Team

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Github : https://github.com/adapaaa/CNN-Project.git

Data Preparation

1. **Load the MNIST dataset:**

The MNIST dataset is loaded using the `fetch_ucirepo` function from the `ucimlrepo` library. The dataset is fetched with the ID 80, which corresponds to the "Optical Recognition of Handwritten Digits" dataset.

2. **Preprocess the data:**

The data is preprocessed using the `preprocess_data` function. The preprocessing steps include:

- Reshaping the data to be compatible with the CNN input shape (8, 8, 1)
- Normalizing the pixel values to be between 0 and 1 by dividing by 16.0

Convolutional Neural Network Architecture:

The CNN architecture consists of the following layers:

1. Convolutional layer with 32 filters, 3x3 kernel size, ReLU activation, and same padding to preserve input dimensions.
2. Max pooling layer with a 2x2 pool size for downsampling.
3. Convolutional layer with 64 filters, 3x3 kernel size, ReLU activation, and same padding.
4. Max pooling layer with a 2x2 pool size for further downsampling.
5. Convolutional layer with 64 filters, 3x3 kernel size, ReLU activation, and same padding.
6. Flatten layer to convert the 3D feature maps to a 1D vector.
7. Fully connected layer with 64 units and ReLU activation.
8. Output layer with 10 units (one for each digit) and softmax activation for classification.

Max Pooling:

Max pooling is implemented after each set of convolutional layers. The max pooling layers have a pool size of 2x2, which means that the input feature maps are downsampled by taking the maximum value over a 2x2 window. This process reduces the spatial dimensions of the feature maps and helps in reducing computation and introducing translation invariance.

Fully Connected Layer and Softmax :

The convolutional layers are followed by a flatten layer, which converts the 3D feature maps into a 1D vector. This 1D vector is then connected to a fully connected layer with 64 units and ReLU activation. The fully connected layer is responsible for learning the high-level features from the convolutional layers.

Finally, an output layer with 10 units and softmax activation is used for classification. The softmax activation function converts the output values into probabilities, where each output represents the probability of the input image belonging to a particular digit class.

Training and Evaluation:

The CNN model is trained and evaluated using the `train_and_evaluate_model` function, which performs K-fold cross-validation with 5 folds.

1. Training:

- The model is compiled with the Adam optimizer and sparse categorical cross-entropy loss function.
- The model is trained for 5 epochs on the training split of each fold.
- The validation loss and accuracy are recorded for each fold.

2. Evaluation:

- After training, the model's predictions are made on the test split of each fold.
- The confusion matrix is computed for each fold to analyze the model's performance.

3. Analysis:

- The validation loss and accuracy curves are plotted for each fold using `plot_loss_curves` and `plot_accuracy_curves` functions.
- The average confusion matrix is computed and plotted using the `plot_confusion_matrix` function.

K-Fold & Confusion Matrix:

K-fold cross-validation with 5 folds is implemented, and the confusion matrix is computed for each fold. The average confusion matrix is also plotted to analyze the model's performance across all folds.

Analysis:

Convolutional layers: Convolutional layers extract low-level features from the input images by applying learnable filters. The ReLU activation function introduces non-linearity, and the padding ensures that the input and output dimensions are preserved.

- **Max pooling layers:** Max pooling layers downsample the feature maps by taking the maximum value in each window, reducing the spatial dimensions and introducing translation invariance.
- **Fully connected layer:** The fully connected layer combines the high-level features extracted by the convolutional layers and learns the mapping to the output classes.
- **Softmax activation:** The softmax activation function produces a probability distribution over the output classes, enabling the model to perform multi-class classification.

cnn-project-2

May 2, 2024

[17]:
```
pip install ucimlrepo
```

Requirement already satisfied: ucimlrepo in c:\users\nmkva\anaconda3\lib\site-packages (0.0.6)
Note: you may need to restart the kernel to use updated packages.

[204]:
```
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
from sklearn.model_selection import KFold
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from ucimlrepo import fetch_ucirepo
from tensorflow.keras.utils import plot_model
```

Load The Dataset from the ucimlrepo

[205]:
```
# fetch dataset
optical_recognition_of_handwritten_digits = fetch_ucirepo(id=80)

# data (as pandas dataframes)
X = optical_recognition_of_handwritten_digits.data.features
y = optical_recognition_of_handwritten_digits.data.targets

# metadata
print(optical_recognition_of_handwritten_digits.metadata)

# variable information
print(optical_recognition_of_handwritten_digits.variables)
```

{'uci_id': 80, 'name': 'Optical Recognition of Handwritten Digits', 'repository_url': 'https://archive.ics.uci.edu/dataset/80/optical+recognition+of+handwritten+digits', 'data_url': 'https://archive.ics.uci.edu/static/public/80/data.csv', 'abstract': 'Two versions of this database available; see folder', 'area': 'Computer Science', 'tasks': ['Classification'], 'characteristics': ['Multivariate'], 'num_instances': 5620, 'num_features': 64, 'feature_types': ['Integer'], 'demographics': [], 'target_col': ['class'], 'index_col': None, 'has_missing_values': 'no', 'missing_values_symbol': None, 'year_of_dataset_creation': 1998, 'last_updated': 'Wed Aug 23 2023', 'dataset_doi': '10.24432/C50P49', 'creators': ['E. Alpaydin', 'C. Kaynak'], 'intro_paper': {'title': 'Methods of Combining Multiple Classifiers and Their Applications to Handwritten Digit Recognition', 'authors': 'C. Kaynak', 'published_in': 'MSc Thesis, Institute of Graduate Studies in Science and Engineering, Bogazici University', 'year': 1995, 'url': None, 'doi': None}, 'additional_info': {'summary': 'We used preprocessing programs made available by NIST to extract normalized bitmaps of handwritten digits from a preprinted form. From a total of 43 people, 30 contributed to the training set and different 13 to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of 4x4 and the number of on pixels are counted in each block. This generates an input matrix of 8x8 where each element is an integer in the range 0..16. This reduces dimensionality and gives invariance to small distortions.\r\n\r\nFor info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G. T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C. L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469, 1994.', 'purpose': None, 'funded_by': None, 'instances_represent': None, 'recommended_data_splits': None, 'sensitive_data': None, 'preprocessing_description': None, 'variable_info': 'All input attributes are integers in the range 0..16.\r\nThe last attribute is the class code 0..9', 'citation': None}}

	name	role	type	demographic	description	units \
0	Attribute1	Feature	Integer	None	None	None
1	Attribute2	Feature	Integer	None	None	None
2	Attribute3	Feature	Integer	None	None	None
3	Attribute4	Feature	Integer	None	None	None
4	Attribute5	Feature	Integer	None	None	None
..	...	...	...	...	...	...
60	Attribute61	Feature	Integer	None	None	None
61	Attribute62	Feature	Integer	None	None	None
62	Attribute63	Feature	Integer	None	None	None
63	Attribute64	Feature	Integer	None	None	None
64	class	Target	Categorical	None	None	None

	missing_values
0	no
1	no
2	no
3	no
4	no
..	...
60	no
61	no
62	no
63	no
64	no

[65 rows x 7 columns]

Preprocess The data reshaping and normalizing

[206]:
```
# Data Preparation
def preprocess_data(X):
    # Reshape data to be compatible with CNN
    # Convert DataFrame to numpy array
    X_array = X.to_numpy()
    X_reshaped = X_array.reshape((X.shape[0], 8, 8, 1))
    # Normalize pixel values to be between 0 and 1
    X_normalized = X_reshaped / 16.0
    return X_normalized
```

Building the CNN Model

[207]:
```
def create_model():
    # Create a sequential model
    model = models.Sequential()

    # Convolutional layers
    # Add the first convolutional layer with 32 filters, each of size 3x3,
    # ReLU activation, and same padding to preserve input dimensions
    model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(8, 8,␣
↪1), padding='same'))
    # Add a max pooling layer to down-sample the feature maps by taking
    # the maximum value over a 2x2 window
    model.add(layers.MaxPooling2D((2, 2)))

    # Add the second convolutional layer with 64 filters, each of size 3x3,
    # ReLU activation, and same padding
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    # Another max pooling layer for further down-sampling
    model.add(layers.MaxPooling2D((2, 2)))

    # Add the third convolutional layer with 64 filters, each of size 3x3,
    # ReLU activation, and same padding
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))

    # Fully connected layers
    # Flatten the 3D feature maps to a 1D vector to feed into the fully␣
↪connected layers
    model.add(layers.Flatten())
    # Add a fully connected layer with 64 neurons and ReLU activation
    model.add(layers.Dense(64, activation='relu'))
    # Add an output layer with 10 neurons (for 10 classes) and softmax␣
↪activation
    # to output probabilities for each class
    model.add(layers.Dense(10, activation='softmax'))
```

```
    return model
```

Training and Evaluation of The Model

[208] :
```
# Training and Evaluation
def train_and_evaluate_model(model, X, y):
    kf = KFold(n_splits=5, shuffle=True, random_state=42)
    fold_accuracies = []
    fold_losses = []
    fold_confusion_matrices = []

    for i, (train_index, test_index) in enumerate(kf.split(X)):
        print(f"Fold {i+1}/{kf.get_n_splits()}")

        X_train, X_test = X[train_index], X[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]    # Resetting␣
↪the index of y

        #Compiling the mode using adam optimizer
        model.compile(optimizer='adam',
                      loss='sparse_categorical_crossentropy',
                      metrics=['accuracy'])

        #Training the model
        history = model.fit(X_train, y_train, epochs=5,␣
↪validation_data=(X_test, y_test))

        fold_accuracies.append(history.history['val_accuracy'])
        fold_losses.append(history.history['val_loss'])

        # Confusion matrix
        y_pred = np.argmax(model.predict(X_test), axis=-1)
        cm = confusion_matrix(y_test, y_pred)
        fold_confusion_matrices.append(cm)

    return fold_losses,fold_accuracies,fold_confusion_matrices
```

Plot Loss Curves

[209]:
```
def plot_loss_curves(losses):
    plt.figure(figsize=(8, 6))
    for i, loss in enumerate(losses):
        plt.plot(loss, label=f'Fold {i+1}')
    plt.title('Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
```

Plot the Accuracy Curves

[210]:
```
def plot_accuracy_curves(accuracies):
    plt.figure(figsize=(8, 6))
    for i, acc in enumerate(accuracies):
        plt.plot(acc, label=f"Fold {i+1}")
    plt.title("Validation Accuracy")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.show()
```

Plot the Confusion Matrix

[211]:
```
def plot_confusion_matrix(cm):
    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation="nearest", cmap=plt.cm.Blues)
    plt.title("Confusion Matrix")
    plt.colorbar()
    tick_marks = np.arange(10)
    plt.xticks(tick_marks, tick_marks)
    plt.yticks(tick_marks, tick_marks)
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
    plt.show()
```

[212]:
```
# Preprocess data
X_normalized = preprocess_data(X)
# Create CNN model
print(X_normalized.shape)
```

```
(5620, 8, 8, 1)
```

[213]:
```
# Create CNN model
cnn_model = create_model()
cnn_model.summary()
```

```
C:\Users\nmkva\anaconda3\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(
```

Model: "sequential_20"

Layer (type)	Output Shape	Param #

conv2d_60 (Conv2D)	(None, 8, 8, 32)	320
max_pooling2d_40 (MaxPooling2D)	(None, 4, 4, 32)	0
conv2d_61 (Conv2D)	(None, 4, 4, 64)	18,496
max_pooling2d_41 (MaxPooling2D)	(None, 2, 2, 64)	0
conv2d_62 (Conv2D)	(None, 2, 2, 64)	36,928
flatten_18 (Flatten)	(None, 256)	0
dense_36 (Dense)	(None, 64)	16,448
dense_37 (Dense)	(None, 10)	650

Total params: 72,842 (284.54 KB)

Trainable params: 72,842 (284.54 KB)

Non-trainable params: 0 (0.00 B)

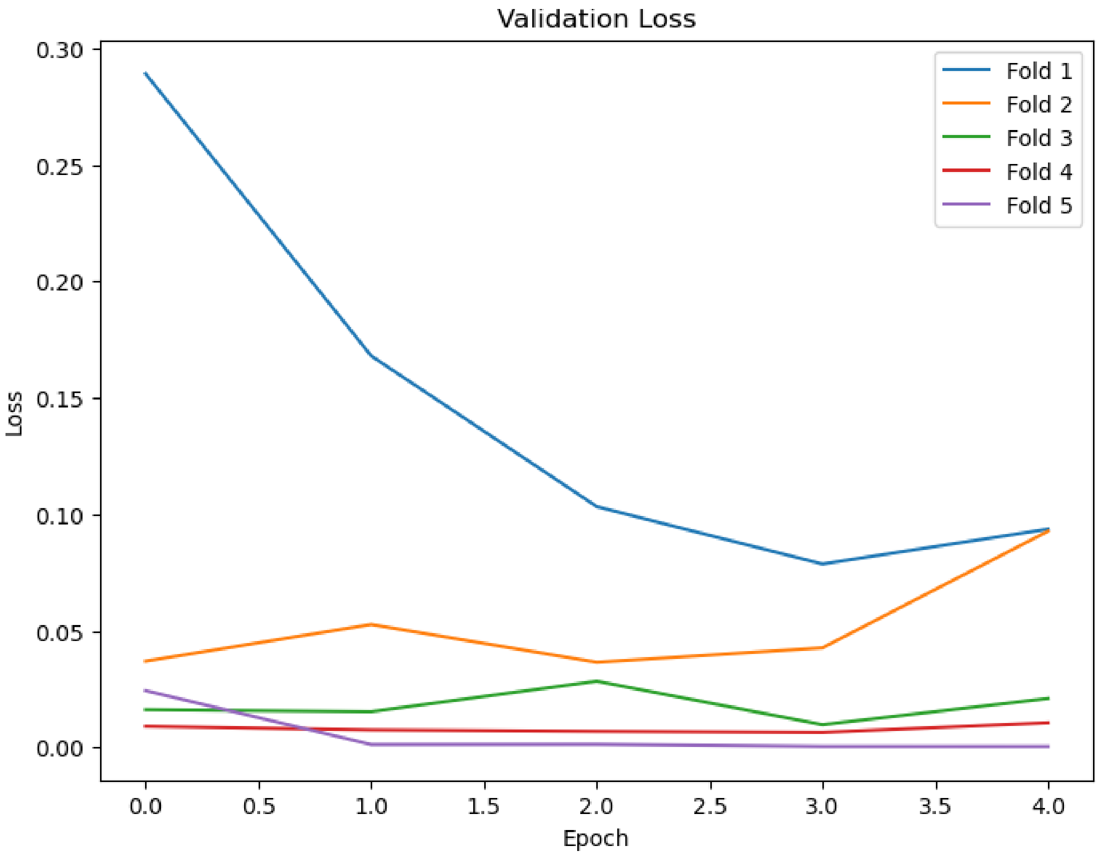
[180]:
```
# Train and evaluate the model
fold_losses,fold_accuracies,fold_confusion_matrices =␣
↪train_and_evaluate_model(cnn_model, X_normalized, y)
```

```
Fold 1/5
Epoch 1/5
141/141 5s 10ms/step -
accuracy: 0.4720 - loss: 1.6700 - val_accuracy: 0.9155 - val_loss: 0.2658
Epoch 2/5
141/141 1s 7ms/step -
accuracy: 0.9403 - loss: 0.1945 - val_accuracy: 0.9617 - val_loss: 0.1332
Epoch 3/5
141/141 1s 7ms/step -
accuracy: 0.9703 - loss: 0.1040 - val_accuracy: 0.9689 - val_loss: 0.1068
Epoch 4/5
141/141 1s 7ms/step -
accuracy: 0.9762 - loss: 0.0768 - val_accuracy: 0.9804 - val_loss: 0.0713
Epoch 5/5
141/141 1s 7ms/step -
accuracy: 0.9842 - loss: 0.0546 - val_accuracy: 0.9778 - val_loss: 0.0663
36/36 0s 6ms/step
```

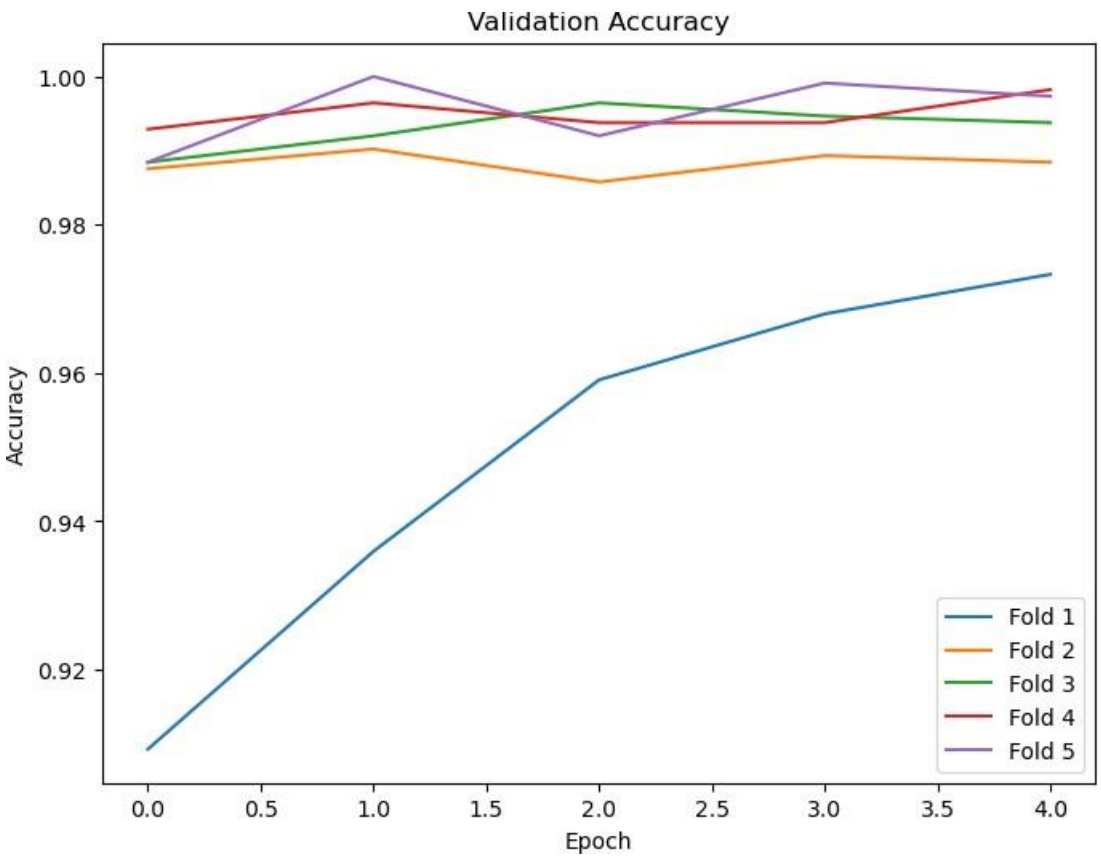
Fold 2/5
Epoch 1/5
141/141 **4s** 9ms/step -
accuracy: 0.9808 - loss: 0.0529 - val_accuracy: 0.9813 - val_loss: 0.0596
Epoch 2/5
141/141 **1s** 6ms/step -
accuracy: 0.9865 - loss: 0.0407 - val_accuracy: 0.9893 - val_loss: 0.0428
Epoch 3/5
141/141 **1s** 6ms/step -
accuracy: 0.9890 - loss: 0.0312 - val_accuracy: 0.9795 - val_loss: 0.0643
Epoch 4/5
141/141 **1s** 6ms/step -
accuracy: 0.9897 - loss: 0.0329 - val_accuracy: 0.9893 - val_loss: 0.0309
Epoch 5/5
141/141 **1s** 6ms/step -
accuracy: 0.9950 - loss: 0.0186 - val_accuracy: 0.9822 - val_loss: 0.0520
36/36 **0s** 5ms/step
Fold 3/5
Epoch 1/5
141/141 **4s** 8ms/step -
accuracy: 0.9893 - loss: 0.0313 - val_accuracy: 0.9875 - val_loss: 0.0406
Epoch 2/5
141/141 **1s** 6ms/step -
accuracy: 0.9916 - loss: 0.0248 - val_accuracy: 0.9956 - val_loss: 0.0112
Epoch 3/5
141/141 **1s** 6ms/step -
accuracy: 0.9944 - loss: 0.0159 - val_accuracy: 0.9929 - val_loss: 0.0214
Epoch 4/5
141/141 **1s** 6ms/step -
accuracy: 0.9970 - loss: 0.0119 - val_accuracy: 0.9947 - val_loss: 0.0174
Epoch 5/5
141/141 **1s** 6ms/step -
accuracy: 0.9940 - loss: 0.0141 - val_accuracy: 0.9947 - val_loss: 0.0193
36/36 **0s** 5ms/step
Fold 4/5
Epoch 1/5
141/141 **3s** 9ms/step -
accuracy: 0.9954 - loss: 0.0125 - val_accuracy: 0.9867 - val_loss: 0.0308
Epoch 2/5
141/141 **1s** 7ms/step -
accuracy: 0.9974 - loss: 0.0102 - val_accuracy: 0.9964 - val_loss: 0.0117
Epoch 3/5
141/141 **1s** 6ms/step -
accuracy: 0.9980 - loss: 0.0061 - val_accuracy: 0.9911 - val_loss: 0.0355
Epoch 4/5
141/141 **1s** 6ms/step -
accuracy: 0.9956 - loss: 0.0090 - val_accuracy: 0.9973 - val_loss: 0.0083
Epoch 5/5

```
141/141 1s 6ms/step -
accuracy: 1.0000 - loss: 0.0020 - val_accuracy: 0.9947 - val_loss: 0.0196
36/36 0s 5ms/step
Fold 5/5
Epoch 1/5
141/141 3s 8ms/step -
accuracy: 0.9949 - loss: 0.0132 - val_accuracy: 1.0000 - val_loss: 6.3302e-04
Epoch 2/5
141/141 1s 7ms/step -
accuracy: 1.0000 - loss: 0.0016 - val_accuracy: 0.9982 - val_loss: 0.0049
Epoch 3/5
141/141 1s 6ms/step -
accuracy: 0.9993 - loss: 0.0027 - val_accuracy: 0.9964 - val_loss: 0.0115
Epoch 4/5
141/141 1s 6ms/step -
accuracy: 0.9940 - loss: 0.0142 - val_accuracy: 0.9982 - val_loss: 0.0048
Epoch 5/5
141/141 1s 6ms/step -
accuracy: 0.9981 - loss: 0.0064 - val_accuracy: 0.9973 - val_loss: 0.0070
36/36 0s 4ms/step
```

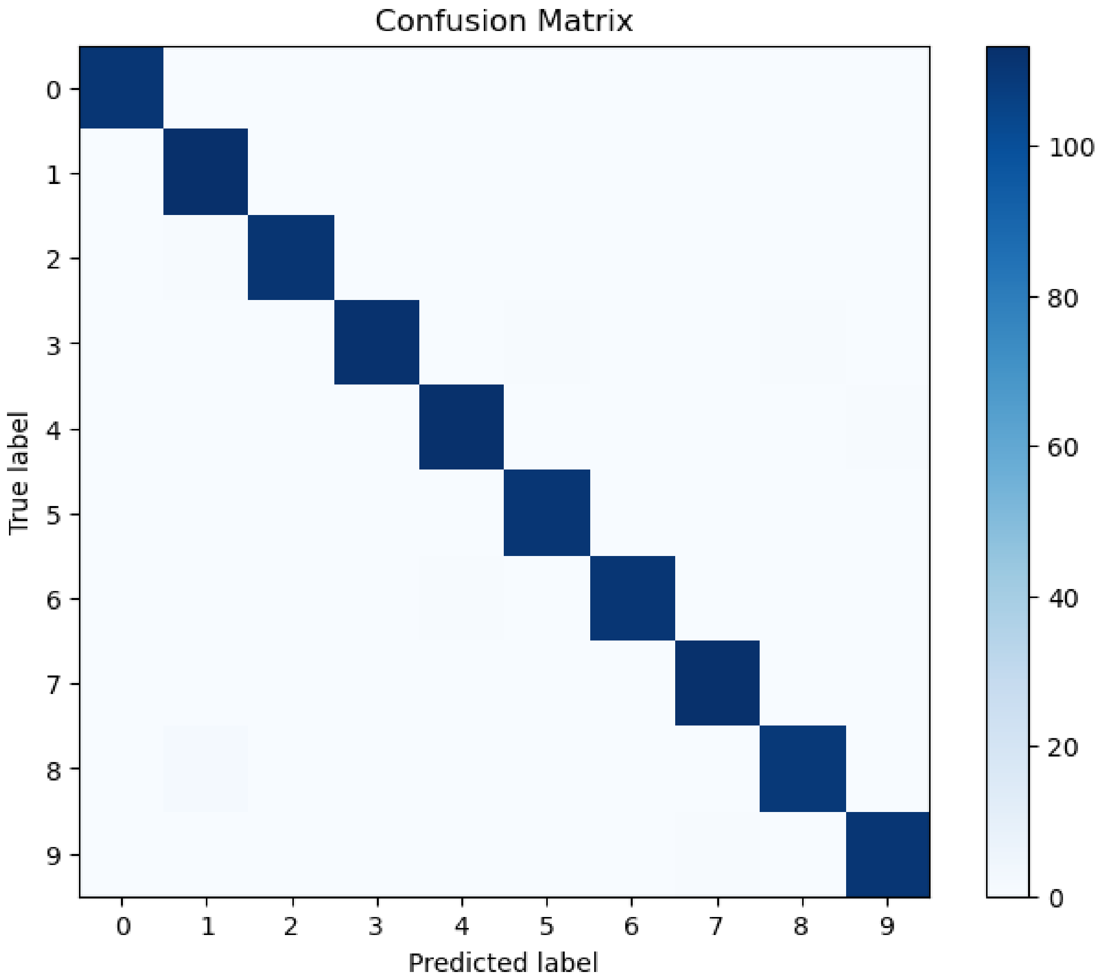
[157]:
```python
# Plotting loss curves
plot_loss_curves(fold_losses)
```



[133]:
```
# Plotting accuracy curves
plot_accuracy_curves(fold_accuracies)
```



[134]:
```
# Average confusion matrix
average_cm = np.mean(fold_confusion_matrices, axis=0)
plot_confusion_matrix(average_cm)
```



Confusion Matrix
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
100
80
60
40
20
0