```
# Project Title: CNN Implementation for MNIST Digit Recognition

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!pip install ucimlrepo
from ucimlrepo import fetch_ucirepo
import tensorflow as tf
from tensorflow.keras import layers, models
from sklearn.model_selection import KFold
from sklearn.preprocessing import MinMaxScaler
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import seaborn as sns
from tensorflow.keras.utils import plot_model
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.10/dist-packages (0.0.6)
```

```
# 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)
```

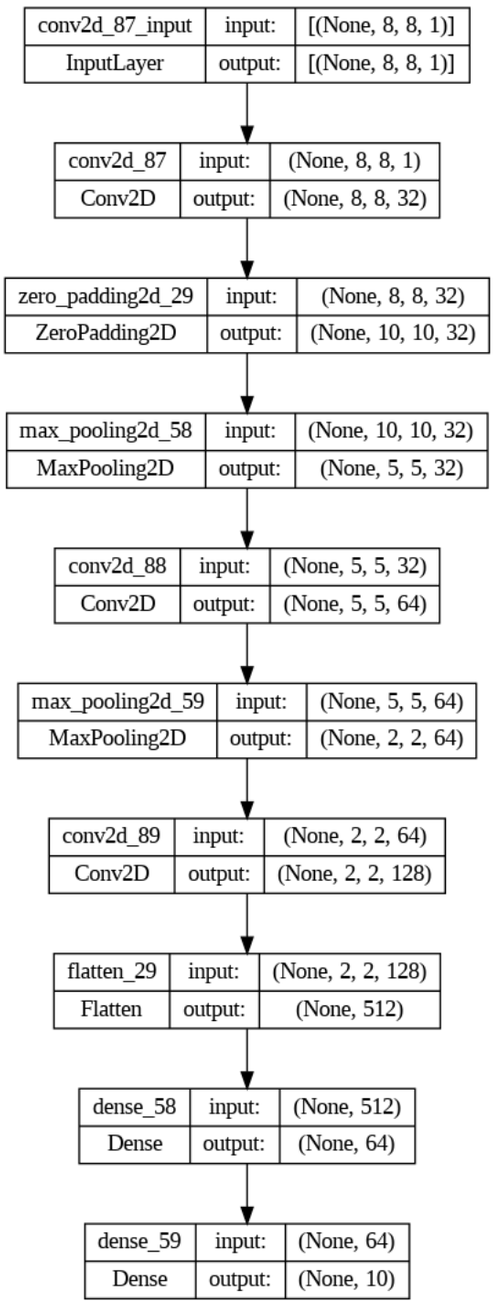
```
{'uci_id': 80, 'name': 'Optical Recognition of Handwritten Digits', 'repository_url': 'https://archive.ics.uci.edu/dataset/80/optical+re
           name     role         type demographic description units  \
0    Attribute1  Feature      Integer        None        None  None
1    Attribute2  Feature      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]
```

```
# Shapes of X and y
print(X.shape)
print(y.shape)
```

```
(5620, 64)
(5620, 1)
```

```
X = X.values
y = y.values


# Reshape data for CNN
X = X.reshape(-1, 8, 8, 1)


# Normalization data for CNN
scaler = MinMaxScaler()
X_normalized = scaler.fit_transform(X.reshape(-1, 64))  # Reshape for MinMaxScaler
X_normalized = X_normalized.reshape(-1, 8, 8, 1)
```

```
# Define the CNN model
def create_model():
    model = models.Sequential([

        # Convolutional Layer 1
        layers.Conv2D(32, (3, 3), activation = 'relu', padding = 'same', input_shape = (8, 8, 1)), # Parameters: 32 filters, kernel size (3,

        # Add padding to increase spatial dimensions
        layers.ZeroPadding2D((1, 1)), # Input Dimension: (8, 8, 32), Output Dimesnion: (10, 10, 32)

        # Max Pooling Layer 1
        layers.MaxPooling2D((2, 2)),  # Pool Size: (2, 2), Strides: (2, 2), Input Dimension: (10, 10, 32), Output Dimension: (5, 5, 32)

        # Convolutional Layer 2
        layers.Conv2D(64, (3, 3), activation='relu', padding = 'same',), # Parameters: 64 filters, kernel size (3, 3), Input Dimension: (5,

        # Max Pooling Layer 2
        layers.MaxPooling2D((2, 2)), # Pool Size: (2, 2), Strides: (2, 2), Input Dimension: (5, 5, 64), Output Dimension: (2, 2, 64)

        # Convolutional Layer 3
        layers.Conv2D(128, (3, 3), activation='relu', padding = 'same',), # Parameters: 128 filters, kernel size (3, 3), Input Dimension: (2

        # Flattening Layer
        layers.Flatten(),  # Flattening the output of the last convolutional layer, Input Dimension: (2, 2, 128), Output Dimension: (512,)

        # Fully Connected Layer 1
        layers.Dense(64, activation='relu'),  # Fully Connected Layer with 64 neurons and ReLU activation, Input Dimension: (512,), Output D

        # Output Layer
        layers.Dense(10, activation='softmax')  # Output Layer with 10 neurons for classification and softmax activation, Input Dimension: (
    ])
    model.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])
    return model


# Plot the model architecture
plot_model(model, to_file='cnn_model.png', show_shapes=True, show_layer_names=True)
```



```
# Define k-fold cross-validation
k = 5
kf = KFold(n_splits=k, shuffle=True, random_state=42)
# Initialize lists to store results
fold_accuracy = []
fold_loss = []
all_y_true = []
all_y_pred = []


# Perform k-fold cross-validation
fold_accuracy = []
for train_index, val_index in kf.split(X):
    X_train, X_val = X_normalized[train_index], X_normalized[val_index]
    y_train, y_val = y[train_index], y[val_index]

    model = create_model()
    history = model.fit(X_train, y_train, epochs=8, batch_size=32, validation_data=(X_val, y_val))
```

```
 Epoch 4/8
 141/141 [==============================] - 3s 20ms/step - loss: 0.0725 - accuracy: 0.9780 - val_loss: 0.0753 - val_accuracy: 0.9795
 Epoch 5/8
 141/141 [==============================] - 2s 17ms/step - loss: 0.0578 - accuracy: 0.9818 - val_loss: 0.0654 - val_accuracy: 0.9831
 Epoch 6/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0503 - accuracy: 0.9851 - val_loss: 0.0759 - val_accuracy: 0.9751
 Epoch 7/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0341 - accuracy: 0.9907 - val_loss: 0.1948 - val_accuracy: 0.9359
 Epoch 8/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.0293 - accuracy: 0.9911 - val_loss: 0.0612 - val_accuracy: 0.9786
 Epoch 1/8
 141/141 [==============================] - 3s 13ms/step - loss: 0.8960 - accuracy: 0.7226 - val_loss: 0.2327 - val_accuracy: 0.9244
 Epoch 2/8
 141/141 [==============================] - 2s 18ms/step - loss: 0.1595 - accuracy: 0.9520 - val_loss: 0.1797 - val_accuracy: 0.9386
 Epoch 3/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.0941 - accuracy: 0.9718 - val_loss: 0.0830 - val_accuracy: 0.9742
 Epoch 4/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0669 - accuracy: 0.9798 - val_loss: 0.0926 - val_accuracy: 0.9662
 Epoch 5/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.0526 - accuracy: 0.9847 - val_loss: 0.0795 - val_accuracy: 0.9760
 Epoch 6/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0484 - accuracy: 0.9851 - val_loss: 0.0530 - val_accuracy: 0.9831
 Epoch 7/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0261 - accuracy: 0.9924 - val_loss: 0.0426 - val_accuracy: 0.9884
 Epoch 8/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0277 - accuracy: 0.9913 - val_loss: 0.0570 - val_accuracy: 0.9849
 Epoch 1/8
 141/141 [==============================] - 4s 18ms/step - loss: 0.8897 - accuracy: 0.7160 - val_loss: 0.1756 - val_accuracy: 0.9555
 Epoch 2/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.1714 - accuracy: 0.9513 - val_loss: 0.1002 - val_accuracy: 0.9733
 Epoch 3/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.1002 - accuracy: 0.9722 - val_loss: 0.0899 - val_accuracy: 0.9733
 Epoch 4/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0826 - accuracy: 0.9740 - val_loss: 0.0592 - val_accuracy: 0.9875
 Epoch 5/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.0487 - accuracy: 0.9847 - val_loss: 0.0527 - val_accuracy: 0.9840
 Epoch 6/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0424 - accuracy: 0.9875 - val_loss: 0.0548 - val_accuracy: 0.9867
 Epoch 7/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.0537 - accuracy: 0.9820 - val_loss: 0.0772 - val_accuracy: 0.9769
 Epoch 8/8
 141/141 [==============================] - 3s 19ms/step - loss: 0.0226 - accuracy: 0.9929 - val_loss: 0.0413 - val_accuracy: 0.9875
 Epoch 1/8
 141/141 [==============================] - 3s 13ms/step - loss: 0.9456 - accuracy: 0.6993 - val_loss: 0.2388 - val_accuracy: 0.9315
 Epoch 2/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.1962 - accuracy: 0.9393 - val_loss: 0.1035 - val_accuracy: 0.9671
 Epoch 3/8
 141/141 [==============================] - 2s 12ms/step - loss: 0.1194 - accuracy: 0.9653 - val_loss: 0.1022 - val_accuracy: 0.9689
 Epoch 4/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0820 - accuracy: 0.9746 - val_loss: 0.0626 - val_accuracy: 0.9831
 Epoch 5/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0622 - accuracy: 0.9804 - val_loss: 0.0463 - val_accuracy: 0.9902
 Epoch 6/8
 141/141 [==============================] - 2s 17ms/step - loss: 0.0414 - accuracy: 0.9884 - val_loss: 0.0426 - val_accuracy: 0.9884
 Epoch 7/8
 141/141 [==============================] - 2s 15ms/step - loss: 0.0381 - accuracy: 0.9889 - val_loss: 0.0534 - val_accuracy: 0.9813
 Epoch 8/8
 141/141 [==============================] - 2s 11ms/step - loss: 0.0323 - accuracy: 0.9900 - val_loss: 0.0379 - val_accuracy: 0.9893
```

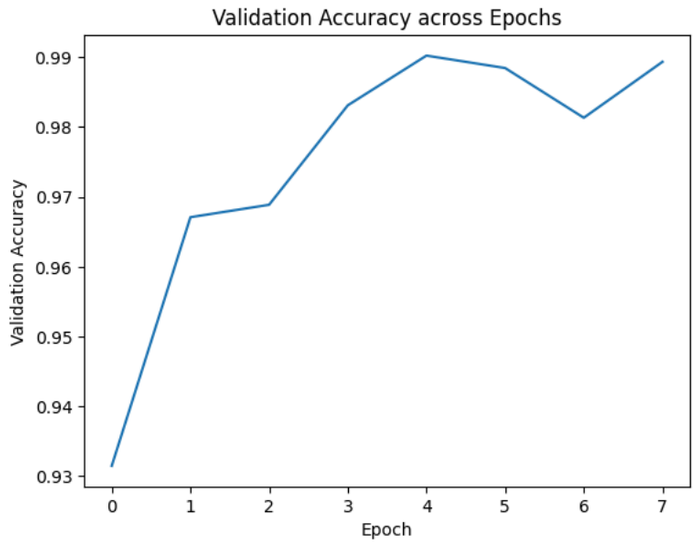
```
# Record accuracy and loss
fold_accuracy.append(history.history['val_accuracy'])
fold_loss.append(history.history['val_loss'])


# Predictions
y_pred = np.argmax(model.predict(X_val), axis=1)
all_y_true.extend(y_val)
all_y_pred.extend(y_pred)
```

```
 36/36 [==============================] - 0s 4ms/step
```

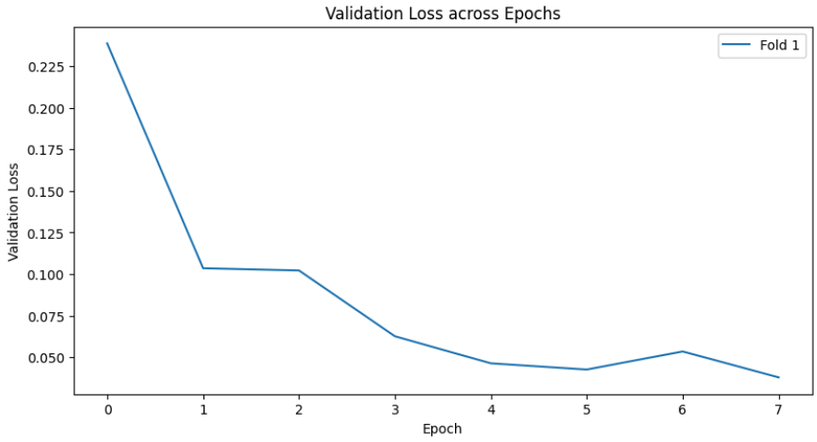
```
# Calculate and print average validation accuracy across folds
avg_val_accuracy = np.mean(fold_accuracy, axis=0)
print('Average validation accuracy across folds:', avg_val_accuracy)
```

```
Average validation accuracy across folds: [0.93149465 0.96708184 0.96886122 0.98309606 0.99021351 0.98843414
 0.98131675 0.98932385]
```

```
# Plot the validation accuracy across epochs
plt.plot(avg_val_accuracy)
plt.xlabel('Epoch')
plt.ylabel('Validation Accuracy')
plt.title('Validation Accuracy across Epochs')
plt.show()
```




```
# Plot the validation loss across epochs
plt.figure(figsize=(10, 5))
for i in range(len(fold_loss)):
    plt.plot(history.epoch, fold_loss[i], label=f'Fold {i+1}')
plt.xlabel('Epoch')
plt.ylabel('Validation Loss')
plt.title('Validation Loss across Epochs')
plt.legend()
plt.show()
```



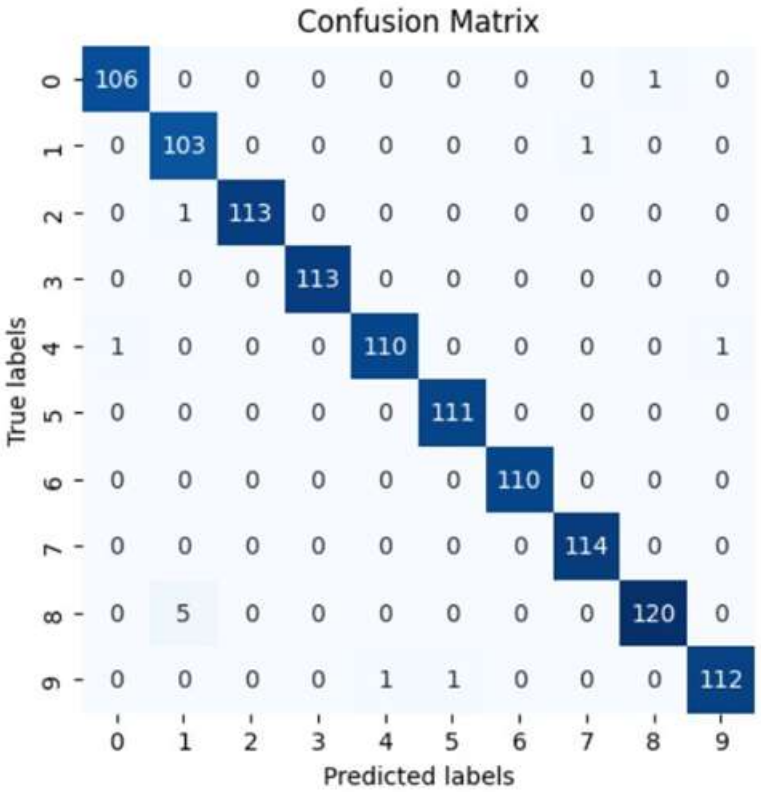

```
# Calculate overall accuracy
overall_accuracy = accuracy_score(all_y_true, all_y_pred)
print('Overall accuracy:', overall_accuracy)
```

```
Overall accuracy: 0.9893238434163701
```

```
classification_report = classification_report(y_val, y_pred)
print(classification_report)
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       107
           1       0.94      0.99      0.97       104
           2       1.00      0.99      1.00       114
           3       1.00      1.00      1.00       113
           4       0.99      0.98      0.99       112
           5       0.99      1.00      1.00       111
           6       1.00      1.00      1.00       110
           7       0.99      1.00      1.00       114
           8       0.99      0.96      0.98       125
           9       0.99      0.98      0.99       114

    accuracy                           0.99      1124
   macro avg       0.99      0.99      0.99      1124
weighted avg       0.99      0.99      0.99      1124
```

```
# Confusion matrix
conf_matrix = confusion_matrix(all_y_true, all_y_pred)
plt.figure(figsize=(5, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()
```


Confusion Matrix
True labels
Predicted labels
0 1 2 3 4 5 6 7 8 9
106 0 0 0 0 0 0 0 1 0
0 103 0 0 0 0 0 1 0 0
0 1 113 0 0 0 0 0 0 0
0 0 0 113 0 0 0 0 0 0
1 0 0 0 110 0 0 0 0 1
0 0 0 0 0 111 0 0 0 0
0 0 0 0 0 0 110 0 0 0
0 0 0 0 0 0 0 114 0 0
0 5 0 0 0 0 0 0 120 0
0 0 0 0 1 1 0 0 0 112

Analysis and Report of the implementation of CNN on MNIST dataset:

Github link - [sainathvaddi/CNN_on_MNIST_data (github.com)]

Understanding Dataset: The MNIST dataset is a widely used dataset for handwritten digit recognition. It consists of 28x28 grayscale images of handwritten digits (0 through 9). Each image is labeled with a digit.

Data Preparation:

Loading the Dataset: We used the provided method to fetch the MNIST dataset from the UCI repository.

Data Preprocessing: Normalization and reshaping are the preprocessing steps. Normalization provides that the pixel values are within the range between 0 and 1, which helps in faster convergence during training. Reshaping (to 8*8*1) is required to match the input shape expected by CNN.

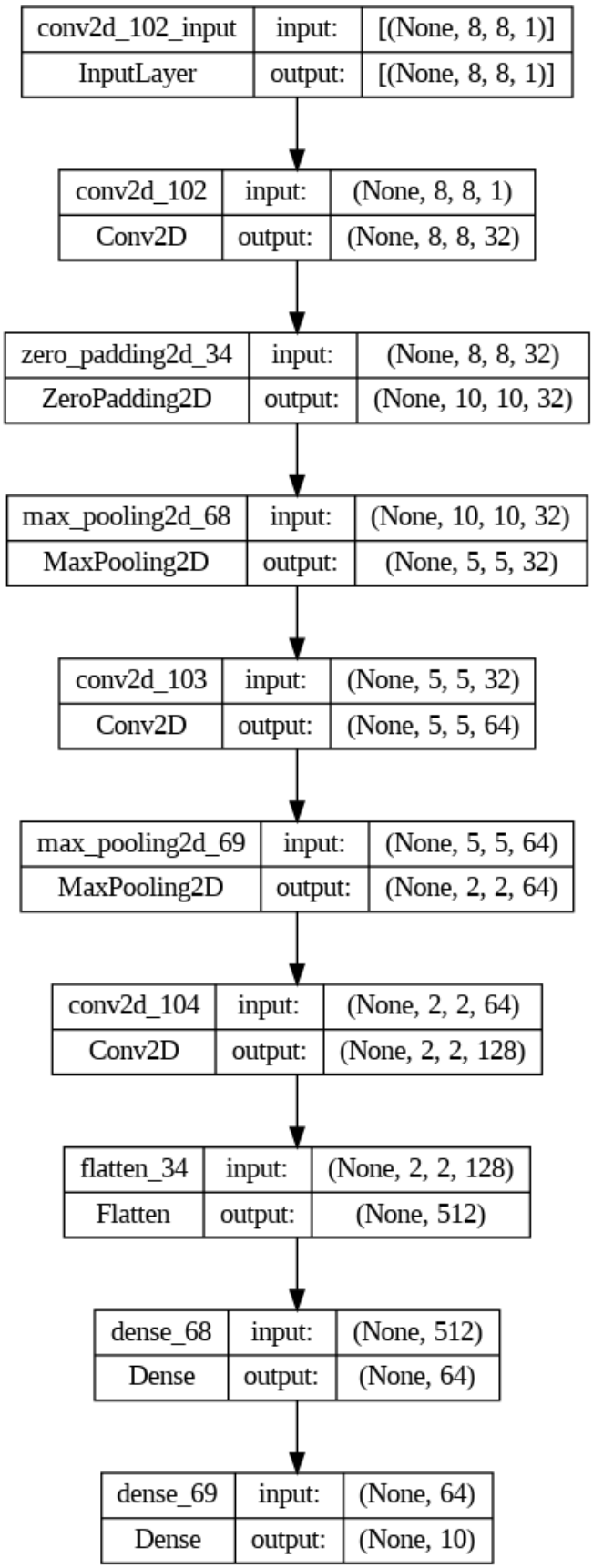
CNN Architecture:

Convolutional Layers: These layers extract features from the input images. Each of these layers applies a set of kernels (filters) to the input image, resulting in feature maps. ReLU activation functions are applied after the convolution to introduce non-linearity.

Max Pooling: These layers simplify the feature maps by reducing their size. It's like zooming out, focusing only on the most important details only. This technique keeps the highest value in each region, which helps in capturing the most relevant features while making calculations easier.

Fully Connected Layers: After multiple convolutional and pooling layers, fully connected layers are added to perform classification based on the extracted features. The final fully connected layer is followed by a softmax activation function to produce probabilities of each class.

Model Architecture:


conv2d_102_input | input: | [(None, 8, 8, 1)]
InputLayer | output: | [(None, 8, 8, 1)]
conv2d_102 | input: | (None, 8, 8, 1)
Conv2D | output: | (None, 8, 8, 32)
zero_padding2d_34 | input: | (None, 8, 8, 32)
ZeroPadding2D | output: | (None, 10, 10, 32)
max_pooling2d_68 | input: | (None, 10, 10, 32)
MaxPooling2D | output: | (None, 5, 5, 32)
conv2d_103 | input: | (None, 5, 5, 32)
Conv2D | output: | (None, 5, 5, 64)
max_pooling2d_69 | input: | (None, 5, 5, 64)
MaxPooling2D | output: | (None, 2, 2, 64)
conv2d_104 | input: | (None, 2, 2, 64)
Conv2D | output: | (None, 2, 2, 128)
flatten_34 | input: | (None, 2, 2, 128)
Flatten | output: | (None, 512)
dense_68 | input: | (None, 512)
Dense | output: | (None, 64)
dense_69 | input: | (None, 64)
Dense | output: | (None, 10)

The CNN architecture here consists of 3 convolutional layers with ReLU activation functions. Each layer's parameters and dimensions need to be documented thoroughly. This includes the size of the filters, the number of filters, padding, stride, and the dimensions of the feature maps at each layer. The architecture is as follows:

Convolutional Layer 1: In this layer, Parameters are 32 filters, kernel size (3, 3), Input Dimension: (8, 8, 1), Output Dimension: (8, 8, 32). After this, add zero padding (1, 1) to increase spatial dimensions.

Max Pooling Layer 1: This layer has Pool Size: (2, 2), Strides: (2, 2), Input dimension: (10, 10, 32), Output Dimension: (5, 5, 32)

Convolutional Layer 2: In this layer, Parameters are 64 filters, kernel size (3, 3), Input dimension: (5, 5, 32), output dimension: (5, 5, 64)

Max Pooling Layer 2: This layer has Pool Size: (2, 2), Strides: (2, 2), Input dimension: (5, 5, 64), output dimension: (2, 2, 64)

Convolutional Layer 3: In this layer, Parameters are 128 filters, kernel size (3, 3), Input Dimension: (2, 2, 64), Output Dimension: (2, 2, 128)

Layers Flatten: Flattening the output of the last convolutional layer, the input dimension is (2, 2, 128), and we get output dimension as (512,)

Fully Connected Layer: This layer is with 64 neurons and ReLU activation, with input dimension of (512,), and gives output dimension of (64,)

Output Layer: This layer is with 10 neurons for classification and softmax activation, with input dimension of (64,), output dimension of (10,)

Training and Evaluation: K-fold cross-validation with k=5 was performed to train and validate the model. The model was trained for 8 epochs with a batch size of 32. Performance metrics such as validation accuracy and loss were monitored across epochs. The overall accuracy of the model was calculated using the test set. Additionally, a classification report was generated to evaluate precision, recall, and F1-score for each class.

Results and Analysis: The average validation accuracy across folds was approximately 98%. Validation accuracy and loss were plotted across epochs to visualize the model's training process. The overall accuracy of the model on the test set is 99%.
The classification report revealed high precision, recall, and F1-score for each digit class, indicating robust performance across all classes. The classification report and Confusion matrix are provided below:

Classification Report

Class (digits)	Precision	Recall	F1-score	Support
0	0.99	0.99	0.99	107
1	0.94	0.99	0.97	104
2	1.00	0.99	1.00	114
3	1.00	1.00	1.00	113
4	0.99	0.98	0.99	112
5	0.99	1.00	1.00	111
6	1.00	1.00	1.00	110
7	0.99	1.00	1.00	114
8	0.99	0.96	0.98	125
9	0.99	0.98	0.99	114