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

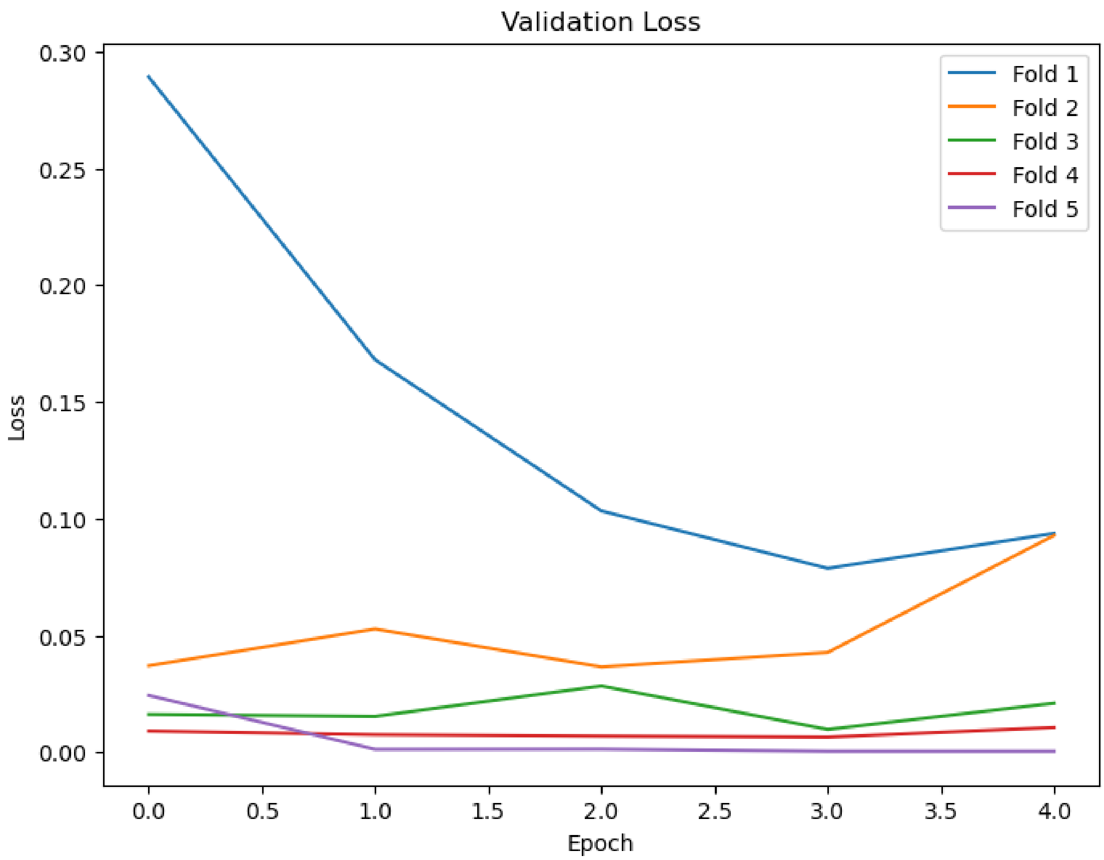
```
Fold 1/5
Epoch 1/5
141/141              5s 10ms/step -
accuracy: 0.4720 - loss: 1.6700 - val_accuracy: 0.9155 - val_loss: 0.2658
Epoch 2/5
141/141              1s 7ms/step -
accuracy: 0.9403 - loss: 0.1945 - val_accuracy: 0.9617 - val_loss: 0.1332
Epoch 3/5
141/141              1s 7ms/step -
accuracy: 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
```

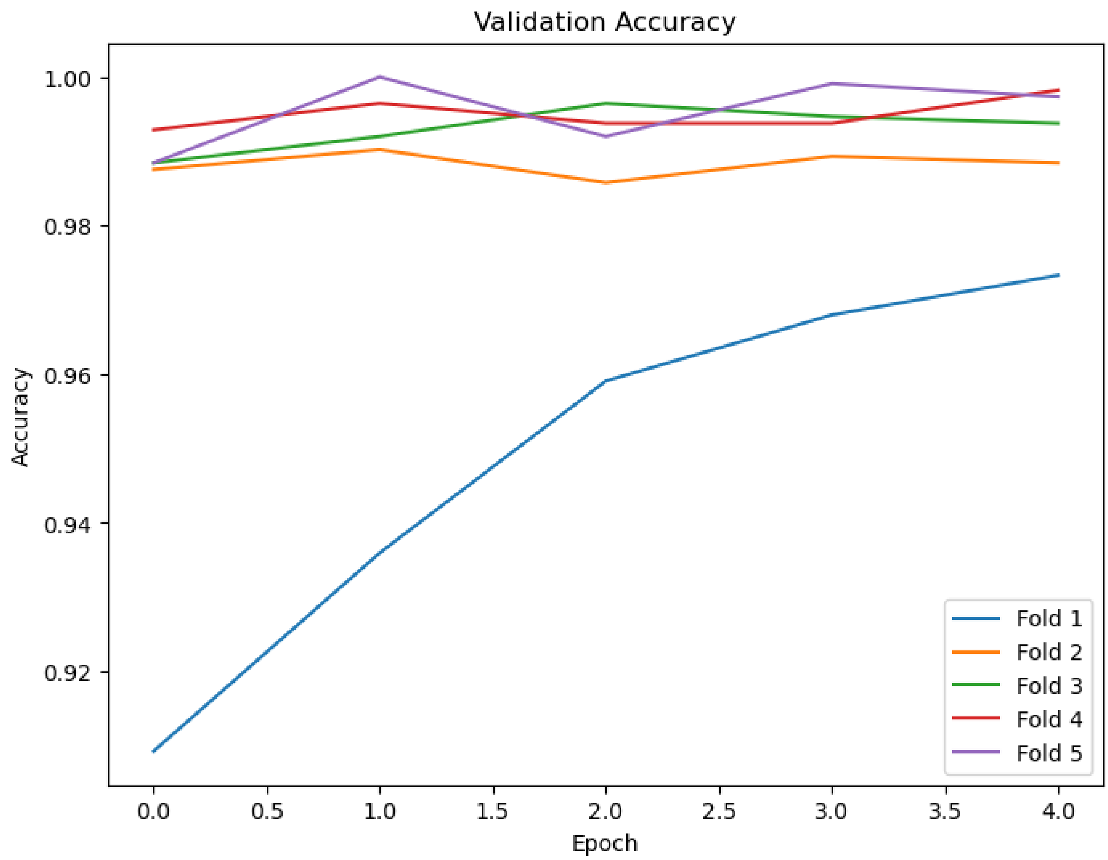
```
141/141              1s 6ms/step -
accuracy: 1.0000 - loss: 0.0020 - val_accuracy: 0.9947 - val_loss: 0.0196
36/36              0s 5ms/step
Fold 5/5
Epoch 1/5
141/141              3s 8ms/step -
accuracy: 0.9949 - loss: 0.0132 - val_accuracy: 1.0000 - val_loss: 6.3302e-04
Epoch 2/5
141/141              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]:

```
# Plotting loss curves
plot_loss_curves(fold_losses)
```

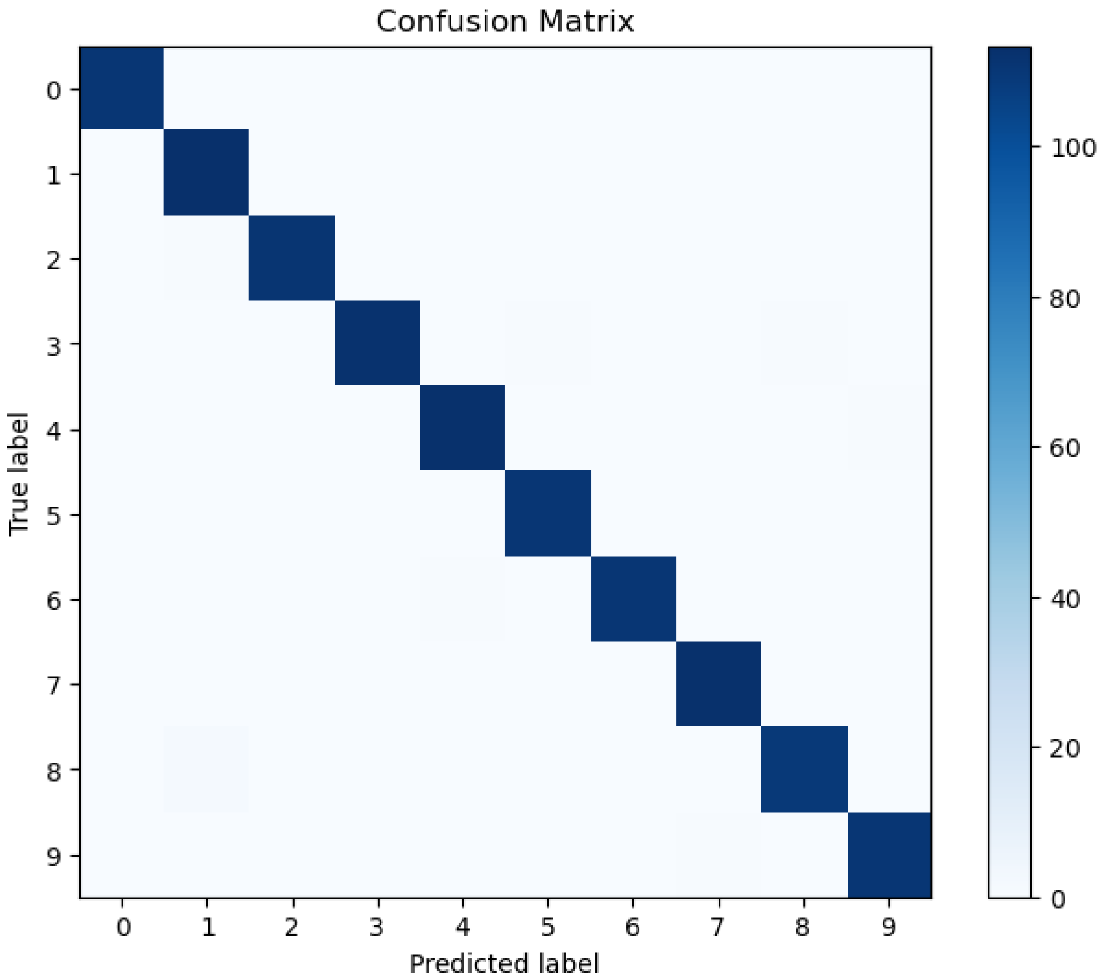


[133]:
```
# Plotting accuracy curves
plot_accuracy_curves(fold_accuracies)
```



[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

Team

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

Data Preparation:

Load the Dataset: The MNIST dataset for optical recognition of handwritten digits is fetched using the `fetch_ucirepo` function from the `ucimlrepo` library.
Preprocess the Data: The data is reshaped and normalized to ensure compatibility with the Convolutional Neural Network (CNN) architecture.

Convolutional Neural Network Architecture:

CNN Architecture: The CNN model comprises three convolutional layers with ReLU activation functions followed by max-pooling layers for down-sampling.
Layer Parameters and Dimensions: Each convolutional layer has specific parameters, including the number of filters, filter size, activation function, and padding. The input and output dimensions of each layer are documented.
Model Diagram: A visual representation of the CNN architecture is prepared to illustrate the flow of data through the layers.

Max Pooling:

Pooling Process: Max pooling is implemented after each convolutional layer to reduce spatial dimensions and extract key features effectively.
Effect on Feature Maps: Max pooling helps in capturing the most prominent features by retaining the maximum activation value within each pooling window.

Fully Connected Layer and Softmax:

Fully Connected Layer:A fully connected layer with ReLU activation is added after flattening the feature maps.
Softmax Activation: Softmax activation is applied to the output layer to classify the input images into ten different categories.

Training and Evaluation:

Model Training: The CNN model is trained on the MNIST dataset using K-Fold cross-validation to ensure robust performance evaluation.

Model Evaluation: The performance of the trained model is evaluated using metrics such as accuracy and loss. Confusion matrices are generated to analyze the model's classification performance.
Analysis: The training process, including loss curves and accuracy metrics, is documented to provide insights into the model's learning behavior.