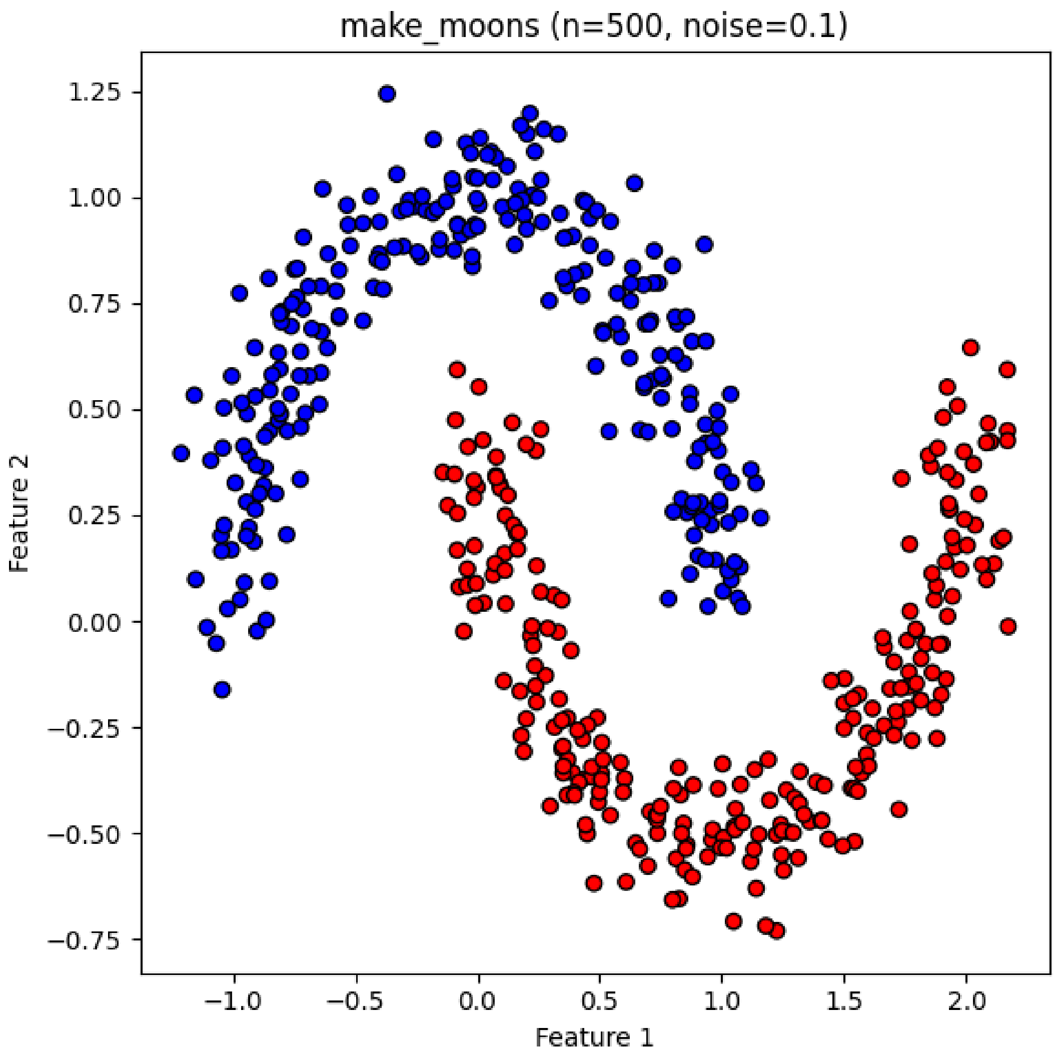
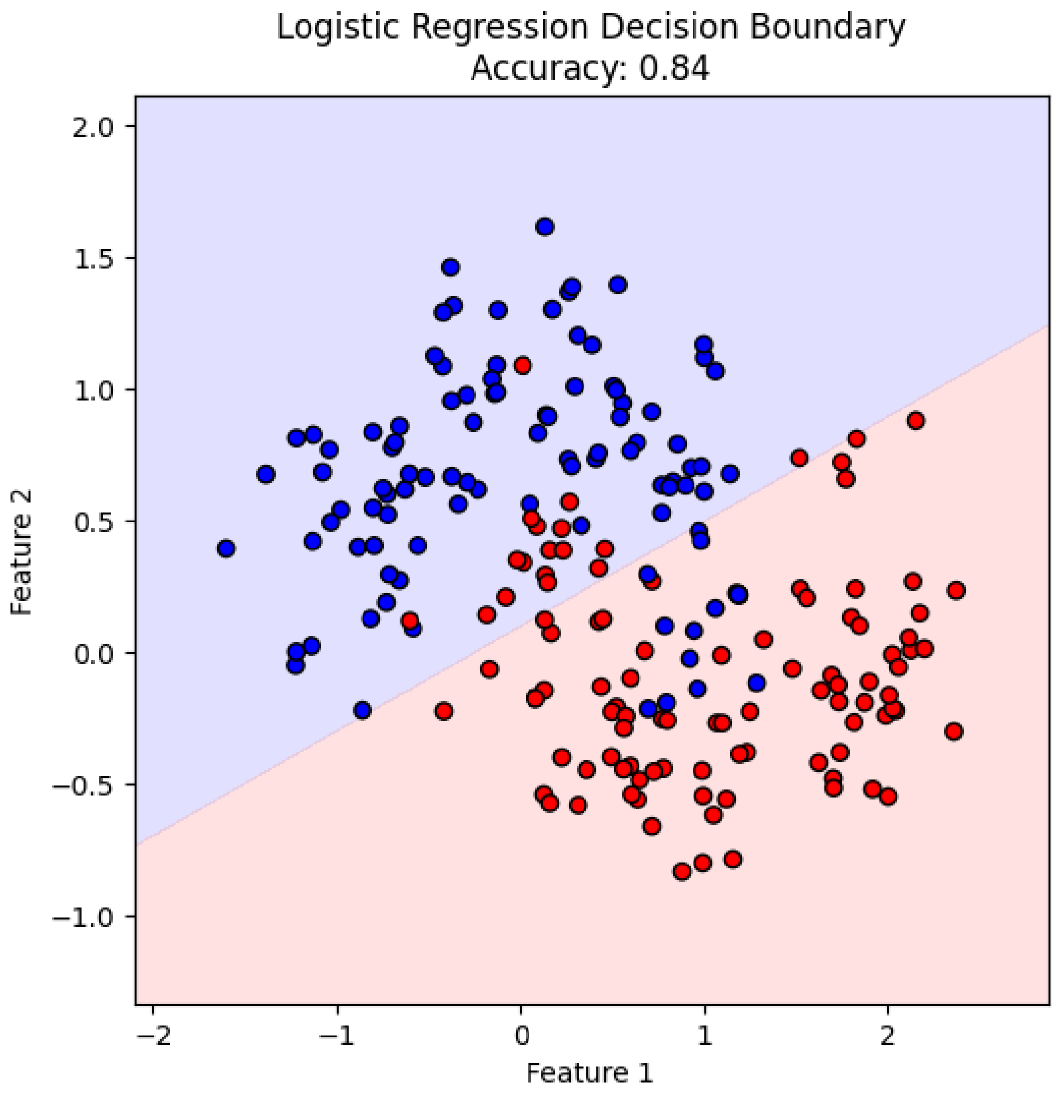
2.3 코드

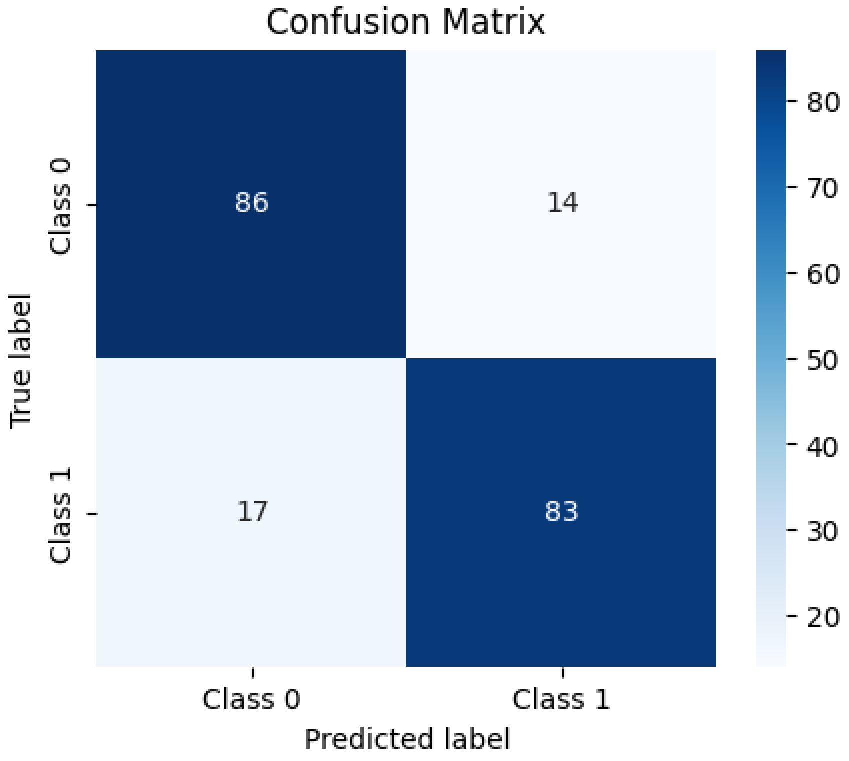
```
#1. 라이브러리 임포트
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_moons

#2. 데이터 생성 및 시각화
# 샘플 수: 500, 노이즈: 0.1, 랜덤 시드: 42
dataset = make_moons(n_samples=500, noise=0.1, random_state=42)
X, y = dataset

plt.figure(figsize=(6,6))
plt.scatter(X[:, 0], X[:, 1], c=y, cmap='bwr', edgecolor='k')
plt.title('make_moons (n=500, noise=0.1)')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.tight_layout()
plt.show()
```



```
#3. 로지스틱 회귀 – 결정 경계 · Seaborn Heatmap 혼동 행렬 · Classification Report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# 모델 학습
model_lr = LogisticRegression()
```

```
model_lr.fit(X, y)
y_pred = model_lr.predict(X)
acc = accuracy_score(y, y_pred)

# ── 결정 경계 시각화 ──
xx, yy = np.meshgrid(
    np.linspace(X[:,0].min()-0.5, X[:,0].max()+0.5, 200),
    np.linspace(X[:,1].min()-0.5, X[:,1].max()+0.5, 200)
)
grid = np.c_[xx.ravel(), yy.ravel()]
probs = model_lr.predict_proba(grid)[:,1].reshape(xx.shape)

plt.figure(figsize=(6,6))
plt.contourf(xx, yy, probs, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')
plt.scatter(X[:,0], X[:,1], c=y, edgecolor='k', cmap='bwr')
plt.title(f'Logistic Regression Decision Boundary\nAccuracy: {acc:.2f}')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

# ── Seaborn Heatmap으로 혼동 행렬 ──
cm = confusion_matrix(y, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Class 0','Class 1'],
            yticklabels=['Class 0','Class 1'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()

# ── Classification Report ──
print(f'Accuracy: {acc:.2f}\n')
print(classification_report(y, y_pred))
```


Logistic Regression Decision Boundary
Accuracy: 0.84


Confusion Matrix

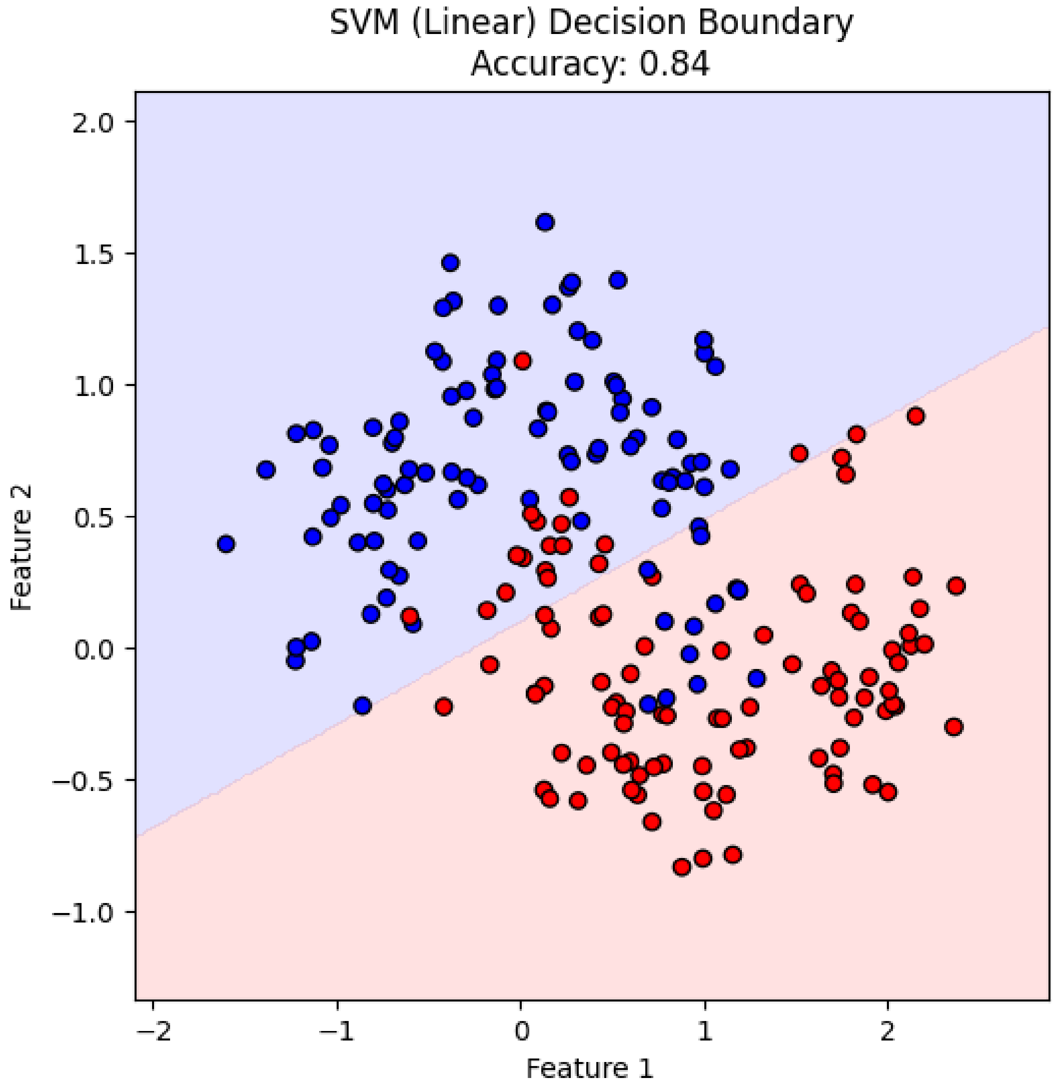
```
Accuracy: 0.84
```

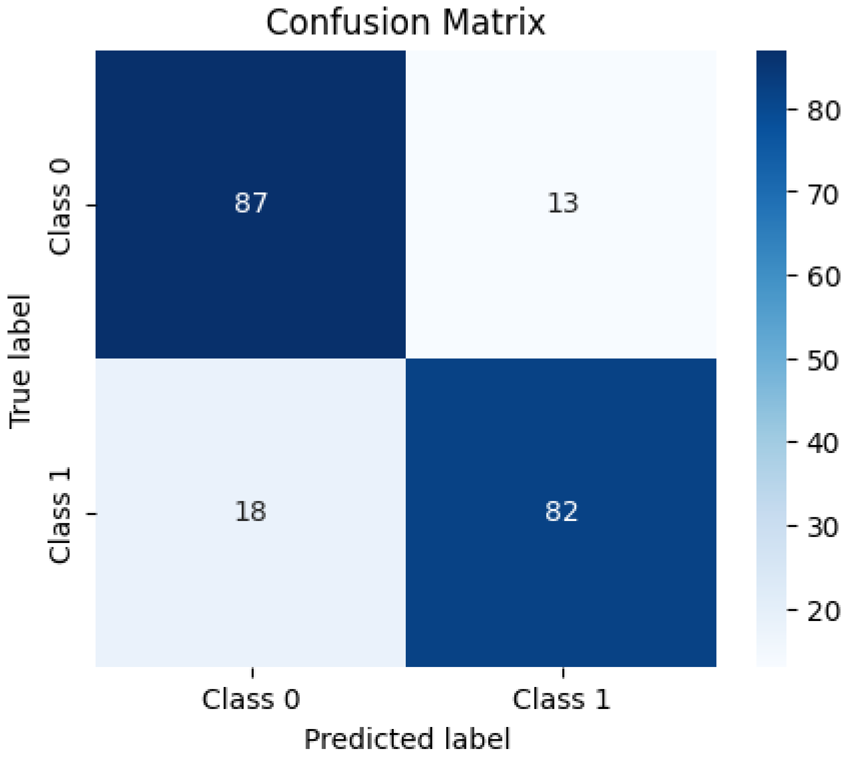
```
        precision    recall  f1-score   support

      0       0.83      0.86      0.85       100
      1       0.86      0.83      0.84       100

  accuracy                          0.84       200
```

```
macro avg       0.85      0.84      0.84       200
weighted avg       0.85      0.84      0.84       200
```

```
# SVM (Linear Kernel) – 결정 경계 · 혼동 행렬 · Classification Report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.svm import SVC          # 또는: from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# ── 모델 학습 ──
model_svm_lin = SVC(kernel='linear', probability=True, random_state=42)
# 만약 LinearSVC를 쓰고 싶다면:
# from sklearn.svm import LinearSVC
# model_svm_lin = LinearSVC(random_state=42)
model_svm_lin.fit(X, y)
y_pred = model_svm_lin.predict(X)
acc = accuracy_score(y, y_pred)

# ── 결정 경계 시각화 ──
xx, yy = np.meshgrid(
    np.linspace(X[:,0].min()-0.5, X[:,0].max()+0.5, 200),
    np.linspace(X[:,1].min()-0.5, X[:,1].max()+0.5, 200)
)
grid = np.c_[xx.ravel(), yy.ravel()]
probs = model_svm_lin.predict_proba(grid)[:,1].reshape(xx.shape)

plt.figure(figsize=(6,6))
plt.contourf(xx, yy, probs, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')
plt.scatter(X[:,0], X[:,1], c=y, edgecolor='k', cmap='bwr')
plt.title(f'SVM (Linear) Decision Boundary\nAccuracy: {acc:.2f}')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

# ── Seaborn Heatmap으로 혼동 행렬 ──
cm = confusion_matrix(y, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Class 0','Class 1'],
            yticklabels=['Class 0','Class 1'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()

# ── Classification Report ──
print(f'Accuracy: {acc:.2f}\n')
print(classification_report(y, y_pred))
```





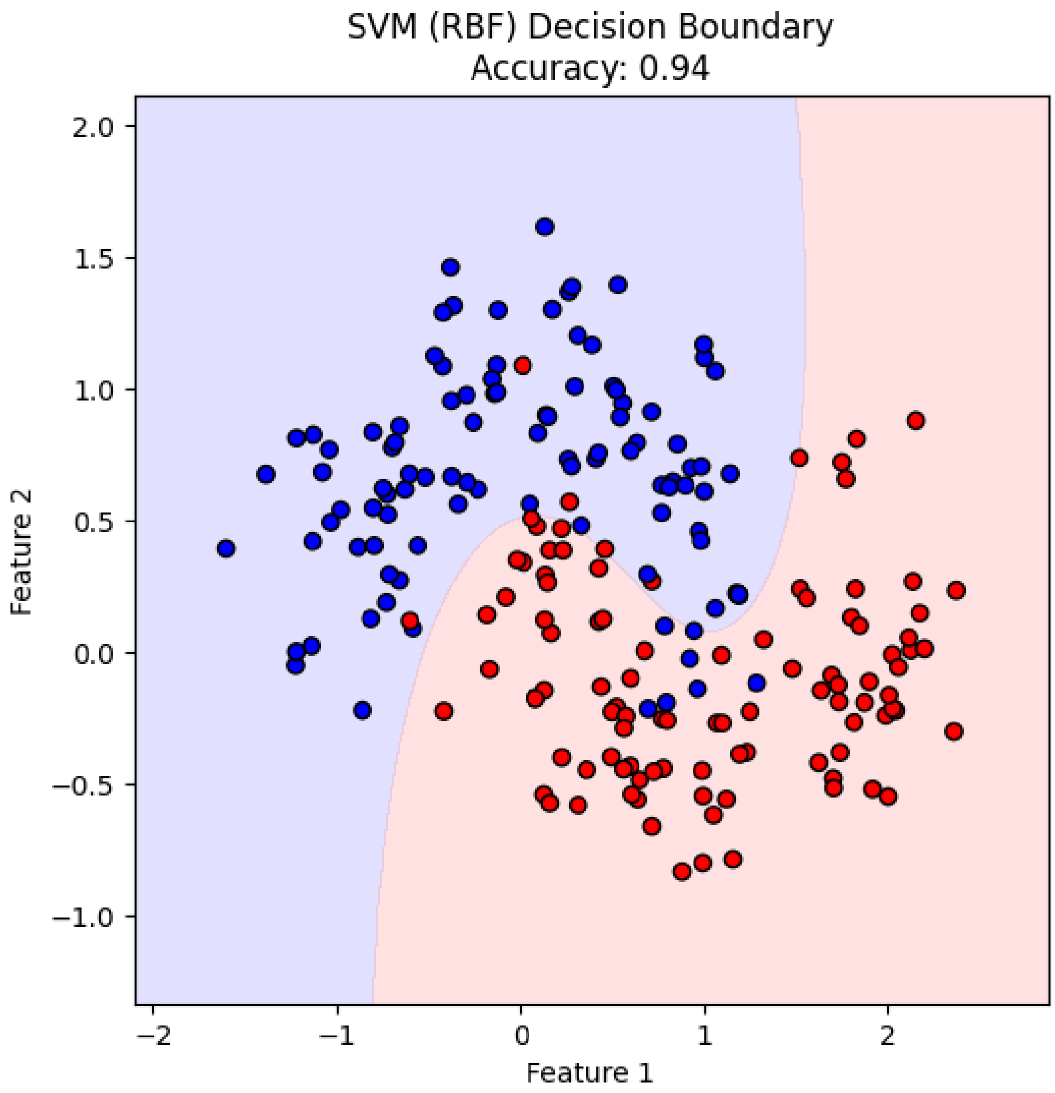
Accuracy: 0.84

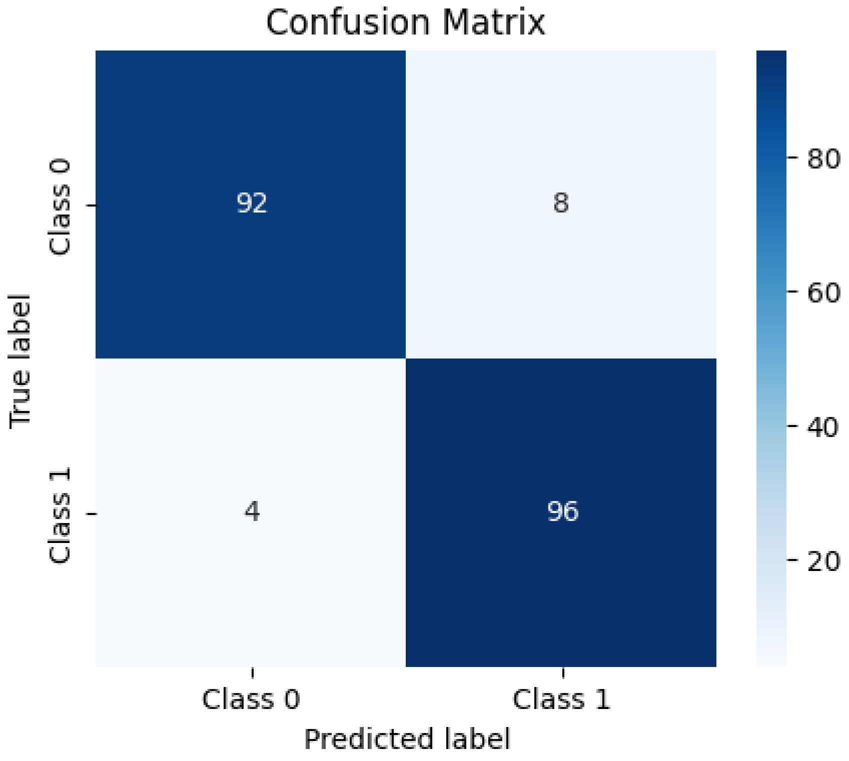
```
         precision    recall  f1-score   support

       0       0.83      0.87      0.85       100
       1       0.86      0.82      0.84       100

  accuracy                           0.84       200
```

```
macro avg       0.85      0.84      0.84       200
weighted avg       0.85      0.84      0.84       200
```

```
#4. SVM (RBF 커널) – 결정 경계 · Seaborn Heatmap 혼동 행렬 · Classification Report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.svm import SVC #support vector classifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# ── 모델 학습 ──
model_svm = SVC(kernel='rbf', probability=True, gamma='scale')
model_svm.fit(X, y)
y_pred = model_svm.predict(X)
acc = accuracy_score(y, y_pred)

# ── 결정 경계 시각화 ──
xx, yy = np.meshgrid(
    np.linspace(X[:,0].min()-0.5, X[:,0].max()+0.5, 200),
    np.linspace(X[:,1].min()-0.5, X[:,1].max()+0.5, 200)
)
grid = np.c_[xx.ravel(), yy.ravel()]
probs = model_svm.predict_proba(grid)[:,1].reshape(xx.shape)

plt.figure(figsize=(6,6))
plt.contourf(xx, yy, probs, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')
plt.scatter(X[:,0], X[:,1], c=y, edgecolor='k', cmap='bwr')
plt.title(f'SVM (RBF) Decision Boundary\nAccuracy: {acc:.2f}')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

# ── Seaborn Heatmap으로 혼동 행렬 ──
cm = confusion_matrix(y, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Class 0','Class 1'],
            yticklabels=['Class 0','Class 1'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()

# ── Classification Report ──
print(f'Accuracy: {acc:.2f}\n')
print(classification_report(y, y_pred))
```





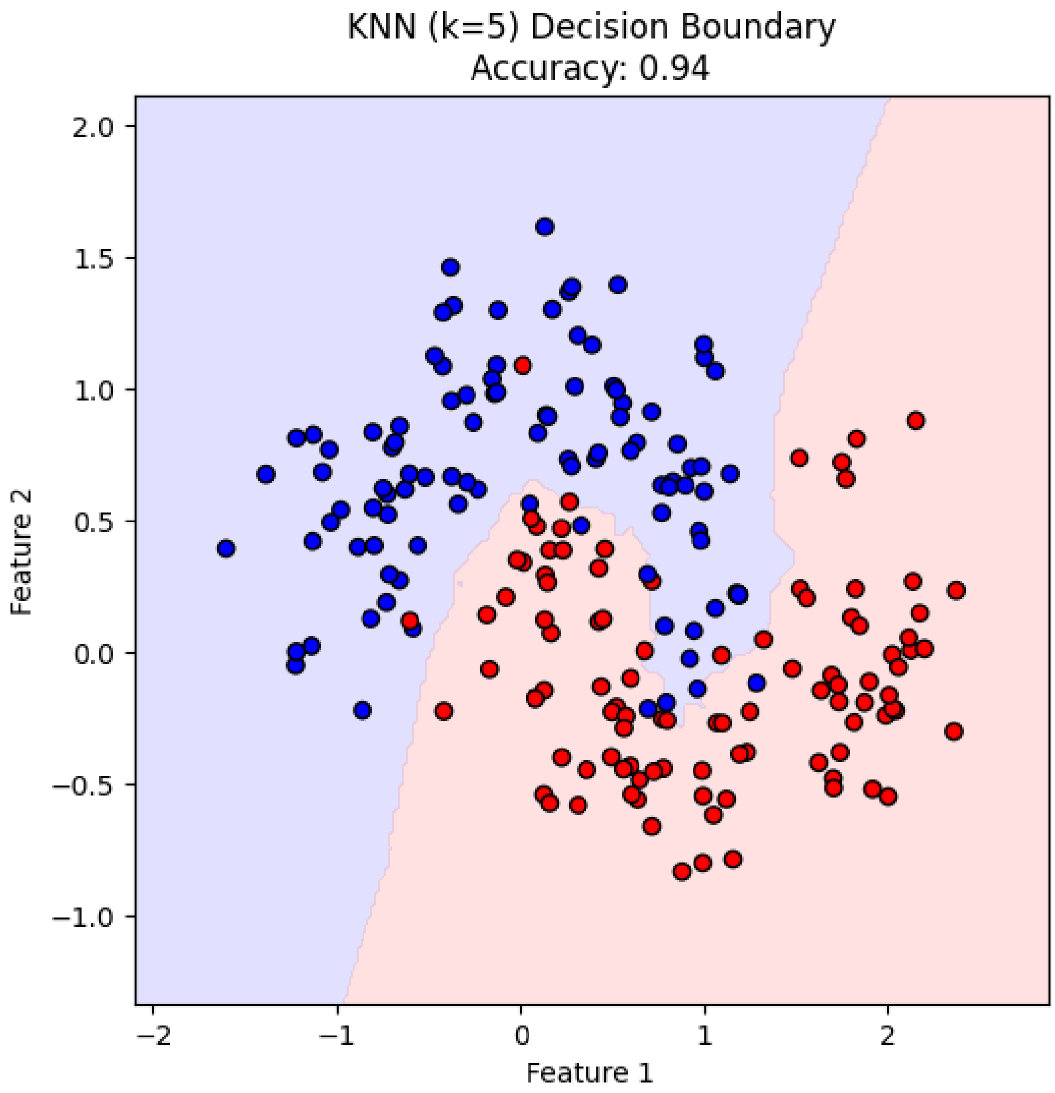
```
Accuracy: 0.94
```

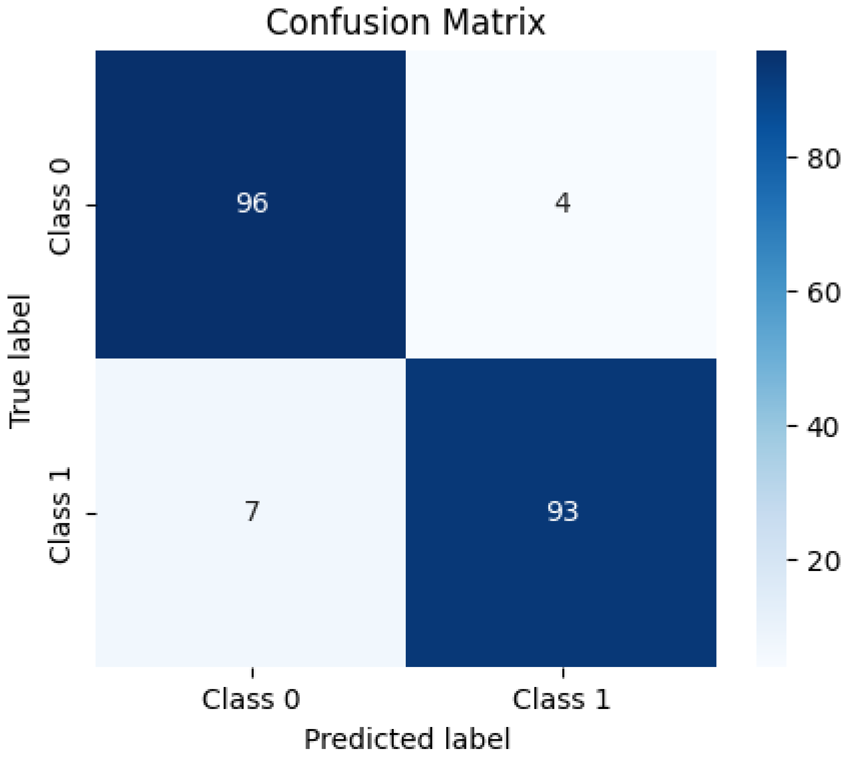
```
          precision    recall  f1-score   support

       0       0.96      0.92      0.94       100
       1       0.92      0.96      0.94       100

accuracy                           0.94       200
```

```
macro avg       0.94      0.94      0.94       200
weighted avg       0.94      0.94      0.94       200
```

```
#5. KNN (k=5) – 결정 경계 · Seaborn Heatmap 혼동 행렬 · Classification Report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# ── 모델 학습 ──
model_knn = KNeighborsClassifier(n_neighbors=5)
model_knn.fit(X, y)
y_pred = model_knn.predict(X)
acc = accuracy_score(y, y_pred)

# ── 결정 경계 시각화 ──
xx, yy = np.meshgrid(
    np.linspace(X[:,0].min()-0.5, X[:,0].max()+0.5, 200),
    np.linspace(X[:,1].min()-0.5, X[:,1].max()+0.5, 200)
)
grid = np.c_[xx.ravel(), yy.ravel()]
probs = model_knn.predict_proba(grid)[:,1].reshape(xx.shape)

plt.figure(figsize=(6,6))
plt.contourf(xx, yy, probs, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')
plt.scatter(X[:,0], X[:,1], c=y, edgecolor='k', cmap='bwr')
plt.title(f'KNN (k=5) Decision Boundary\nAccuracy: {acc:.2f}')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

# ── Seaborn Heatmap으로 혼동 행렬 ──
cm = confusion_matrix(y, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Class 0','Class 1'],
            yticklabels=['Class 0','Class 1'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()

# ── Classification Report ──
print(f'Accuracy: {acc:.2f}\n')
print(classification_report(y, y_pred))
```

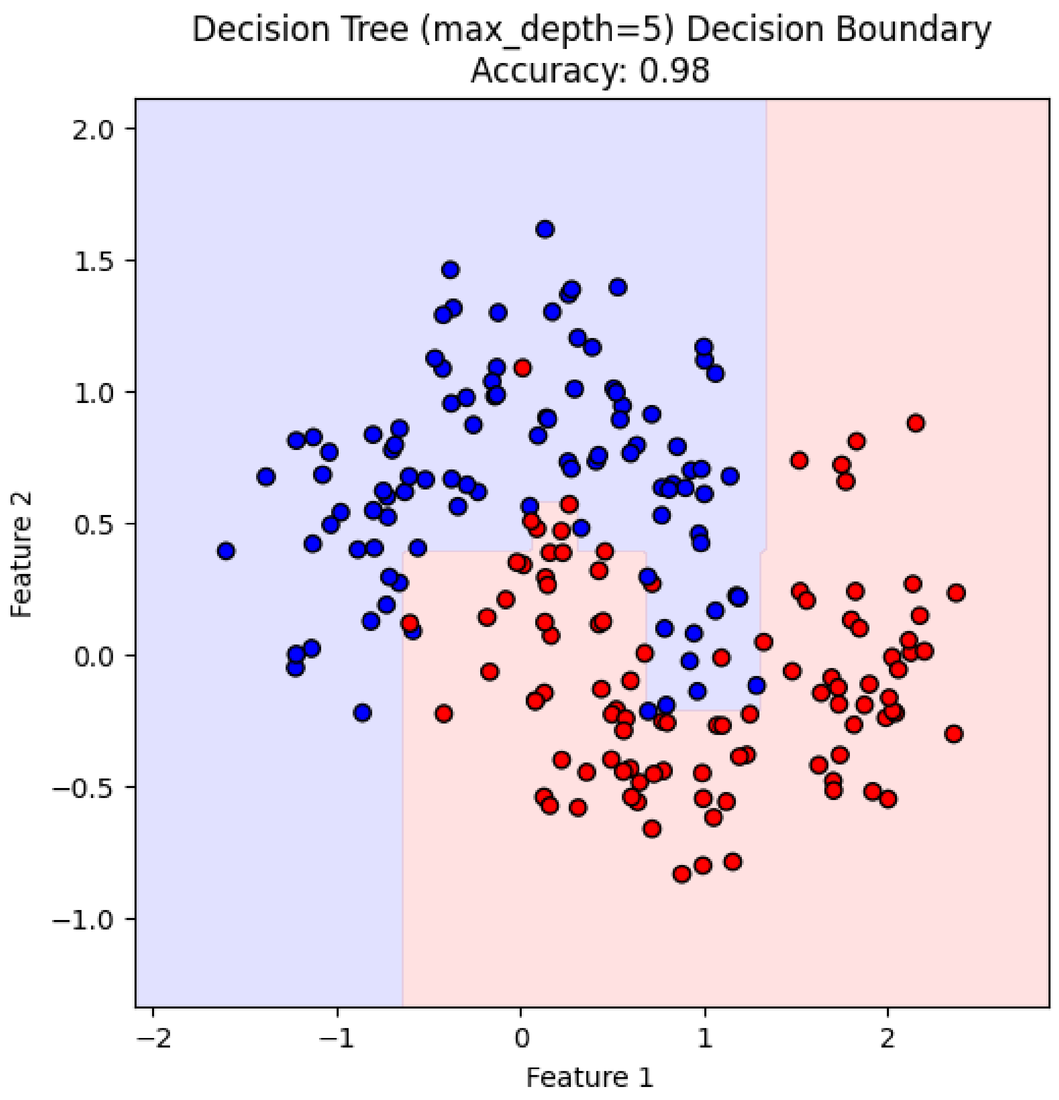


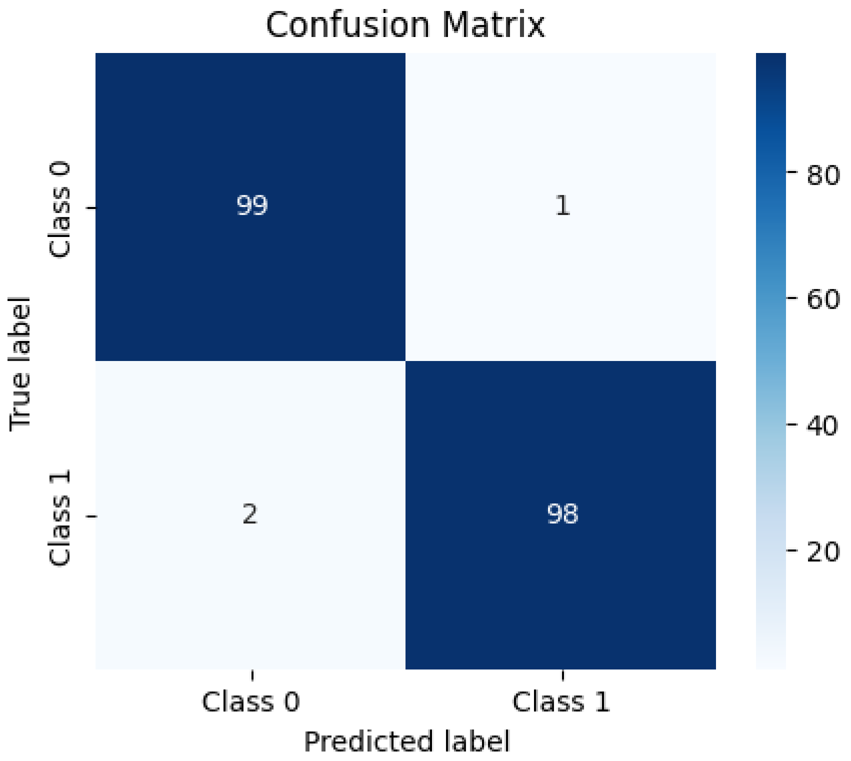


```
Accuracy: 0.94

              precision    recall  f1-score   support

           0       0.93      0.96      0.95       100
           1       0.96      0.93      0.94       100

    accuracy                           0.94       200
   macro avg       0.95      0.95      0.94       200
weighted avg       0.95      0.94      0.94       200
```

```
#6. Decision Tree (max_depth=5) — 결정 경계 · Seaborn Heatmap 혼동 행렬 · Classification Report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# ── 모델 학습 ──
model_dt = DecisionTreeClassifier(max_depth=5, random_state=42)
model_dt.fit(X, y)
y_pred = model_dt.predict(X)
acc = accuracy_score(y, y_pred)

# ── 결정 경계 시각화 ──
xx, yy = np.meshgrid(
    np.linspace(X[:,0].min()-0.5, X[:,0].max()+0.5, 200),
    np.linspace(X[:,1].min()-0.5, X[:,1].max()+0.5, 200)
)
grid = np.c_[xx.ravel(), yy.ravel()]
probs = model_dt.predict_proba(grid)[:,1].reshape(xx.shape)

plt.figure(figsize=(6,6))
plt.contourf(xx, yy, probs, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')
plt.scatter(X[:,0], X[:,1], c=y, edgecolor='k', cmap='bwr')
plt.title(f'Decision Tree (max_depth=5) Decision Boundary\nAccuracy: {acc:.2f}')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

# ── Seaborn Heatmap으로 혼동 행렬 ──
cm = confusion_matrix(y, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Class 0','Class 1'],
            yticklabels=['Class 0','Class 1'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()

# ── Classification Report ──
print(f'Accuracy: {acc:.2f}\n')
print(classification_report(y, y_pred))


#7. Decision Tree 구조 시각화
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt


plt.figure(figsize=(12, 8))
plot_tree(
    model_dt,
    max_depth=2,
    feature_names=['Feature 1', 'Feature 2'],
    class_names=['Class 0', 'Class 1'],
    filled=True,
    rounded=True,
    fontsize=10
)
plt.title('Decision Tree Structure')
plt.show()
```

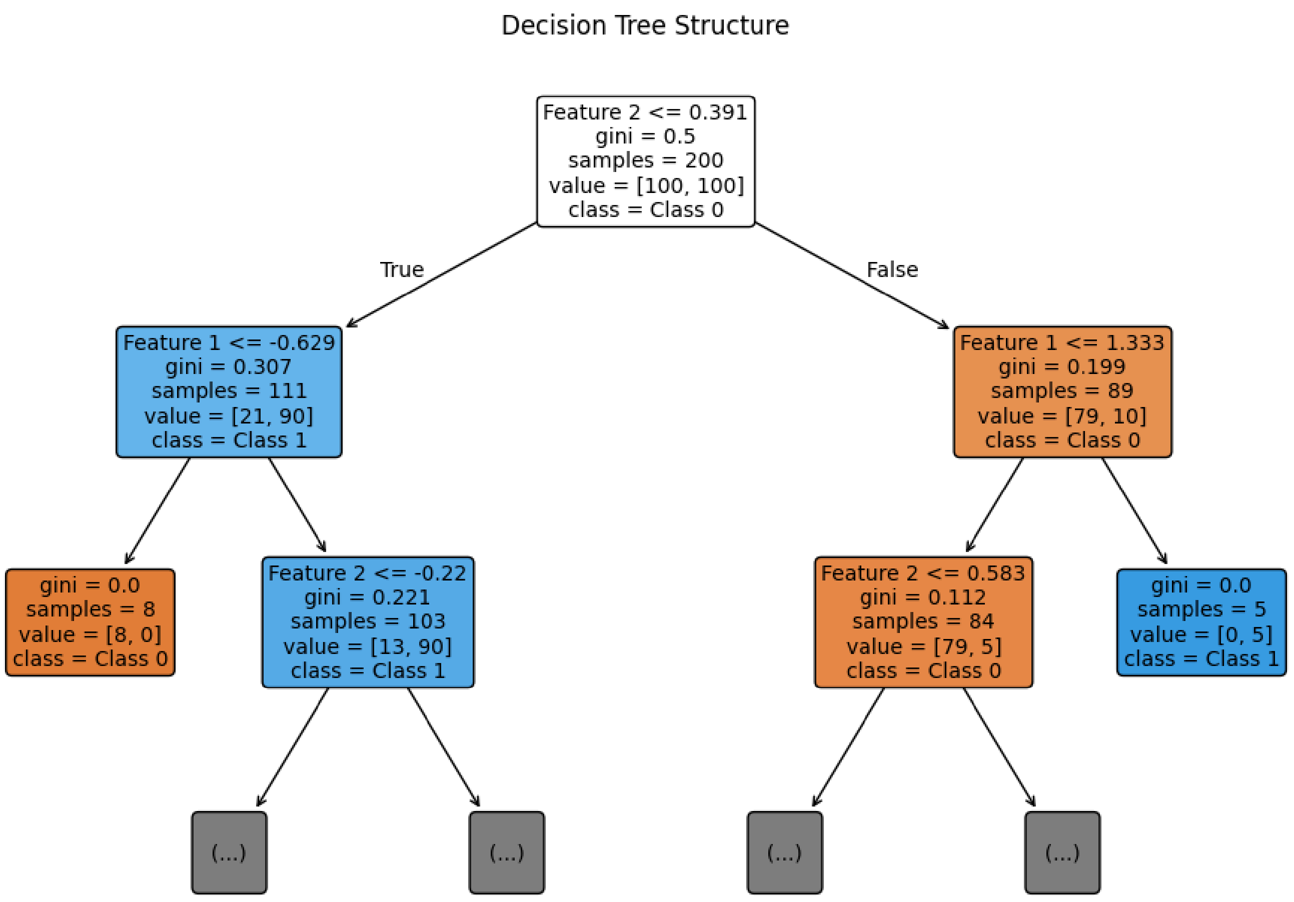




Accuracy: 0.98

```
          precision    recall  f1-score   support

       0       0.98      0.99      0.99       100
       1      0.99      0.98      0.98      100

  accuracy                           0.98      200
```

```
macro avg       0.99       0.98       0.98       200
weighted avg       0.99       0.98       0.98       200
```


Decision Tree Structure
Feature 2 <= 0.391
gini = 0.5
samples = 200
value = [100, 100]
class = Class 0
True
False
Feature 1 <= -0.629
gini = 0.307
samples = 111
value = [21, 90]
class = Class 1
Feature 1 <= 1.333
gini = 0.199
samples = 89
value = [79, 10]
class = Class 0
gini = 0.0
samples = 8
value = [8, 0]
class = Class 0
Feature 2 <= -0.22
gini = 0.221
samples = 103
value = [13, 90]
class = Class 1
Feature 2 <= 0.583
gini = 0.112
samples = 84
value = [79, 5]
class = Class 0
gini = 0.0
samples = 5
value = [0, 5]
class = Class 1
(...)
(...)
(...)
(...)