Objective of the Problem

This problem solves **binary classification** task using machine learning techniques, where we aim to predict whether a loan would be approved or not based on the customer details provided while filling out the online application form.
This notebook is divided into the following 3 sections:

1. **Introduction to the Problem**
2. **Exploratory Data Analysis (EDA) and Preprocessing**
3. **Feature Engineering and Model Building**

Assignment Name: "Credit Worthiness of Customer (Classification Problem)"
Assignment done by: Aahna Shresth
Roll No.: DST-24/25-023

1.Description of Dataset

The dataset consists of information collected from applicants for a loan. It includes demographic details, income-related information, credit history, and the loan status (i.e., whether the loan was approved or not). There are a total of **13 columns**, with a mix of categorical and numerical variables.
Below is a brief description of each column:

- **Loan_ID**: Unique identifier for each loan application.
- **Gender**: Gender of the applicant (Male/Female).
- **Married**: Marital status of the applicant (Yes/No).
- **Dependents**: Number of dependents the applicant has (0, 1, 2, 3+).
- **Education**: Education level of the applicant (Graduate/Not Graduate).
- **Self_Employed**: Indicates whether the applicant is self-employed (Yes/No).
- **ApplicantIncome**: Monthly income of the applicant.
- **CoapplicantIncome**: Monthly income of the co-applicant (if any).
- **LoanAmount**: Loan amount (in thousands).
- **Loan_Amount_Term**: Term of the loan (in months).
- **Credit_History**: Credit history of the applicant (1.0 indicates good credit, 0.0 indicates poor credit).
- **Property_Area**: Area where the property is located (Urban/Semiurban/Rural).
- **Loan_Status**: Target variable indicating whether the loan was approved (Y) or not (N).

In [1]:
```
# Import Libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
```

```
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
```

In [2]:
```
df=pd.read_csv(r'C:/Users/Ela_shresth/Documents/jupyter_notebook/loan_sanction_i
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 981 entries, 0 to 980
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        981 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 99.8+ KB
```

In [5]:
```
df['Loan_Status'].value_counts()
```

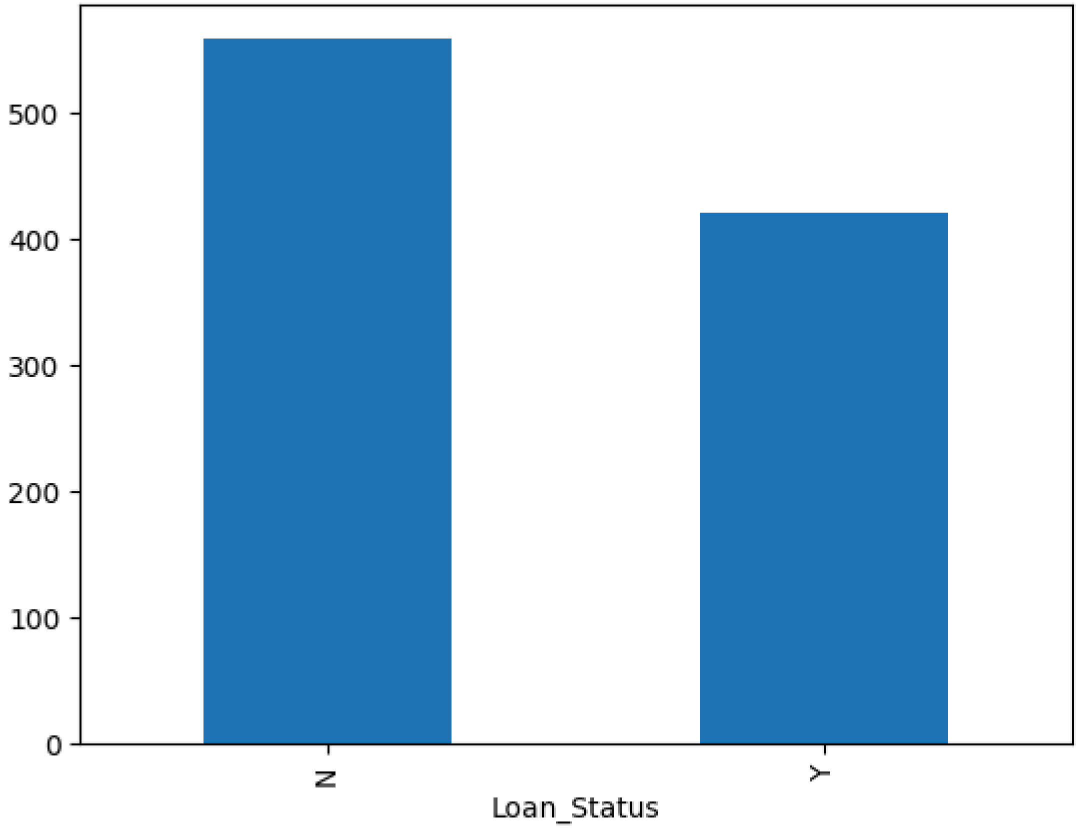
Out[5]:
```
Loan_Status
N    559
Y    422
Name: count, dtype: int64
```

In [6]:
```
df['Loan_Status'].value_counts(normalize=True)
```

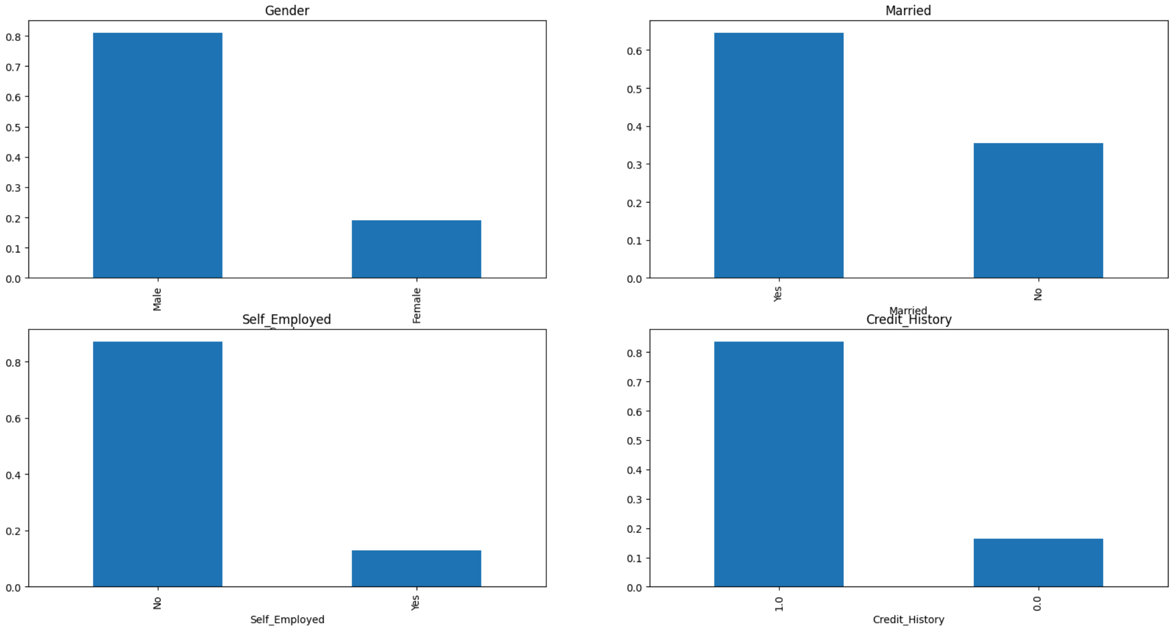
Out[6]:
```
Loan_Status
N    0.569827
Y    0.430173
Name: proportion, dtype: float64
```

In [7]:
```
df['Loan_Status'].value_counts().plot.bar()
```

Out[7]:
```
<Axes: xlabel='Loan_Status'>
```

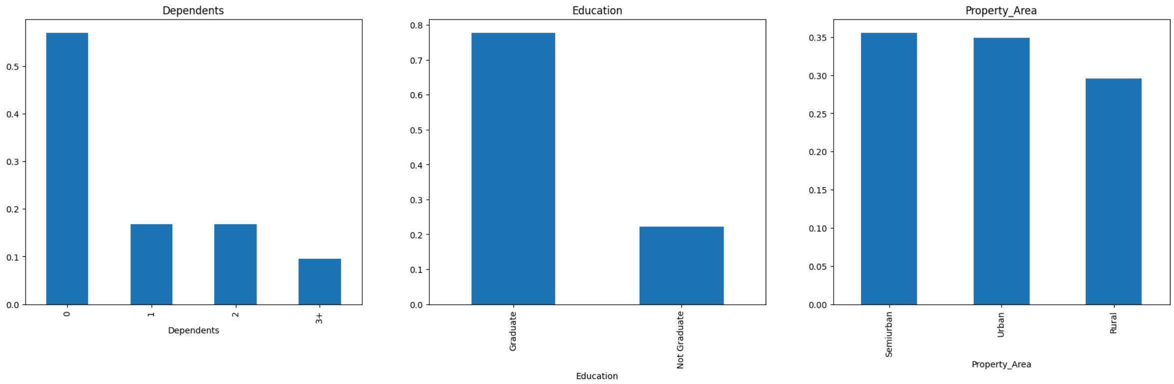


In [8]:
```
plt.figure(1)
plt.subplot(221)
df['Gender'].value_counts(normalize=True).plot.bar(figsize=(20,10), title= 'Gend
plt.subplot(222)
df['Married'].value_counts(normalize=True).plot.bar(title= 'Married')
plt.subplot(223)
df['Self_Employed'].value_counts(normalize=True).plot.bar(title= 'Self_Employed'
plt.subplot(224)
df['Credit_History'].value_counts(normalize=True).plot.bar(title= 'Credit_Histor
plt.show()
```

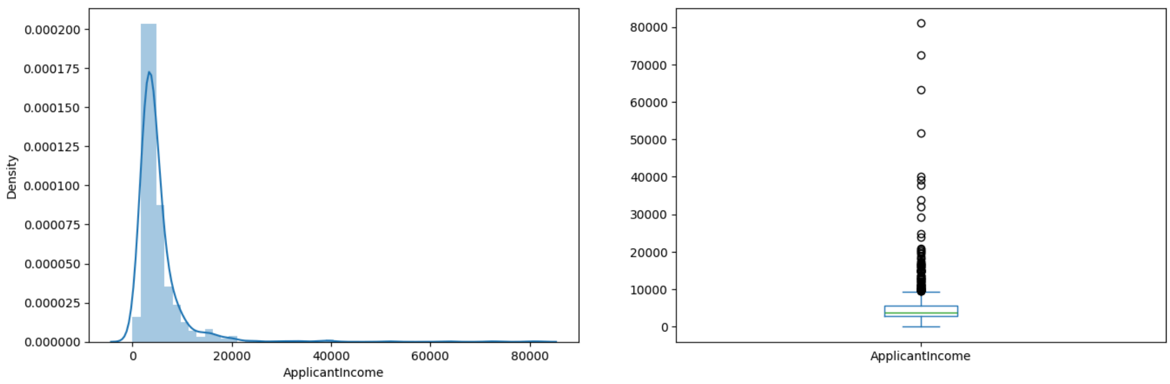


In [9]:
```
plt.figure(1)
plt.subplot(131)
df['Dependents'].value_counts(normalize=True).plot.bar(figsize=(24,6), title= 'D
```

```
plt.subplot(132)
df['Education'].value_counts(normalize=True).plot.bar(title= 'Education')
plt.subplot(133)
df['Property_Area'].value_counts(normalize=True).plot.bar(title= 'Property_Area'
plt.show()
```

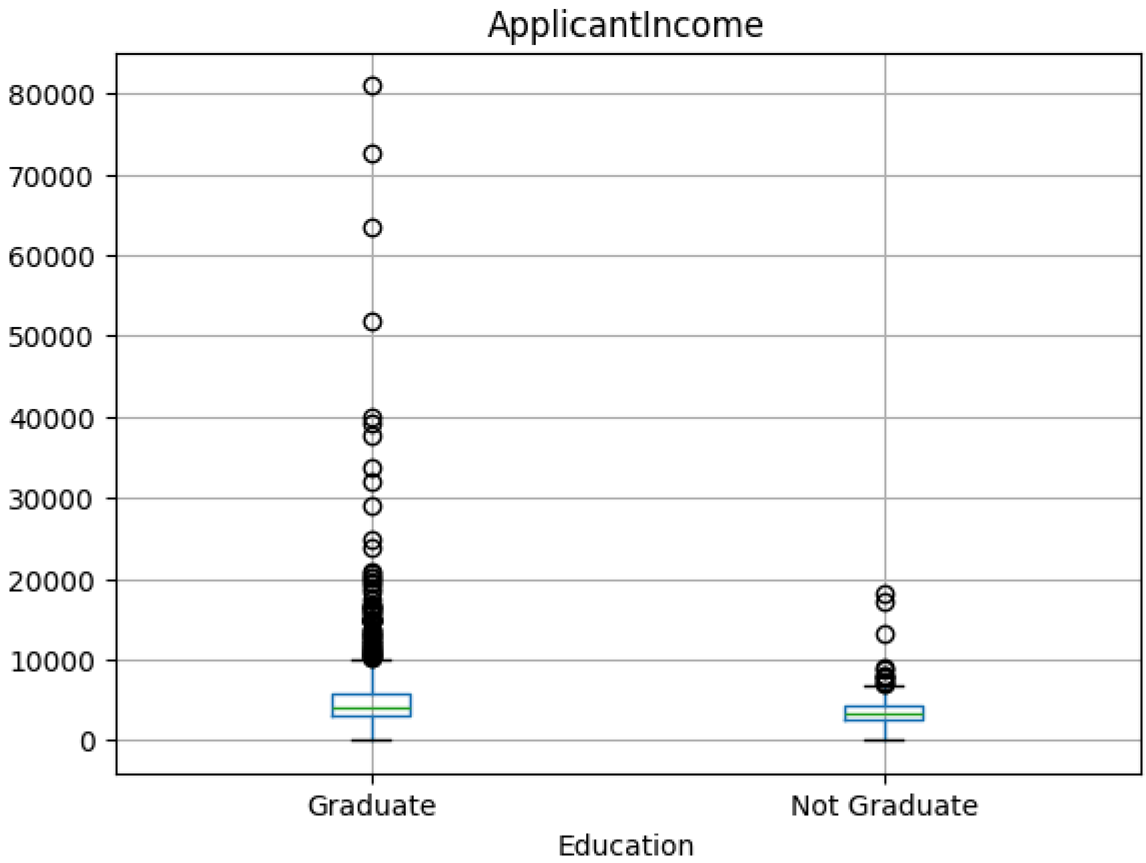


In [10]:
```
plt.figure(1)
plt.subplot(121)
sns.distplot(df['ApplicantIncome']);
plt.subplot(122)
df['ApplicantIncome'].plot.box(figsize=(16,5))
plt.show()
```

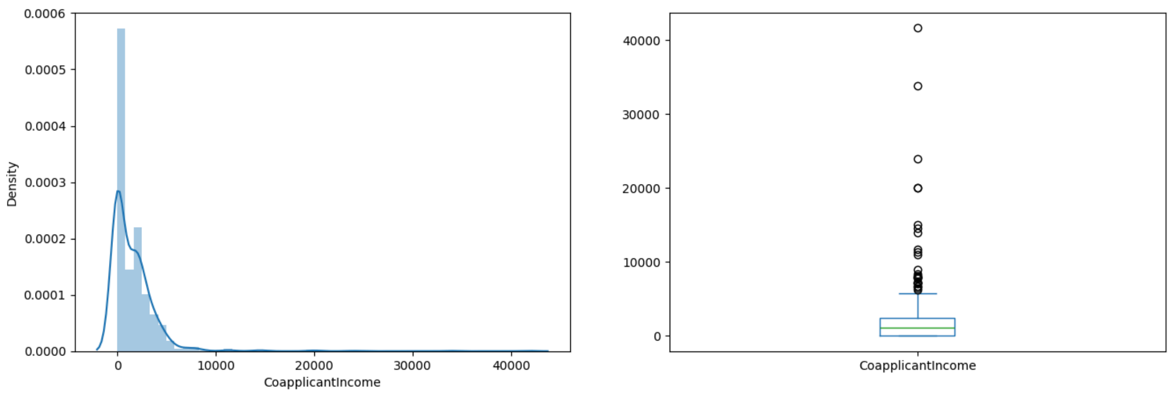


In [11]:
```
df.boxplot(column='ApplicantIncome', by = 'Education')
plt.suptitle("")
```

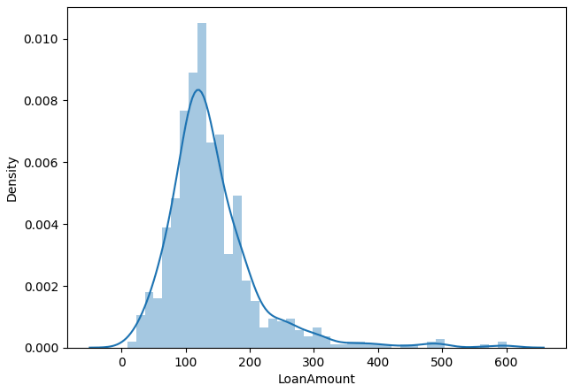
Out[11]:
```
Text(0.5, 0.98, '')
```

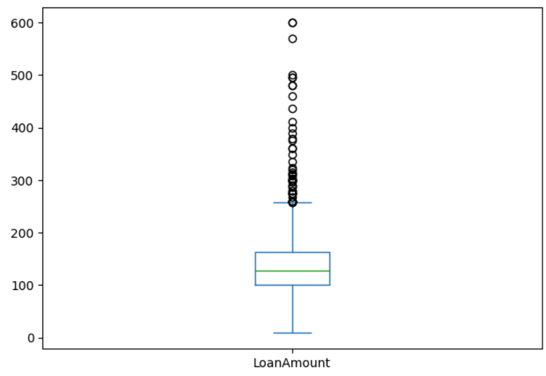


In [12]:
```
plt.figure(1)
plt.subplot(121)
sns.distplot(df['CoapplicantIncome']);
plt.subplot(122)
df['CoapplicantIncome'].plot.box(figsize=(16,5))
plt.show()
```



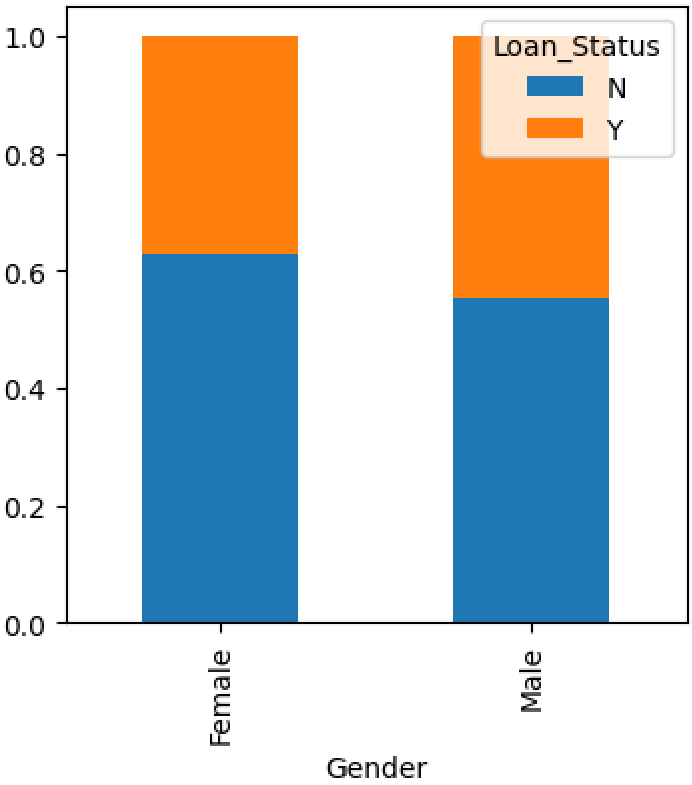
In [13]:
```
plt.figure(1)
plt.subplot(121)
df=df.dropna()
sns.distplot(df['LoanAmount']);
plt.subplot(122)
df['LoanAmount'].plot.box(figsize=(16,5))
plt.show()
```



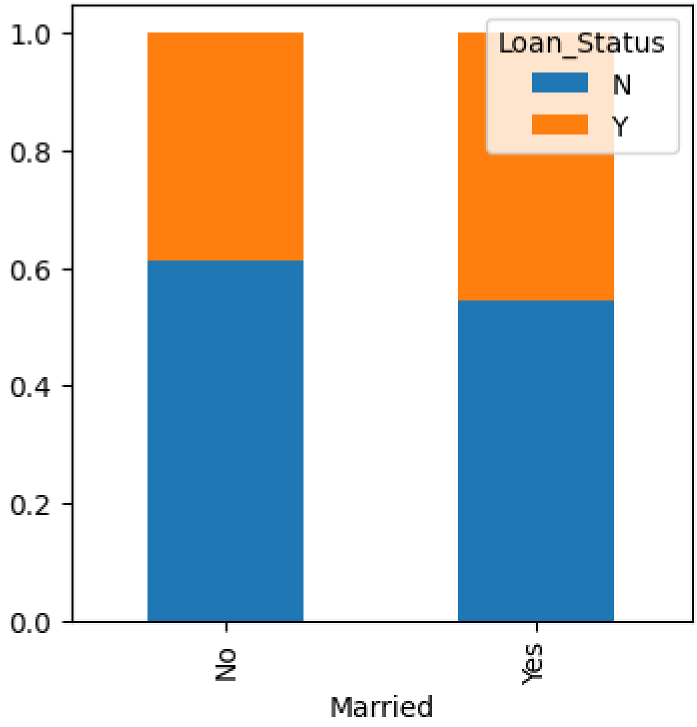


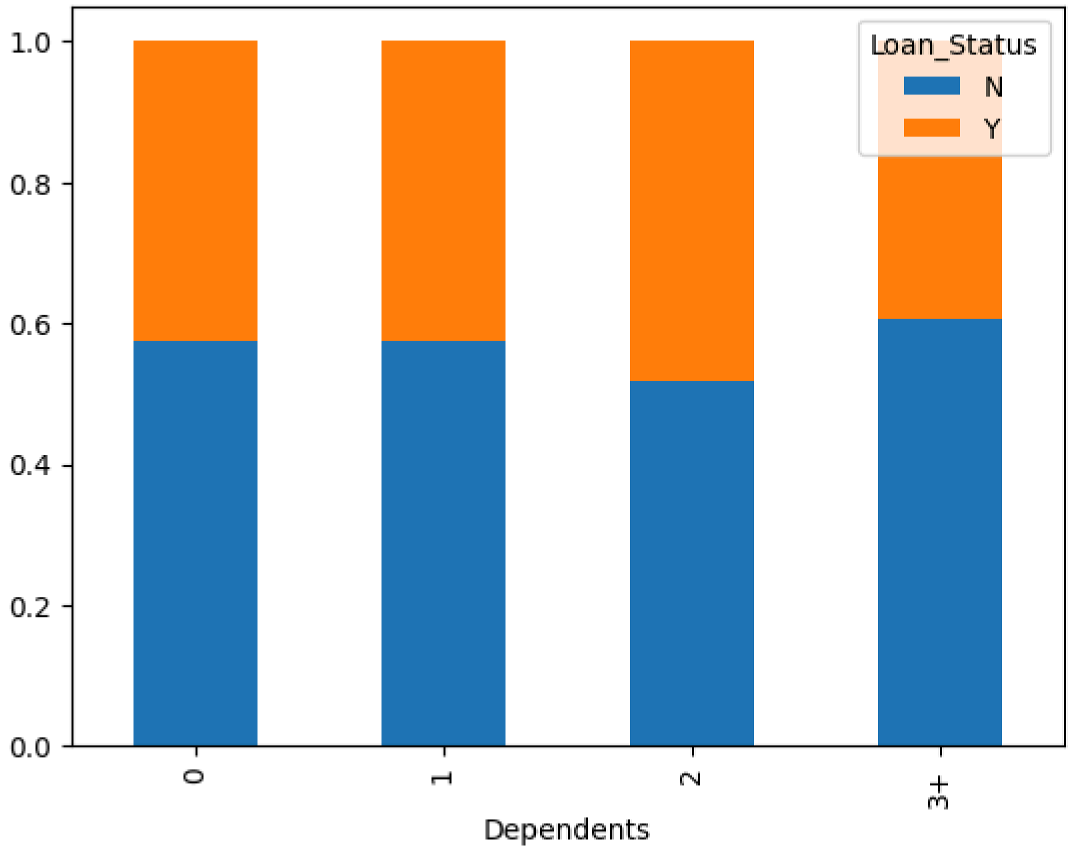
In [14]:
```
Gender=pd.crosstab(df['Gender'],df['Loan_Status'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar", stacked=True, f
```

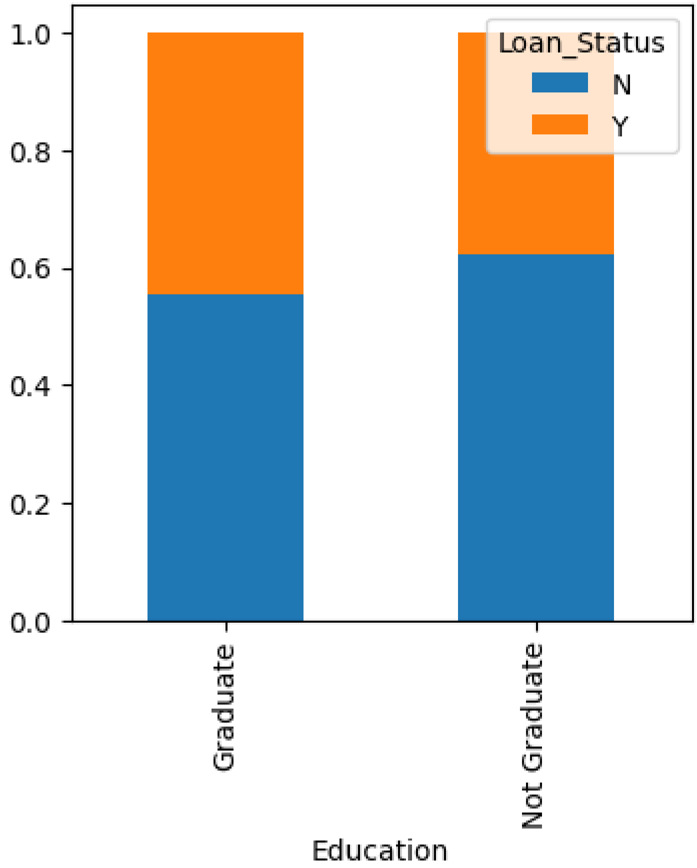
Out[14]: <Axes: xlabel='Gender'>

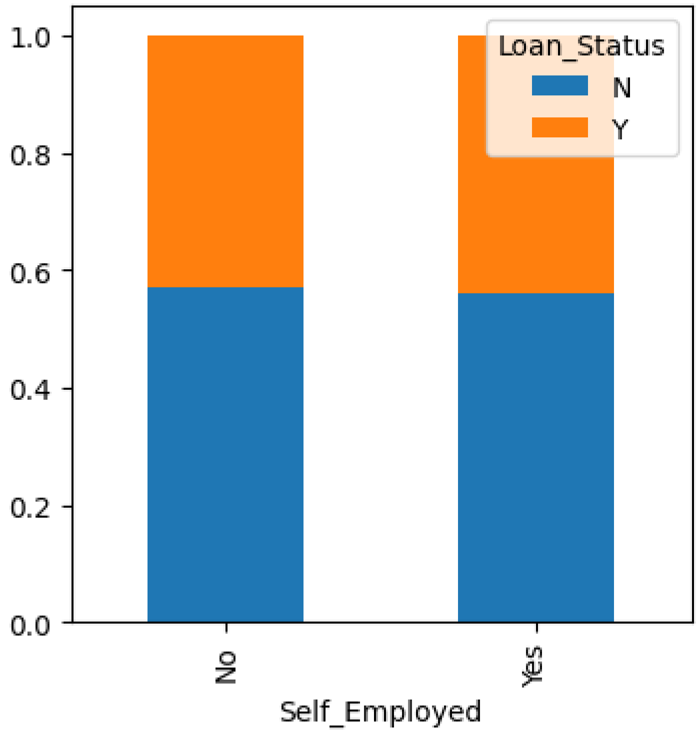


In [15]:
```
Married=pd.crosstab(df['Married'],df['Loan_Status'])
Dependents=pd.crosstab(df['Dependents'],df['Loan_Status'])
Education=pd.crosstab(df['Education'],df['Loan_Status'])
Self_Employed=pd.crosstab(df['Self_Employed'],df['Loan_Status'])
Married.div(Married.sum(1).astype(float), axis=0).plot(kind="bar", stacked=True,
plt.show()
Dependents.div(Dependents.sum(1).astype(float), axis=0).plot(kind="bar", stacked
plt.show()
Education.div(Education.sum(1).astype(float), axis=0).plot(kind="bar", stacked=T
plt.show()
Self_Employed.div(Self_Employed.sum(1).astype(float), axis=0).plot(kind="bar", s
plt.show()
```


Loan_Status
N
Y
1.0
0.8
0.6
0.4
0.2
0.0
No
Yes
Married

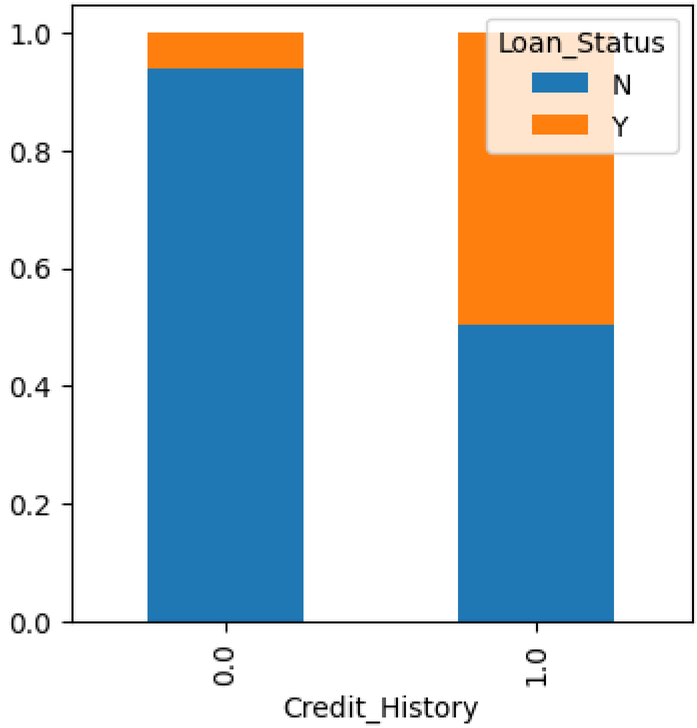

Loan_Status
N
Y
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
3+
Dependents

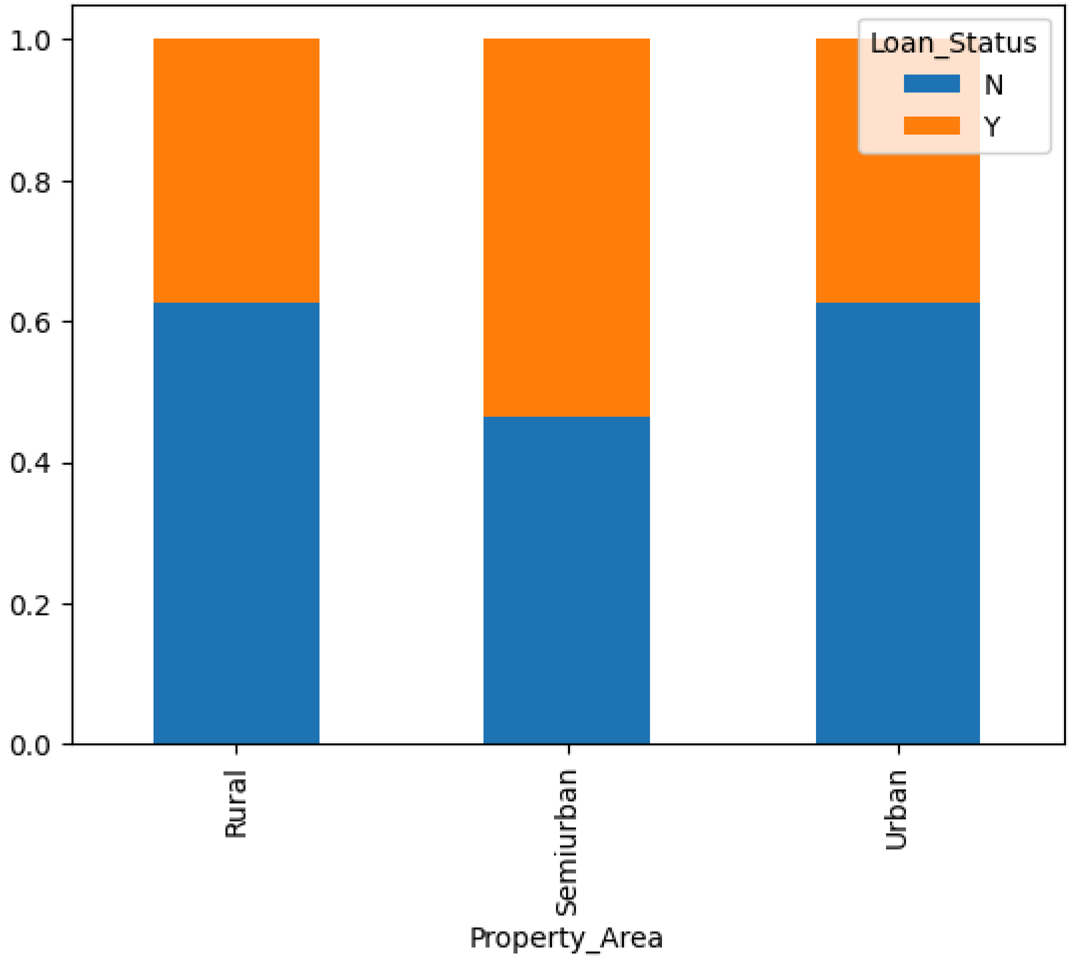




In [16]:

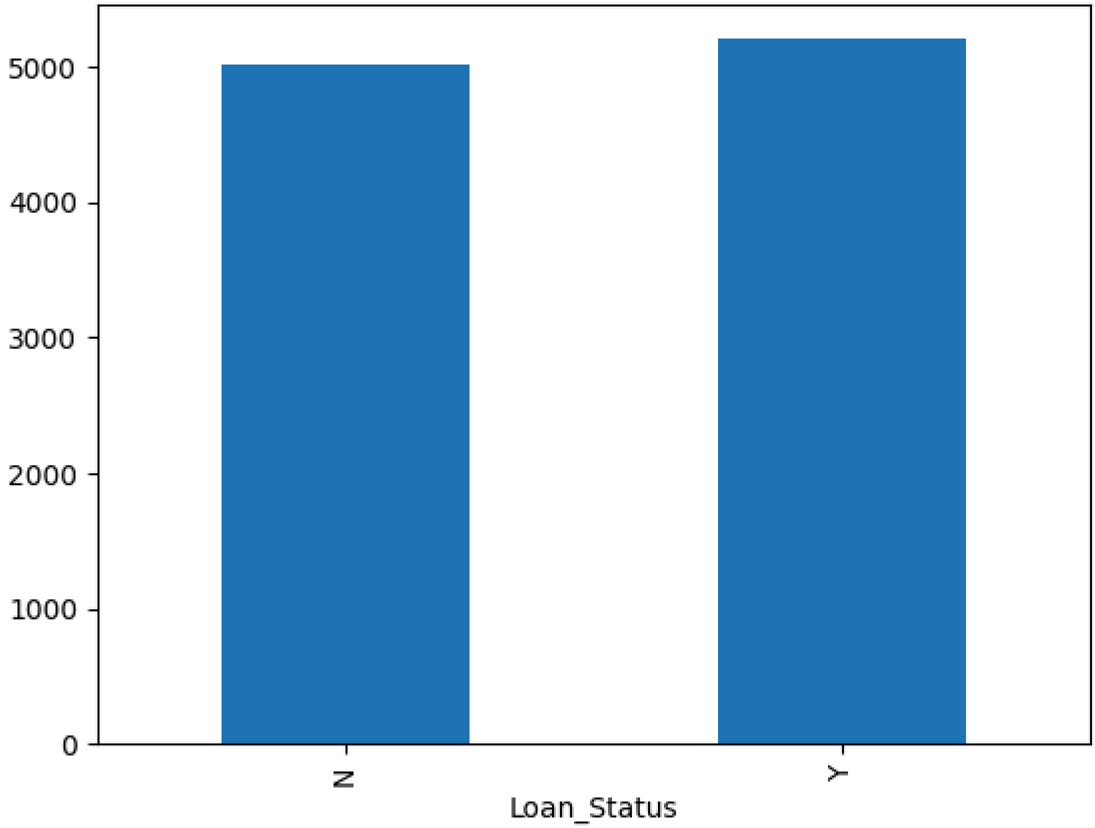
```
Credit_History=pd.crosstab(df['Credit_History'],df['Loan_Status'])
Property_Area=pd.crosstab(df['Property_Area'],df['Loan_Status'])
Credit_History.div(Credit_History.sum(1).astype(float), axis=0).plot(kind="bar",
plt.show()
Property_Area.div(Property_Area.sum(1).astype(float), axis=0).plot(kind="bar", s
plt.show()
```



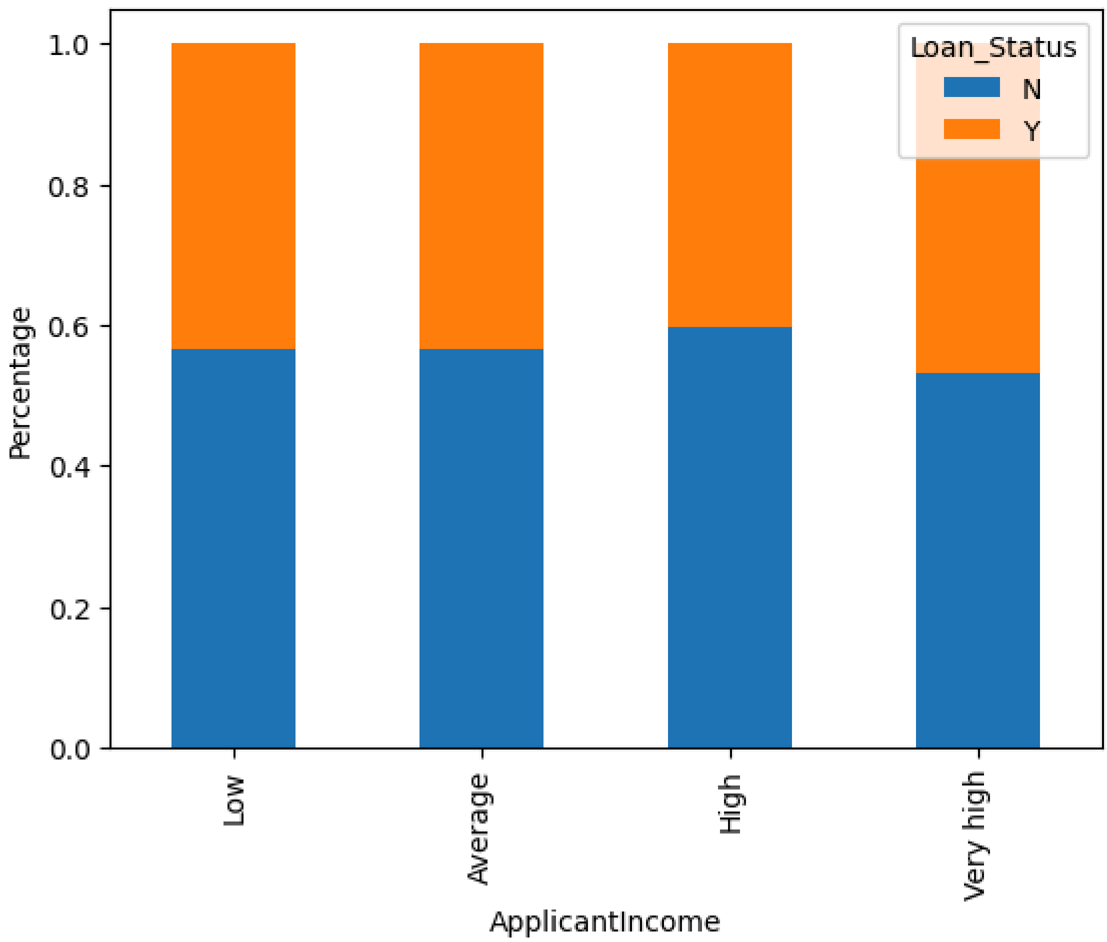


In [17]:
```
df.groupby('Loan_Status')['ApplicantIncome'].mean().plot.bar()
```

Out[17]: <Axes: xlabel='Loan_Status'>

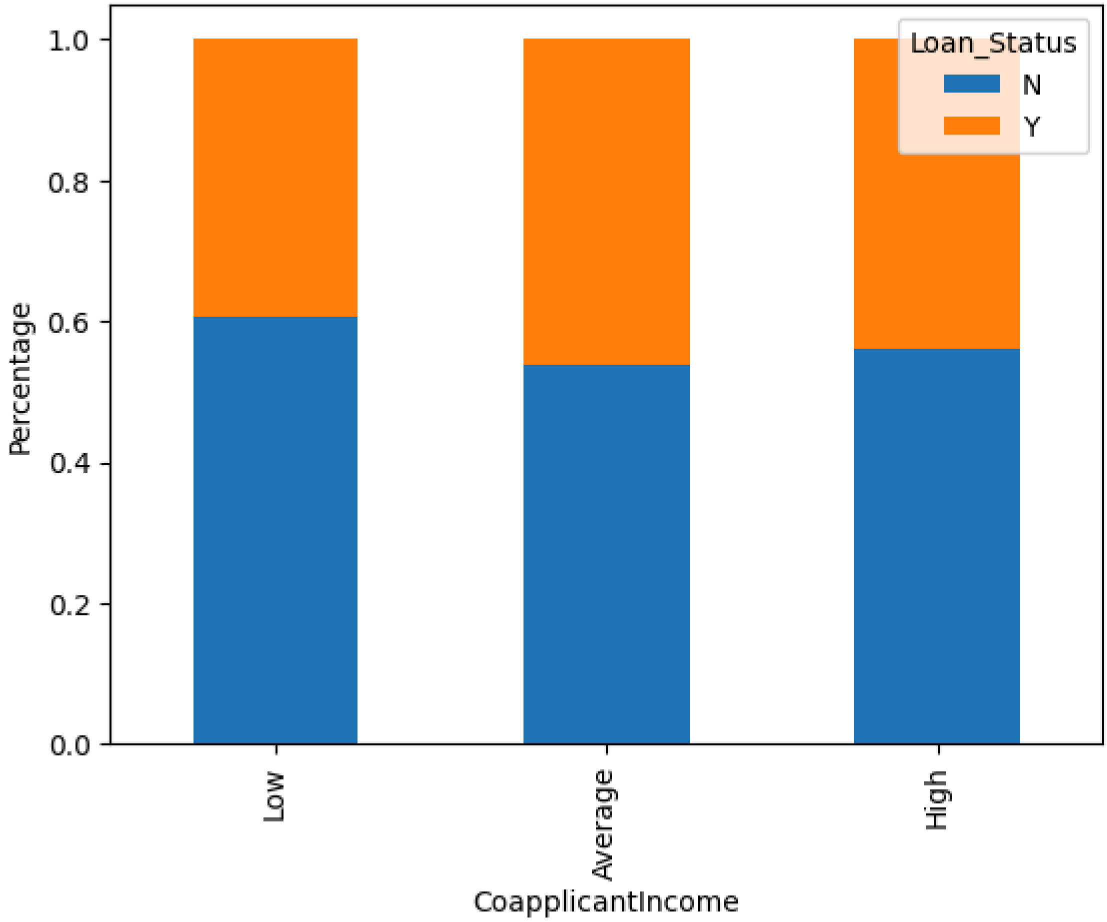


In [18]:
```
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High', 'Very high']
df['Income_bin']=pd.cut(df['ApplicantIncome'],bins,labels=group)
Income_bin=pd.crosstab(df['Income_bin'],df['Loan_Status'])
Income_bin.div(Income_bin.sum(1).astype(float), axis=0).plot(kind="bar", stacked
plt.xlabel('ApplicantIncome')
P = plt.ylabel('Percentage')
```

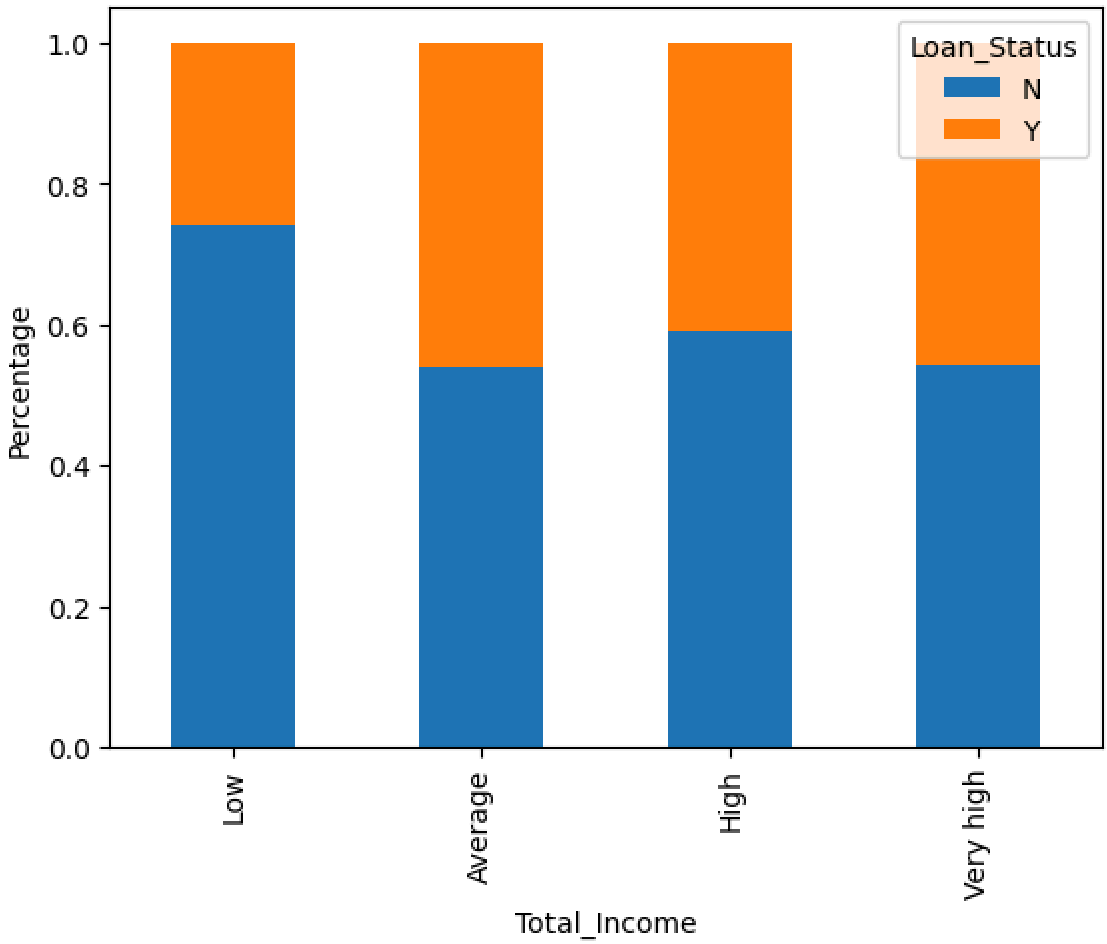


In [19]:
```
bins=[0,1000,3000,42000]
group=['Low','Average','High']
df['Coapplicant_Income_bin']=pd.cut(df['CoapplicantIncome'],bins,labels=group)
```

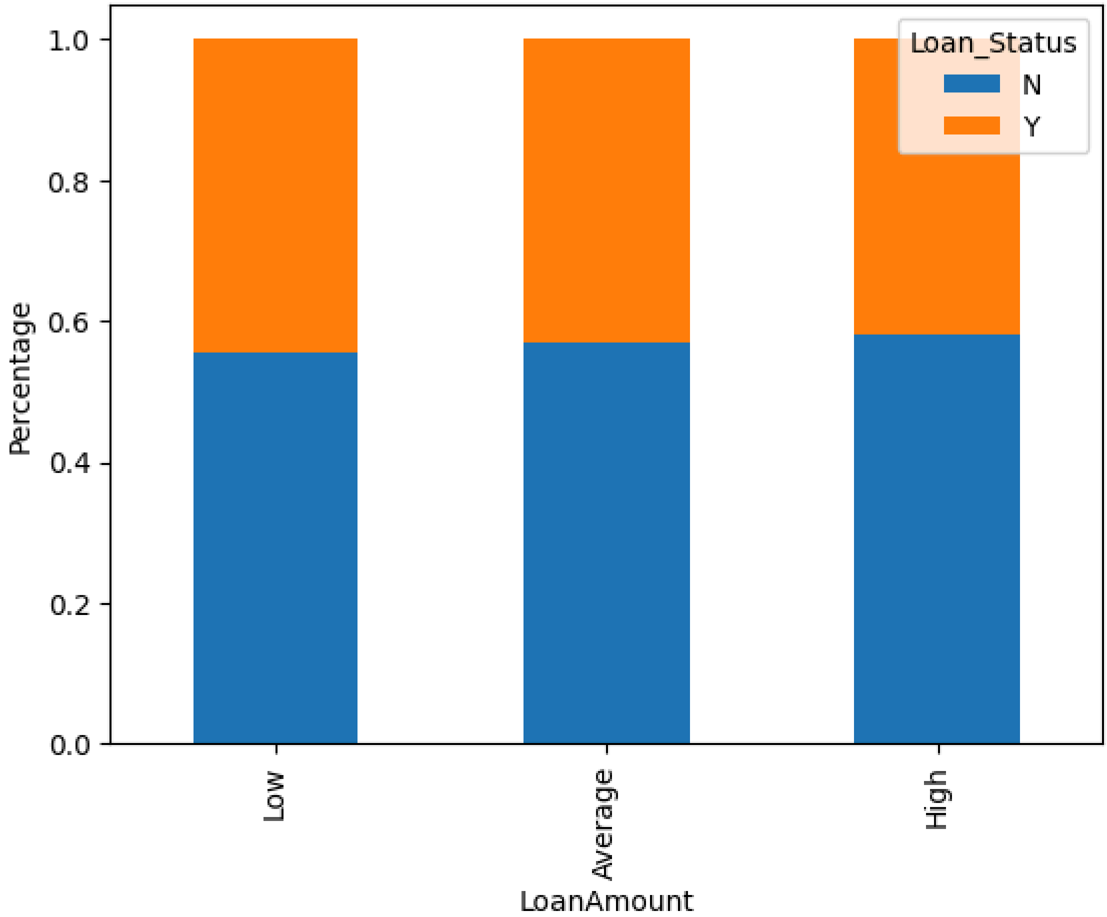
In [20]:
```
Coapplicant_Income_bin=pd.crosstab(df['Coapplicant_Income_bin'],df['Loan_Status'
Coapplicant_Income_bin.div(Coapplicant_Income_bin.sum(1).astype(float), axis=0).
plt.xlabel('CoapplicantIncome')
P = plt.ylabel('Percentage')
```



In [21]:
```
df['Total_Income']=df['ApplicantIncome']+df['CoapplicantIncome']
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High', 'Very high']
df['Total_Income_bin']=pd.cut(df['Total_Income'],bins,labels=group)
Total_Income_bin=pd.crosstab(df['Total_Income_bin'],df['Loan_Status'])
Total_Income_bin.div(Total_Income_bin.sum(1).astype(float), axis=0).plot(kind="b
plt.xlabel('Total_Income')
P = plt.ylabel('Percentage')
```



In [22]:
```
bins=[0,100,200,700]
group=['Low','Average','High']
df['LoanAmount_bin']=pd.cut(df['LoanAmount'],bins,labels=group)
LoanAmount_bin=pd.crosstab(df['LoanAmount_bin'],df['Loan_Status'])
LoanAmount_bin.div(LoanAmount_bin.sum(1).astype(float), axis=0).plot(kind="bar",
plt.xlabel('LoanAmount')
P = plt.ylabel('Percentage')
```



In [23]:
```
df=df.drop(['Income_bin', 'Coapplicant_Income_bin', 'LoanAmount_bin', 'Total_Inc
df['Dependents'].replace('3+', 3,inplace=True)
df['Loan_Status'].replace('N', 0,inplace=True)
df['Loan_Status'].replace('Y', 1,inplace=True)
```

In [24]:
```
df.head()
```

Out[24]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
1	LP001003	Male	Yes	1	Graduate	No	458:
2	LP001005	Male	Yes	0	Graduate	Yes	300(
3	LP001006	Male	Yes	0	Not Graduate	No	258:
4	LP001008	Male	No	0	Graduate	No	600(
5	LP001011	Male	Yes	2	Graduate	Yes	541

In [25]:
```
df.isnull().sum()
```

Out[25]:
```
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
```

Imputation

In [26]:
```
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)
```

In [27]:
```
df['Loan_Amount_Term'].value_counts()
```

Out[27]:
```
Loan_Amount_Term
360.0    659
180.0     55
480.0     19
300.0     15
84.0       5
120.0      4
240.0      4
36.0       3
60.0       2
12.0       1
350.0      1
6.0        1
Name: count, dtype: int64
```

In [28]:
```
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0], inplace=True)
```

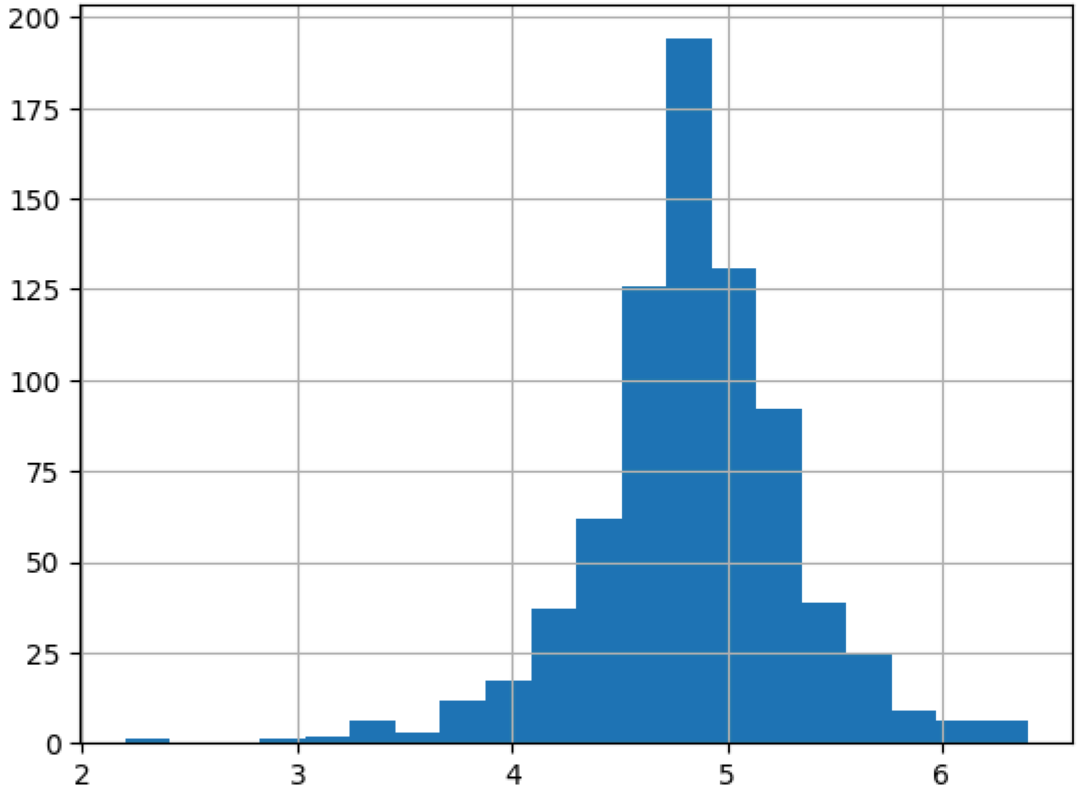
In [29]:
```
df['LoanAmount'].fillna(df['LoanAmount'].median(), inplace=True)
```

In [30]:
```
df.isnull().sum()
```

Out[30]:
```
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 [31]:
```
df['LoanAmount_log'] = np.log(df['LoanAmount'])
df['LoanAmount_log'].hist(bins=20)
```

Out[31]: <Axes: >



2.Model Selection and Algorithms Used

To solve this binary classification problem, I have experimented with multiple machine learning algorithms to identify the best-performing model for predicting loan approval status. The following models were implemented and evaluated:

- **Logistic Regression**: A effective linear model suitable for binary classification tasks.
- **Random Forest Classifier**: An ensemble method based on decision trees, known for its robustness and ability to handle overfitting.
- **AdaBoost Classifier**: An ensemble boosting algorithm that combines weak learners to form a strong classifier.

- **XGBoost Classifier**: A highly efficient and scalable gradient boosting algorithm, often delivering superior performance in structured data problems.

Model selection was guided by evaluating key performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC using cross-validation. Hyperparameter tuning was also performed to optimize each model's performance.

In [32]:
```
df=df.drop('Loan_ID',axis=1)
```

In [34]:
```
X = df.drop('Loan_Status',axis = 1)
y = df.Loan_Status
```

In [35]:
```
X=pd.get_dummies(X)
df=pd.get_dummies(df)
```

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

Logistic Regression

In [38]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,ConfusionMatri
                            precision_score, recall_score, f1_score, roc_auc_scor
```

In [39]:
```
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
```

Out[39]:
```
▾ LogisticRegression
LogisticRegression()
```

In [40]:
```
# Make predictions
y_train_pred = log_reg.predict(X_train)
y_test_pred = log_reg.predict(X_test)
# Training set performance
model_train_accuracy = accuracy_score(y_train, y_train_pred) # Calculate Accurac
model_train_f1 = f1_score(y_train, y_train_pred, average='weighted') # Calculate
model_train_precision = precision_score(y_train, y_train_pred) # Calculate Preci
model_train_recall = recall_score(y_train, y_train_pred) # Calculate Recall
model_train_rocauc_score = roc_auc_score(y_train, y_train_pred)

# Test set performance
model_test_accuracy = accuracy_score(y_test, y_test_pred) # Calculate Accuracy
model_test_f1 = f1_score(y_test, y_test_pred, average='weighted') # Calculate F1
model_test_precision = precision_score(y_test, y_test_pred) # Calculate Precisio
model_test_recall = recall_score(y_test, y_test_pred) # Calculate Recall
model_test_rocauc_score = roc_auc_score(y_test, y_test_pred) #Calculate Roc
```

```
print('Model performance for Training set')
print("- Accuracy: {:.4f}".format(model_train_accuracy))
print('- F1 score: {:.4f}'.format(model_train_f1))
print('- Precision: {:.4f}'.format(model_train_precision))
print('- Recall: {:.4f}'.format(model_train_recall))
print('- Roc Auc Score: {:.4f}'.format(model_train_rocauc_score))

print('----------------------------------')
print('Model performance for Test set')
print('- Accuracy: {:.4f}'.format(model_test_accuracy))
print('- F1 score: {:.4f}'.format(model_test_f1))
print('- Precision: {:.4f}'.format(model_test_precision))
print('- Recall: {:.4f}'.format(model_test_recall))
print('- Roc Auc Score: {:.4f}'.format(model_test_rocauc_score))
```

```
Model performance for Training set
- Accuracy: 0.6195
- F1 score: 0.6086
- Precision: 0.5950
- Recall: 0.4375
- Roc Auc Score: 0.6007
----------------------------------
Model performance for Test set
- Accuracy: 0.6494
- F1 score: 0.6392
- Precision: 0.6122
- Recall: 0.4615
- Roc Auc Score: 0.6240
```

AdaBoost Classifier

In [41]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.datasets import make_classification
```

In [42]:
```
ada_clf = AdaBoostClassifier(n_estimators=100, random_state=0)
ada_clf.fit(X_train, y_train)
```

Out[42]:
```
AdaBoostClassifier

AdaBoostClassifier(n_estimators=100, random_state=0)
```

In [43]:
```
# Make predictions
y_train_pred = ada_clf.predict(X_train)
y_test_pred = ada_clf.predict(X_test)
# Training set performance
model_train_accuracy = accuracy_score(y_train, y_train_pred) # Calculate Accurac
model_train_f1 = f1_score(y_train, y_train_pred, average='weighted') # Calculate
model_train_precision = precision_score(y_train, y_train_pred) # Calculate Preci
model_train_recall = recall_score(y_train, y_train_pred) # Calculate Recall
model_train_rocauc_score = roc_auc_score(y_train, y_train_pred)

# Test set performance
model_test_accuracy = accuracy_score(y_test, y_test_pred) # Calculate Accuracy
model_test_f1 = f1_score(y_test, y_test_pred, average='weighted') # Calculate F1
model_test_precision = precision_score(y_test, y_test_pred) # Calculate Precisic
model_test_recall = recall_score(y_test, y_test_pred) # Calculate Recall
```

```
model_test_rocauc_score = roc_auc_score(y_test, y_test_pred) #Calculate Roc


print('Model performance for Training set')
print("- Accuracy: {:.4f}".format(model_train_accuracy))
print('- F1 score: {:.4f}'.format(model_train_f1))
print('- Precision: {:.4f}'.format(model_train_precision))
print('- Recall: {:.4f}'.format(model_train_recall))
print('- Roc Auc Score: {:.4f}'.format(model_train_rocauc_score))

print('----------------------------------')
print('Model performance for Test set')
print('- Accuracy: {:.4f}'.format(model_test_accuracy))
print('- F1 score: {:.4f}'.format(model_test_f1))
print('- Precision: {:.4f}'.format(model_test_precision))
print('- Recall: {:.4f}'.format(model_test_recall))
print('- Roc Auc Score: {:.4f}'.format(model_test_rocauc_score))
```

```
Model performance for Training set
- Accuracy: 0.6537
- F1 score: 0.6548
- Precision: 0.5987
- Recall: 0.6581
- Roc Auc Score: 0.6541
----------------------------------
Model performance for Test set
- Accuracy: 0.6753
- F1 score: 0.6772
- Precision: 0.5949
- Recall: 0.7231
- Roc Auc Score: 0.6818
```

Random Forest Classifier

In [44]:

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

In [45]:

```
rf_clf = RandomForestClassifier(random_state=1, max_depth=10)
rf_clf.fit(X_train, y_train)
```

Out[45]:

```
RandomForestClassifier
RandomForestClassifier(max_depth=10, random_state=1)
```

In [46]:

```
# Make predictions
y_train_pred = rf_clf.predict(X_train)
y_test_pred = rf_clf.predict(X_test)
# Training set performance
model_train_accuracy = accuracy_score(y_train, y_train_pred) # Calculate Accurac
model_train_f1 = f1_score(y_train, y_train_pred, average='weighted') # Calculate
model_train_precision = precision_score(y_train, y_train_pred) # Calculate Preci
model_train_recall = recall_score(y_train, y_train_pred) # Calculate Recall
model_train_rocauc_score = roc_auc_score(y_train, y_train_pred)

# Test set performance
model_test_accuracy = accuracy_score(y_test, y_test_pred) # Calculate Accuracy
model_test_f1 = f1_score(y_test, y_test_pred, average='weighted') # Calculate F1
model_test_precision = precision_score(y_test, y_test_pred) # Calculate Precisio
```

```
model_test_recall = recall_score(y_test, y_test_pred) # Calculate Recall
model_test_rocauc_score = roc_auc_score(y_test, y_test_pred) #Calculate Roc


print('Model performance for Training set')
print("- Accuracy: {:.4f}".format(model_train_accuracy))
print('- F1 score: {:.4f}'.format(model_train_f1))
print('- Precision: {:.4f}'.format(model_train_precision))
print('- Recall: {:.4f}'.format(model_train_recall))
print('- Roc Auc Score: {:.4f}'.format(model_train_rocauc_score))

print('----------------------------------')
print('Model performance for Test set')
print('- Accuracy: {:.4f}'.format(model_test_accuracy))
print('- F1 score: {:.4f}'.format(model_test_f1))
print('- Precision: {:.4f}'.format(model_test_precision))
print('- Recall: {:.4f}'.format(model_test_recall))
print('- Roc Auc Score: {:.4f}'.format(model_test_rocauc_score))
```

```
Model performance for Training set
- Accuracy: 0.9610
- F1 score: 0.9610
- Precision: 0.9559
- Recall: 0.9559
- Roc Auc Score: 0.9604
----------------------------------
Model performance for Test set
- Accuracy: 0.8831
- F1 score: 0.8835
- Precision: 0.8406
- Recall: 0.8923
- Roc Auc Score: 0.8844
```

XGboost

In [50]:

```
from xgboost import XGBClassifier
```

In [51]:

```
xgb_clf = XGBClassifier(n_estimators=50, max_depth=4)
xgb_clf.fit(X_train, y_train)
```

Out[51]:

▾ XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rou
nds=None,
              enable_categorical=False, eval_metric=None, feature_ty
pes=None,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=No
```

In [52]:

```
# Make predictions
y_train_pred = xgb_clf.predict(X_train)
y_test_pred = xgb_clf.predict(X_test)
```

```
# Training set performance
model_train_accuracy = accuracy_score(y_train, y_train_pred) # Calculate Accurac
model_train_f1 = f1_score(y_train, y_train_pred, average='weighted') # Calculate
model_train_precision = precision_score(y_train, y_train_pred) # Calculate Preci
model_train_recall = recall_score(y_train, y_train_pred) # Calculate Recall
model_train_rocauc_score = roc_auc_score(y_train, y_train_pred)

# Test set performance
model_test_accuracy = accuracy_score(y_test, y_test_pred) # Calculate Accuracy
model_test_f1 = f1_score(y_test, y_test_pred, average='weighted') # Calculate F1
model_test_precision = precision_score(y_test, y_test_pred) # Calculate Precisio
model_test_recall = recall_score(y_test, y_test_pred) # Calculate Recall
model_test_rocauc_score = roc_auc_score(y_test, y_test_pred) #Calculate Roc


print('Model performance for Training set')
print("- Accuracy: {:.4f}".format(model_train_accuracy))
print('- F1 score: {:.4f}'.format(model_train_f1))
print('- Precision: {:.4f}'.format(model_train_precision))
print('- Recall: {:.4f}'.format(model_train_recall))
print('- Roc Auc Score: {:.4f}'.format(model_train_rocauc_score))

print('----------------------------------')
print('Model performance for Test set')
print('- Accuracy: {:.4f}'.format(model_test_accuracy))
print('- F1 score: {:.4f}'.format(model_test_f1))
print('- Precision: {:.4f}'.format(model_test_precision))
print('- Recall: {:.4f}'.format(model_test_recall))
print('- Roc Auc Score: {:.4f}'.format(model_test_rocauc_score))
```

```
Model performance for Training set
- Accuracy: 0.9154
- F1 score: 0.9153
- Precision: 0.9135
- Recall: 0.8934
- Roc Auc Score: 0.9132
----------------------------------
Model performance for Test set
- Accuracy: 0.8312
- F1 score: 0.8315
- Precision: 0.7910
- Recall: 0.8154
- Roc Auc Score: 0.8290
```

Final Model Selection

Based on the performance on the test set, the **Random Forest Classifier** achieved the best overall results:

Accuracy: 91.56%

F1 Score: 91.58%

Precision: 88.24%

Recall: 92.31%

ROC AUC Score: 91.66%

Soft voting (Aggregation Rule)

In [53]:
```
# Get predicted probabilities
log_pred_prob = log_reg.predict_proba(X_test)
ada_pred_prob = ada_clf.predict_proba(X_test)
rf_pred_prob = rf_clf.predict_proba(X_test)
xgb_pred_prob = xgb_clf.predict_proba(X_test)

# Average the probabilities
avg_pred_prob = (log_pred_prob + ada_pred_prob + rf_pred_prob + xgb_pred_prob) /

# Final prediction based on highest average probability
final_preds = np.argmax(avg_pred_prob, axis=1)
```

In [54]:
```
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_sc

# Assuming y_test is your true labels
accuracy = accuracy_score(y_test, final_preds)
f1 = f1_score(y_test, final_preds)
precision = precision_score(y_test, final_preds)
recall = recall_score(y_test, final_preds)

print(f"Ensemble Model Performance:")
print(f"Accuracy: {accuracy:.4f}")
print(f"F1 Score: {f1:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
```

```
Ensemble Model Performance:
Accuracy: 0.8442
F1 Score: 0.8261
Precision: 0.7808
Recall: 0.8769
```

VotingClassifier (Alternative)

In [55]:
```
from sklearn.ensemble import VotingClassifier

ensemble_model = VotingClassifier(
    estimators=[
        ('lr', log_reg),
        ('ada', ada_clf),
        ('rf', rf_clf),
        ('xgb', xgb_clf)
    ],
    voting='soft'  # Use 'hard' for majority voting
)

ensemble_model.fit(X_train, y_train)
y_pred_ensemble = ensemble_model.predict(X_test)

print("Voting Classifier Accuracy:", accuracy_score(y_test, y_pred_ensemble))
```

```
Voting Classifier Accuracy: 0.8441558441558441
```

Aggregation Rule

We used soft voting: averaging the predicted probabilities of all 4 models.

This ensemble reduces individual model bias and leverages the strengths of all classifiers.

Then Evaluated on test data and compared with individual models.

In [ ]:

```
```