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# -*- coding: utf-8 -*-  
...
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In this assignment:

- You learn how build a Convolution Neural Network for image classification a compute
- The image classification task is the handwritten digit classification using the MNI

Dataset

The MNIST dataset is an acronym that stands for the Modified National Institute of Standards

It is a dataset of 60,000 small square 28×28 pixel grayscale images of handwritten single di

The task is to classify a given image of a handwritten digit into one of 10 classes represer

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import numpy as np  
from tensorflow import keras  
from tensorflow.keras import layers  
#Prepare the data  
# Model / data parameters  
num_classes = 10  
input_shape = (28, 28, 1)  
  
# the data, split between train and test sets  
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()
```

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# Scale images to the [0, 1] range
x_train = x_train.astype("float32") / 255
x_test = x_test.astype("float32") / 255
# Make sure images have shape (28, 28, 1)
x_train = np.expand_dims(x_train, -1)
x_test = np.expand_dims(x_test, -1)
print("x_train shape:", x_train.shape)
print(x_train.shape[0], "train samples")
print(x_test.shape[0], "test samples")
# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
# Set the model to be a simple feed-forward (layered) architecture
# See https://keras.io/api/models/ and https://keras.io/api/models/sequential/
# not to be confused with a sequence-based alg/model to process sequential data
model = keras.Sequential()
# Add an input layer with shape=(28, 28, 1)
# See https://keras.io/api/layers/core_layers/input/
model.add(keras.Input(shape=(28, 28, 1)))
# Add a Conv2D hidden layer with 32 relu activation units and kernel_size of 3*3
# See https://keras.io/api/layers/convolution_layers/convolution2d/
model.add(layers.Conv2D(32, kernel_size=(3, 3), activation='relu'))
# Add a MaxPooling hidden layer and set pool_size of 2*2
# See https://keras.io/api/layers/pooling_layers/max_pooling2d/
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
# Add a Conv2D hidden layer with 64 relu activation units and kernel_size of 3*3
# See https://keras.io/api/layers/convolution_layers/convolution2d/
model.add(layers.Conv2D(64, kernel_size=(3, 3), activation='relu'))
# Add a MaxPooling hidden layer and set pool_size of 2*2
# See https://keras.io/api/layers/pooling_layers/max_pooling2d/
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
# Add a Flatten hidden layer
# See https://keras.io/api/layers/reshaping_layers/flatten/
model.add(layers.Flatten())
# Add a Dropout hidden layer and set rate=0.5
# See https://keras.io/api/layers/regularization_layers/dropout/
model.add(layers.Dropout(0.5))
# Add a dense output layer with units=10 and softmax activation unit
# https://keras.io/api/layers/core_layers/dense/
model.add(layers.Dense(units=10, activation='softmax'))
model.summary()

# Compile the model, specifying (1) the Adam optimizer,
# (2) the 'categorical_crossentropy' loss function, and (3) metrics=['accuracy']
# See https://keras.io/api/models/model_training_apis/
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
# fit the keras model on the _TRAIN_ dataset set epochs to 15, batch_size to 128, validation
model.fit(x_train, y_train, batch_size=128, epochs=15, validation_split=0.1)

```

60000 train samples  
 10000 test samples  
 Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dropout (Dropout)	(None, 1600)	0
dense (Dense)	(None, 10)	16010

=====  
 Total params: 34826 (136.04 KB)  
 Trainable params: 34826 (136.04 KB)  
 Non-trainable params: 0 (0.00 Byte)

Epoch 1/15  
 422/422 [=====] - 51s 118ms/step - loss: 0.3752 - accuracy: 0.0000  
 Epoch 2/15  
 422/422 [=====] - 45s 107ms/step - loss: 0.1098 - accuracy: 0.0000  
 Epoch 3/15  
 422/422 [=====] - 46s 110ms/step - loss: 0.0830 - accuracy: 0.0000  
 Epoch 4/15  
 422/422 [=====] - 44s 105ms/step - loss: 0.0702 - accuracy: 0.0000  
 Epoch 5/15  
 422/422 [=====] - 44s 105ms/step - loss: 0.0616 - accuracy: 0.0000  
 Epoch 6/15  
 422/422 [=====] - 54s 127ms/step - loss: 0.0562 - accuracy: 0.0000  
 Epoch 7/15  
 422/422 [=====] - 44s 104ms/step - loss: 0.0493 - accuracy: 0.0000  
 Epoch 8/15  
 422/422 [=====] - 43s 101ms/step - loss: 0.0474 - accuracy: 0.0000  
 Epoch 9/15  
 422/422 [=====] - 44s 105ms/step - loss: 0.0438 - accuracy: 0.0000  
 Epoch 10/15  
 422/422 [=====] - 43s 102ms/step - loss: 0.0422 - accuracy: 0.0000  
 Epoch 11/15  
 422/422 [=====] - 58s 138ms/step - loss: 0.0393 - accuracy: 0.0000  
 Epoch 12/15  
 422/422 [=====] - 43s 103ms/step - loss: 0.0362 - accuracy: 0.0000

422/422 [=====] - 43s 102ms/step - loss: 0.0354 - accuracy: 0.9922

```
score = model.evaluate(x_test, y_test, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])
```

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Test loss: 0.023518381640315056
Test accuracy: 0.9922000169754028
```

## ✓ QUESTIONS

Why are Convolutional Neural Networks more popular than Feed Forward Neural Networks in Computer Vision?

CNNs are widely preferred over Feed Forward Neural Networks in computer vision because they are specifically designed for image data. They use convolutional layers to identify patterns in images, allowing them to understand shapes and objects regardless of their position. This makes them effective for tasks like recognizing objects, dividing images into parts, and deciding what an image contains. Compared to traditional neural networks, CNNs perform better on large image datasets because they can learn from shared features and ignore irrelevant details.