SVM_Project (1)

December 9, 2024

[196]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

Import Libraries

[197]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Machine Learning tools

[198]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
 ↪TimeSeriesSplit, cross_val_score
from sklearn.metrics import classification_report, roc_curve, auc,␣
 ↪precision_recall_curve, confusion_matrix
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import TomekLinks
from sklearn import metrics
from scipy.stats import uniform, randint
from sklearn.decomposition import PCA

import warnings
warnings.filterwarnings('ignore')
```

[199]:
```
df = pd.read_csv('/content/drive/My Drive/ML Assignment/TSLA.csv')
df.head()
```

[199]:
```
         Date       High        Low       Open      Close      Volume  \
0  2019-09-30  48.796001  47.222000  48.599998  48.174000  29399000.0
1  2019-10-01  49.189999  47.826000  48.299999  48.938000  30813000.0
2  2019-10-02  48.930000  47.886002  48.658001  48.625999  28157000.0
3  2019-10-03  46.896000  44.855999  46.372002  46.605999  75422500.0
```

```
4  2019-10-04  46.956001  45.613998  46.321999  46.285999  39975000.0

   Adj Close
0  48.174000
1  48.938000
2  48.625999
3  46.605999
4  46.285999
```

[200]:
```
df.tail()
```

[200]:
```
           Date         High          Low         Open        Close  \
634  2022-04-05  1152.869995  1087.300049  1136.300049  1091.260010
635  2022-04-06  1079.000000  1027.699951  1073.469971  1045.760010
636  2022-04-07  1076.589966  1021.539978  1052.390015  1057.260010
637  2022-04-08  1048.439941  1022.440002  1043.209961  1025.489990
638  2022-04-11  1008.469971   974.640015   980.400024   975.929993

         Volume    Adj Close
634  26691700.0  1091.260010
635  29782800.0  1045.760010
636  26482400.0  1057.260010
637  18293300.0  1025.489990
638  19660500.0   975.929993
```

[201]:
```
df.shape
```

[201]: (639, 7)

[202]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 639 entries, 0 to 638
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       639 non-null    object
 1   High       639 non-null    float64
 2   Low        639 non-null    float64
 3   Open       639 non-null    float64
 4   Close      639 non-null    float64
 5   Volume     639 non-null    float64
 6   Adj Close  639 non-null    float64
dtypes: float64(6), object(1)
memory usage: 35.1+ KB
```

[203]:
```
df.describe()
```

[203]:

```
              High          Low         Open        Close        Volume  \
count   639.000000   639.000000   639.000000   639.000000  6.390000e+02
mean    543.362885   517.883537   531.004088   531.298030  4.819130e+07
std     340.837426   325.395864   333.534448   333.362040  3.579030e+07
min      46.896000    44.855999    45.959999    46.285999  9.800600e+06
25%     170.258003   162.379997   167.349998   164.783005  2.392195e+07
50%     620.409973   595.500000   603.880005   605.130005  3.448900e+07
75%     796.584991   767.744995   779.445007   781.304993  6.329725e+07
max    1243.489990  1217.000000  1234.410034  1229.910034  3.046940e+08

         Adj Close
count   639.000000
mean    531.298030
std     333.362040
min      46.285999
25%     164.783005
50%     605.130005
75%     781.304993
max    1229.910034
```

Feature engineering

[204]:
```
df['Price Change'] = df['Close'] - df['Open']
df['Price Direction'] = np.where(df['Price Change'] > 0, 1, 0)
```

[205]:
```
X = df[['High', 'Low', 'Open', 'Close', 'Volume']]
y = df['Price Direction']
```

Scaling features

[206]:
```
scaler = StandardScaler()
```

[207]:
```
X_scaled = scaler.fit_transform(X)
```

Train-validation-test split

[208]:
```
train_size = int(len(df) * 0.7)  # 70% training
valid_size = int(len(df) * 0.15)  # 15% validation
test_size = len(df) - train_size - valid_size
```

[209]:
```
X_train, X_valid, X_test = X_scaled[:train_size], X_scaled[train_size:
 ↪train_size + valid_size], X_scaled[train_size + valid_size:]
y_train, y_valid, y_test = y[:train_size], y[train_size:train_size +␣
 ↪valid_size], y[train_size + valid_size:]
```

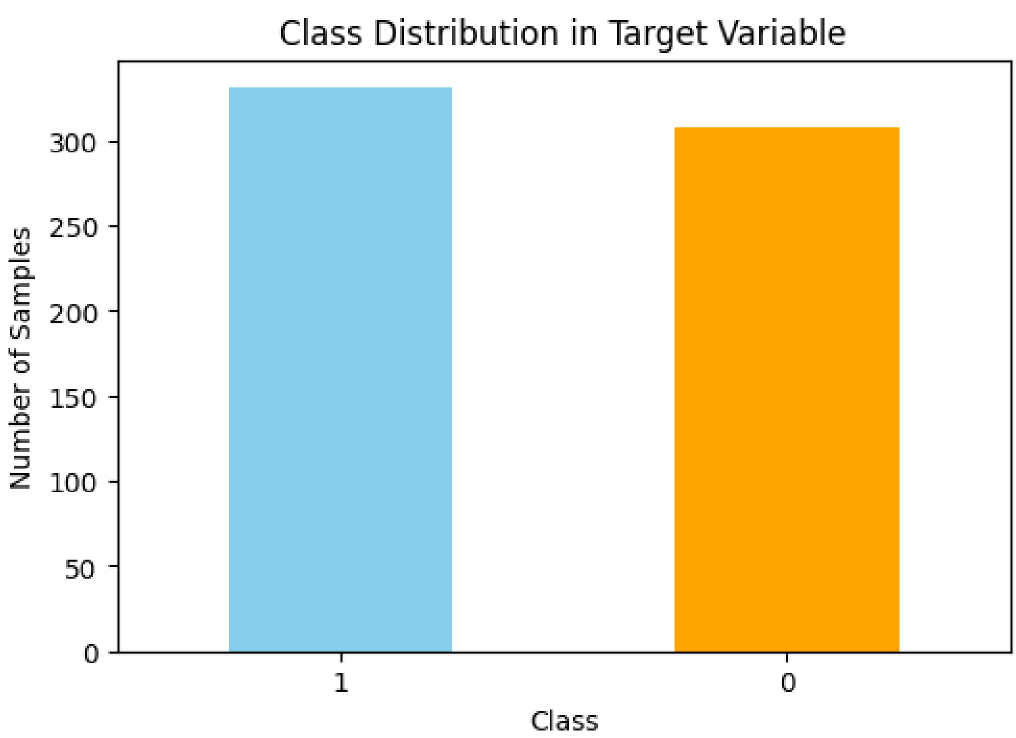
Check the class distribution

[210]:
```
class_counts = df['Price Direction'].value_counts()
print("Class Distribution:")
print(class_counts)
```

```
Class Distribution:
Price Direction
1    331
0    308
Name: count, dtype: int64
```

Visualize the class distribution

[211]:
```
plt.figure(figsize=(6, 4))
class_counts.plot(kind='bar', color=['skyblue', 'orange'])
plt.title("Class Distribution in Target Variable")
plt.xlabel("Class")
plt.ylabel("Number of Samples")
plt.xticks(rotation=0)
plt.show()
```



Calculate the imbalanced ratio

[212]:
```
imbalance_ratio = class_counts.max() / class_counts.min()
print(f"\nImbalance Ratio: {imbalance_ratio:.2f}")
```

```
Imbalance Ratio: 1.07
```

[213]:
```python
if imbalance_ratio > 1.5:
    print("The dataset is imbalanced.")
else:
    print("The dataset is balanced.")
```

```
The dataset is balanced.
```

Apply SMOTE to balance the classes in the training set

[214]:
```python
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

Apply Tomek Links to remove noise and refine boundaries

[215]:
```python
tomek = TomekLinks()
X_train_res, y_train_res = tomek.fit_resample(X_train_res, y_train_res)
```

Hyperparameter tuning using RandomizedSearchCV for SVM

[216]:
```python
param_dist = {
    'C': uniform(0.1, 10),  # generate random values between 0.1 and 10
    'gamma': ['scale', 'auto', 0.1, 0.5, 1],  # Gamma values for kernel
    'kernel': ['linear'],  # Different kernel types
    'class_weight': ['balanced', None],
    'degree': [3],  # Degree for polynomial kernel
    'tol': [1e-3, 1e-4]  # Tolerance for stopping criterion
}
```

Time series split for time series validation

[217]:
```python
tscv = TimeSeriesSplit(n_splits=3)  #Avoid data leakage
```

Perform RandomizedSearchCV for SVM

[218]:
```python
random_search = RandomizedSearchCV(SVC(probability=True),␣
 ↪param_distributions=param_dist, n_iter=100, cv=tscv, scoring='roc_auc',␣
 ↪random_state=42, n_jobs=-1)
random_search.fit(X_train_res, y_train_res)
```

[218]:
```
RandomizedSearchCV(cv=TimeSeriesSplit(gap=0, max_train_size=None, n_splits=3,
test_size=None),
                   estimator=SVC(probability=True), n_iter=100, n_jobs=-1,
                   param_distributions={'C':
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x7bae2275f850>,
                                        'class_weight': ['balanced', None],
```

```
                                        'degree': [3],
                                        'gamma': ['scale', 'auto', 0.1, 0.5, 1],
                                        'kernel': ['linear'],
                                        'tol': [0.001, 0.0001]},
                    random_state=42, scoring='roc_auc')
```

Best model from RandomizedSearchCV

[219]:
```
best_model_svm = random_search.best_estimator_
print("\nBest Parameters from RandomizedSearchCV:", random_search.best_params_)
```

```
Best Parameters from RandomizedSearchCV: {'C': 9.494989415641891,
'class_weight': None, 'degree': 3, 'gamma': 0.5, 'kernel': 'linear', 'tol':
0.0001}
```

Train the best SVM model

[220]:
```
best_model_svm.fit(X_train_res, y_train_res)
```

[220]:
```
SVC(C=9.494989415641891, gamma=0.5, kernel='linear', probability=True,
    tol=0.0001)
```

Evaluate model on validation set

[221]:
```
y_pred_svm = best_model_svm.predict(X_valid)
```

[222]:
```
y_pred_proba_svm = best_model_svm.predict_proba(X_valid)[:, 1]
```

Evaluate model on test set

[223]:
```
y_test_pred = best_model_svm.predict(X_test)
y_test_proba = best_model_svm.predict_proba(X_test)[:, 1]
```

Print classification report

[224]:
```
print("\nClassification Report (Validation Data):")
print(classification_report(y_valid, y_pred_svm))
```

```
Classification Report (Validation Data):
              precision    recall  f1-score   support

           0       0.67      0.95      0.79        43
           1       0.94      0.62      0.74        52

    accuracy                           0.77        95
   macro avg       0.81      0.78      0.77        95
weighted avg       0.82      0.77      0.76        95
```

[225]:
```
print("\nClassification Report (Test Data):")
print(classification_report(y_test, y_test_pred))
```

```
Classification Report (Test Data):
              precision    recall  f1-score   support

           0       0.98      0.98      0.98        46
           1       0.98      0.98      0.98        51

    accuracy                           0.98        97
   macro avg       0.98      0.98      0.98        97
weighted avg       0.98      0.98      0.98        97
```

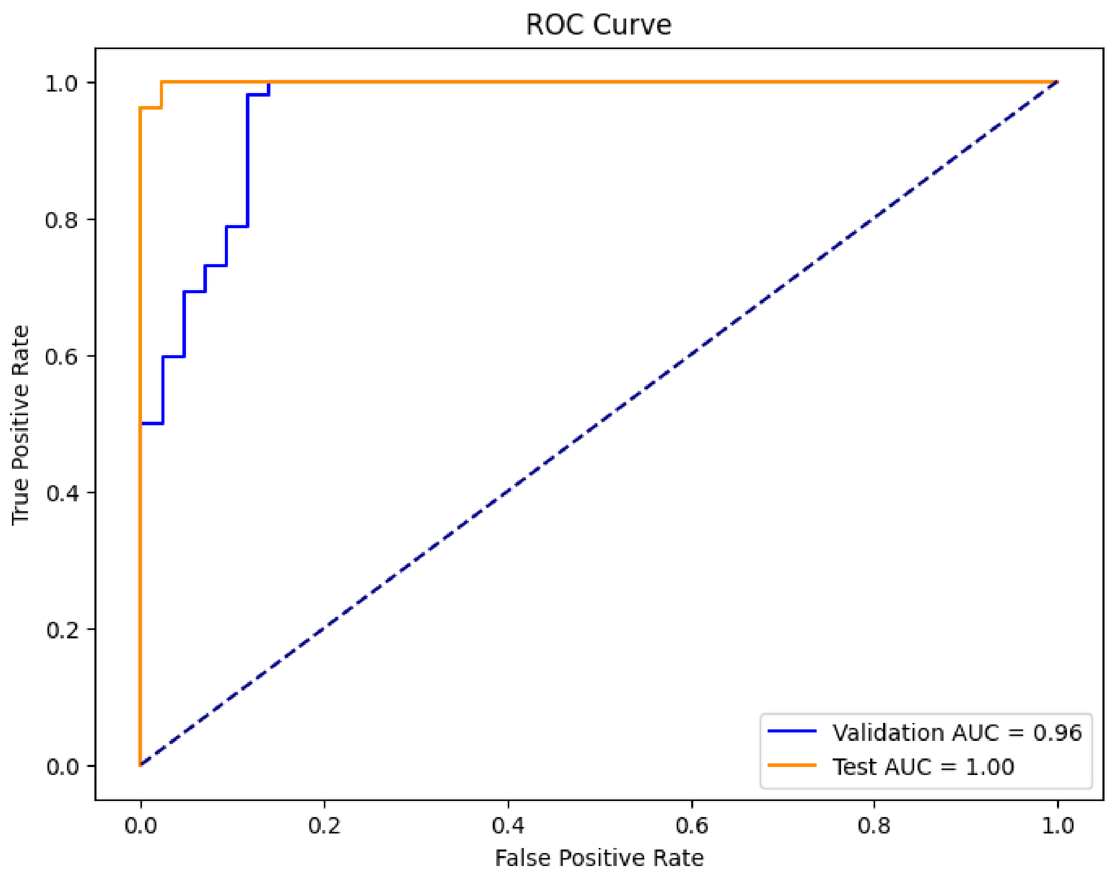
Reduce to 3 Principal components

[226]:
```
pca = PCA(n_components=3)   #For demensionality reduction and faster training
```

[227]:
```
X_scaled_pca = pca.fit_transform(X_scaled)
```

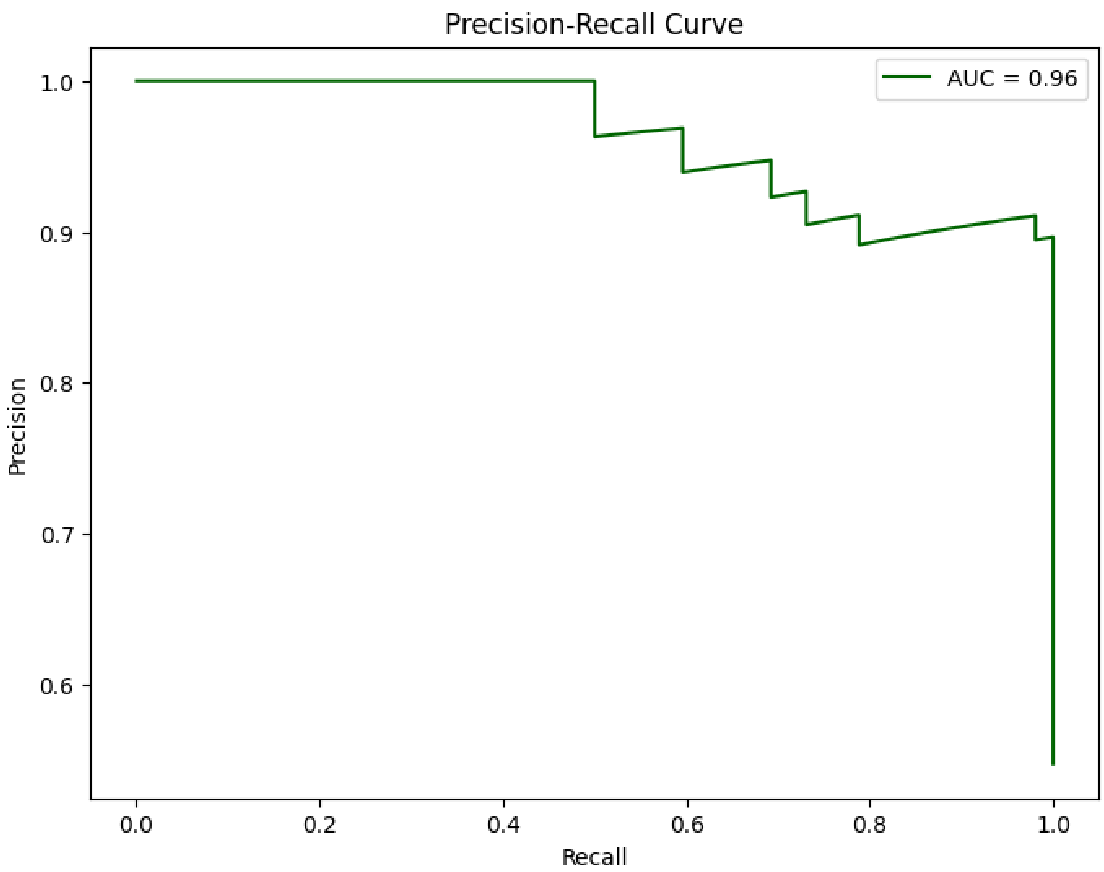
Compute AUC and plot ROC curve

[228]:
```
fpr_valid, tpr_valid, _ = roc_curve(y_valid, y_pred_proba_svm)
fpr_test, tpr_test, _ = roc_curve(y_test, y_test_proba)

roc_auc_valid = auc(fpr_valid, tpr_valid)
roc_auc_test = auc(fpr_test, tpr_test)

plt.figure(figsize=(8, 6))
plt.plot(fpr_valid, tpr_valid, label=f'Validation AUC = {roc_auc_valid:.2f}',␣
 ↪color='blue')
plt.plot(fpr_test, tpr_test, label=f'Test AUC = {roc_auc_test:.2f}',␣
 ↪color='darkorange')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='best')
plt.show()
```

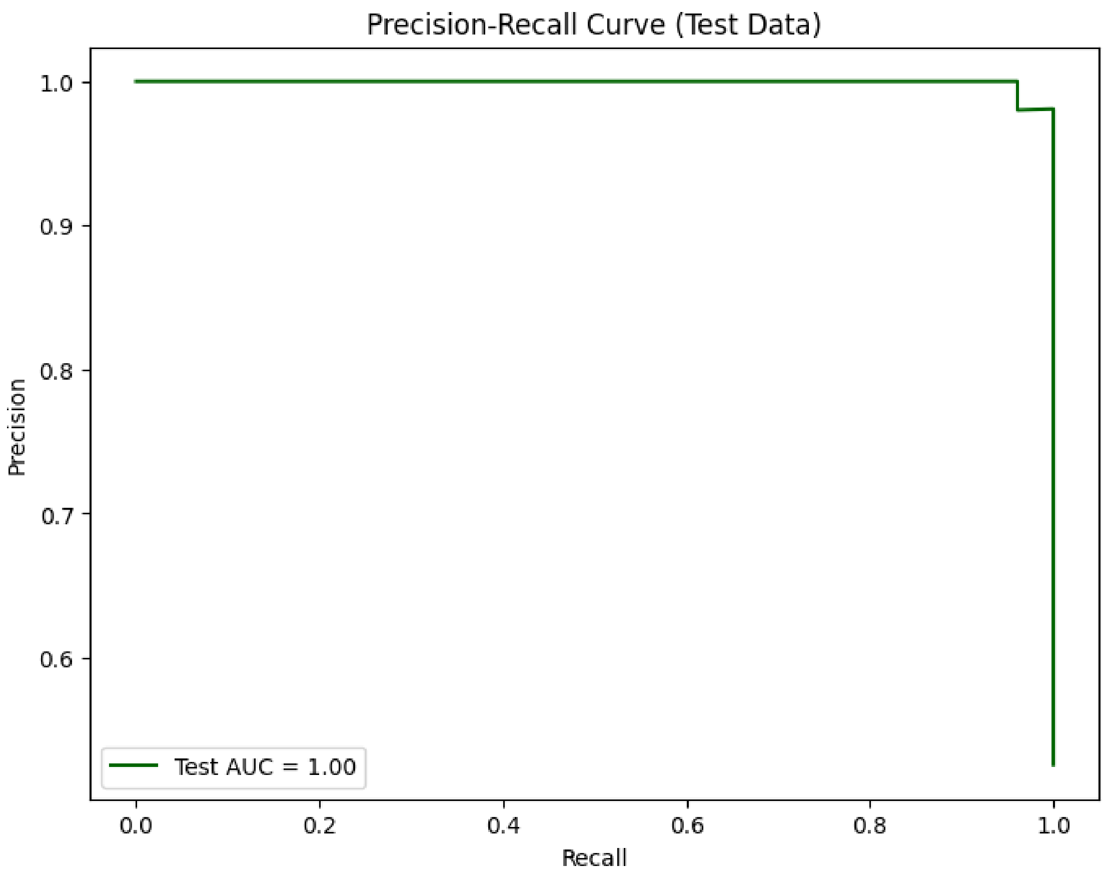


Plot precision-Recall curve

[229]:
```
precision, recall, _ = precision_recall_curve(y_valid, y_pred_proba_svm)

plt.figure(figsize=(8, 6))
plt.plot(recall, precision, label=f'AUC = {auc(recall, precision):.2f}',␣
↪color='darkgreen')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='best')
plt.show()
```

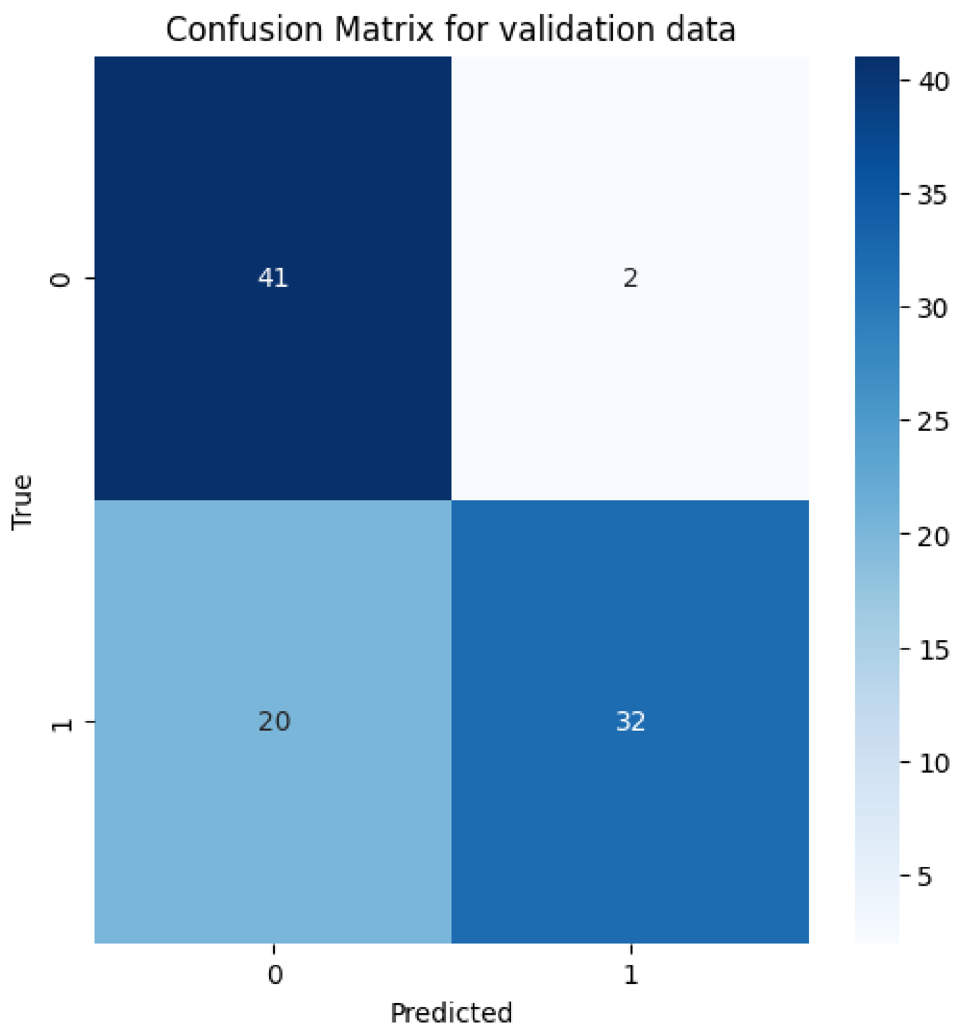


[230]:
```
precision_test, recall_test, _ = precision_recall_curve(y_test, y_test_proba)

plt.figure(figsize=(8, 6))
plt.plot(recall_test, precision_test, label=f'Test AUC = {auc(recall_test,␣
 ↪precision_test):.2f}', color='darkgreen')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve (Test Data)')
plt.legend(loc='best')
plt.show()
```

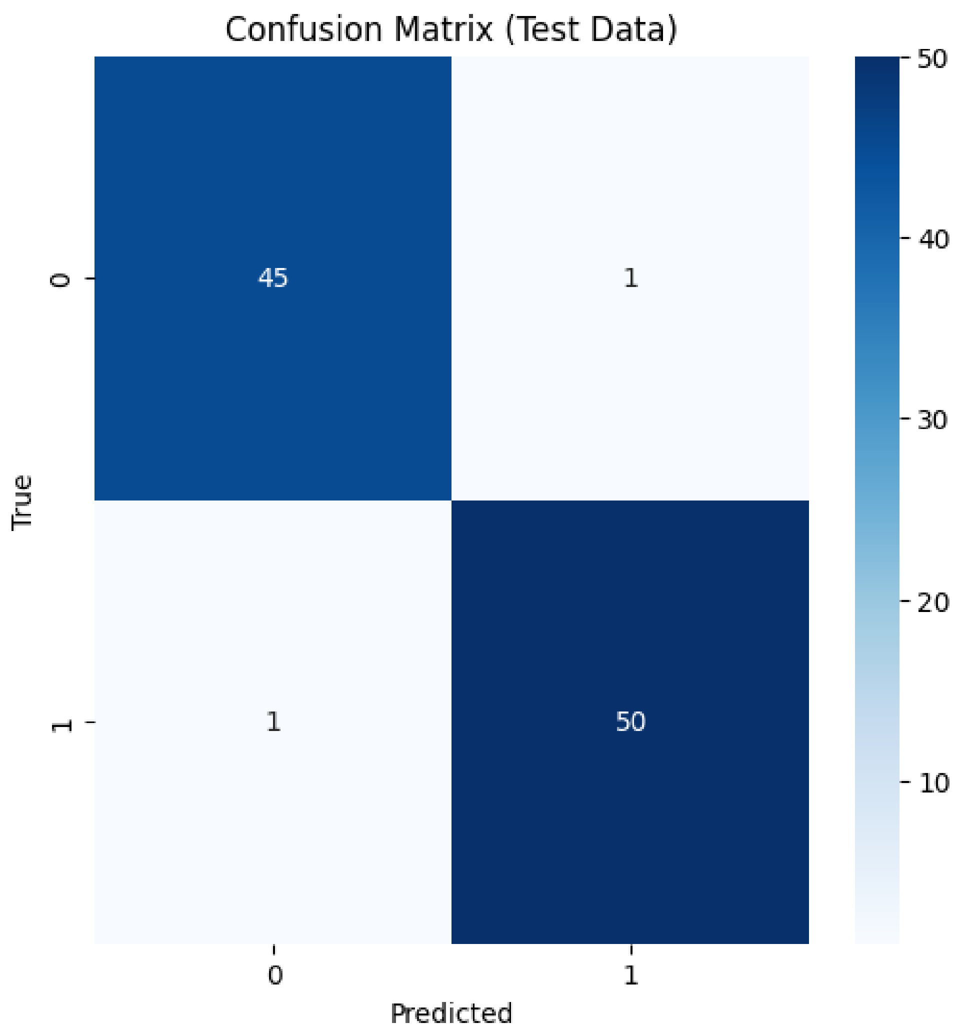


Confusion Matrix for validation data

[231]:
```
conf_matrix = confusion_matrix(y_valid, y_pred_svm)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=[0, 1],␣
↪yticklabels=[0, 1])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for validation data')
plt.show()
```



[232]:
```
conf_matrix_test = confusion_matrix(y_test, y_test_pred)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix_test, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=[0, 1], yticklabels=[0, 1])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Test Data)')
plt.show()
```



Cross-validation with SVM

[233]:
```
cv_scores_res_svm = cross_val_score(best_model_svm, X_train_res, y_train_res,␣
↪cv=tscv, scoring='roc_auc')
print(f"\nCross-Validation AUC After SMOTE and Tomek Links: {cv_scores_res_svm.
↪mean():.4f} ± {cv_scores_res_svm.std():.4f}")
```

```
Cross-Validation AUC After SMOTE and Tomek Links: 0.8491 ± 0.2044
```

Evaluate model on original data

[234]:
```
train_auc = metrics.roc_auc_score(y_train_res, best_model_svm.
↪predict_proba(X_train_res)[:, 1])
valid_auc = metrics.roc_auc_score(y_valid, y_pred_proba_svm)
test_auc = metrics.roc_auc_score(y_test, y_test_proba)
```

```python
print(f"\nSVM Model Performance (AUC):")
print(f"Training AUC: {train_auc:.4f}")
print(f"Validation AUC: {valid_auc:.4f}")
print(f"Test AUC: {test_auc:.4f}")
```

```
SVM Model Performance (AUC):
Training AUC: 0.9045
Validation AUC: 0.9602
Test AUC: 0.9991
```

Comparison

1.AUC:

SVM has a significantly higher Test AUC (0.9991) compared to Logistic Regression (0.9961). Higher AUC suggests that SVM is better at distinguishing between classes across all threshold values.

2.Accuracy:

*SVM achieves higher Test Accuracy (0.98) than Logistic Regression Test Accuracy (0.94).

3.Precision, Recall, F1-Score:

*SVM has consistently higher scores (0.98) compared to Logistic Regression (0.94) on Test Data.

4.Validation Performance:

*Logistic Regression performs better in Validation Classification Report (Accuracy: 0.89) compared to SVM (Accuracy: 0.77).

*Logistic Regression shows better balance between classes in Validation Data.

5.Overfitting:

*SVM shows signs of potential overfitting since its performance drops on Validation Data (AUC: 0.9602) compared to Test Data (AUC: 0.9991). Logistic Regression appears more stable between Validation and Test Data.

Conclusion

*Test Performance is Critical

SVM is preferable, as it has higher AUC, Accuracy, and better classification metrics on the Test Data.

*Validation Performance is Important

Logistic Regression is more balanced, especially for unseen data (Validation Set), and less prone to overfitting.

Summary

Based on the given matrices SVM is better model when we prioritize overall test performance and higher AUC.

But according to my model, SVM may be overfitting because of that I think Logistic regression is better.