

Week1_MNIST_CNN-Implementation

January 18, 2020

1 MNIST - Convolutional Neural Networks

Here a state of the art Convolutional Neural Networks is shown to perform decently on the MNIST dataset. Keras module makes this implementation very simple. See how the model can achieve high performance.

```
In [4]: # TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras

# Helper libraries
import numpy as np
import matplotlib.pyplot as plt
import random

print(tf.__version__)
```

2.1.0

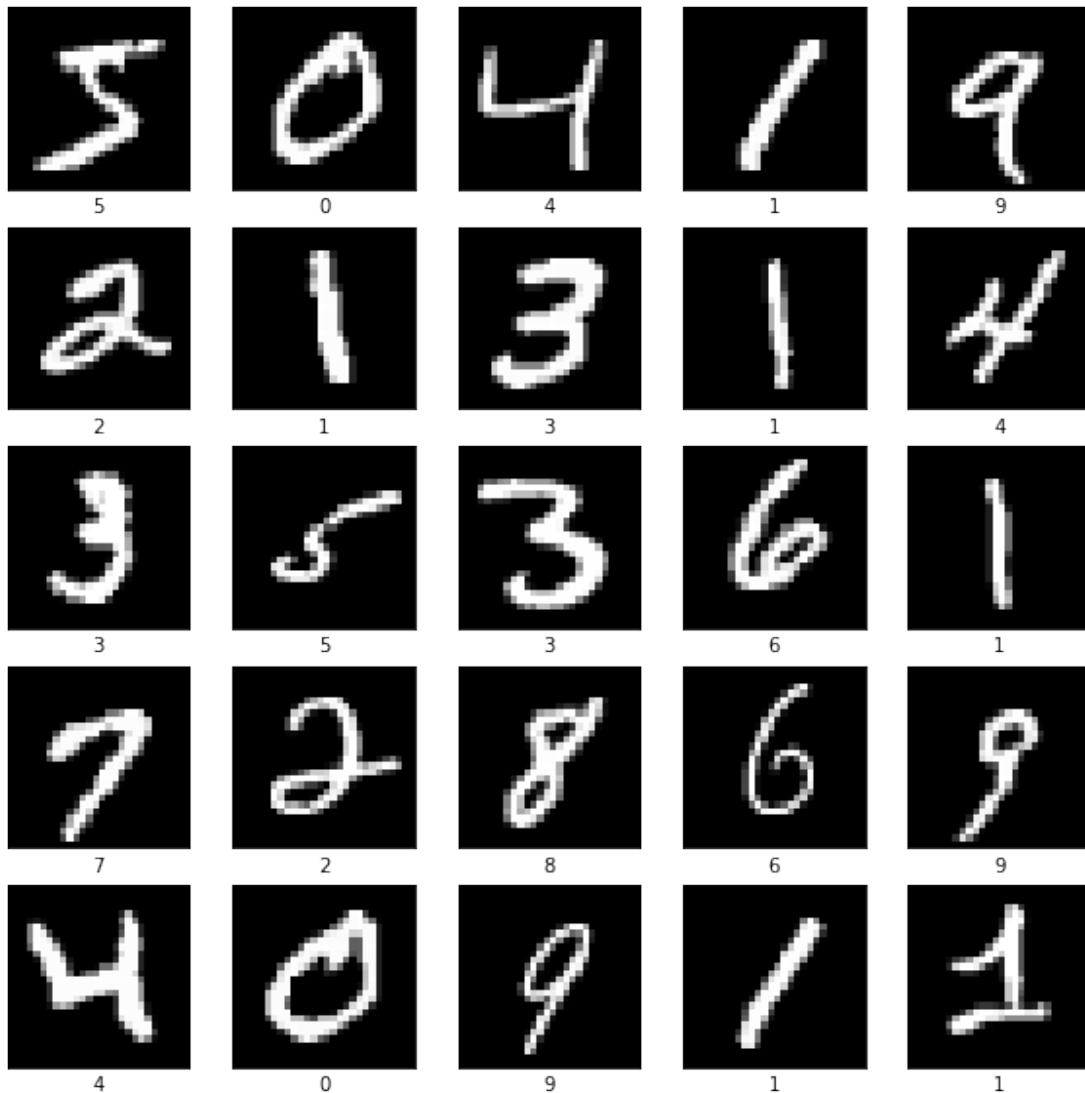
```
In [5]: # Keras provides a handy API to download the MNIST dataset, and split them into
# "train" dataset and "test" dataset.
mnist = keras.datasets.mnist
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

```
In [6]: # Normalize the input image so that each pixel value is between 0 to 1.
train_images = train_images / 255.0
test_images = test_images / 255.0
print('Pixels are normalized')
```

Pixels are normalized

```
In [7]: # Show the first 25 images in the training dataset.
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
```

```
plt.yticks([])
plt.grid(False)
plt.imshow(train_images[i], cmap=plt.cm.gray)
plt.xlabel(train_labels[i])
plt.show()
```



```
In [8]: # Define the model architecture
model = keras.Sequential([
    keras.layers.InputLayer(input_shape=(28, 28)),
    keras.layers.Reshape(target_shape=(28, 28, 1)),
    keras.layers.Conv2D(filters=12, kernel_size=(3, 3), activation=tf.nn.relu),
    keras.layers.MaxPooling2D(pool_size=(2, 2)),
    keras.layers.Flatten(),
```

```

        keras.layers.Dense(10, activation=tf.nn.softmax)
    ])

    # Define how to train the model
    model.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

    # Train the digit classification model
    model.fit(train_images, train_labels, epochs=5)

```

Train on 60000 samples

Epoch 1/5

60000/60000 [=====] - 8s 139us/sample - loss: 0.3124 - accuracy: 0.91

Epoch 2/5

60000/60000 [=====] - 8s 135us/sample - loss: 0.1317 - accuracy: 0.96

Epoch 3/5

60000/60000 [=====] - 8s 134us/sample - loss: 0.0887 - accuracy: 0.97

Epoch 4/5

60000/60000 [=====] - 8s 137us/sample - loss: 0.0715 - accuracy: 0.97

Epoch 5/5

60000/60000 [=====] - 8s 133us/sample - loss: 0.0603 - accuracy: 0.98

Out[8]: <tensorflow.python.keras.callbacks.History at 0x16821f400>

In [9]: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
reshape (Reshape)	(None, 28, 28, 1)	0
conv2d (Conv2D)	(None, 26, 26, 12)	120
max_pooling2d (MaxPooling2D)	(None, 13, 13, 12)	0
flatten (Flatten)	(None, 2028)	0
dense (Dense)	(None, 10)	20290

Total params: 20,410

Trainable params: 20,410

Non-trainable params: 0

In [10]: # Evaluate the model using all images in the test dataset.

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
```

```

print('Test accuracy:', test_acc)

10000/10000 [=====] - 1s 57us/sample - loss: 0.0614 - accuracy: 0.9807
Test accuracy: 0.9807

```

```





































































































In [11]: # A helper function that returns 'red'/'black' depending on if its two input
# parameter matches or not.
def get_label_color(val1, val2):
    if val1 == val2:
        return 'black'
    else:
        return 'red'

# Predict the labels of digit images in our test dataset.
predictions = model.predict(test_images)

# As the model output 10 float representing the probability of the input image
# being a digit from 0 to 9, we need to find the largest probability value
# to find out which digit the model predicts to be most likely in the image.
prediction_digits = np.argmax(predictions, axis=1)

# Then plot 100 random test images and their predicted labels.
# If a prediction result is different from the label provided label in "test"
# dataset, we will highlight it in red color.
plt.figure(figsize=(18, 18))
for i in range(100):
    ax = plt.subplot(10, 10, i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    image_index = random.randint(0, len(prediction_digits))
    plt.imshow(test_images[image_index], cmap=plt.cm.gray)
    ax.xaxis.label.set_color(get_label_color(prediction_digits[image_index],\
                                              test_labels[image_index]))
    plt.xlabel('Predicted: %d' % prediction_digits[image_index])
plt.show()

```

									
Predicted: 9	Predicted: 5	Predicted: 1	Predicted: 3	Predicted: 2	Predicted: 4	Predicted: 2	Predicted: 8	Predicted: 2	Predicted: 1
									
Predicted: 9	Predicted: 2	Predicted: 8	Predicted: 1	Predicted: 3	Predicted: 3	Predicted: 9	Predicted: 8	Predicted: 9	Predicted: 0
									
Predicted: 1	Predicted: 4	Predicted: 6	Predicted: 4	Predicted: 0	Predicted: 4	Predicted: 5	Predicted: 1	Predicted: 2	Predicted: 1
									
Predicted: 1	Predicted: 3	Predicted: 3	Predicted: 7	Predicted: 9	Predicted: 2	Predicted: 4	Predicted: 0	Predicted: 7	Predicted: 5
									
Predicted: 1	Predicted: 0	Predicted: 2	Predicted: 1	Predicted: 3	Predicted: 3	Predicted: 0	Predicted: 0	Predicted: 0	Predicted: 5
									
Predicted: 6	Predicted: 7	Predicted: 9	Predicted: 8	Predicted: 4	Predicted: 2	Predicted: 6	Predicted: 6	Predicted: 9	Predicted: 0
									
Predicted: 9	Predicted: 5	Predicted: 5	Predicted: 1	Predicted: 1	Predicted: 9	Predicted: 7	Predicted: 4	Predicted: 5	Predicted: 7
									
Predicted: 2	Predicted: 8	Predicted: 4	Predicted: 6	Predicted: 7	Predicted: 1	Predicted: 8	Predicted: 3	Predicted: 4	Predicted: 9
									
Predicted: 7	Predicted: 5	Predicted: 7	Predicted: 4	Predicted: 9	Predicted: 1	Predicted: 7	Predicted: 0	Predicted: 1	Predicted: 3
									
Predicted: 8	Predicted: 1	Predicted: 9	Predicted: 7	Predicted: 1	Predicted: 9	Predicted: 7	Predicted: 8	Predicted: 8	Predicted: 9