

# DL\_Practical\_3

November 12, 2025

Assignment No: 03

Aim: To Implement Image classification model using CNN Deep Learning Architecture.

Problem Statement: Build the Image classification model using CNN Deep Learning Architecture by dividing the model into following 4 stages: a. Loading and preprocessing the image data b. Defining the model's architecture c. Training the model d. Estimating the model's performance

```
[1]: # Assignment 3: Image Classification using CNN on MNIST

# a) Loading and preprocessing the image data

import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

print("Imports success!\n")

# Load the MNIST dataset
with np.load(r"C:\Users\kusha\Desktop\mnist_dataset.npz") as data:
    x_train = data["X_train"]
    y_train = data["y_train"]
    x_test = data["X_test"]
    y_test = data["y_test"]

    print(
        f"x_train:\n"
        f"  Data type: {x_train.dtype}\n"
        f"  Shape     : {x_train.shape}\n"
        f"  Pixel value range: {x_train.min()} to {x_train.max()}\n"
    )
    print(
        f"y_train:\n"
        f"  Data type: {y_train.dtype}\n"
        f"  Shape     : {y_train.shape}\n"
        f"  First 10 labels: {y_train[:10]}\n"
    )
```

```

print(
    f"x_test:\n"
    f" Data type: {x_test.dtype}\n"
    f" Shape : {x_test.shape}\n"
    f" Pixel value range: {x_test.min()} to {x_test.max()}\n"
)
print(
    f"y_test:\n"
    f" Data type: {y_test.dtype}\n"
    f" Shape : {y_test.shape}\n"
    f" First 10 labels: {y_test[:10]}\n"
)
print(f"First image sample of x_train (pixel values):\n{x_train[0]}\n")

# --- Preprocessing ---
# Normalize images to [0, 1] float and reshape for CNN input
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

x_train = x_train[..., None] # (samples, 28, 28, 1)
x_test = x_test[..., None]

print(
    f"\nAfter normalization and reshaping for CNN:\n"
    f"x_train:\n"
    f" Data type: {x_train.dtype}\n"
    f" Shape : {x_train.shape}\n"
    f" Pixel value range: {x_train.min()} to {x_train.max()}\n"
    f"y_train:\n"
    f" Data type: {y_train.dtype}\n"
    f" Shape : {y_train.shape}\n"
)
print(f" Sample normalized image of x_train (first image pixels):\n{x_train[0].squeeze()}\n")

```

Imports success!

```

x_train:
Data type: uint8
Shape : (60000, 28, 28)
Pixel value range: 0 to 255

y_train:
Data type: uint8
Shape : (60000,)
First 10 labels: [5 0 4 1 9 2 1 3 1 4]

```



After normalization and reshaping for CNN:

x\_train:

```
Data type: float32  
Shape      : (60000, 28, 28, 1)  
Pixel value range: 0.0 to 1.0
```

y\_train:

Data type: uint8  
Shape : (60000,)

Sample normalized image of x\_train (first image pixels):

```
[0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
[0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
[0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.  
[0.          0.          0.          0.          0.          0.  
 0.          0.          0.          0.          0.          0.]
```

0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.01176471	0.07058824	0.07058824	0.07058824	0.49411765	0.53333336
0.6862745	0.10196079	0.6509804	1.	0.96862745	0.49803922
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.11764706	0.14117648	0.36862746	0.6039216
0.6666667	0.99215686	0.99215686	0.99215686	0.99215686	0.99215686
0.88235295	0.6745098	0.99215686	0.9490196	0.7647059	0.2509804
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.19215687	0.93333334	0.99215686	0.99215686	0.99215686
0.99215686	0.99215686	0.99215686	0.99215686	0.99215686	0.9843137
0.3647059	0.32156864	0.32156864	0.21960784	0.15294118	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.07058824	0.85882354	0.99215686	0.99215686	0.99215686
0.99215686	0.99215686	0.7764706	0.7137255	0.96862745	0.94509804
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.3137255	0.6117647	0.41960785	0.99215686
0.99215686	0.8039216	0.04313726	0.	0.16862746	0.6039216
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.05490196	0.00392157	0.6039216
0.99215686	0.3529412	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.54509807
0.99215686	0.74509805	0.00784314	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.04313726
0.74509805	0.99215686	0.27450982	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	

[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.13725491	0.94509804	0.88235295	0.627451	0.42352942	0.00392157
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.31764707	0.9411765	0.99215686	0.99215686	0.46666667
0.09803922	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.1764706	0.7294118	0.99215686	0.99215686
0.5882353	0.10588235	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.0627451	0.3647059	0.9882353
0.99215686	0.73333335	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.9764706
0.99215686	0.9764706	0.2509804	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.18039216	0.50980395	0.7176471	0.99215686
0.99215686	0.8117647	0.00784314	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.15294118	0.5803922	0.8980392	0.99215686	0.99215686	0.99215686
0.98039216	0.7137255	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.09411765	0.44705883
0.8666667	0.99215686	0.99215686	0.99215686	0.99215686	0.7882353
0.30588236	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.	0.	0.09019608	0.25882354	0.8352941	0.99215686
0.99215686	0.99215686	0.99215686	0.7764706	0.31764707	0.00784314
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	]	
[0.	0.	0.	0.	0.	0.
0.07058824	0.67058825	0.85882354	0.99215686	0.99215686	0.99215686
0.99215686	0.7647059	0.3137255	0.03529412	0.	0.

```

0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.
[0.          0.          0.          0.          0.21568628 0.6745098
0.8862745  0.99215686  0.99215686  0.99215686  0.99215686  0.95686275
0.52156866  0.04313726  0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.
[0.          0.          0.          0.          0.53333336 0.99215686
0.99215686  0.99215686  0.83137256  0.5294118   0.5176471   0.0627451
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.
[0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.
[0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.
[0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.
[0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          0.          0.
0.          0.          0.          0.          ]          0.

```

[2]: # b) Defining the model's architecture (CNN)

```
model = keras.Sequential([
    layers.Input(shape=(28, 28, 1)),
    layers.Conv2D(32, kernel_size=3, activation="relu", padding="same"),
    layers.MaxPooling2D(pool_size=2),
    layers.Conv2D(64, kernel_size=3, activation="relu", padding="same"),
    layers.MaxPooling2D(pool_size=2),
    layers.Flatten(),
    layers.Dense(128, activation="relu"),
    layers.Dense(10, activation="softmax"),
])

model.summary()
```

Model defined. Summary:

Model: "sequential"

Layer (type)	Output Shape	
Param #		
conv2d (Conv2D) ↳ 320	(None, 28, 28, 32)	□
max_pooling2d (MaxPooling2D) ↳ 0	(None, 14, 14, 32)	□
conv2d_1 (Conv2D) ↳ 18,496	(None, 14, 14, 64)	□
max_pooling2d_1 (MaxPooling2D) ↳ 0	(None, 7, 7, 64)	□
flatten (Flatten) ↳ 0	(None, 3136)	□
dense (Dense) ↳ 401,536	(None, 128)	□
dense_1 (Dense) ↳ 1,290	(None, 10)	□

Total params: 421,642 (1.61 MB)

Trainable params: 421,642 (1.61 MB)

Non-trainable params: 0 (0.00 B)

[3]: # c) Training the model

```
model.compile(
    optimizer=keras.optimizers.SGD(learning_rate=0.01, momentum=0.9),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)

print("Training started...\n")
history = model.fit(
    x_train, y_train,
    validation_data=(x_test, y_test),
```

```

    epochs=10,
    batch_size=64,
    verbose=2
)
print("\nTraining completed!")

```

Training started...

```

Epoch 1/10
938/938 - 11s - 12ms/step - accuracy: 0.9259 - loss: 0.2468 - val_accuracy:
0.9794 - val_loss: 0.0638
Epoch 2/10
938/938 - 10s - 11ms/step - accuracy: 0.9794 - loss: 0.0671 - val_accuracy:
0.9860 - val_loss: 0.0438
Epoch 3/10
938/938 - 10s - 11ms/step - accuracy: 0.9857 - loss: 0.0464 - val_accuracy:
0.9868 - val_loss: 0.0387
Epoch 4/10
938/938 - 10s - 11ms/step - accuracy: 0.9889 - loss: 0.0350 - val_accuracy:
0.9887 - val_loss: 0.0333
Epoch 5/10
938/938 - 10s - 11ms/step - accuracy: 0.9907 - loss: 0.0291 - val_accuracy:
0.9880 - val_loss: 0.0367
Epoch 6/10
938/938 - 11s - 12ms/step - accuracy: 0.9925 - loss: 0.0235 - val_accuracy:
0.9899 - val_loss: 0.0325
Epoch 7/10
938/938 - 11s - 12ms/step - accuracy: 0.9941 - loss: 0.0187 - val_accuracy:
0.9906 - val_loss: 0.0289
Epoch 8/10
938/938 - 10s - 11ms/step - accuracy: 0.9954 - loss: 0.0157 - val_accuracy:
0.9907 - val_loss: 0.0282
Epoch 9/10
938/938 - 10s - 11ms/step - accuracy: 0.9957 - loss: 0.0133 - val_accuracy:
0.9914 - val_loss: 0.0292
Epoch 10/10
938/938 - 11s - 12ms/step - accuracy: 0.9966 - loss: 0.0110 - val_accuracy:
0.9898 - val_loss: 0.0330

```

Training completed!

[4]: # d) Estimating the model's performance

```

test_loss, test_acc = model.evaluate(x_test, y_test, verbose=1)
print(f"\nTest accuracy: {test_acc:.4f}")
print(f"Test loss: {test_loss:.4f}")

```

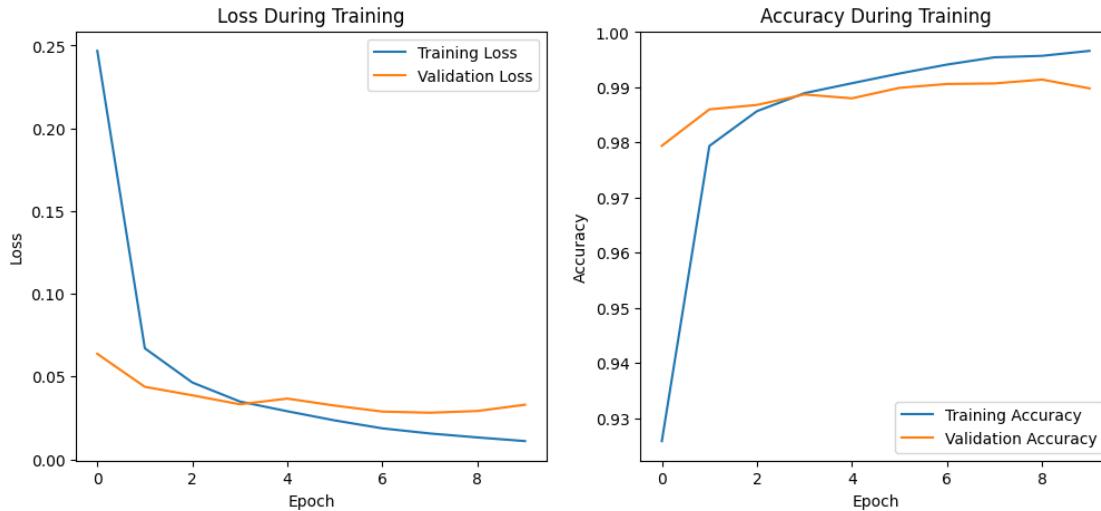
```

plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss During Training')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy During Training')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

```

313/313 1s 3ms/step -  
accuracy: 0.9881 - loss: 0.0408

Test accuracy: 0.9898  
Test loss: 0.0330



[5]: # Visualize predictions on test samples (first 11 digits)

```

count = 11
predictions = model.predict(x_test[:count])
predicted_labels = np.argmax(predictions, axis=1)

plt.figure(figsize=(12, 5))

```

```
for i in range(count):
    plt.subplot(1, count, i + 1)
    plt.imshow(x_test[i].squeeze(), cmap='gray')
    plt.title(f"Pred: {predicted_labels[i]}\nTrue: {y_test[i]}")
    plt.axis('off')
plt.suptitle("CNN Predictions vs Actual MNIST Labels")
plt.show()
```

1/1

0s 82ms/step

CNN Predictions vs Actual MNIST Labels

Pred: 7	Pred: 2	Pred: 1	Pred: 0	Pred: 4	Pred: 1	Pred: 4	Pred: 9	Pred: 5	Pred: 9	Pred: 0
True: 7	True: 2	True: 1	True: 0	True: 4	True: 1	True: 4	True: 9	True: 5	True: 9	True: 0
										