 0.5628
- val_accuracy: 0.6848
Epoch 33/100
429/429 [==============================] - 0s 84us/step - loss: 0.5648 - accuracy: 0.6876 - val_loss: 0.5612
- val_accuracy: 0.6848
Epoch 34/100
429/429 [==============================] - 0s 82us/step - loss: 0.5631 - accuracy: 0.6876 - val_loss: 0.5598
- val_accuracy: 0.6848
Epoch 35/100
429/429 [==============================] - 0s 72us/step - loss: 0.5613 - accuracy: 0.6900 - val_loss: 0.5582
- val_accuracy: 0.6957
Epoch 36/100
429/429 [==============================] - 0s 79us/step - loss: 0.5598 - accuracy: 0.6970 - val_loss: 0.5567
- val_accuracy: 0.6957
Epoch 37/100
429/429 [==============================] - 0s 83us/step - loss: 0.5584 - accuracy: 0.6993 - val_loss: 0.5553
- val_accuracy: 0.7065
Epoch 38/100
429/429 [==============================] - 0s 84us/step - loss: 0.5570 - accuracy: 0.7040 - val_loss: 0.5539
- val_accuracy: 0.7065
Epoch 39/100
429/429 [==============================] - 0s 81us/step - loss: 0.5551 - accuracy: 0.7110 - val_loss: 0.5523
- val_accuracy: 0.7065
Epoch 40/100
429/429 [==============================] - 0s 86us/step - loss: 0.5538 - accuracy: 0.7179 - val_loss: 0.5509
- val_accuracy: 0.7065
Epoch 41/100
429/429 [==============================] - 0s 84us/step - loss: 0.5523 - accuracy: 0.7273 - val_loss: 0.5492
- val_accuracy: 0.7065
Epoch 42/100
429/429 [==============================] - 0s 85us/step - loss: 0.5507 - accuracy: 0.7226 - val_loss: 0.5477
- val_accuracy: 0.7065
Epoch 43/100
429/429 [==============================] - 0s 81us/step - loss: 0.5489 - accuracy: 0.7273 - val_loss: 0.5462
- val_accuracy: 0.7065
Epoch 44/100
429/429 [==============================] - 0s 87us/step - loss: 0.5474 - accuracy: 0.7296 - val_loss: 0.5446
- val_accuracy: 0.7065
Epoch 45/100
429/429 [==============================] - 0s 85us/step - loss: 0.5459 - accuracy: 0.7319 - val_loss: 0.5429
- val_accuracy: 0.7065
Epoch 46/100
429/429 [==============================] - 0s 84us/step - loss: 0.5443 - accuracy: 0.7413 - val_loss: 0.5414
- val_accuracy: 0.7065
Epoch 47/100
429/429 [==============================] - 0s 91us/step - loss: 0.5428 - accuracy: 0.7483 - val_loss: 0.5400
- val_accuracy: 0.7065
Epoch 48/100
429/429 [==============================] - 0s 81us/step - loss: 0.5411 - accuracy: 0.7529 - val_loss: 0.5386
- val_accuracy: 0.7174
Epoch 49/100
429/429 [==============================] - 0s 86us/step - loss: 0.5397 - accuracy: 0.7552 - val_loss: 0.5370
- val_accuracy: 0.7174
Epoch 50/100
429/429 [==============================] - 0s 77us/step - loss: 0.5381 - accuracy: 0.7576 - val_loss: 0.5353
- val_accuracy: 0.7174
Epoch 51/100
429/429 [==============================] - 0s 72us/step - loss: 0.5365 - accuracy: 0.7552 - val_loss: 0.5341
- val_accuracy: 0.7283
Epoch 52/100
429/429 [==============================] - 0s 82us/step - loss: 0.5348 - accuracy: 0.7576 - val_loss: 0.5323
- val_accuracy: 0.7391
Epoch 53/100
429/429 [==============================] - 0s 81us/step - loss: 0.5333 - accuracy: 0.7576 - val_loss: 0.5307
- val_accuracy: 0.7500
Epoch 54/100
```

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429/429 [==============================] - 0s 81us/step - loss: 0.5319 - accuracy: 0.7622 - val_loss: 0.5291
- val_accuracy: 0.7500
Epoch 55/100
429/429 [==============================] - 0s 81us/step - loss: 0.5301 - accuracy: 0.7622 - val_loss: 0.5281
- val_accuracy: 0.7609
Epoch 56/100
429/429 [==============================] - 0s 84us/step - loss: 0.5286 - accuracy: 0.7646 - val_loss: 0.5263
- val_accuracy: 0.7717
Epoch 57/100
429/429 [==============================] - 0s 86us/step - loss: 0.5274 - accuracy: 0.7646 - val_loss: 0.5248
- val_accuracy: 0.7717
Epoch 58/100
429/429 [==============================] - 0s 81us/step - loss: 0.5258 - accuracy: 0.7669 - val_loss: 0.5232
- val_accuracy: 0.7717
Epoch 59/100
429/429 [==============================] - 0s 91us/step - loss: 0.5240 - accuracy: 0.7669 - val_loss: 0.5219
- val_accuracy: 0.7826
Epoch 60/100
429/429 [==============================] - 0s 103us/step - loss: 0.5228 - accuracy: 0.7786 - val_loss: 0.520
3 - val_accuracy: 0.7826
Epoch 61/100
429/429 [==============================] - 0s 133us/step - loss: 0.5213 - accuracy: 0.7809 - val_loss: 0.518
9 - val_accuracy: 0.8043
Epoch 62/100
429/429 [==============================] - 0s 128us/step - loss: 0.5200 - accuracy: 0.7809 - val_loss: 0.517
5 - val_accuracy: 0.8043
Epoch 63/100
429/429 [==============================] - 0s 137us/step - loss: 0.5187 - accuracy: 0.7809 - val_loss: 0.516
1 - val_accuracy: 0.8152
Epoch 64/100
429/429 [==============================] - 0s 135us/step - loss: 0.5172 - accuracy: 0.7832 - val_loss: 0.514
9 - val_accuracy: 0.8152
Epoch 65/100
429/429 [==============================] - 0s 142us/step - loss: 0.5156 - accuracy: 0.7832 - val_loss: 0.513
5 - val_accuracy: 0.8152
Epoch 66/100
429/429 [==============================] - 0s 135us/step - loss: 0.5145 - accuracy: 0.7879 - val_loss: 0.512
1 - val_accuracy: 0.8152
Epoch 67/100
429/429 [==============================] - 0s 137us/step - loss: 0.5133 - accuracy: 0.7879 - val_loss: 0.511
2 - val_accuracy: 0.8261
Epoch 68/100
429/429 [==============================] - 0s 135us/step - loss: 0.5120 - accuracy: 0.7995 - val_loss: 0.509
5 - val_accuracy: 0.8261
Epoch 69/100
429/429 [==============================] - 0s 128us/step - loss: 0.5107 - accuracy: 0.7995 - val_loss: 0.508
8 - val_accuracy: 0.8370
Epoch 70/100
429/429 [==============================] - 0s 133us/step - loss: 0.5097 - accuracy: 0.7995 - val_loss: 0.507
2 - val_accuracy: 0.8370
Epoch 71/100
429/429 [==============================] - 0s 140us/step - loss: 0.5084 - accuracy: 0.7972 - val_loss: 0.506
5 - val_accuracy: 0.8370
Epoch 72/100
429/429 [==============================] - 0s 130us/step - loss: 0.5075 - accuracy: 0.7995 - val_loss: 0.504
4 - val_accuracy: 0.8370
Epoch 73/100
429/429 [==============================] - 0s 133us/step - loss: 0.5063 - accuracy: 0.7995 - val_loss: 0.503
0 - val_accuracy: 0.8370
Epoch 74/100
429/429 [==============================] - 0s 129us/step - loss: 0.5049 - accuracy: 0.7995 - val_loss: 0.501
6 - val_accuracy: 0.8370
Epoch 75/100
429/429 [==============================] - 0s 133us/step - loss: 0.5039 - accuracy: 0.7995 - val_loss: 0.500
1 - val_accuracy: 0.8370
Epoch 76/100
429/429 [==============================] - 0s 140us/step - loss: 0.5029 - accuracy: 0.7995 - val_loss: 0.498
8 - val_accuracy: 0.8370
Epoch 77/100
429/429 [==============================] - 0s 133us/step - loss: 0.5018 - accuracy: 0.7995 - val_loss: 0.497
5 - val_accuracy: 0.8370
Epoch 78/100
429/429 [==============================] - 0s 132us/step - loss: 0.5009 - accuracy: 0.7995 - val_loss: 0.496
4 - val_accuracy: 0.8370
Epoch 79/100
429/429 [==============================] - 0s 133us/step - loss: 0.4999 - accuracy: 0.7995 - val_loss: 0.495
2 - val_accuracy: 0.8370
Epoch 80/100
429/429 [==============================] - 0s 130us/step - loss: 0.4995 - accuracy: 0.7972 - val_loss: 0.493
9 - val_accuracy: 0.8370
Epoch 81/100
429/429 [==============================] - 0s 135us/step - loss: 0.4979 - accuracy: 0.7995 - val_loss: 0.493
2 - val_accuracy: 0.8370
Epoch 82/100
429/429 [==============================] - 0s 134us/step - loss: 0.4969 - accuracy: 0.7972 - val_loss: 0.492
0 - val_accuracy: 0.8370
Epoch 83/100
429/429 [==============================] - 0s 127us/step - loss: 0.4959 - accuracy: 0.7972 - val_loss: 0.491
0 - val_accuracy: 0.8370
Epoch 84/100
429/429 [==============================] - 0s 130us/step - loss: 0.4953 - accuracy: 0.7972 - val_loss: 0.489
7 - val_accuracy: 0.8370
Epoch 85/100
429/429 [==============================] - 0s 128us/step - loss: 0.4941 - accuracy: 0.7972 - val_loss: 0.489
1 - val_accuracy: 0.8370
Epoch 86/100
429/429 [==============================] - 0s 123us/step - loss: 0.4935 - accuracy: 0.7972 - val_loss: 0.488
0 - val_accuracy: 0.8370
Epoch 87/100
429/429 [==============================] - 0s 122us/step - loss: 0.4928 - accuracy: 0.7972 - val_loss: 0.486
8 - val_accuracy: 0.8370
Epoch 88/100
429/429 [==============================] - ETA: 0s - loss: 0.4212 - accuracy: 0.84 - 0s 122us/step - loss:
0.4921 - accuracy: 0.7972 - val_loss: 0.4858 - val_accuracy: 0.8370
Epoch 89/100
429/429 [==============================] - 0s 125us/step - loss: 0.4912 - accuracy: 0.7972 - val_loss: 0.485
1 - val_accuracy: 0.8370
Epoch 90/100
429/429 [==============================] - 0s 132us/step - loss: 0.4908 - accuracy: 0.7972 - val_loss: 0.484
1 - val_accuracy: 0.8370
Epoch 91/100
429/429 [==============================] - 0s 121us/step - loss: 0.4897 - accuracy: 0.7972 - val_loss: 0.483
4 - val_accuracy: 0.8370
Epoch 92/100
429/429 [==============================] - 0s 126us/step - loss: 0.4892 - accuracy: 0.7972 - val_loss: 0.482
9 - val_accuracy: 0.8370
Epoch 93/100
429/429 [==============================] - 0s 132us/step - loss: 0.4887 - accuracy: 0.7972 - val_loss: 0.482
0 - val_accuracy: 0.8370
Epoch 94/100
429/429 [==============================] - 0s 129us/step - loss: 0.4878 - accuracy: 0.7972 - val_loss: 0.480
7 - val_accuracy: 0.8370
Epoch 95/100
429/429 [==============================] - 0s 131us/step - loss: 0.4870 - accuracy: 0.7972 - val_loss: 0.479
8 - val_accuracy: 0.8370
Epoch 96/100
429/429 [==============================] - 0s 123us/step - loss: 0.4868 - accuracy: 0.7972 - val_loss: 0.479
1 - val_accuracy: 0.8370
Epoch 97/100
429/429 [==============================] - 0s 126us/step - loss: 0.4860 - accuracy: 0.7972 - val_loss: 0.478
2 - val_accuracy: 0.8370
Epoch 98/100
429/429 [==============================] - 0s 123us/step - loss: 0.4851 - accuracy: 0.7972 - val_loss: 0.477
5 - val_accuracy: 0.8370
Epoch 99/100
429/429 [==============================] - 0s 126us/step - loss: 0.4846 - accuracy: 0.7972 - val_loss: 0.477
0 - val_accuracy: 0.8370
Epoch 100/100
429/429 [==============================] - 0s 133us/step - loss: 0.4840 - accuracy: 0.7972 - val_loss: 0.476
3 - val_accuracy: 0.8370
```

In [86]:

```
model.evaluate(X_test,Y_test)[1]
```

In [ ]: