Machine Learning

Lab 04

```
import pandas as pd
import numpy as np
import statistics
import seaborn as sns
import matplotlib.pyplot as plt
import random
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import pickle
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

A1

```
def create_intensity_classes(df):
    # Define thresholds based on percentiles or domain knowledge
    low_threshold = df['max'].quantile(0.33)
    high_threshold = df['max'].quantile(0.66)

    # Create class labels
    conditions = [
        (df['max'] < low_threshold),
        (df['max'] >= low_threshold) & (df['max'] < high_threshold),
        (df['max'] >= high_threshold)
    ]
    class_labels = [0, 1, 2]  # or ['Low', 'Medium', 'High']
```

```
    return np.select(conditions, class_labels)

data = pd.read_csv("combined_seismic_data.csv")
data["class"] = create_intensity_classes(data)

class_1_and_2 = data[data['class'].isin([1, 2])]

# Extract features and labels again after filtering
X = class_1_and_2[['max', 'distance_to_event']].values
y = class_1_and_2['class'].values

# Split the data into training and test sets (70% train, 30% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

filename = "Lab03_KNN.pkl"
loaded_model = pickle.load(open(filename, 'rb'))
# Make predictions on the training and test sets
y_train_pred = loaded_model.predict(X_train)
y_test_pred = loaded_model.predict(X_test)

# Confusion Matrix for both training and test sets
train_confusion_matrix = confusion_matrix(y_train, y_train_pred)
test_confusion_matrix = confusion_matrix(y_test, y_test_pred)

# Print confusion matrices
print("Training Confusion Matrix:")
print(train_confusion_matrix)
print("\nTest Confusion Matrix:")
print(test_confusion_matrix)

print("\nTraining Classification Report:")
print(classification_report(y_train, y_train_pred))
print("\nTest Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Training Confusion Matrix:
[[200   0]
```

```
 [  0 197]]

Test Confusion Matrix:
[[80  0]
 [ 1 90]]

Training Classification Report:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00       200
           2       1.00      1.00      1.00       197

    accuracy                           1.00       397
   macro avg       1.00      1.00      1.00       397
weighted avg       1.00      1.00      1.00       397


Test Classification Report:
              precision    recall  f1-score   support

           1       0.99      1.00      0.99        80
           2       1.00      0.99      0.99        91

    accuracy                           0.99       171
   macro avg       0.99      0.99      0.99       171
weighted avg       0.99      0.99      0.99       171
```

Given that the model performs almost perfectly on both the training and test data, with only a very small drop in performance on the test set, the model is most likely regular-fit (well-generalized).

It is not underfitting because the model is achieving near-perfect results on both training and test data. It is also not overfitting because the performance drop from training to test data is minimal and within acceptable ranges.

A2

```
data = np.load("payements_true_predicted.npz")
true_data = data['arr_0']
predicted_data = data['arr_1']


def mse(y_true, y_pred):
    return np.mean((y_true - y_pred) ** 2)

def rmse(y_true, y_pred):
    return np.sqrt(mse(y_true, y_pred))

def mape(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

def r2(y_true, y_pred):
    ss_total = np.sum((y_true - np.mean(y_true)) ** 2)
    ss_residual = np.sum((y_true - y_pred) ** 2)
    return 1 - (ss_residual / ss_total)


print("MSE: ", mse(true_data, predicted_data))
print("RMSE: ", rmse(true_data, predicted_data))
print("MAPE: ", mape(true_data, predicted_data))
print("R2: ", r2(true_data, predicted_data))
```

```
MSE:  6.664296927307107e-28
RMSE:  2.5815299586305613e-14
MAPE:  4.210920741310997e-15
R2:  1.0
```

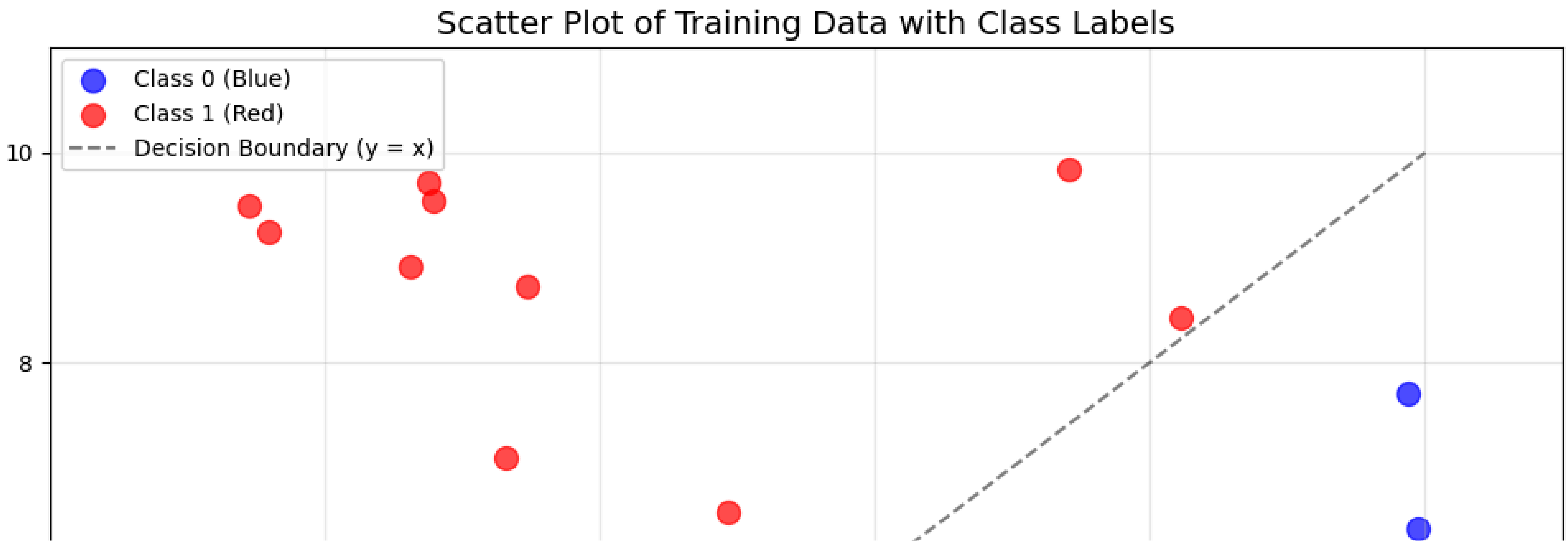
We see that all the values are nearly 0. Thus, it is an accurate model.

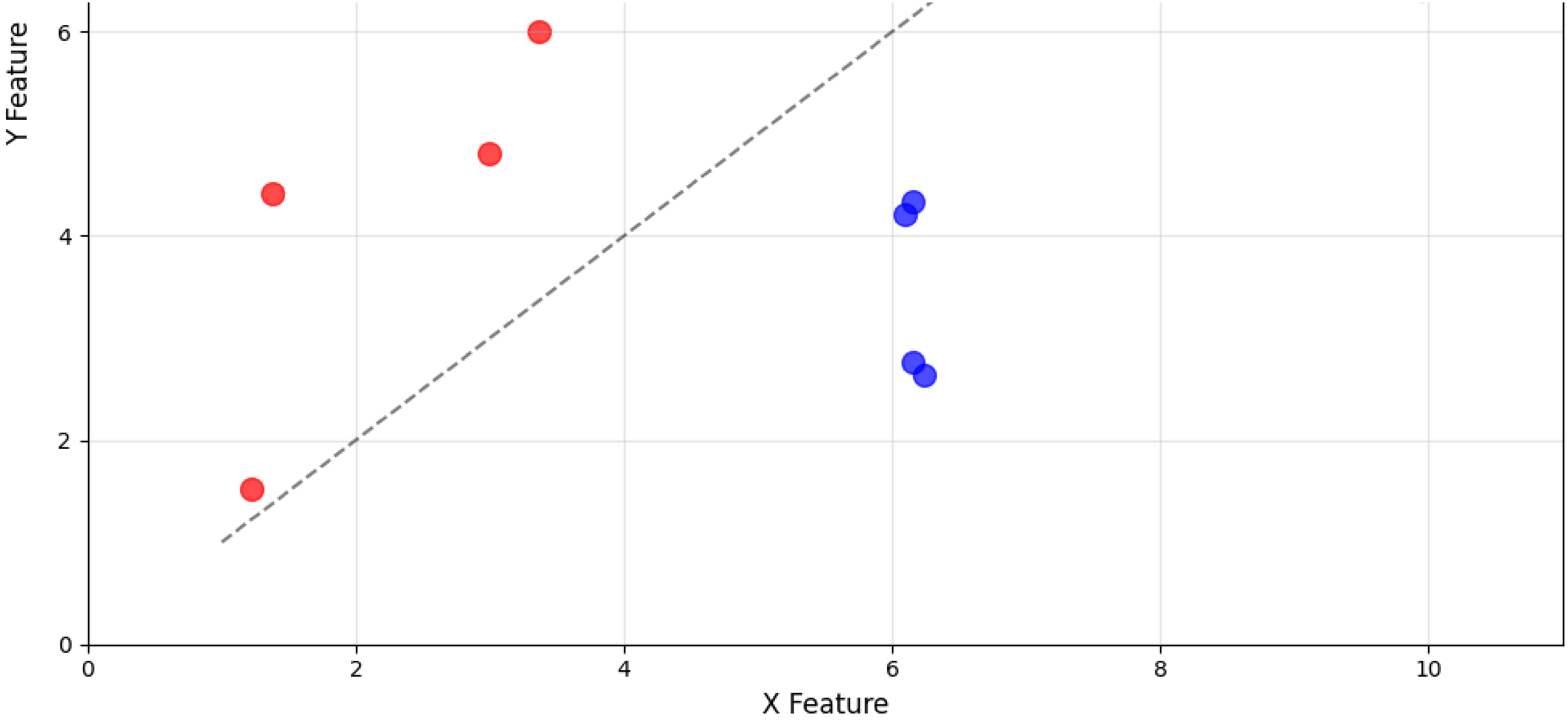
A3

```
def generate_data():
    # Generate X and Y values randomly between 1 and 10
    X = np.random.uniform(1, 10, 20)
    Y = np.random.uniform(1, 10, 20)

    classes = []
    for i in range(20):
        if Y[i] > X[i]:
            classes.append(1)  # Red
        else:
            classes.append(0)  # Blue

    # Create a DataFrame to store the data
    df = pd.DataFrame({
        'X': X,
        'Y': Y,
        'Class': classes
    })

    return df

# Generate the data
data = generate_data()

# Display the data
print("Generated Data:")
print(data)

# Plot the data
plt.figure(figsize=(10, 8))
colors = ['blue', 'red']
labels = ['Class 0 (Blue)', 'Class 1 (Red)']

# Separate the classes for plotting
class0 = data[data['Class'] == 0]
class1 = data[data['Class'] == 1]
```

```
# Plot each class with a different color
plt.scatter(class0['X'], class0['Y'], c='blue', label='Class 0 (Blue)', s=100, alpha=0.7)
plt.scatter(class1['X'], class1['Y'], c='red', label='Class 1 (Red)', s=100, alpha=0.7)

# Add a line showing the decision boundary (y = x in this case)
plt.plot([1, 10], [1, 10], 'k--', alpha=0.5, label='Decision Boundary (y = x)')

# Add labels and title
plt.xlabel('X Feature', fontsize=12)
plt.ylabel('Y Feature', fontsize=12)
plt.title('Scatter Plot of Training Data with Class Labels', fontsize=14)
plt.grid(True, alpha=0.3)
plt.legend()

# Set axis limits
plt.xlim(0, 11)
plt.ylim(0, 11)

plt.tight_layout()
plt.show()

# Count the number of points in each class
class_counts = data['Class'].value_counts().sort_index()
print("\nClass Distribution:")
print(f"Class 0 (Blue): {class_counts[0]} points")
print(f"Class 1 (Red): {class_counts[1]} points")
```

```
Generated Data:
           X         Y  Class
0   2.794021  9.539072      1
1   2.751098  9.723387      1
2   6.150988  2.768890      0
3   3.316542  7.085660      1
4   3.359011  6.001209      1
5   1.589732  9.237257      1
6   3.474290  8.726618      1
7   4.929774  6.562814      1
8   2.993207  4.803703      1
9   9.951057  6.416653      0
10  7.414347  9.848709      1
11  1.226742  1.523556      1
12  1.382787  4.407397      1
13  6.151307  4.329128      0
14  6.088565  4.206655      0
15  1.445249  9.489158      1
16  2.624563  8.908155      1
17  6.235109  2.643684      0
18  9.875273  7.695026      0
19  8.224976  8.424575      1
```






```
Class Distribution:
Class 0 (Blue): 6 points
Class 1 (Red): 14 points
```

A4

```
def generate_training_data():
    # Generate X and Y values randomly between 1 and 10
    X = np.random.uniform(1, 10, 20)
    Y = np.random.uniform(1, 10, 20)

    # Assign classes based on a simple rule: if y > x, then class 1 (Red), else class 0 (Blue)
    classes = []
    for i in range(20):
        if Y[i] > X[i]:
            classes.append(1)  # Red
        else:
            classes.append(0)  # Blue

    # Create a DataFrame to store the data
    df = pd.DataFrame({
        'X': X,
        'Y': Y,
        'Class': classes
    })

    return df

def generate_test_data():
    # Create a grid of points from 0 to 10 with 0.1 increments
    x = np.arange(0, 10.1, 0.1)
    y = np.arange(0, 10.1, 0.1)

    # Create all combinations of x and y
    X, Y = np.meshgrid(x, y)
    X_flat = X.flatten()
    Y_flat = Y.flatten()

    # Create a DataFrame to store the test data
```

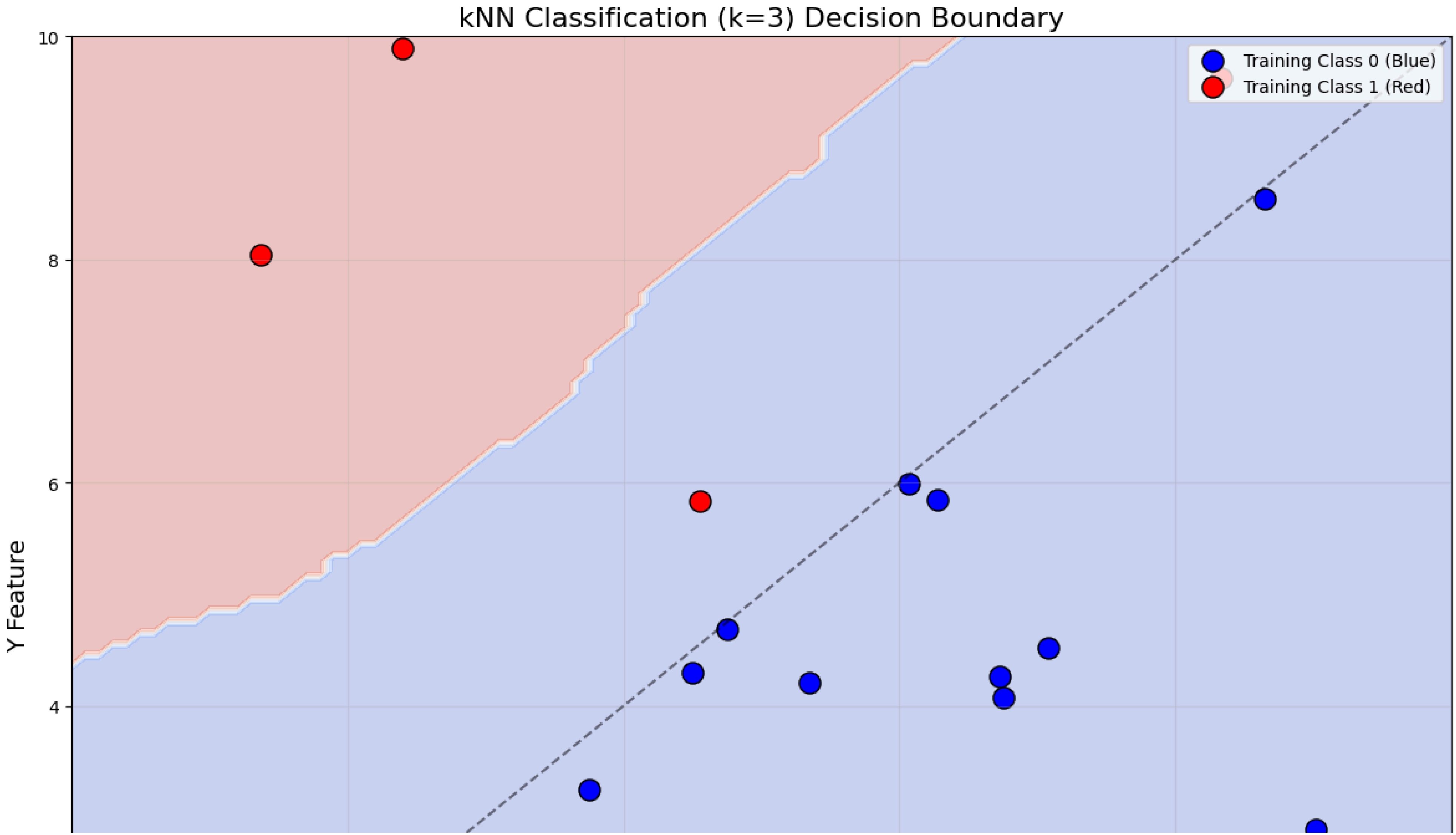
```
        test_df = pd.DataFrame({
            'X': X_flat,
            'Y': Y_flat
        })

        return test_df, X, Y

    def knn_classification(train_df, test_df, k=3):
        # Extract features and target from training data
        X_train = train_df[['X', 'Y']].values
        y_train = train_df['Class'].values

        # Create and train the kNN classifier
        knn = KNeighborsClassifier(n_neighbors=k)
        knn.fit(X_train, y_train)

        # Make predictions on the test data
        X_test = test_df[['X', 'Y']].values
        y_pred = knn.predict(X_test)

        # Add predictions to the test DataFrame
        test_df['Predicted_Class'] = y_pred

        return test_df, knn

    def visualize_results(train_df, test_df, X_grid, Y_grid):
        plt.figure(figsize=(12, 10))

        # Create a meshgrid for coloring the decision regions
        predictions = test_df['Predicted_Class'].values
        Z = predictions.reshape(X_grid.shape)

        # Plot the decision boundary
        plt.contourf(X_grid, Y_grid, Z, alpha=0.3, cmap=plt.cm.coolwarm)

        # Plot the training data
        class0 = train_df[train_df['Class'] == 0]
```

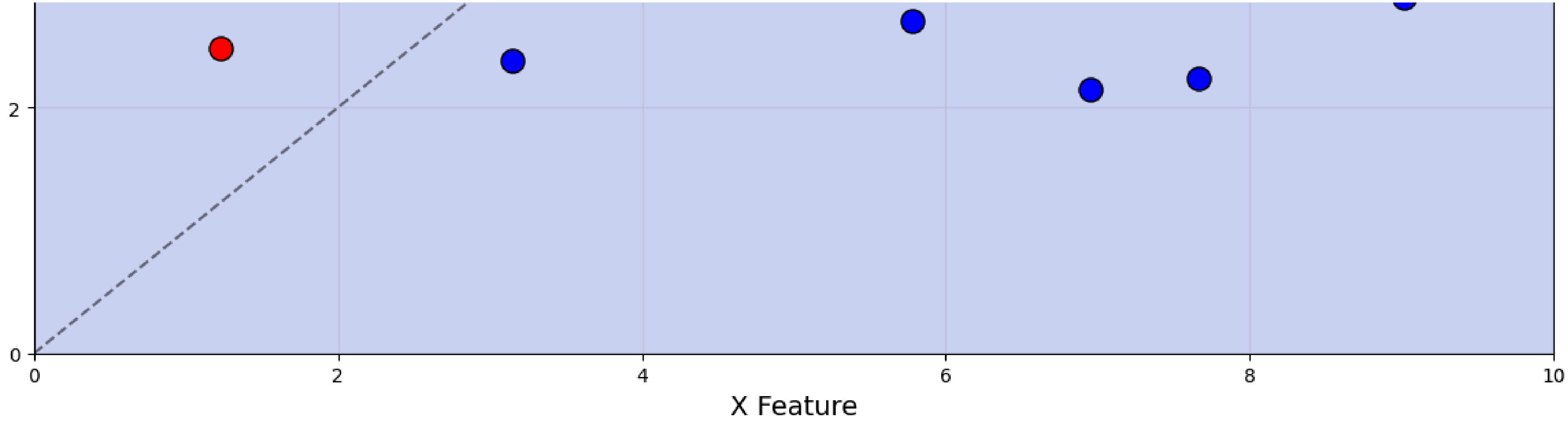
```
class1 = train_df[train_df['Class'] == 1]

plt.scatter(class0['X'], class0['Y'], c='blue', edgecolors='k', s=150, marker='o', label='Training Class 0 (Blue)')
plt.scatter(class1['X'], class1['Y'], c='red', edgecolors='k', s=150, marker='o', label='Training Class 1 (Red)')

# Add labels and title
plt.xlabel('X Feature', fontsize=14)
plt.ylabel('Y Feature', fontsize=14)
plt.title('kNN Classification (k=3) Decision Boundary', fontsize=16)
plt.grid(True, alpha=0.3)
plt.legend(loc='upper right')

# Set axis limits
plt.xlim(0, 10)
plt.ylim(0, 10)

# Add a reference line for y = x
plt.plot([0, 10], [0, 10], 'k--', alpha=0.5, label='y = x line')

plt.tight_layout()

# Create a separate figure for a small sample of test points
plt.figure(figsize=(12, 10))

# Sample test points for visualization (to avoid plotting all 10,000+ points)
sample_size = 1000
test_sample = test_df.sample(sample_size, random_state=42)

# Plot the sampled test points
test_class0 = test_sample[test_sample['Predicted_Class'] == 0]
test_class1 = test_sample[test_sample['Predicted_Class'] == 1]

plt.scatter(test_class0['X'], test_class0['Y'], c='blue', s=30, alpha=0.6, label='Test Class 0 (Blue)')
plt.scatter(test_class1['X'], test_class1['Y'], c='red', s=30, alpha=0.6, label='Test Class 1 (Red)')

# Plot the training data on top
plt.scatter(class0['X'], class0['Y'], c='blue', edgecolors='k', s=150, marker='o', label='Training Class 0 (Blue)')
```

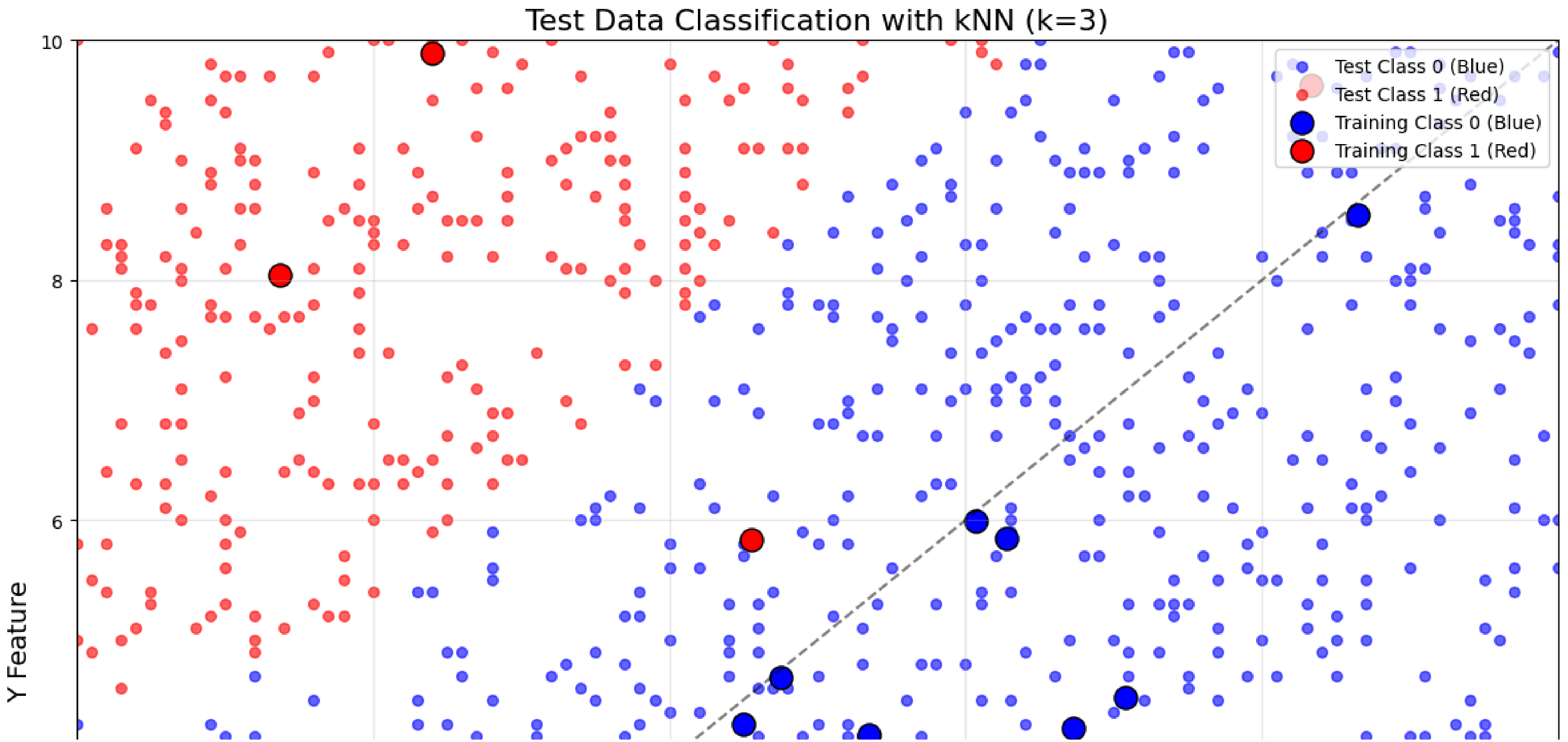
```
    plt.scatter(class1['X'], class1['Y'], c='red', edgecolors='k', s=150, marker='o', label='Training Class 1 (Red)')

    # Plot the y = x line
    plt.plot([0, 10], [0, 10], 'k--', alpha=0.5)

    # Add labels and title
    plt.xlabel('X Feature', fontsize=14)
    plt.ylabel('Y Feature', fontsize=14)
    plt.title('Test Data Classification with kNN (k=3)', fontsize=16)
    plt.grid(True, alpha=0.3)
    plt.legend(loc='upper right')

    # Set axis limits
    plt.xlim(0, 10)
    plt.ylim(0, 10)

    plt.tight_layout()


train_data = generate_training_data()
test_data, X_grid, Y_grid = generate_test_data()
classified_test_data, knn_model = knn_classification(train_data, test_data, k=3)


print("Training Data Summary:")
print(f"Number of points: {len(train_data)}")
print(f"Class 0 (Blue): {len(train_data[train_data['Class'] == 0])}")
print(f"Class 1 (Red): {len(train_data[train_data['Class'] == 1])}")
print("\nTest Data Summary:")
print(f"Number of points: {len(test_data)}")
print(f"Predicted Class 0 (Blue): {len(classified_test_data[classified_test_data['Predicted_Class'] == 0])}")
print(f"Predicted Class 1 (Red): {len(classified_test_data[classified_test_data['Predicted_Class'] == 1])}")

# Visualize results
visualize_results(train_data, classified_test_data, X_grid, Y_grid)
```

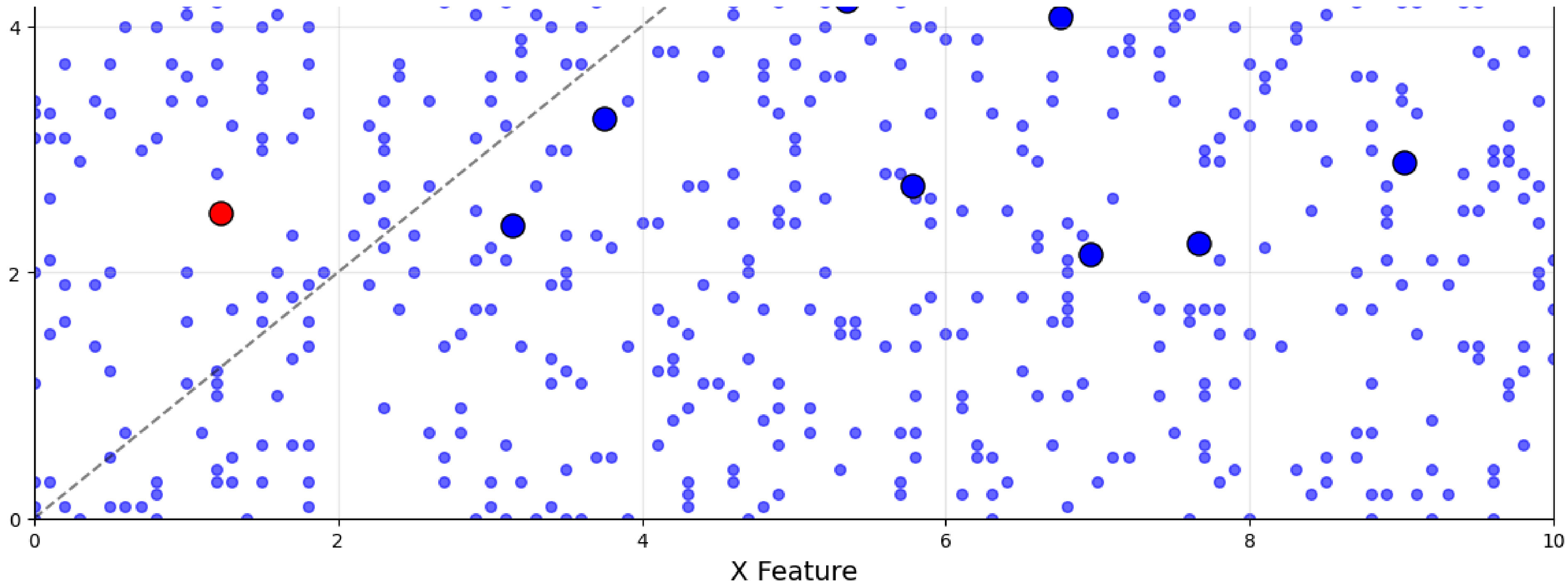
```
    # Show plots
    plt.show()
```

```
Training Data Summary:
Number of points: 20
Class 0 (Blue): 15
Class 1 (Red): 5

Test Data Summary:
Number of points: 10201
Predicted Class 0 (Blue): 8057
Predicted Class 1 (Red): 2144
```




2
0
0
2
4
6
8
10
X Feature


Test Data Classification with kNN (k=3)
10
8
6
Y Feature
Test Class 0 (Blue)
Test Class 1 (Red)
Training Class 0 (Blue)
Training Class 1 (Red)


4
2
0
0
2
4
6
8
10
X Feature

A5

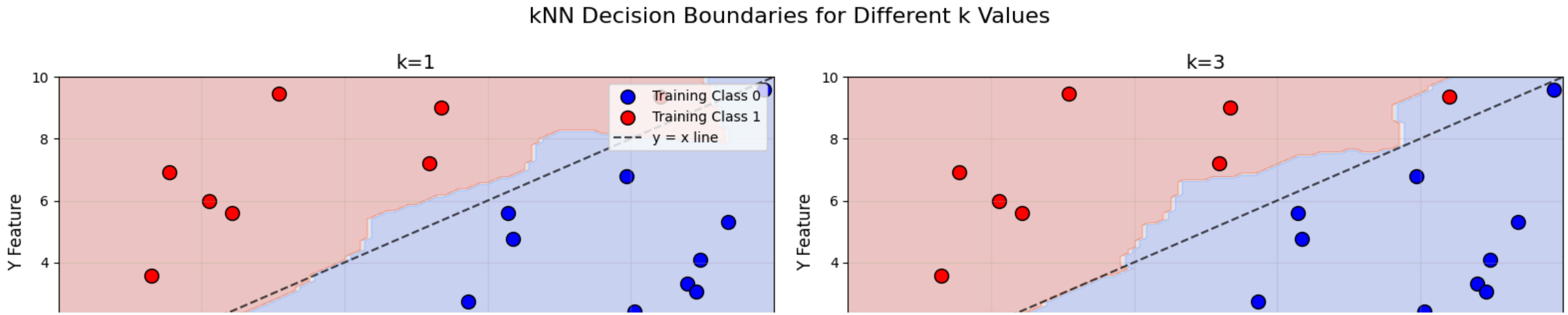
```
def knn_classification(train_df, test_df, k):
    # Extract features and target from training data
    X_train = train_df[['X', 'Y']].values
    y_train = train_df['Class'].values

    # Create and train the kNN classifier
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)

    # Make predictions on the test data
    X_test = test_df[['X', 'Y']].values
    y_pred = knn.predict(X_test)

    # Add predictions to the test DataFrame
    test_df[f'Predicted_Class_k{k}'] = y_pred

    return test_df, knn

# Step 4: Visualize the results for multiple k values
def visualize_results_for_multiple_k(train_df, test_df, X_grid, Y_grid, k_values):
    # Create a figure for the multiple subplots
    fig, axes = plt.subplots(len(k_values)//2 + len(k_values)%2, 2, figsize=(16, 4*len(k_values)//2 + 4*len(k_values)%2))
    axes = axes.flatten()  # Flatten the axes array for easier indexing

    for i, k in enumerate(k_values):
        # Get the predictions for the current k value
        pred_col = f'Predicted_Class_k{k}'
        predictions = test_df[pred_col].values
        Z = predictions.reshape(X_grid.shape)

        # Plot the decision boundary
        im = axes[i].contourf(X_grid, Y_grid, Z, alpha=0.3, cmap=plt.cm.coolwarm)
```

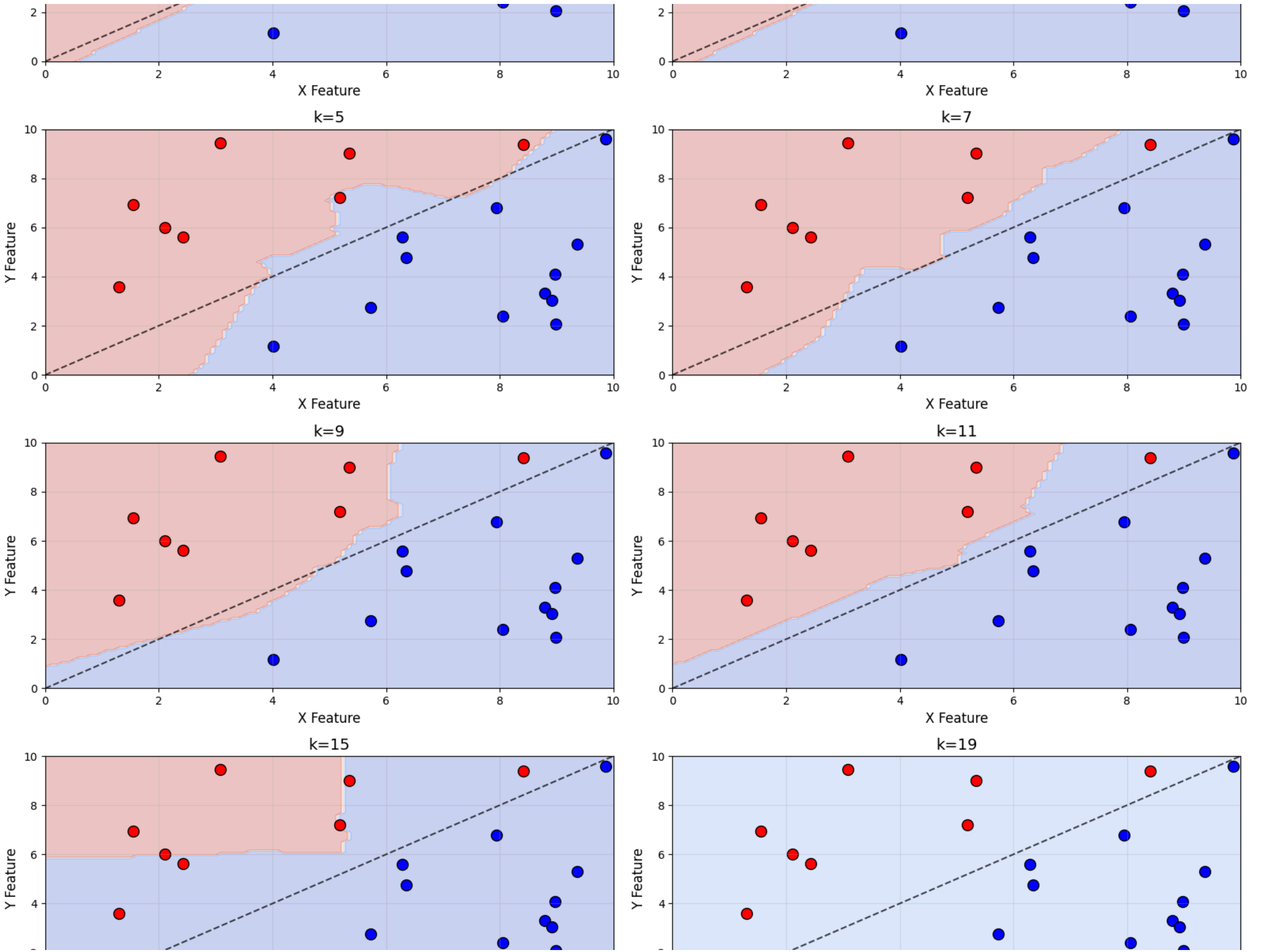
```
        # Plot the training data
        class0 = train_df[train_df['Class'] == 0]
        class1 = train_df[train_df['Class'] == 1]

        axes[i].scatter(class0['X'], class0['Y'], c='blue', edgecolors='k', s=100, marker='o', label='Training Class 0')
        axes[i].scatter(class1['X'], class1['Y'], c='red', edgecolors='k', s=100, marker='o', label='Training Class 1')

        # Add a reference line for y = x (the true boundary)
        axes[i].plot([0, 10], [0, 10], 'k--', alpha=0.7, label='y = x line')

        # Add labels
        axes[i].set_xlabel('X Feature', fontsize=12)
        axes[i].set_ylabel('Y Feature', fontsize=12)
        axes[i].set_title(f'k={k}', fontsize=14)
        axes[i].grid(True, alpha=0.3)
        axes[i].set_xlim(0, 10)
        axes[i].set_ylim(0, 10)

        # Only add legend to the first plot to avoid cluttering
        if i == 0:
            axes[i].legend(loc='upper right')

    # Remove any empty subplots
    for j in range(i+1, len(axes)):
        fig.delaxes(axes[j])

    plt.tight_layout()
    plt.suptitle('kNN Decision Boundaries for Different k Values', fontsize=16, y=1.02)

    # Create a more detailed figure showing the evolution of the boundary as k increases
    plt.figure(figsize=(16, 12))

    # Use a colormap to distinguish different k values
    cmap = plt.cm.viridis
    colors = cmap(np.linspace(0, 1, len(k_values)))

    # Plot the training data
```

```
        class0 = train_df[train_df['Class'] == 0]
        class1 = train_df[train_df['Class'] == 1]

        plt.scatter(class0['X'], class0['Y'], c='blue', edgecolors='k', s=150, marker='o', label='Training Class 0')
        plt.scatter(class1['X'], class1['Y'], c='red', edgecolors='k', s=150, marker='o', label='Training Class 1')

        # Plot the y = x line (true boundary)
        plt.plot([0, 10], [0, 10], 'k--', linewidth=2, label='True Boundary (y = x)')

        # Create a grid for extracting contours
        plt.grid(True, alpha=0.3)

        # Plot the decision boundary contours for each k
        for i, k in enumerate(k_values):
            pred_col = f'Predicted_Class_k{k}'
            predictions = test_df[pred_col].values
            Z = predictions.reshape(X_grid.shape)

            # Plot the contour line where Z = 0.5 (the decision boundary)
            contour = plt.contour(X_grid, Y_grid, Z, levels=[0.5], colors=[colors[i]], linewidths=2)

        plt.xlabel('X Feature', fontsize=14)
        plt.ylabel('Y Feature', fontsize=14)
        plt.title('Comparison of kNN Decision Boundaries for Different k Values', fontsize=16)
        plt.xlim(0, 10)
        plt.ylim(0, 10)
        plt.legend(loc='upper right')

        plt.tight_layout()

    # Main execution
    train_data = generate_training_data()
    test_data, X_grid, Y_grid = generate_test_data()

    # Define a range of k values to test
    k_values = [1, 3, 5, 7, 9, 11, 15, 19]
```

```
    # Perform classification with different k values
    for k in k_values:
        test_data, _ = knn_classification(train_data, test_data, k)

    # Print summary
    print("Training Data Summary:")
    print(f"Number of points: {len(train_data)}")
    print(f"Class 0 (Blue): {len(train_data[train_data['Class'] == 0])}")
    print(f"Class 1 (Red): {len(train_data[train_data['Class'] == 1])}")
    print("\nTest Data Summary:")
    for k in k_values:
        pred_col = f'Predicted_Class_k{k}'
        print(f"k={k}:")
        print(f"  Predicted Class 0 (Blue): {len(test_data[test_data[pred_col] == 0])}")
        print(f"  Predicted Class 1 (Red): {len(test_data[test_data[pred_col] == 1])}")

    # Visualize results for multiple k values
    visualize_results_for_multiple_k(train_data, test_data, X_grid, Y_grid, k_values)
    plt.show()
```

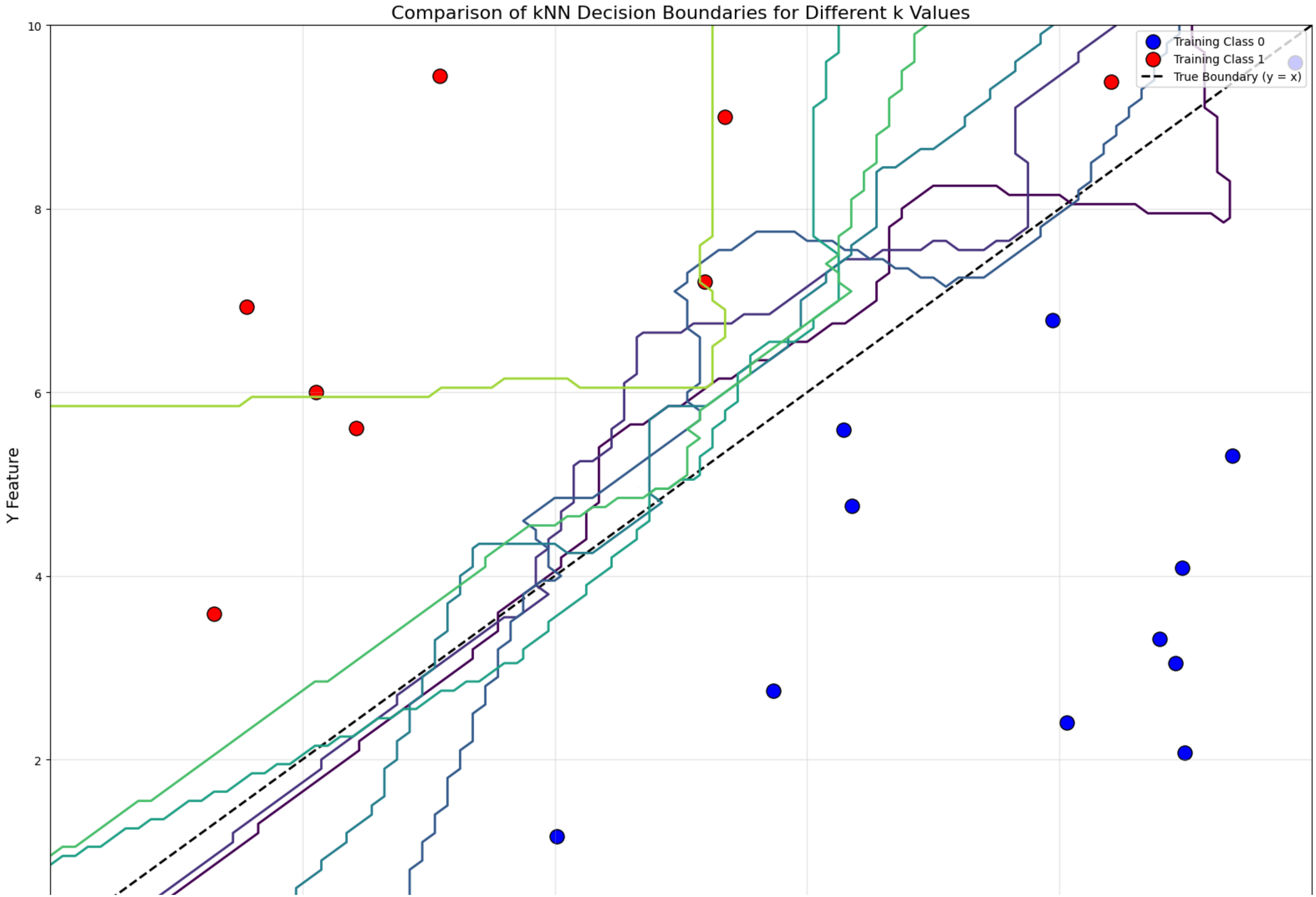
```
Training Data Summary:
Number of points: 20
Class 0 (Blue): 12
Class 1 (Red): 8

Test Data Summary:
k=1:
  Predicted Class 0 (Blue): 5235
  Predicted Class 1 (Red): 4966
k=3:
  Predicted Class 0 (Blue): 5637
  Predicted Class 1 (Red): 4564
k=5:
  Predicted Class 0 (Blue): 5043
  Predicted Class 1 (Red): 5158
k=7:
  Predicted Class 0 (Blue): 5501
  Predicted Class 1 (Red): 4700
k=9:
  Predicted Class 0 (Blue): 5934
  Predicted Class 1 (Red): 4267
k=11:
  Predicted Class 0 (Blue): 6151
  Predicted Class 1 (Red): 4050
k=15:
  Predicted Class 0 (Blue): 8041
  Predicted Class 1 (Red): 2160
k=19:
  Predicted Class 0 (Blue): 10201
  Predicted Class 1 (Red): 0
```




X Feature
X Feature
k=5
k=7
Y Feature
X Feature
X Feature
k=9
k=11
Y Feature
X Feature
X Feature
k=15
k=19
Y Feature


X Feature


X Feature


Comparison of kNN Decision Boundaries for Different k Values
Training Class 0
Training Class 1
True Boundary (y = x)
Y Feature


0
0
2
4
6
8
10
X Feature

A6

```
# A3: Make a scatter plot of the training data colored by class
def plot_training_data(data):
    plt.figure(figsize=(10, 8))

    # Scatter plot with colors based on class
    for class_label, color, label in zip([1, 2], ['green', 'red'], ['Medium', 'High']):
        mask = data['class'] == class_label
        plt.scatter(
            data.loc[mask, 'max'],
            data.loc[mask, 'distance_to_event'],
            c=color,
            label=f'Class {label}',
            alpha=0.7,
            edgecolors='k'
        )

    # Add labels and title
    plt.xlabel('Maximum Amplitude (max)', fontsize=12)
    plt.ylabel('Distance to Event', fontsize=12)
    plt.title('Seismic Data: Max Amplitude vs Distance to Event', fontsize=14)
    plt.grid(True, alpha=0.3)
    plt.legend()

    plt.tight_layout()

    # Display class distribution
    class_counts = data['class'].value_counts().sort_index()
    print("Class Distribution:")
    for i, count in enumerate(class_counts):
        class_name = ['Low', 'Medium', 'High'][i]
        print(f"Class {i} ({class_name}): {count} samples")

    return plt
```

```
# A4: Generate test grid and apply kNN classification
def apply_knn_classification(train_data, k=3):
    # Create a grid of test points
    x_min, x_max = train_data['max'].min(), train_data['max'].max()
    y_min, y_max = train_data['distance_to_event'].min(), train_data['distance_to_event'].max()

    # Add some margin
    x_margin = (x_max - x_min) * 0.05
    y_margin = (y_max - y_min) * 0.05

    x_min -= x_margin
    x_max += x_margin
    y_min -= y_margin
    y_max += y_margin

    # Create grid with reasonable increments
    x_step = (x_max - x_min) / 100
    y_step = (y_max - y_min) / 100

    xx, yy = np.meshgrid(
        np.arange(x_min, x_max, x_step),
        np.arange(y_min, y_max, y_step)
    )

    # Transform the grid into a feature array
    test_points = np.c_[xx.ravel(), yy.ravel()]

    # Fit a kNN classifier
    X_train = train_data[['max', 'distance_to_event']].values
    y_train = train_data['class'].values

    # Scale the features for better distance calculation
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    test_points_scaled = scaler.transform(test_points)
```

```
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)

    # Predict the class for each test point
    y_pred = knn.predict(test_points_scaled)

    # Reshape the predictions to match the grid
    grid_predictions = y_pred.reshape(xx.shape)

    # Visualize the results
    plt.figure(figsize=(12, 10))

    # Plot the decision boundaries
    plt.contourf(xx, yy, grid_predictions, alpha=0.3, cmap=plt.cm.viridis)

    # Plot the training data
    for class_label, color, label in zip([1, 2], ['green', 'red'], ['Medium', 'High']):
        mask = train_data['class'] == class_label
        plt.scatter(
            train_data.loc[mask, 'max'],
            train_data.loc[mask, 'distance_to_event'],
            c=color,
            label=f'Class {label}',
            edgecolors='k'
        )

    plt.xlabel('Maximum Amplitude (max)', fontsize=14)
    plt.ylabel('Distance to Event', fontsize=14)
    plt.title(f'kNN Classification (k={k}) of Seismic Data', fontsize=16)
    plt.grid(True, alpha=0.3)
    plt.legend()

    plt.tight_layout()

    return plt, grid_predictions

# A5: Compare different k values
```

```
def compare_k_values(train_data, k_values):
    # Create a figure for multiple subplots
    n_rows = len(k_values) // 2 + len(k_values) % 2
    fig, axes = plt.subplots(n_rows, 2, figsize=(16, 5*n_rows))
    axes = axes.flatten() if n_rows > 1 else [axes] if isinstance(axes, np.ndarray) else [axes]

    # Create a grid of test points
    x_min, x_max = train_data['max'].min(), train_data['max'].max()
    y_min, y_max = train_data['distance_to_event'].min(), train_data['distance_to_event'].max()

    # Add some margin
    x_margin = (x_max - x_min) * 0.05
    y_margin = (y_max - y_min) * 0.05

    x_min -= x_margin
    x_max += x_margin
    y_min -= y_margin
    y_max += y_margin

    # Create grid with reasonable increments
    x_step = (x_max - x_min) / 100
    y_step = (y_max - y_min) / 100

    xx, yy = np.meshgrid(
        np.arange(x_min, x_max, x_step),
        np.arange(y_min, y_max, y_step)
    )

    # Transform the grid into a feature array
    test_points = np.c_[xx.ravel(), yy.ravel()]

    # Prepare the training data
    X_train = train_data[['max', 'distance_to_event']].values
    y_train = train_data['class'].values

    # Scale the features
    scaler = StandardScaler()
```

```
    X_train_scaled = scaler.fit_transform(X_train)
    test_points_scaled = scaler.transform(test_points)

    # For each k value
    for i, k in enumerate(k_values):
        # Fit a kNN classifier
        knn = KNeighborsClassifier(n_neighbors=k)
        knn.fit(X_train_scaled, y_train)

        # Predict the class for each test point
        y_pred = knn.predict(test_points_scaled)

        # Reshape the predictions to match the grid
        grid_predictions = y_pred.reshape(xx.shape)

        # Plot on the corresponding subplot
        axes[i].contourf(xx, yy, grid_predictions, alpha=0.3, cmap=plt.cm.viridis)

        # Plot the training data
        for class_label, color in zip([1, 2], ['green', 'red']):
            mask = train_data['class'] == class_label
            axes[i].scatter(
                train_data.loc[mask, 'max'],
                train_data.loc[mask, 'distance_to_event'],
                c=color,
                s=50,
                alpha=0.7,
                edgecolors='k'
            )

        axes[i].set_xlabel('Maximum Amplitude (max)')
        axes[i].set_ylabel('Distance to Event')
        axes[i].set_title(f'k={k}')
        axes[i].grid(True, alpha=0.3)

    # Hide any unused subplots
    for j in range(i+1, len(axes)):
```

```
            axes[j].set_visible(False)

        plt.suptitle('kNN Classification with Different k Values', fontsize=16)
        plt.tight_layout(rect=[0, 0, 1, 0.96])  # Adjust for the suptitle

        return plt

    data = pd.read_csv("combined_seismic_data.csv")
    data["class"] = create_intensity_classes(data)

    # A3: Plot the training data
    training_plot = plot_training_data(data)
    plt.show()

    # A4: Apply kNN with k=3
    knn_plot, predictions = apply_knn_classification(data, k=3)
    plt.show()

    # A5: Compare different k values
    k_values = [1, 3, 5, 7, 9, 15]
    comparison_plot = compare_k_values(data, k_values)
    plt.show()
```