MLF_CNN

May 1, 2024

[1]:
```
import pandas as pd
import numpy as np
from sklearn.datasets import fetch_openml
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,␣
↪Dropout
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold
from tensorflow.keras import layers, models, utils
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
from tensorflow.keras.utils import to_categorical  # Correctly importing␣
↪to_categorical
from ucimlrepo import fetch_ucirepo
```

[2]:
```
# 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)

# Optionally, print some information about the data
print("Features shape:", X.shape)
print("Target shape:", y.shape)
print("Unique digits in target:", np.unique(y))
```

```
{'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]
Features shape: (5620, 64)
Target shape: (5620, 1)
Unique digits in target: [0 1 2 3 4 5 6 7 8 9]
```

[3]:
```python
def create_model():
    model = models.Sequential([
        layers.Conv2D(32, kernel_size=(3, 3), activation='relu',␣
 ↪input_shape=(8, 8, 1)),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Dropout(0.25),
        layers.Conv2D(64, (3, 3), activation='relu'),
        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(10, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
    return model

model = create_model()
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 6, 6, 32)          320

 max_pooling2d (MaxPooling2  (None, 3, 3, 32)          0
 D)

 dropout (Dropout)           (None, 3, 3, 32)          0

 conv2d_1 (Conv2D)           (None, 1, 1, 64)          18496

 flatten (Flatten)           (None, 64)                0

 dense (Dense)               (None, 128)               8320

 dropout_1 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 10)                1290
```

```
=================================================================
Total params: 28426 (111.04 KB)
Trainable params: 28426 (111.04 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[4]:
```
# Convert features and labels to numpy arrays (if they are not already)
X = np.array(X)
y = np.array(y)

# Reshape X to fit the model input shape: (n_samples, 8, 8, 1)
X = X.reshape(-1, 8, 8, 1)

# Normalize the feature data
X = X.astype('float32') / 16  # Assuming pixel values range from 0 to 16

# One-hot encode the target labels
y = to_categorical(y, num_classes=10)
```

[5]:
```
# Initialize lists to store test labels and predictions
y_true = []
y_pred = []
all_train_loss = []
all_val_loss = []
all_train_acc = []
all_val_acc = []

num_folds = 5
kf = KFold(n_splits=num_folds, shuffle=True, random_state=42)
fold_no = 1

for train, test in kf.split(X):
    print(f'Training fold {fold_no}...')
   ␣
 ↪print('------------------------------------------------------------------------')
    print(f'Training for fold {fold_no} ...')

    # Fit data to model
    history = model.fit(X[train], y[train],
                        batch_size=32,
                        epochs=10,
                        verbose=1,
                        validation_data=(X[test], y[test]))

    # Append loss and accuracy
    all_train_loss.extend(history.history['loss'])
    all_val_loss.extend(history.history['val_loss'])
```

```python
    all_train_acc.extend(history.history['accuracy'])
    all_val_acc.extend(history.history['val_accuracy'])

    # Generate generalization metrics
    scores = model.evaluate(X[test], y[test], verbose=0)
    print(f'Score for fold {fold_no}: {model.metrics_names[0]} of {scores[0]};␣
↪{model.metrics_names[1]} of {scores[1]*100}%')

    # Predict on the test data
    predictions = model.predict(X[test], batch_size=32)
    y_pred.extend(np.argmax(predictions, axis=1))
    y_true.extend(np.argmax(y[test], axis=1))

    fold_no += 1
```

```
Training fold 1…
------------------------------------------------------------------------
Training for fold 1 …
Epoch 1/10
141/141 [==============================] - 1s 3ms/step - loss: 1.4540 -
accuracy: 0.5347 - val_loss: 0.3917 - val_accuracy: 0.9128
Epoch 2/10
141/141 [==============================] - 0s 2ms/step - loss: 0.4386 -
accuracy: 0.8648 - val_loss: 0.2316 - val_accuracy: 0.9288
Epoch 3/10
141/141 [==============================] - 0s 2ms/step - loss: 0.3113 -
accuracy: 0.9070 - val_loss: 0.1645 - val_accuracy: 0.9466
Epoch 4/10
141/141 [==============================] - 0s 2ms/step - loss: 0.2383 -
accuracy: 0.9315 - val_loss: 0.1366 - val_accuracy: 0.9573
Epoch 5/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1842 -
accuracy: 0.9464 - val_loss: 0.1118 - val_accuracy: 0.9671
Epoch 6/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1718 -
accuracy: 0.9475 - val_loss: 0.1018 - val_accuracy: 0.9751
Epoch 7/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1382 -
accuracy: 0.9584 - val_loss: 0.0866 - val_accuracy: 0.9786
Epoch 8/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1198 -
accuracy: 0.9646 - val_loss: 0.0820 - val_accuracy: 0.9742
Epoch 9/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1105 -
accuracy: 0.9682 - val_loss: 0.0727 - val_accuracy: 0.9786
Epoch 10/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1015 -
accuracy: 0.9693 - val_loss: 0.0658 - val_accuracy: 0.9795
```

```
Score for fold 1: loss of 0.0657673254609108; accuracy of 97.95373678207397%
36/36 [==============================] - 0s 777us/step
Training fold 2…
------------------------------------------------------------------------
Training for fold 2 …
Epoch 1/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0937 -
accuracy: 0.9693 - val_loss: 0.0420 - val_accuracy: 0.9867
Epoch 2/10
141/141 [==============================] - 0s 2ms/step - loss: 0.1025 -
accuracy: 0.9691 - val_loss: 0.0396 - val_accuracy: 0.9893
Epoch 3/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0853 -
accuracy: 0.9751 - val_loss: 0.0402 - val_accuracy: 0.9893
Epoch 4/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0697 -
accuracy: 0.9782 - val_loss: 0.0475 - val_accuracy: 0.9840
Epoch 5/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0749 -
accuracy: 0.9780 - val_loss: 0.0431 - val_accuracy: 0.9831
Epoch 6/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0745 -
accuracy: 0.9760 - val_loss: 0.0404 - val_accuracy: 0.9858
Epoch 7/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0705 -
accuracy: 0.9789 - val_loss: 0.0356 - val_accuracy: 0.9893
Epoch 8/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0592 -
accuracy: 0.9827 - val_loss: 0.0394 - val_accuracy: 0.9867
Epoch 9/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0593 -
accuracy: 0.9798 - val_loss: 0.0459 - val_accuracy: 0.9831
Epoch 10/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0518 -
accuracy: 0.9849 - val_loss: 0.0519 - val_accuracy: 0.9813
Score for fold 2: loss of 0.05190756916999817; accuracy of 98.13167452812195%
36/36 [==============================] - 0s 829us/step
Training fold 3…
------------------------------------------------------------------------
Training for fold 3 …
Epoch 1/10
141/141 [==============================] - 0s 3ms/step - loss: 0.0681 -
accuracy: 0.9775 - val_loss: 0.0187 - val_accuracy: 0.9920
Epoch 2/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0597 -
accuracy: 0.9804 - val_loss: 0.0165 - val_accuracy: 0.9929
Epoch 3/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0551 -
```

```
accuracy: 0.9824 - val_loss: 0.0185 - val_accuracy: 0.9938
Epoch 4/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0464 -
accuracy: 0.9878 - val_loss: 0.0223 - val_accuracy: 0.9902
Epoch 5/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0485 -
accuracy: 0.9840 - val_loss: 0.0211 - val_accuracy: 0.9920
Epoch 6/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0452 -
accuracy: 0.9844 - val_loss: 0.0193 - val_accuracy: 0.9920
Epoch 7/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0423 -
accuracy: 0.9858 - val_loss: 0.0226 - val_accuracy: 0.9938
Epoch 8/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0402 -
accuracy: 0.9878 - val_loss: 0.0248 - val_accuracy: 0.9920
Epoch 9/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0459 -
accuracy: 0.9851 - val_loss: 0.0206 - val_accuracy: 0.9929
Epoch 10/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0334 -
accuracy: 0.9893 - val_loss: 0.0232 - val_accuracy: 0.9929
Score for fold 3: loss of 0.02319428138434887; accuracy of 99.28825497627258%
36/36 [==============================] - 0s 798us/step
Training fold 4…
------------------------------------------------------------------------
Training for fold 4 …
Epoch 1/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0391 -
accuracy: 0.9878 - val_loss: 0.0063 - val_accuracy: 0.9991
Epoch 2/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0358 -
accuracy: 0.9907 - val_loss: 0.0115 - val_accuracy: 0.9956
Epoch 3/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0426 -
accuracy: 0.9873 - val_loss: 0.0125 - val_accuracy: 0.9947
Epoch 4/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0341 -
accuracy: 0.9889 - val_loss: 0.0088 - val_accuracy: 0.9964
Epoch 5/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0342 -
accuracy: 0.9898 - val_loss: 0.0122 - val_accuracy: 0.9956
Epoch 6/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0291 -
accuracy: 0.9915 - val_loss: 0.0160 - val_accuracy: 0.9947
Epoch 7/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0279 -
accuracy: 0.9902 - val_loss: 0.0130 - val_accuracy: 0.9964
```

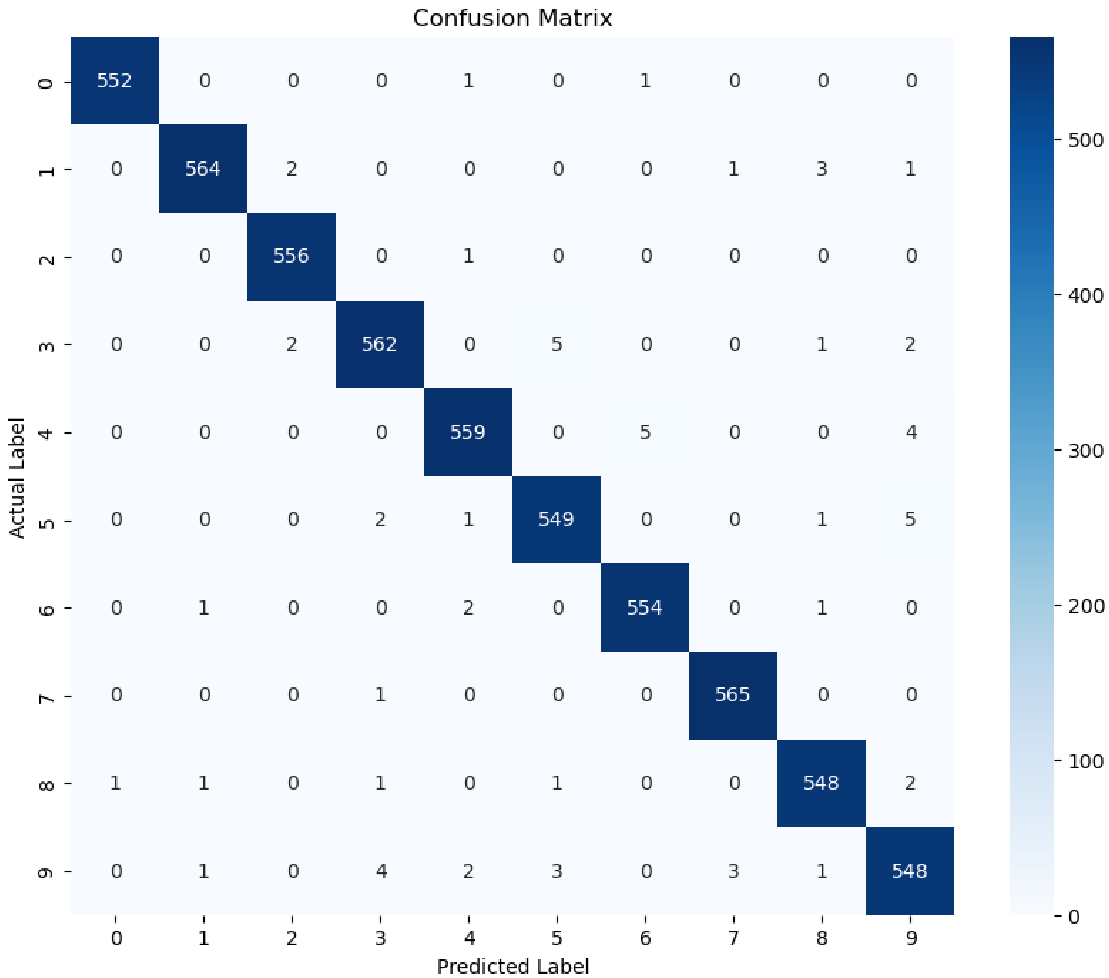
```
Epoch 8/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0298 -
accuracy: 0.9907 - val_loss: 0.0108 - val_accuracy: 0.9964
Epoch 9/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0298 -
accuracy: 0.9900 - val_loss: 0.0126 - val_accuracy: 0.9947
Epoch 10/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0227 -
accuracy: 0.9929 - val_loss: 0.0136 - val_accuracy: 0.9947
Score for fold 4: loss of 0.013570494949817657; accuracy of 99.46619272232056%
36/36 [==============================] - 0s 799us/step
Training fold 5…
------------------------------------------------------------------------
Training for fold 5 …
Epoch 1/10
141/141 [==============================] - 0s 3ms/step - loss: 0.0278 -
accuracy: 0.9913 - val_loss: 0.0040 - val_accuracy: 0.9982
Epoch 2/10
141/141 [==============================] - 0s 3ms/step - loss: 0.0207 -
accuracy: 0.9944 - val_loss: 0.0048 - val_accuracy: 0.9973
Epoch 3/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0309 -
accuracy: 0.9902 - val_loss: 0.0063 - val_accuracy: 0.9973
Epoch 4/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0286 -
accuracy: 0.9911 - val_loss: 0.0100 - val_accuracy: 0.9973
Epoch 5/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0285 -
accuracy: 0.9920 - val_loss: 0.0071 - val_accuracy: 0.9982
Epoch 6/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0235 -
accuracy: 0.9927 - val_loss: 0.0111 - val_accuracy: 0.9956
Epoch 7/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0245 -
accuracy: 0.9918 - val_loss: 0.0132 - val_accuracy: 0.9956
Epoch 8/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0217 -
accuracy: 0.9935 - val_loss: 0.0092 - val_accuracy: 0.9964
Epoch 9/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0274 -
accuracy: 0.9904 - val_loss: 0.0069 - val_accuracy: 0.9973
Epoch 10/10
141/141 [==============================] - 0s 2ms/step - loss: 0.0181 -
accuracy: 0.9944 - val_loss: 0.0086 - val_accuracy: 0.9956
Score for fold 5: loss of 0.008615042082965374; accuracy of 99.5551586151123%
36/36 [==============================] - 0s 794us/step
```

[6]:

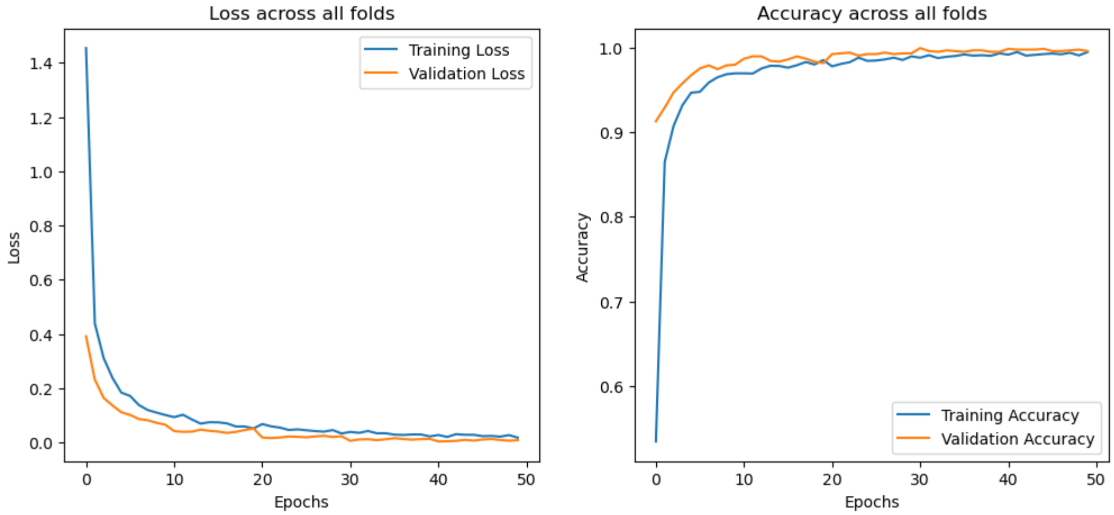
```python
# Generate the confusion matrix
cm = confusion_matrix(y_true, y_pred)
print("Confusion Matrix:")
print(cm)

# Classification report
report = classification_report(y_true, y_pred)
print("Classification Report:")
print(report)

# Plotting the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt="d", cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('Actual Label')
plt.xlabel('Predicted Label')
plt.show()

# Calculate average loss and accuracy
average_loss = np.mean(all_val_loss)
average_accuracy = np.mean(all_val_acc) * 100

print(f'Average Loss: {average_loss}')
print(f'Average Accuracy: {average_accuracy}%')

# Plot training & validation loss values
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(all_train_loss, label='Training Loss')
plt.plot(all_val_loss, label='Validation Loss')
plt.title('Loss across all folds')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training & validation accuracy values
plt.subplot(1, 2, 2)
plt.plot(all_train_acc, label='Training Accuracy')
plt.plot(all_val_acc, label='Validation Accuracy')
plt.title('Accuracy across all folds')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```

```
Confusion Matrix:
[[552   0   0   0   1   0   1   0   0   0]
```

```
 [  0 564   2   0   0   0   0   1   3   1]
 [  0   0 556   0   1   0   0   0   0   0]
 [  0   0   2 562   0   5   0   0   1   2]
 [  0   0   0   0 559   0   5   0   0   4]
 [  0   0   0   2   1 549   0   0   1   5]
 [  0   1   0   0   2   0 554   0   1   0]
 [  0   0   0   1   0   0   0 565   0   0]
 [  1   1   0   1   0   1   0   0 548   2]
 [  0   1   0   4   2   3   0   3   1 548]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       554
           1       0.99      0.99      0.99       571
           2       0.99      1.00      1.00       557
           3       0.99      0.98      0.98       572
           4       0.99      0.98      0.99       568
           5       0.98      0.98      0.98       558
           6       0.99      0.99      0.99       558
           7       0.99      1.00      1.00       566
           8       0.99      0.99      0.99       554
           9       0.98      0.98      0.98       562

    accuracy                           0.99      5620
   macro avg       0.99      0.99      0.99      5620
weighted avg       0.99      0.99      0.99      5620
```




```
Average Loss: 0.04553227401338518
Average Accuracy: 98.61743795871735%
```


Loss across all folds
Training Loss
Validation Loss
Loss
Epochs
Accuracy across all folds
Training Accuracy
Validation Accuracy
Accuracy
Epochs