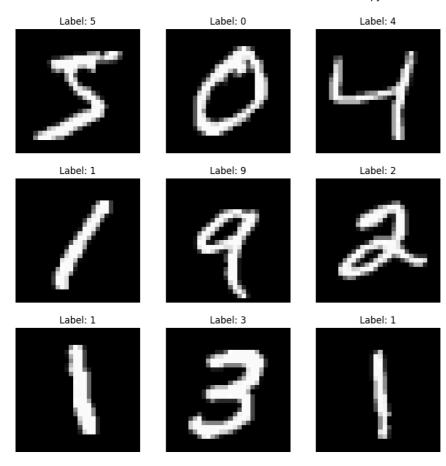
```
# Import basic libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# Import the libraries for performing classification
from sklearn.svm import SVC
from sklearn.pipeline import Pipeline
from \ sklearn.preprocessing \ import \ MinMaxScaler
from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV
from \ sklearn.metrics \ import \ classification\_report, \ confusion\_matrix
# Fetch the MNIST dataset from openml
from sklearn.datasets import fetch_openml
mnist = fetch_openml('mnist_784', version=1)
X, y = mnist["data"], mnist["target"]
# Convert target labels to integers
y = y.astype(np.int8)
# Check the shapes of the dataset
print("Shape of X (data):", X.shape) # Should be (70000, 784)
print("Shape of y (labels):", y.shape) # Should be (70000,)
 🧓 /usr/local/lib/python3.10/dist-packages/sklearn/datasets/_openml.py:1022: FutureWarning: The default value of `parser` will change ។
      warn(
     Shape of X (data): (70000, 784)
     Shape of y (labels): (70000,)
                                                                                                                                         >
# Plot the first few images from the dataset
plt.figure(figsize=(10, 10))
for i in range(9):
    plt.subplot(3, 3, i+1)
    # Access the i-th row of the DataFrame using .iloc[]
    plt.imshow(X.iloc[i].values.reshape(28, 28), cmap='gray')
    plt.title(f"Label: {y[i]}")
    plt.axis('off')
plt.show()
```



```
\mbox{\tt\#} Flatten each input image into a vector of length 784 and normalize the data
X = X / 255.0 # Normalize
# Check the shape of the dataset
print("Shape after flattening and normalizing, X:", X.shape)

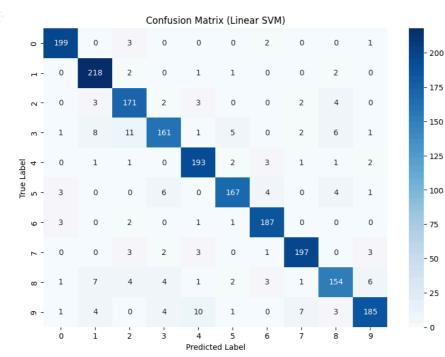
    Shape after flattening and normalizing, X: (70000, 784)

# Splitting the dataset
X_train, X_test, y_train, y_test = X[:10000], X[10000:12000], y[:10000], y[10000:12000]
# Check the shape of the training and testing sets
print("Training data shape:", X_train.shape)
print("Testing data shape:", X_test.shape)
Training data shape: (10000, 784)
     Testing data shape: (2000, 784)
# Train Linear SVM using a pipeline with MinMaxScaler and SVC with a linear kernel
pipe_1 = Pipeline([('scaler', MinMaxScaler()),
                   ('classifier', SVC(kernel='linear', C=1))])
# Fit the model
pipe_1.fit(X_train, y_train.ravel())
# Evaluate using cross-validation
acc = cross_val_score(pipe_1, X_train, y_train.ravel(), cv=2)
print("Training Accuracy with Linear SVM: {:.2f} %".format(acc.mean() * 100))

→ Training Accuracy with Linear SVM: 91.07 %

# Predicting on test data
y_pred = pipe_1.predict(X_test)
```

```
# contusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
\ensuremath{\text{\#}} Plotting heatmap for confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix (Linear SVM)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
# Classification report
print("Classification Report for Linear SVM:\n")
print(classification_report(y_test, y_pred))
```



Classification Report for Linear SVM:

	precision	recall	f1-score	support
0	0.06	0.07	0.06	205
0	0.96	0.97	0.96	205
1	0.90	0.97	0.94	224
2	0.87	0.92	0.90	185
3	0.90	0.82	0.86	196
4	0.91	0.95	0.93	204
5	0.93	0.90	0.92	185
6	0.94	0.96	0.95	194
7	0.94	0.94	0.94	209
8	0.89	0.84	0.86	183
9	0.93	0.86	0.89	215
accuracy			0.92	2000
macro avg	0.92	0.91	0.91	2000
weighted avg	0.92	0.92	0.92	2000

```
# Train Nonlinear SVM using a pipeline with MinMaxScaler and SVC with RBF kernel
pipe_2 = Pipeline([('scaler', MinMaxScaler()),
                   ('classifier', SVC(kernel='rbf', gamma=0.1, C=1))])
# Fit the model
pipe_2.fit(X_train, y_train.ravel())
# Evaluate using cross-validation
acc = cross_val_score(pipe_2, X_train, y_train.ravel(), cv=2)
print("Training Accuracy with Nonlinear SVM: {:.2f} %".format(acc.mean() * 100))
```

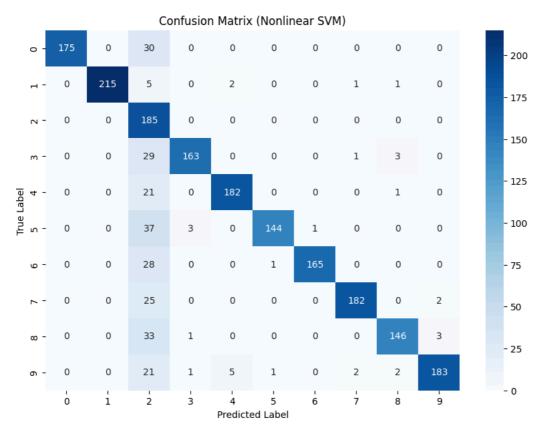
Training Accuracy with Nonlinear SVM: 82.87 %

```
# Predicting on test data
y_pred_rbf = pipe_2.predict(X_test)

# Confusion matrix
conf_matrix_rbf = confusion_matrix(y_test, y_pred_rbf)

# Plotting heatmap for confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_rbf, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix (Nonlinear SVM)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()

# Classification report
print("Classification Report for Nonlinear SVM:\n")
print(classification_report(y_test, y_pred_rbf))
```



 ${\tt Classification}\ {\tt Report}\ {\tt for}\ {\tt Nonlinear}\ {\tt SVM:}$

	precision	recall	f1-score	support
0	1.00	0.85	0.92	205
1	1.00	0.96	0.98	224
2	0.45	1.00	0.62	185
3	0.97	0.83	0.90	196
4	0.96	0.89	0.93	204
5	0.99	0.78	0.87	185
6	0.99	0.85	0.92	194
7	0.98	0.87	0.92	209
8	0.95	0.80	0.87	183
9	0.97	0.85	0.91	215
accuracy			0.87	2000
macro avg	0.93	0.87	0.88	2000
weighted avg	0.93	0.87	0.89	2000

```
# Best parameters
print("Best parameters found by GridSearch:", grid_search.best_params_)
# Evaluate best model
best_model = grid_search.best_estimator_
y_pred_best = best_model.predict(X_test)
# Confusion matrix and classification report for the best model
conf_matrix_best = confusion_matrix(y_test, y_pred_best)
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_best, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix (Best Model)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
# Print classification report
print("Classification Report for Best Model:\n")
print(classification_report(y_test, y_pred_best))
```

→ Best parameters found by GridSearch: {'classifier_C': 10, 'classifier_gamma': 0.01}

