loanpred-2

November 17, 2024

[109]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
```

0.1 Data Collection and Preprocessing

[110]:
```
df=pd.read_csv('loans.csv')
```

[111]:
```
df.head()
```

[111]:
```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
```

[112]:
```
df.shape
```

[112]: (614, 13)

[113]:
```
df.describe()
```

[113]:
```
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

[114]:
```
df.isnull().sum()
```

[114]:
```
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
```

[115]:
```
df.interpolate(method='linear', inplace=True)
```

```
<ipython-input-115-a83f336b1194>:1: FutureWarning: DataFrame.interpolate with
object dtype is deprecated and will raise in a future version. Call
obj.infer_objects(copy=False) before interpolating instead.
  df.interpolate(method='linear', inplace=True)
```

[116]:
```
df.isnull().sum()
```

[116]:
```
Loan_ID              0
Gender              13
Married              3
Dependents          15
Education            0
Self_Employed       32
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           1
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

[117]:
```
df['Gender'].fillna(df['Gender'].mode()[0], inplace=True)
```

```
<ipython-input-117-90613879d37d>:1: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

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


  df['Gender'].fillna(df['Gender'].mode()[0], inplace=True)
```

[118]:
```
df['Married'].fillna(df['Married'].mode()[0], inplace=True)
```

```
<ipython-input-118-d3b1bb51508f>:1: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

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


  df['Married'].fillna(df['Married'].mode()[0], inplace=True)
```

[119]:
```python
df['Dependents'].fillna(df['Dependents'].mode()[0], inplace=True)
```

```
<ipython-input-119-ff7bb676ed6c>:1: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

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


  df['Dependents'].fillna(df['Dependents'].mode()[0], inplace=True)
```

[120]:
```python
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0], inplace=True)
```

```
<ipython-input-120-9efd06336c1f>:1: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

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


  df['Self_Employed'].fillna(df['Self_Employed'].mode()[0], inplace=True)
```

[121]:
```python
df.isnull().sum()
```

[121]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           1
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
```

```
dtype: int64
```

[122]:
```
df=df.dropna()
```

[123]:
```
df.isnull().sum()
```

[123]:
```
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
```

[124]:
```
df
```

[124]:
```
      Loan_ID  Gender Married Dependents     Education Self_Employed  \
1    LP001003    Male     Yes          1      Graduate            No
2    LP001005    Male     Yes          0      Graduate           Yes
3    LP001006    Male     Yes          0  Not Graduate            No
4    LP001008    Male      No          0      Graduate            No
5    LP001011    Male     Yes          2      Graduate           Yes
..        …       …       …          …             …            …
609  LP002978  Female      No          0      Graduate            No
610  LP002979    Male     Yes         3+      Graduate            No
611  LP002983    Male     Yes          1      Graduate            No
612  LP002984    Male     Yes          2      Graduate            No
613  LP002990  Female      No          0      Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
5               5417             4196.0       267.0             360.0
..               …                  …           …                …
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
```

```
613            4583                 0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
1               1.0         Rural           N
2               1.0         Urban           Y
3               1.0         Urban           Y
4               1.0         Urban           Y
5               1.0         Urban           Y
..              …           …         …
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

[613 rows x 13 columns]
```

[125]:

```
# label encoding
df.replace({"Loan_Status":{'N':0,'Y':1}},inplace=True)
```

```
<ipython-input-125-fd55fff36a47>:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df.replace({"Loan_Status":{'N':0,'Y':1}},inplace=True)
```

[126]:

```
df.head()
```

[126]:

```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No
5  LP001011   Male     Yes          2      Graduate           Yes

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0
5             5417             4196.0       267.0             360.0

   Credit_History Property_Area  Loan_Status
1             1.0         Rural            0
2             1.0         Urban            1
3             1.0         Urban            1
4             1.0         Urban            1
```

```
5               1.0         Urban             1
```

[127]:
```
df['Dependents'].value_counts()
```

[127]:
```
Dependents
0     359
1     102
2     101
3+     51
Name: count, dtype: int64
```

[128]:
```
# Replcae 3+ with 4
df=df.replace(to_replace='3+',value=4)
```

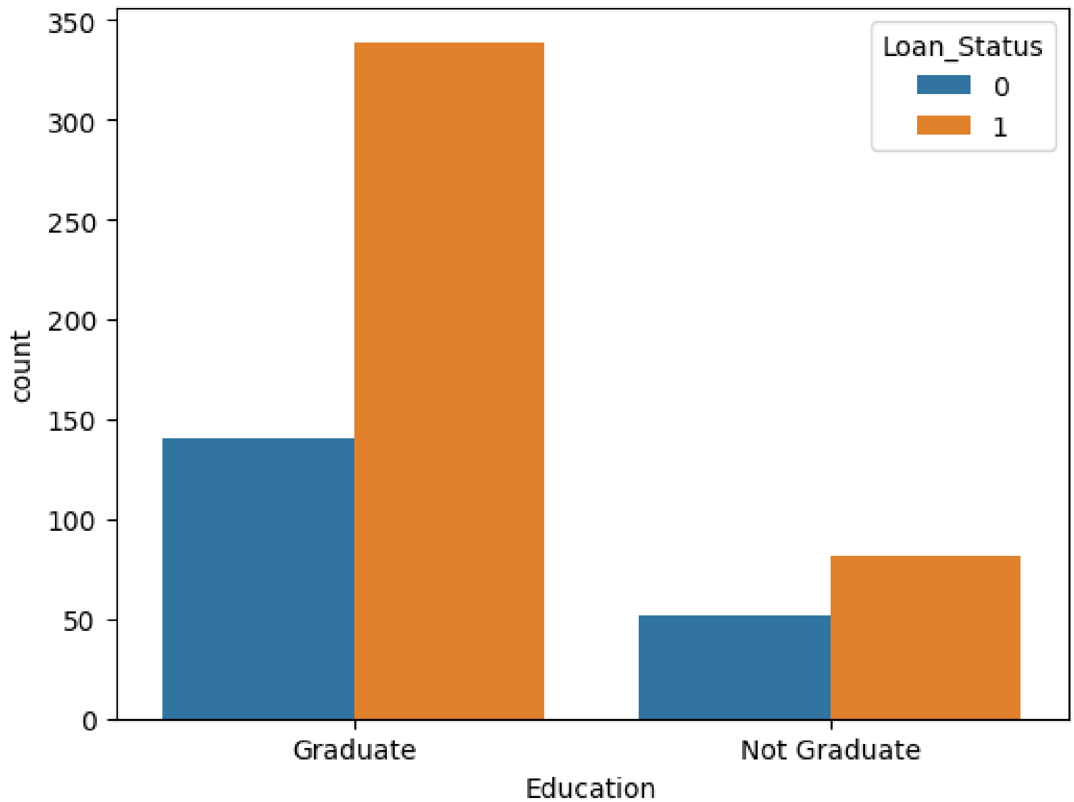
[129]:
```
df['Dependents'].value_counts()
```

[129]:
```
Dependents
0    359
1    102
2    101
4     51
Name: count, dtype: int64
```

0.2 Data Visualization

[130]:
```
#Education vs Loan Status
sns.countplot(x='Education',hue='Loan_Status',data=df)
```

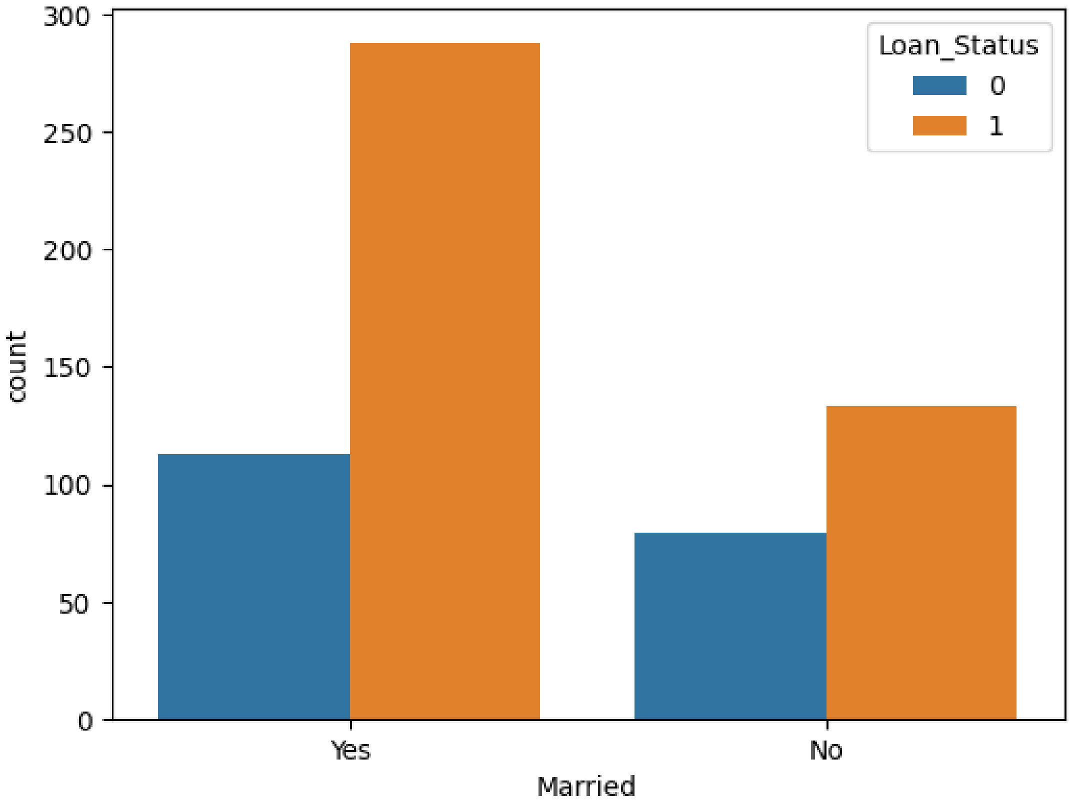
[130]:
```
<Axes: xlabel='Education', ylabel='count'>
```



[131]:
```
# Maritial Status vs Loan-status

sns.countplot(x='Married',hue='Loan_Status',data=df)
```

[131]: <Axes: xlabel='Married', ylabel='count'>



[132]:
```
# convert categorical columns to numerical values
df.replace({'Married':{'No':0,'Yes':1},'Gender':{'Male':1,'Female':
 ↪0},'Self_Employed':{'No':0,'Yes':1},'Property_Area':{'Rural':0,'Semiurban':
 ↪1,'Urban':2},'Education':{'Graduate':1,'Not Graduate':0}},inplace=True)
```

```
<ipython-input-132-d220f740e670>:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df.replace({'Married':{'No':0,'Yes':1},'Gender':{'Male':1,'Female':0},'Self_Em
ployed':{'No':0,'Yes':1},'Property_Area':{'Rural':0,'Semiurban':1,'Urban':2},'Ed
ucation':{'Graduate':1,'Not Graduate':0}},inplace=True)
```

[133]:
```
df.head()
```

[133]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	\
1	LP001003	1	1	1	1	0	
2	LP001005	1	1	0	1	1	
3	LP001006	1	1	0	0	0	
4	LP001008	1	0	0	1	0	
5	LP001011	1	1	2	1	1	

```
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0
5             5417             4196.0       267.0             360.0

   Credit_History  Property_Area  Loan_Status
1             1.0              0            0
2             1.0              2            1
3             1.0              2            1
4             1.0              2            1
5             1.0              2            1
```

[134]:
```python
X=df.drop(columns=['Loan_ID','Loan_Status'],axis=1)
```

[135]:
```python
Y=df['Loan_Status']
```

[136]:
```python
X
```

[136]:
```
     Gender  Married Dependents  Education  Self_Employed  ApplicantIncome  \
1         1        1          1          1              0             4583
2         1        1          0          1              1             3000
3         1        1          0          0              0             2583
4         1        0          0          1              0             6000
5         1        1          2          1              1             5417
..      …        …          …          …              …                …
609       0        0          0          1              0             2900
610       1        1          4          1              0             4106
611       1        1          1          1              0             8072
612       1        1          2          1              0             7583
613       0        0          0          1              1             4583

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
1               1508.0       128.0             360.0             1.0
2                  0.0        66.0             360.0             1.0
3               2358.0       120.0             360.0             1.0
4                  0.0       141.0             360.0             1.0
5               4196.0       267.0             360.0             1.0
..                 …           …                 …               …
609                0.0        71.0             360.0             1.0
610                0.0        40.0             180.0             1.0
611              240.0       253.0             360.0             1.0
612                0.0       187.0             360.0             1.0
613                0.0       133.0             360.0             0.0
```

```
     Property_Area
1                0
2                2
3                2
4                2
5                2
..             ...
609              0
610              0
611              2
612              2
613              1

[613 rows x 11 columns]
```

[137]:
```
Y
```

[137]:
```
1      0
2      1
3      1
4      1
5      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 613, dtype: int64
```

[138]:
```
# Train Test Split

X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.
 ↪1,stratify=Y,random_state=2)
```

[139]:
```
print(X_train.shape,X_test.shape)
```

```
(551, 11) (62, 11)
```

[140]:
```
# Model - Support Vector Machaine Model
```

[141]:
```
classifier=svm.SVC(kernel='linear')
```

[142]:
```
#training

classifier.fit(X_train,Y_train)
```

[142]: SVC(kernel='linear')

0.3 Model Evaluation

[143]:
```
# check accuracy Scores

X_train_pred=classifier.predict(X_train)
training_data_accuracy=accuracy_score(X_train_pred,Y_train)
```

[144]:
```
print(training_data_accuracy)
```

```
0.8039927404718693
```

[145]:
```
X_test_pred=classifier.predict(X_test)
test_data_accuracy=accuracy_score(X_test_pred,Y_test)
```

[146]:
```
print(test_data_accuracy)
```

```
0.8225806451612904
```

[147]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report

# Evaluate the model on the training dataset
X_train_pred = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_pred, Y_train)
training_data_precision = precision_score(Y_train, X_train_pred,␣
↪average='binary')  # Adjust average for multiclass
training_data_recall = recall_score(Y_train, X_train_pred, average='binary')
training_data_f1 = f1_score(Y_train, X_train_pred, average='binary')

# Print training metrics
print("Training Data Metrics:")
print(f"Accuracy: {training_data_accuracy:.2f}")
print(f"Precision: {training_data_precision:.2f}")
print(f"Recall: {training_data_recall:.2f}")
print(f"F1 Score: {training_data_f1:.2f}")
print("\nDetailed Training Classification Report:")
print(classification_report(Y_train, X_train_pred))

# Evaluate the model on the testing dataset
X_test_pred = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_pred, Y_test)
test_data_precision = precision_score(Y_test, X_test_pred, average='binary')  #␣
↪Adjust average for multiclass
test_data_recall = recall_score(Y_test, X_test_pred, average='binary')
test_data_f1 = f1_score(Y_test, X_test_pred, average='binary')
```

```python
# Print testing metrics
print("\nTesting Data Metrics:")
print(f"Accuracy: {test_data_accuracy:.2f}")
print(f"Precision: {test_data_precision:.2f}")
print(f"Recall: {test_data_recall:.2f}")
print(f"F1 Score: {test_data_f1:.2f}")
print("\nDetailed Testing Classification Report:")
print(classification_report(Y_test, X_test_pred))

# Document model performance
print("\nPerformance Summary:")
print(f"Training Accuracy: {training_data_accuracy:.2f}, Testing Accuracy:␣
↪{test_data_accuracy:.2f}")
print("Observations:")
if training_data_accuracy > test_data_accuracy:
    print("The model might be overfitting as it performs better on training␣
↪data than testing data.")
elif training_data_accuracy < test_data_accuracy:
    print("The model might be underfitting or over-generalizing.")
else:
    print("The model shows consistent performance across training and testing␣
↪datasets.")
```

```
Training Data Metrics:
Accuracy: 0.80
Precision: 0.79
Recall: 0.96
F1 Score: 0.87

Detailed Training Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.46      0.59       173
           1       0.79      0.96      0.87       378

    accuracy                           0.80       551
   macro avg       0.82      0.71      0.73       551
weighted avg       0.81      0.80      0.78       551


Testing Data Metrics:
Accuracy: 0.82
Precision: 0.81
Recall: 0.98
F1 Score: 0.88
```

```
Detailed Testing Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.47      0.62        19
           1       0.81      0.98      0.88        43

    accuracy                           0.82        62
   macro avg       0.85      0.73      0.75        62
weighted avg       0.84      0.82      0.80        62


Performance Summary:
Training Accuracy: 0.80, Testing Accuracy: 0.82
Observations:
The model might be underfitting or over-generalizing.
```

[148]:

```
import pickle
```

[149]:

```
filename = 'loan_status_model.pkl'
pickle.dump(classifier, open(filename, 'wb'))
```

[150]:

```
classifier = RandomForestClassifier(random_state=2)
classifier.fit(X_train, Y_train)
# Random Forest Model
X_train_pred = classifier.predict(X_train)
X_training_data_accuracy = accuracy_score(X_train_pred, Y_train)
print(f"Random Forest - Training Data Accuracy: {X_training_data_accuracy}")

X_test_pred = classifier.predict(X_test)
X_test_data_accuracy = accuracy_score(X_test_pred, Y_test)
print(f"Random Forest - Test Data Accuracy: {X_test_data_accuracy}")

# Saving the Random Forest model
X_filename = 'loan_status_rf_model.pkl'
pickle.dump(classifier, open(X_filename, 'wb'))
```

```
Random Forest - Training Data Accuracy: 1.0
Random Forest - Test Data Accuracy: 0.7903225806451613
```

[151]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report

# Evaluate the model on the training dataset
X_train_pred = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_pred, Y_train)
training_data_precision = precision_score(Y_train, X_train_pred,␣
↪average='binary')  # Adjust average for multiclass
```

```
training_data_recall = recall_score(Y_train, X_train_pred, average='binary')
training_data_f1 = f1_score(Y_train, X_train_pred, average='binary')

# Print training metrics
print("Training Data Metrics:")
print(f"Accuracy: {training_data_accuracy:.2f}")
print(f"Precision: {training_data_precision:.2f}")
print(f"Recall: {training_data_recall:.2f}")
print(f"F1 Score: {training_data_f1:.2f}")
print("\nDetailed Training Classification Report:")
print(classification_report(Y_train, X_train_pred))

# Evaluate the model on the testing dataset
X_test_pred = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_pred, Y_test)
test_data_precision = precision_score(Y_test, X_test_pred, average='binary')  #␣
↪Adjust average for multiclass
test_data_recall = recall_score(Y_test, X_test_pred, average='binary')
test_data_f1 = f1_score(Y_test, X_test_pred, average='binary')

# Print testing metrics
print("\nTesting Data Metrics:")
print(f"Accuracy: {test_data_accuracy:.2f}")
print(f"Precision: {test_data_precision:.2f}")
print(f"Recall: {test_data_recall:.2f}")
print(f"F1 Score: {test_data_f1:.2f}")
print("\nDetailed Testing Classification Report:")
print(classification_report(Y_test, X_test_pred))

# Document model performance
print("\nPerformance Summary:")
print(f"Training Accuracy: {training_data_accuracy:.2f}, Testing Accuracy:␣
↪{test_data_accuracy:.2f}")
print("Observations:")
if training_data_accuracy > test_data_accuracy:
    print("The model might be overfitting as it performs better on training␣
↪data than testing data.")
elif training_data_accuracy < test_data_accuracy:
    print("The model might be underfitting or over-generalizing.")
else:
    print("The model shows consistent performance across training and testing␣
↪datasets.")
```

```
Training Data Metrics:
Accuracy: 1.00
Precision: 1.00
Recall: 1.00
```

```
F1 Score: 1.00

Detailed Training Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       173
           1       1.00      1.00      1.00       378

    accuracy                           1.00       551
   macro avg       1.00      1.00      1.00       551
weighted avg       1.00      1.00      1.00       551


Testing Data Metrics:
Accuracy: 0.79
Precision: 0.81
Recall: 0.91
F1 Score: 0.86

Detailed Testing Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.53      0.61        19
           1       0.81      0.91      0.86        43

    accuracy                           0.79        62
   macro avg       0.76      0.72      0.73        62
weighted avg       0.78      0.79      0.78        62


Performance Summary:
Training Accuracy: 1.00, Testing Accuracy: 0.79
Observations:
The model might be overfitting as it performs better on training data than
testing data.
```

[158]:

```python
from xgboost import XGBClassifier
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
import pickle

# Initialize the XGBoost classifier with support for categorical dat
# Fit the model
classifier.fit(X_train, Y_train)

# XGBoost Accuracy
```

```
X_train_pred = classifier.predict(X_train)
X_training_data_accuracy = accuracy_score(X_train_pred, Y_train)
print(f"XGBoost - Training Data Accuracy: {X_training_data_accuracy}")

X_test_pred = classifier.predict(X_test)
X_test_data_accuracy = accuracy_score(X_test_pred, Y_test)
print(f"XGBoost - Test Data Accuracy: {X_test_data_accuracy}")

# Save XGBoost Model
xgb_filename = 'loan_status_xgb_model.pkl'
pickle.dump(classifier, open(xgb_filename, 'wb'))
```

```
XGBoost - Training Data Accuracy: 0.8457350272232305
XGBoost - Test Data Accuracy: 0.8387096774193549
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/ensemble/_weight_boosting.py:527: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

[159]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report

# Evaluate the model on the training dataset
X_train_pred = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_pred, Y_train)
training_data_precision = precision_score(Y_train, X_train_pred,␣
↪average='binary')  # Adjust average for multiclass
training_data_recall = recall_score(Y_train, X_train_pred, average='binary')
training_data_f1 = f1_score(Y_train, X_train_pred, average='binary')

# Print training metrics
print("Training Data Metrics:")
print(f"Accuracy: {training_data_accuracy:.2f}")
print(f"Precision: {training_data_precision:.2f}")
print(f"Recall: {training_data_recall:.2f}")
print(f"F1 Score: {training_data_f1:.2f}")
print("\nDetailed Training Classification Report:")
print(classification_report(Y_train, X_train_pred))

# Evaluate the model on the testing dataset
X_test_pred = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_pred, Y_test)
test_data_precision = precision_score(Y_test, X_test_pred, average='binary')  #␣
↪Adjust average for multiclass
test_data_recall = recall_score(Y_test, X_test_pred, average='binary')
```

```python
test_data_f1 = f1_score(Y_test, X_test_pred, average='binary')

# Print testing metrics
print("\nTesting Data Metrics:")
print(f"Accuracy: {test_data_accuracy:.2f}")
print(f"Precision: {test_data_precision:.2f}")
print(f"Recall: {test_data_recall:.2f}")
print(f"F1 Score: {test_data_f1:.2f}")
print("\nDetailed Testing Classification Report:")
print(classification_report(Y_test, X_test_pred))

# Document model performance
print("\nPerformance Summary:")
print(f"Training Accuracy: {training_data_accuracy:.2f}, Testing Accuracy: 
 ↪{test_data_accuracy:.2f}")
print("Observations:")
if training_data_accuracy > test_data_accuracy:
    print("The model might be overfitting as it performs better on training 
 ↪data than testing data.")
elif training_data_accuracy < test_data_accuracy:
    print("The model might be underfitting or over-generalizing.")
else:
    print("The model shows consistent performance across training and testing 
 ↪datasets.")
```

```
Training Data Metrics:
Accuracy: 0.85
Precision: 0.84
Recall: 0.97
F1 Score: 0.90

Detailed Training Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.58      0.70       173
           1       0.84      0.97      0.90       378

    accuracy                           0.85       551
   macro avg       0.86      0.77      0.80       551
weighted avg       0.85      0.85      0.84       551


Testing Data Metrics:
Accuracy: 0.84
Precision: 0.82
Recall: 0.98
F1 Score: 0.89
```

```
Detailed Testing Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.53      0.67        19
           1       0.82      0.98      0.89        43

    accuracy                           0.84        62
   macro avg       0.87      0.75      0.78        62
weighted avg       0.85      0.84      0.82        62


Performance Summary:
Training Accuracy: 0.85, Testing Accuracy: 0.84
Observations:
The model might be overfitting as it performs better on training data than
testing data.
```

Decision Tree Model

[155]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
import pickle

# Decision Tree Model
classifier = DecisionTreeClassifier(random_state=2)
classifier.fit(X_train, Y_train)

# Decision Tree Accuracy
X_train_pred = classifier.predict(X_train)
X_training_data_accuracy = accuracy_score(X_train_pred, Y_train)
print(f"Decision Tree - Training Data Accuracy: {X_training_data_accuracy}")

X_test_pred = classifier.predict(X_test)
X_test_data_accuracy = accuracy_score(X_test_pred, Y_test)
print(f"Decision Tree - Test Data Accuracy: {X_test_data_accuracy}")

# Save Decision Tree Model
dt_filename = 'loan_status_dt_model.pkl'
pickle.dump(classifier, open(dt_filename, 'wb'))
```

```
Decision Tree - Training Data Accuracy: 1.0
Decision Tree - Test Data Accuracy: 0.7580645161290323
```

[156]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report

# Evaluate the model on the training dataset
```

```python
X_train_pred = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_pred, Y_train)
training_data_precision = precision_score(Y_train, X_train_pred, average='binary')  # Adjust average for multiclass
training_data_recall = recall_score(Y_train, X_train_pred, average='binary')
training_data_f1 = f1_score(Y_train, X_train_pred, average='binary')

# Print training metrics
print("Training Data Metrics:")
print(f"Accuracy: {training_data_accuracy:.2f}")
print(f"Precision: {training_data_precision:.2f}")
print(f"Recall: {training_data_recall:.2f}")
print(f"F1 Score: {training_data_f1:.2f}")
print("\nDetailed Training Classification Report:")
print(classification_report(Y_train, X_train_pred))

# Evaluate the model on the testing dataset
X_test_pred = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_pred, Y_test)
test_data_precision = precision_score(Y_test, X_test_pred, average='binary')  # Adjust average for multiclass
test_data_recall = recall_score(Y_test, X_test_pred, average='binary')
test_data_f1 = f1_score(Y_test, X_test_pred, average='binary')

# Print testing metrics
print("\nTesting Data Metrics:")
print(f"Accuracy: {test_data_accuracy:.2f}")
print(f"Precision: {test_data_precision:.2f}")
print(f"Recall: {test_data_recall:.2f}")
print(f"F1 Score: {test_data_f1:.2f}")
print("\nDetailed Testing Classification Report:")
print(classification_report(Y_test, X_test_pred))

# Document model performance
print("\nPerformance Summary:")
print(f"Training Accuracy: {training_data_accuracy:.2f}, Testing Accuracy: {test_data_accuracy:.2f}")
print("Observations:")
if training_data_accuracy > test_data_accuracy:
    print("The model might be overfitting as it performs better on training data than testing data.")
elif training_data_accuracy < test_data_accuracy:
    print("The model might be underfitting or over-generalizing.")
else:
    print("The model shows consistent performance across training and testing datasets.")
```

```
Training Data Metrics:
Accuracy: 1.00
Precision: 1.00
Recall: 1.00
F1 Score: 1.00

Detailed Training Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       173
           1       1.00      1.00      1.00       378

    accuracy                           1.00       551
   macro avg       1.00      1.00      1.00       551
weighted avg       1.00      1.00      1.00       551


Testing Data Metrics:
Accuracy: 0.76
Precision: 0.83
Recall: 0.81
F1 Score: 0.82

Detailed Testing Classification Report:
              precision    recall  f1-score   support

           0       0.60      0.63      0.62        19
           1       0.83      0.81      0.82        43

    accuracy                           0.76        62
   macro avg       0.72      0.72      0.72        62
weighted avg       0.76      0.76      0.76        62


Performance Summary:
Training Accuracy: 1.00, Testing Accuracy: 0.76
Observations:
The model might be overfitting as it performs better on training data than
testing data.
```

[157]:

```
from sklearn.ensemble import AdaBoostClassifier
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import pickle
from sklearn.metrics import accuracy_score
# AdaBoost Model
classifier = AdaBoostClassifier(random_state=2)
```

```
classifier.fit(X_train, Y_train)

# AdaBoost Accuracy
X_train_pred = classifier.predict(X_train)
X_training_data_accuracy = accuracy_score(X_train_pred, Y_train)
print(f"AdaBoost - Training Data Accuracy: {X_training_data_accuracy}")

X_test_pred = classifier.predict(X_test)
X_test_data_accuracy = accuracy_score(X_test_pred, Y_test)
print(f"AdaBoost - Test Data Accuracy: {X_test_data_accuracy}")

# Save AdaBoost Model
ab_filename = 'loan_status_ab_model.pkl'
pickle.dump(classifier, open(ab_filename, 'wb'))
```

```
AdaBoost - Training Data Accuracy: 0.8457350272232305
AdaBoost - Test Data Accuracy: 0.8387096774193549
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/ensemble/_weight_boosting.py:527: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

[63]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report

# Evaluate the model on the training dataset
X_train_pred = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_pred, Y_train)
training_data_precision = precision_score(Y_train, X_train_pred,␣
↪average='binary')  # Adjust average for multiclass
training_data_recall = recall_score(Y_train, X_train_pred, average='binary')
training_data_f1 = f1_score(Y_train, X_train_pred, average='binary')

# Print training metrics
print("Training Data Metrics:")
print(f"Accuracy: {training_data_accuracy:.2f}")
print(f"Precision: {training_data_precision:.2f}")
print(f"Recall: {training_data_recall:.2f}")
print(f"F1 Score: {training_data_f1:.2f}")
print("\nDetailed Training Classification Report:")
print(classification_report(Y_train, X_train_pred))

# Evaluate the model on the testing dataset
X_test_pred = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_pred, Y_test)
```

```python
test_data_precision = precision_score(Y_test, X_test_pred, average='binary')  #␣
↪Adjust average for multiclass
test_data_recall = recall_score(Y_test, X_test_pred, average='binary')
test_data_f1 = f1_score(Y_test, X_test_pred, average='binary')

# Print testing metrics
print("\nTesting Data Metrics:")
print(f"Accuracy: {test_data_accuracy:.2f}")
print(f"Precision: {test_data_precision:.2f}")
print(f"Recall: {test_data_recall:.2f}")
print(f"F1 Score: {test_data_f1:.2f}")
print("\nDetailed Testing Classification Report:")
print(classification_report(Y_test, X_test_pred))

# Document model performance
print("\nPerformance Summary:")
print(f"Training Accuracy: {training_data_accuracy:.2f}, Testing Accuracy:␣
↪{test_data_accuracy:.2f}")
print("Observations:")
if training_data_accuracy > test_data_accuracy:
    print("The model might be overfitting as it performs better on training␣
↪data than testing data.")
elif training_data_accuracy < test_data_accuracy:
    print("The model might be underfitting or over-generalizing.")
else:
    print("The model shows consistent performance across training and testing␣
↪datasets.")
```

```
Training Data Metrics:
Accuracy: 0.85
Precision: 0.84
Recall: 0.97
F1 Score: 0.90

Detailed Training Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.58      0.70       173
           1       0.84      0.97      0.90       378

    accuracy                           0.85       551
   macro avg       0.86      0.77      0.80       551
weighted avg       0.85      0.85      0.84       551


Testing Data Metrics:
Accuracy: 0.84
```

```
Precision: 0.82
Recall: 0.98
F1 Score: 0.89

Detailed Testing Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.53      0.67        19
           1       0.82      0.98      0.89        43

    accuracy                           0.84        62
   macro avg       0.87      0.75      0.78        62
weighted avg       0.85      0.84      0.82        62


Performance Summary:
Training Accuracy: 0.85, Testing Accuracy: 0.84
Observations:
The model might be overfitting as it performs better on training data than
testing data.
```

[ ]: