ARN - Practical work 4

Group information:

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Learning algorithm

We will use the same learning algorithm for the first 3 experiments: RMSprop. We will also use the same parameters for all the experiments.

Optimizer:	RMSprop
learning_rate:	0.001
momentum:	0.1
loss:	categorical_crossentropy
batch_size:	128
n_epoch:	50

The equation for the loss function is:

$$E[g^2]_t = \beta E[g^2]_{t-1} + (1-\beta)\left(\frac{\delta C}{\delta w}\right)^2$$

$$w_t = w_{t-1} - \frac{\eta}{\sqrt{E[g^2]_t}} \frac{\delta C}{\delta w}$$

E[g] — moving average of squared gradients. dC/dw — gradient of the cost function with respect to the weight. n — learning rate. Beta — moving average parameter (good default value — 0.9)

How the number of weights is calculated

The number of weights between two layers is calculated by multiplying the number of neurons in the first layer by the number of neurons in the second layer. We also add the number of biases in the second layer.

$$P = \sum_{l=1}^{l-1} (N_l \times N_{l+1}) + \ N_{l+1}$$

Example

The input layer has 784 neurons and the output layer has 10 neurons.

If we have a hidden layer with 16 neurons, the number of weights is calculated as follows:

Layer 1: $784 \times 16 + 16 = 12560$
Layer 2: $16 \times 10 + 10 = 170$
Total: $12560 + 170 = 12730$

Inputs 392

Do deeper networks have more weights than shallow ones?

The answer is perhaps. The number of weights in a neural network is not only determined by the number of layers, but also by the number of neurons in each layer. A deep network with few neurons in each layer can have fewer weights than a shallow network with many neurons in each layer.

The performance of a neural network is also not only determined by the number of weights. A deep network can have a better performance than a shallow network with the same number of weights. It is important to find the right balance between the number of layers and the number of neurons in each layer. Also activation functions and learning algorithms play an important role in the performance of a neural network.

MLP from raw data

We will test three different models with different number of neurons in the hidden layers.

For the first model, we chose a low number of neurons in the hidden layers to see how the model would perform with insufficient capacity. We hope to see the highest error rate in this model.

For the second model, we chose a number of neurons in the hidden layers that is higher than the number of neurons in the input layer. We hope to see a better performance than the first model.

For the third model, we chose a high number of neurons in the hidden layers to see how the model would perform with a high capacity. We hope to see the lowest error rate in this model, but we also expect to see overfitting.

We have the same number of inputs and outputs for all models. The input layer has 784 neurons and the output layer has 10 neurons.

First model

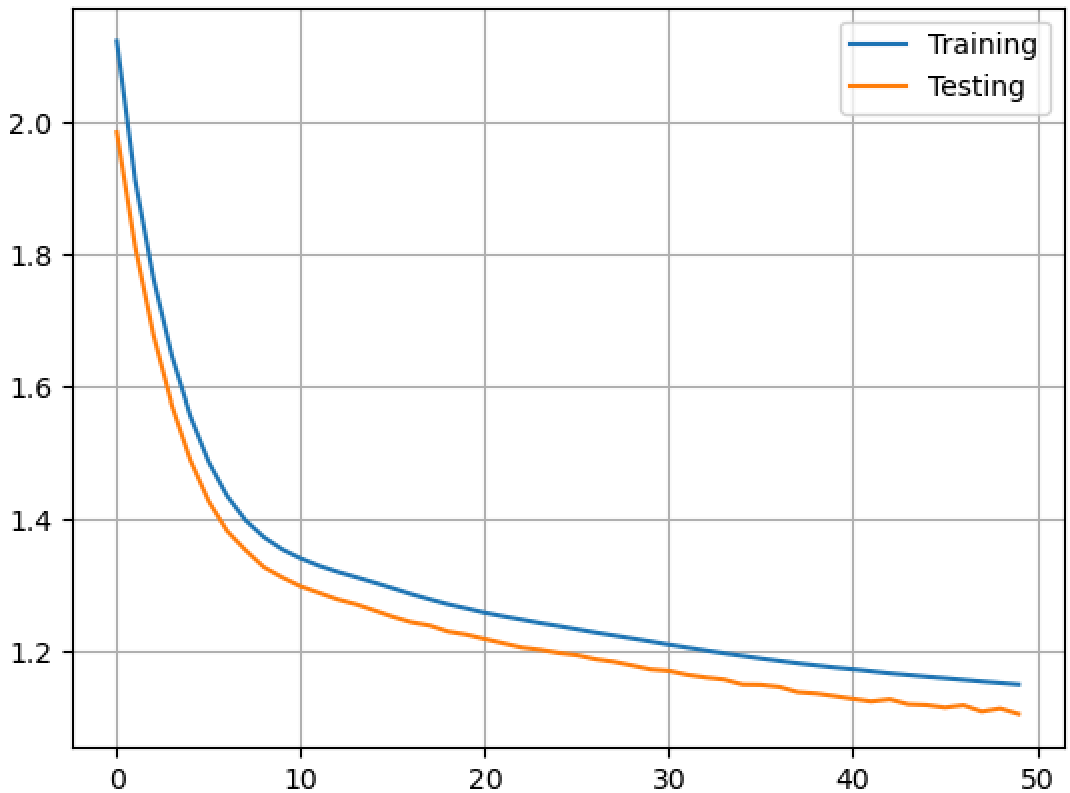
model = Sequential

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 2)	1,570
dense_74 (Dense)	(None, 10)	30

Total params:	1,600 (6.25 KB)
Trainable params:	1,600 (6.25 KB)
Non-trainable params:	0 (0.00 B)

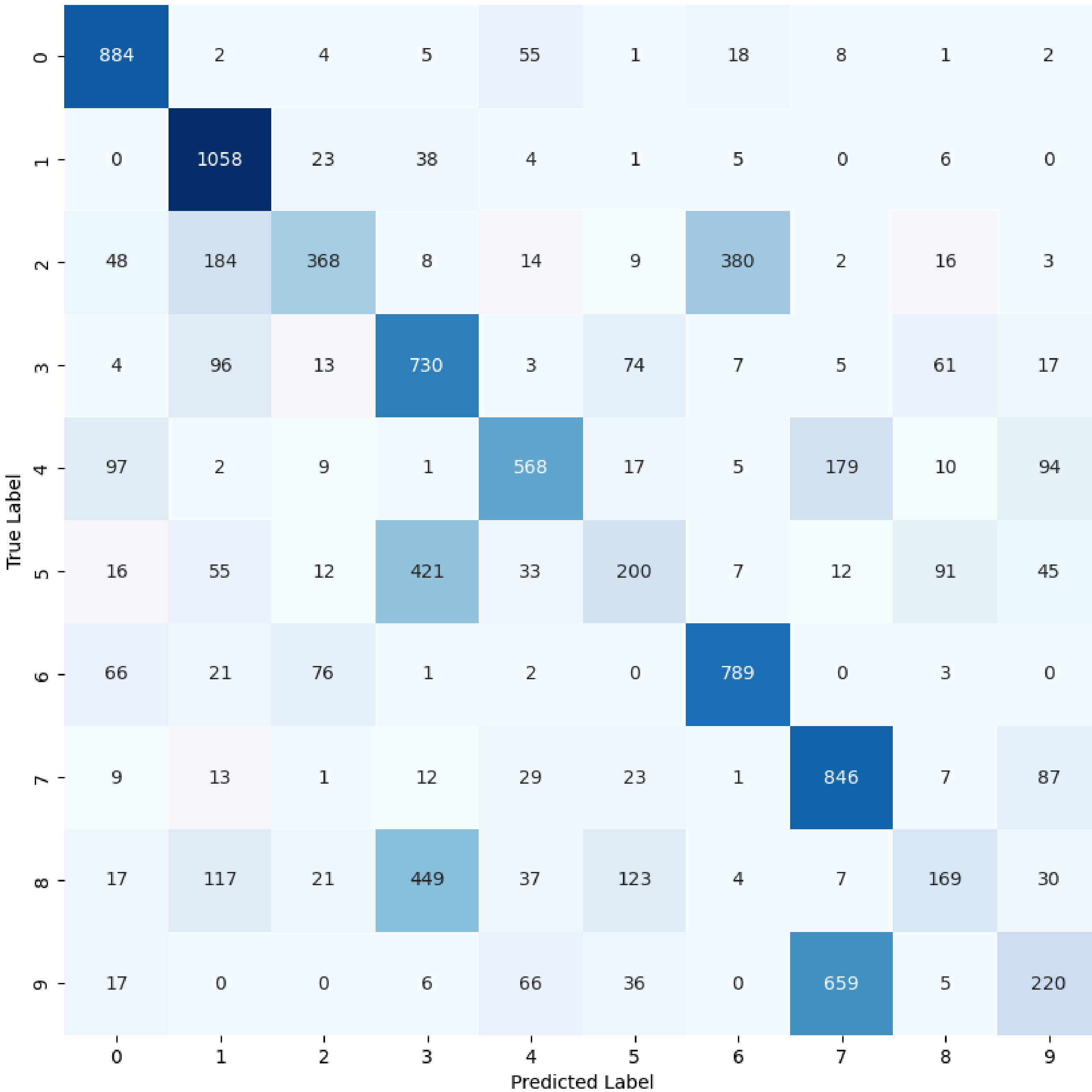
Performance

Test score:	1.1609300374984741
Test accuracy:	0.5831999778747559



Confusion matrix

F1 macro Score:	0.5442219669271385
F1 weighted Score:	0.5492755535704517
F1 micro Score:	0.5832



Second model

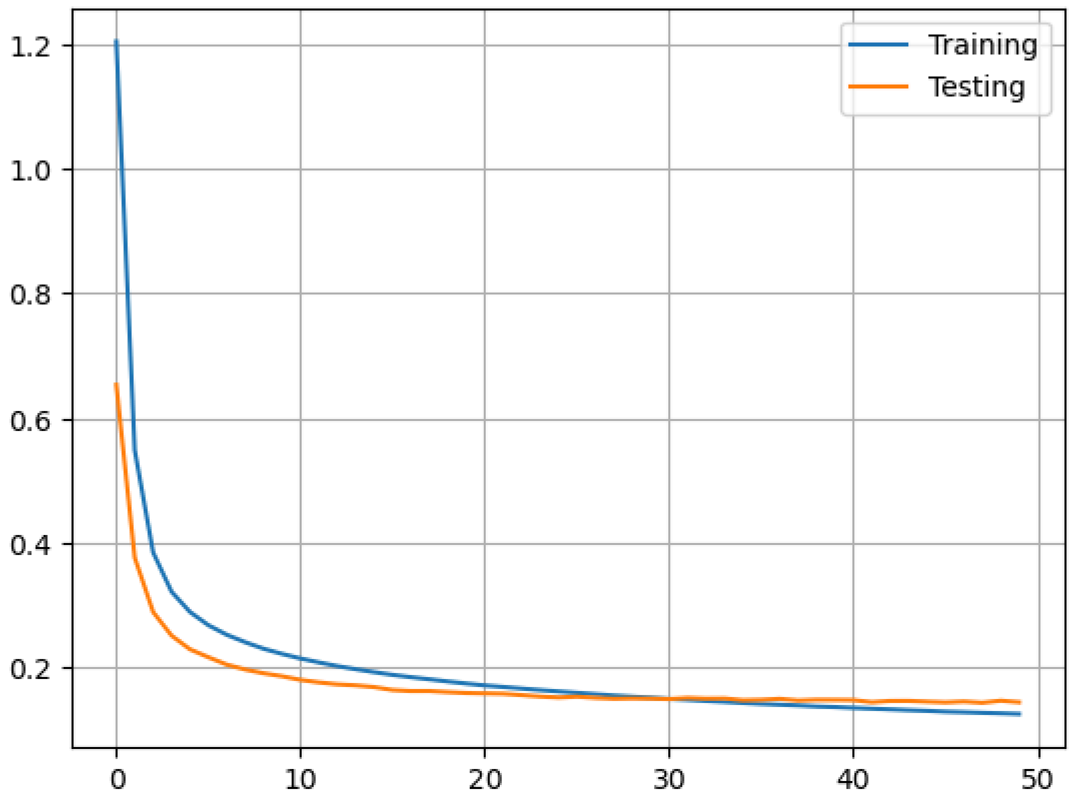
model = Sequential

Layer (type)	Output Shape	Param #
dense_72 (Dense)	(None, 16)	12,560
dense_74 (Dense)	(None, 10)	170

Total params:	12,730 (49.73 KB)
Trainable params:	12,730 (49.73 KB)
Non-trainable params:	0 (0.00 B)

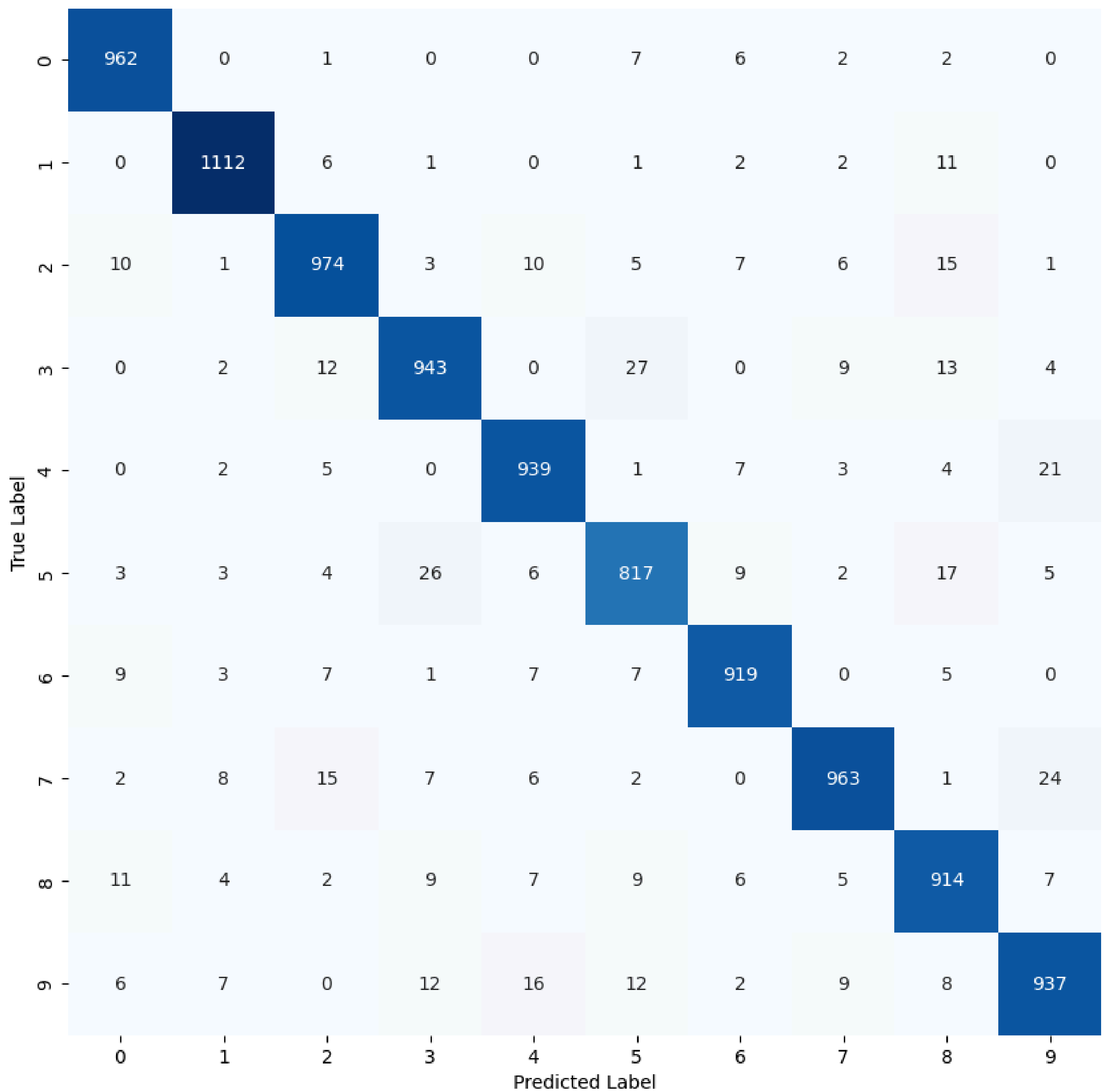
Performance

Test score:	0.17095278203487396
Test accuracy:	0.9480000138282776



Confusion matrix

F1 macro Score:	0.9473270917753236
F1 weighted Score:	0.9479600401672442
F1 micro Score:	0.948



Third model

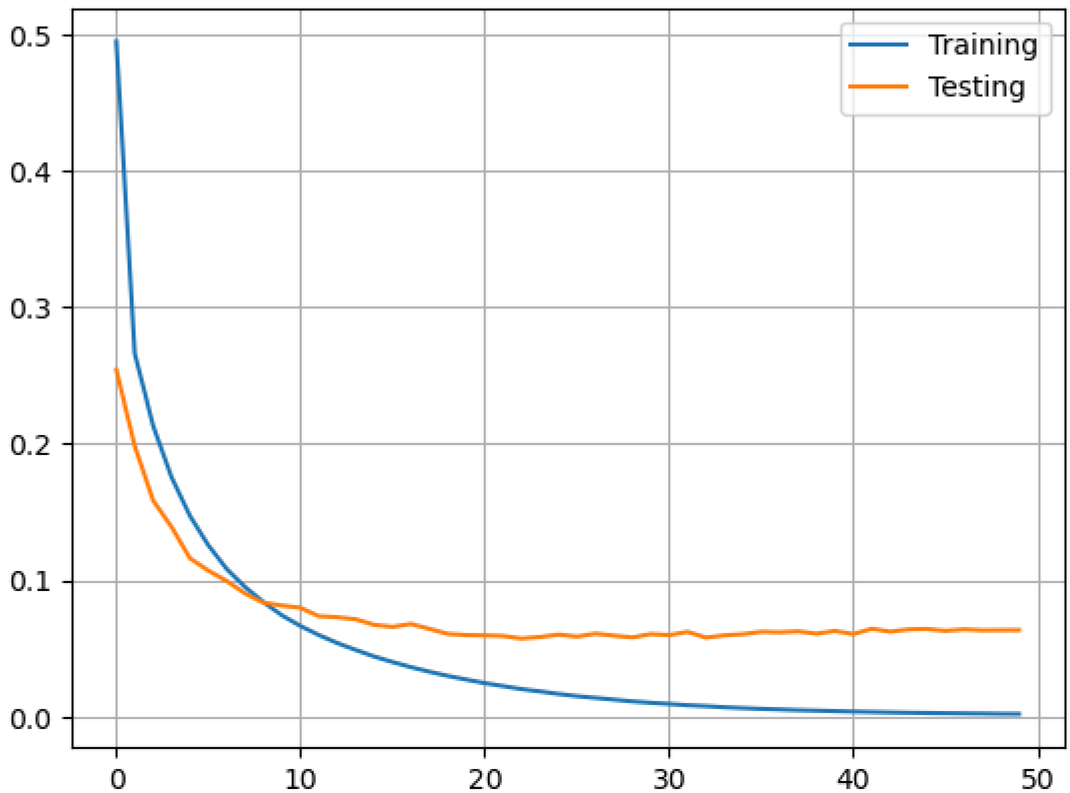
model = Sequential

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 254)	199,390
dense (Dense)	(None, 10)	2,550

Total params:	201,940 (788.83 KB)
Trainable params:	201,940 (788.83 KB)
Non-trainable params:	0 (0.00 B)

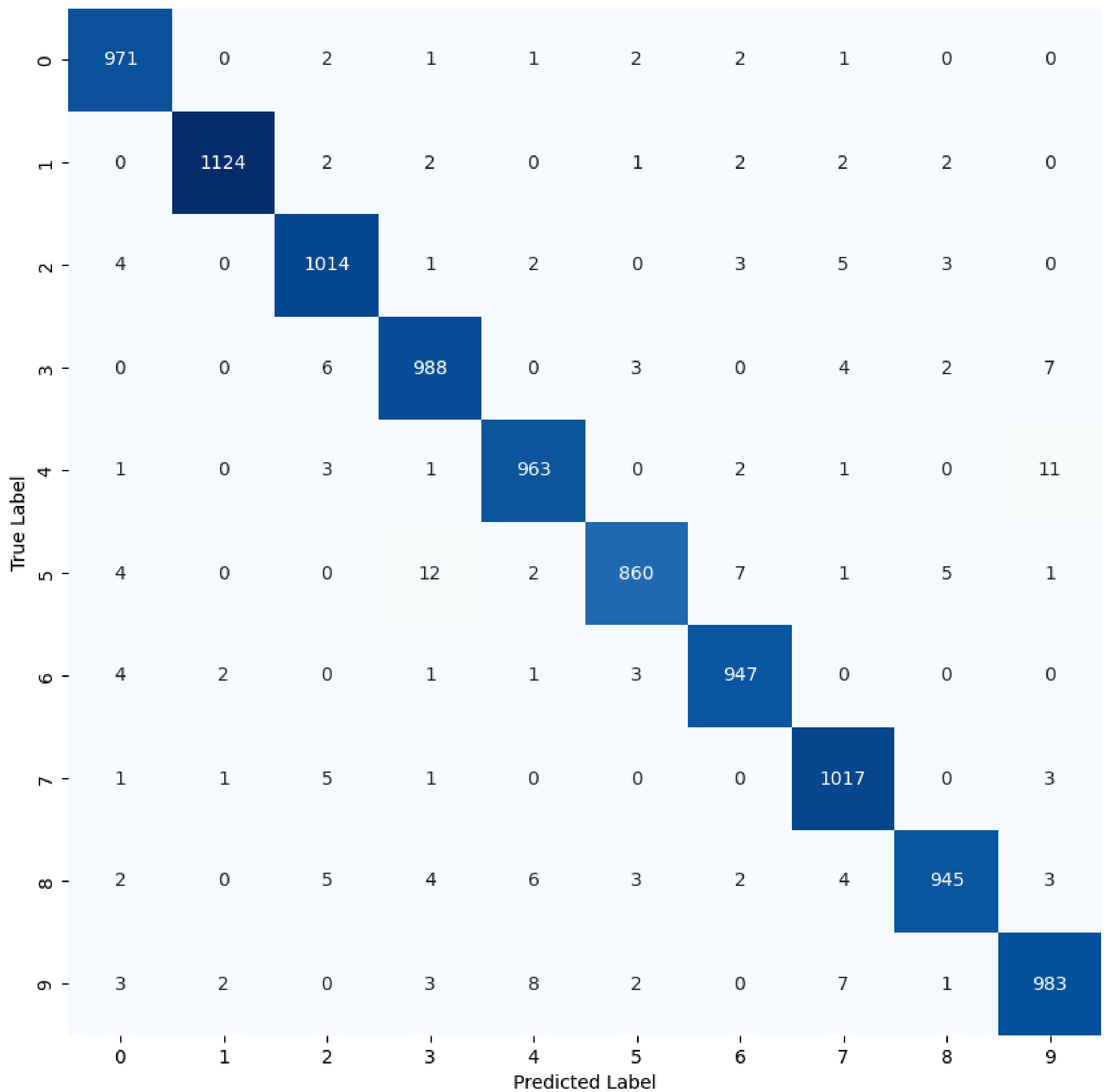
Performance

Test score:	0.06881905347108841
Test accuracy:	0.9811999797821045



Confusion matrix

F1 macro Score:	0.9809796904590385
F1 weighted Score:	0.9811910297485315
F1 micro Score:	0.9812



Conclusion of the first exercise

First model has the highest error rate, as expected, because it has the lowest capacity.

The second model has a better performance than the first model, but it is still not as good as the third model.

The third model has the lowest error rate, but it is also the model with the highest capacity. We can see in the performance plots that the third model is overfitting the training data.

MLP form HOG

We will test three different models with different number of pix_p_cells, orientations and hidden neurons.

The first one, we will keep the parameters as we got them in den notebook.

For the second one, we will increase the number of pix_p_cells to 7 and increase the hidden neurons to 16.

For the third one, we will increase the number of orientations to 16.

First model

model = Sequential

Input layer: 392 neurons
Output layer: 10 neurons

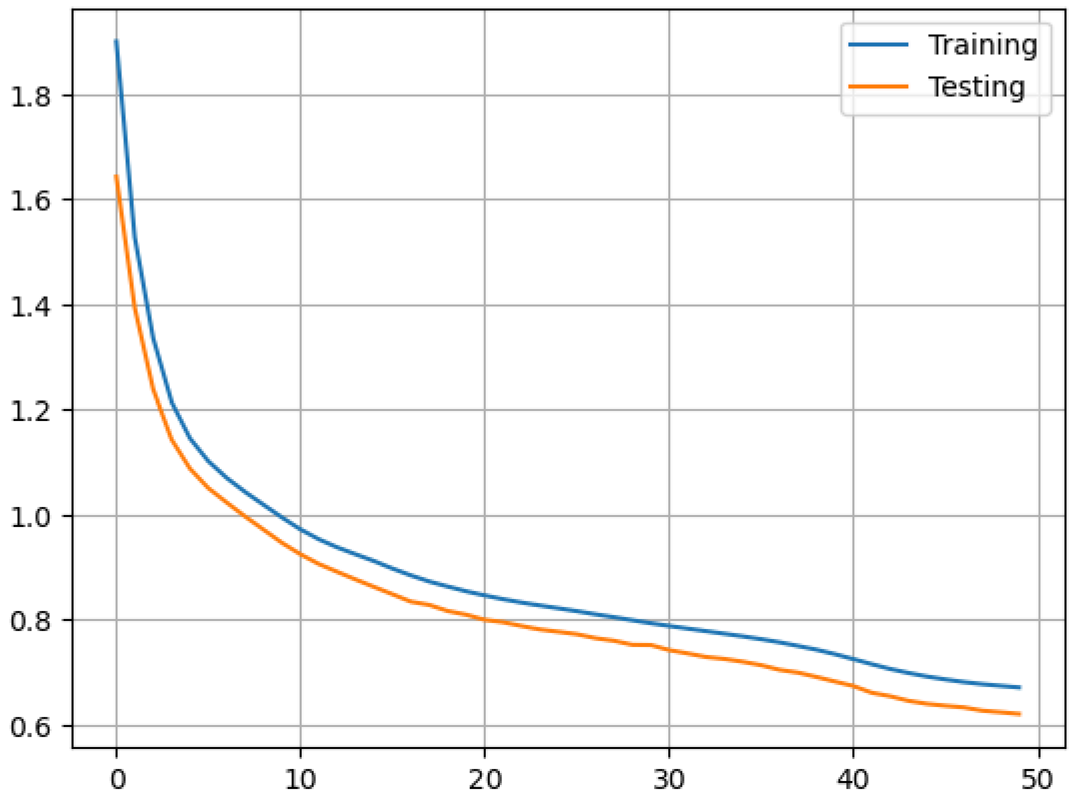
pix_p_cell:	4
orientations:	8

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 2)	786
dense_74 (Dense)	(None, 10)	30

Total params:	816 (3.19 KB)
Trainable params:	816 (3.19 KB)
Non-trainable params:	0 (0.00 B)

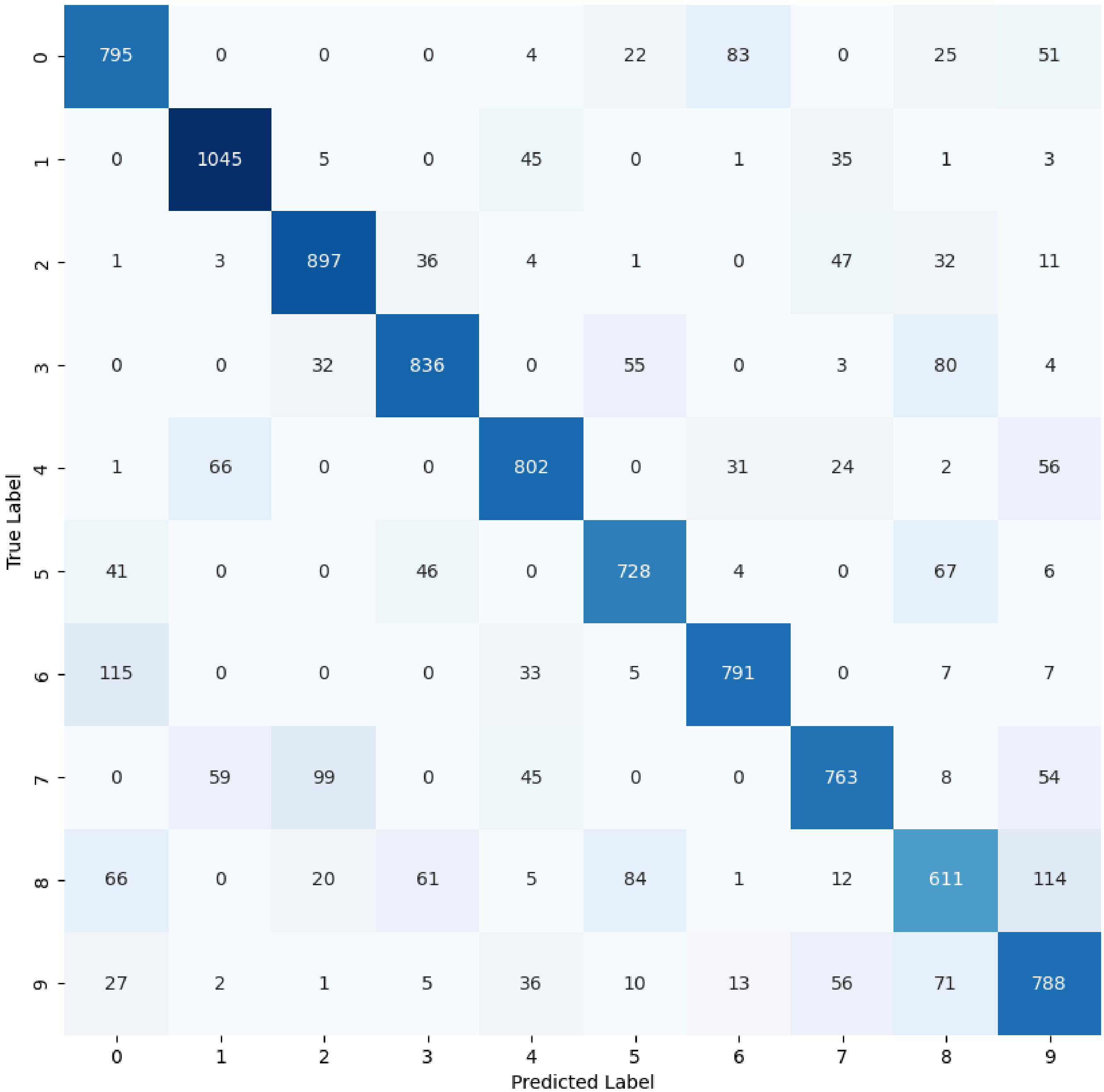
Performance

Test score:	0.6384848356246948
Test accuracy:	0.8055999875068665



Confusion matrix

F1 macro Score:	0.8034473897606494
F1 weighted Score:	0.8050793032002753
F1 micro Score:	0.8056000000000001



Second model

model = Sequential

Input layer: 128
Output layer: 10

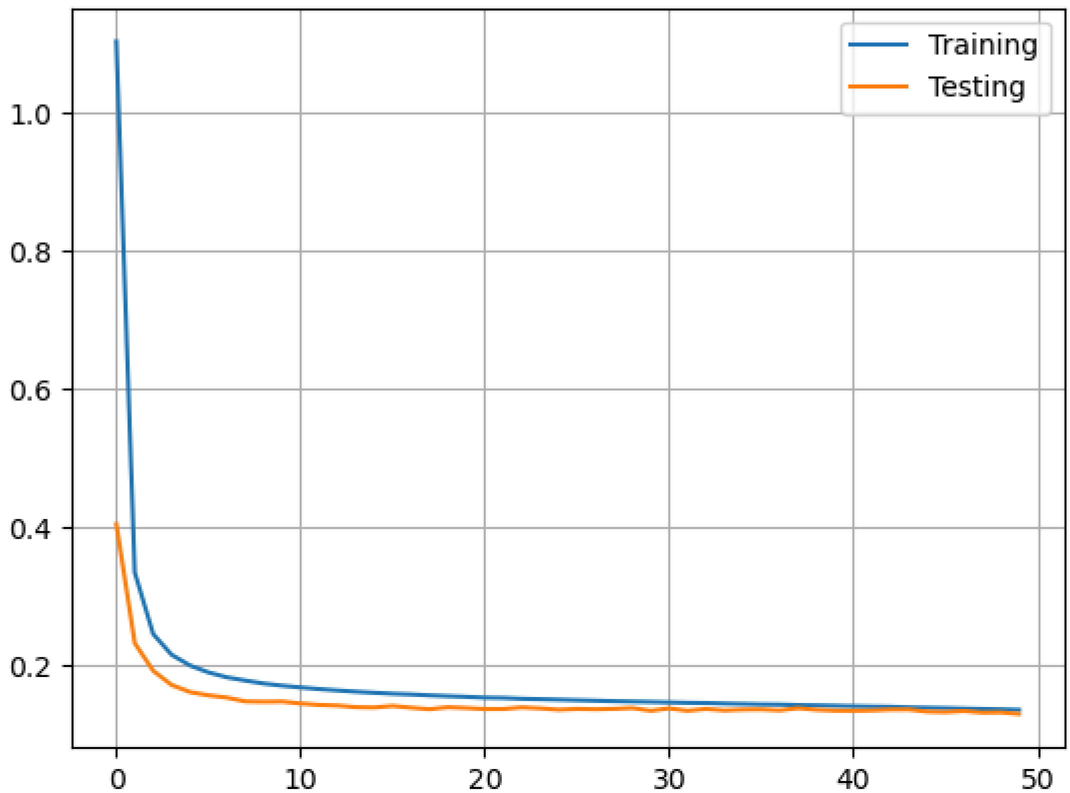
pix_p_cell:	7
orientations:	8

Layer (type)	**Output Shape**	**Param #**
dense_72 (Dense)	(None, 16)	2,064
dense_74 (Dense)	(None, 10)	170

Total params:	2,234 (8.73 KB)
Trainable params:	2,234 (8.73 KB)
Non-trainable params:	0 (0.00 B)

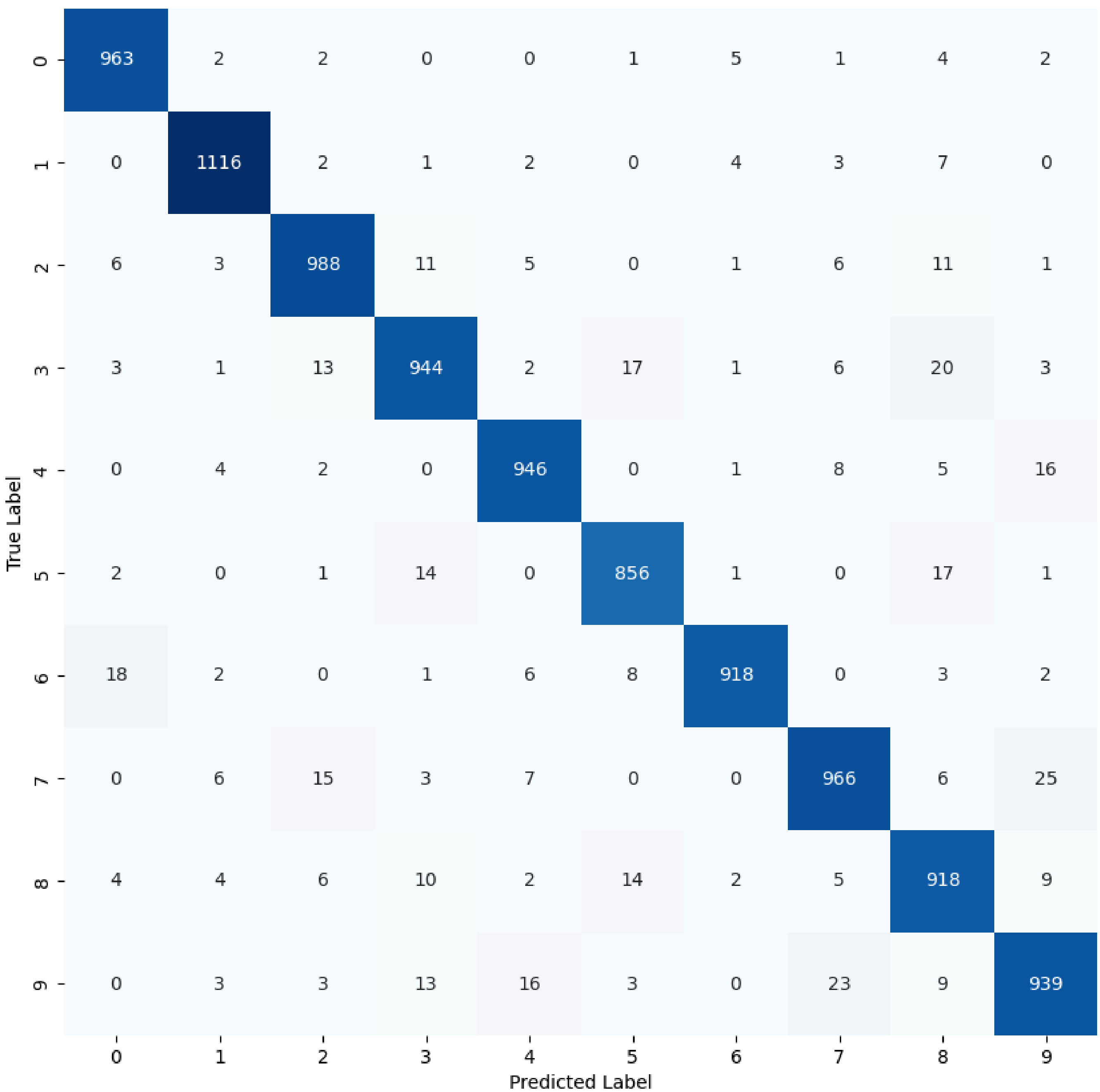
Performance

Test score:	0.13750861585140228
Test accuracy:	0.9553999900817871



Confusion matrix

F1 macro Score:	0.9551721269922793
F1 weighted Score:	0.9554019788594343
F1 micro Score:	0.9554



Third model

model = Sequential

Input layer: 256
Output layer: 10

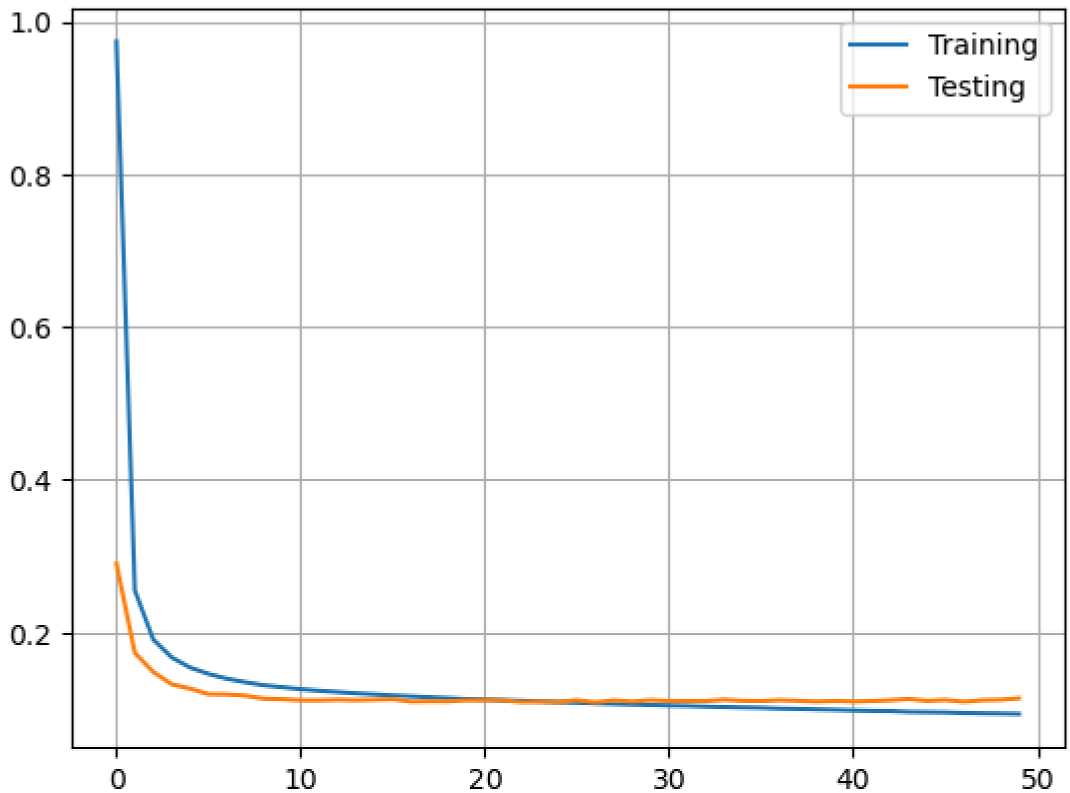
pix_p_cell:	7
orientations:	16

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 16)	4,112
dense (Dense)	(None, 10)	170

Total params:	4,282 (16.73 KB)
Trainable params:	4,282 (16.73 KB)
Non-trainable params:	0 (0.00 B)

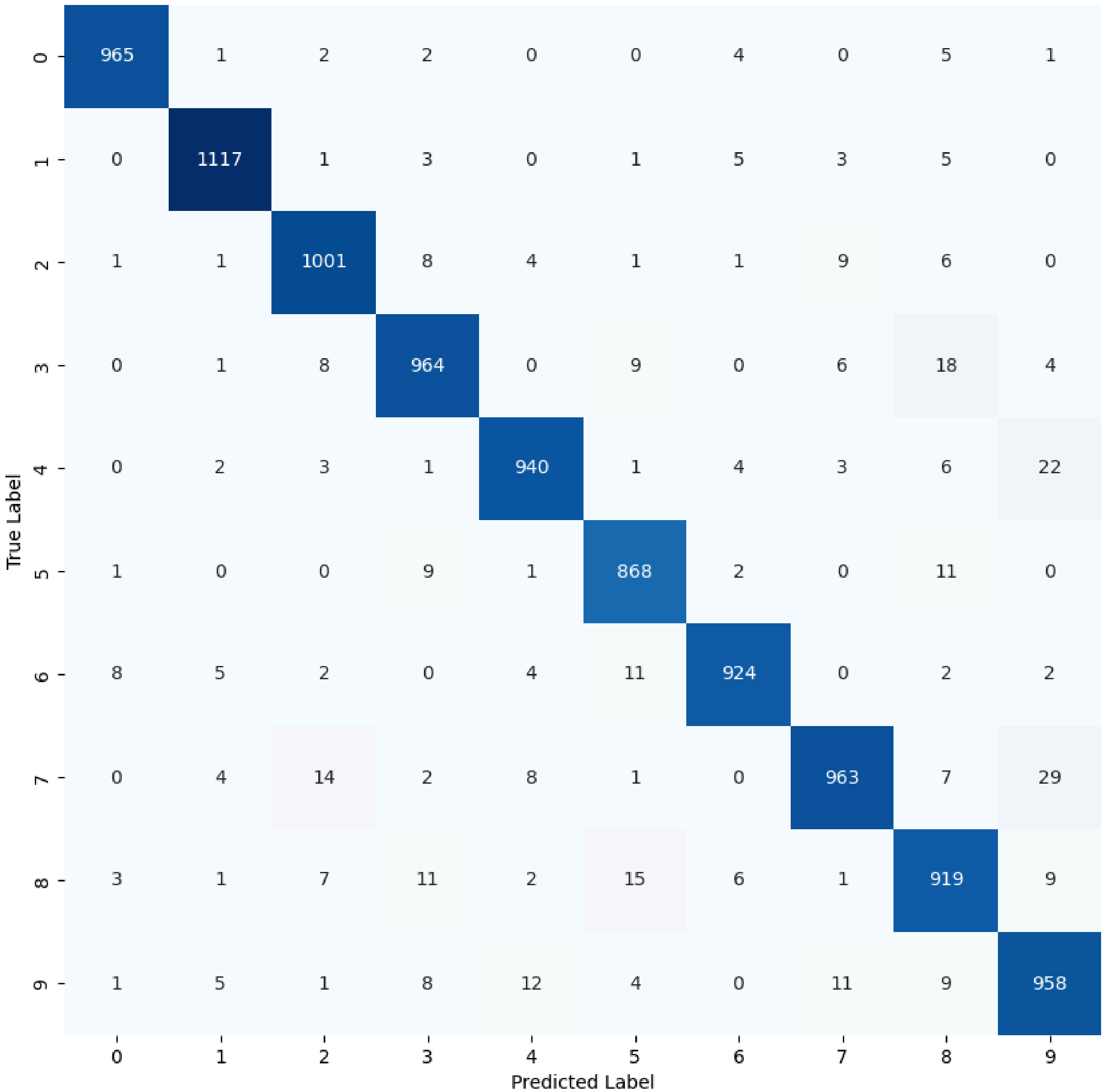
Performance

Test score:	0.1171414703130722
Test accuracy:	0.961899995803833



Confusion matrix

F1 macro Score:	0.9616971327055737
F1 weighted Score:	0.9619184118610641
F1 micro Score:	0.9619



Conclusion of the second exercise

The first model has the lowest performance, as expected, because it has the lowest capacity. But it has still a good performance: ~80% accuracy. This is better than the first model of the first exercise which has the same capacity.

The second model has a better performance, but the training stops at ~40 epochs. This is probably because the model is overfitting the training data.

The third model has the best performance, but it is also the one which overfits the most. It begins to overfit the training data at ~20 epochs.

CNN

In this exercise, we will test three different models with different number of neurons in the feed-forward part. We will start with a low number of neurons and increase the number of neurons in each model.

First model

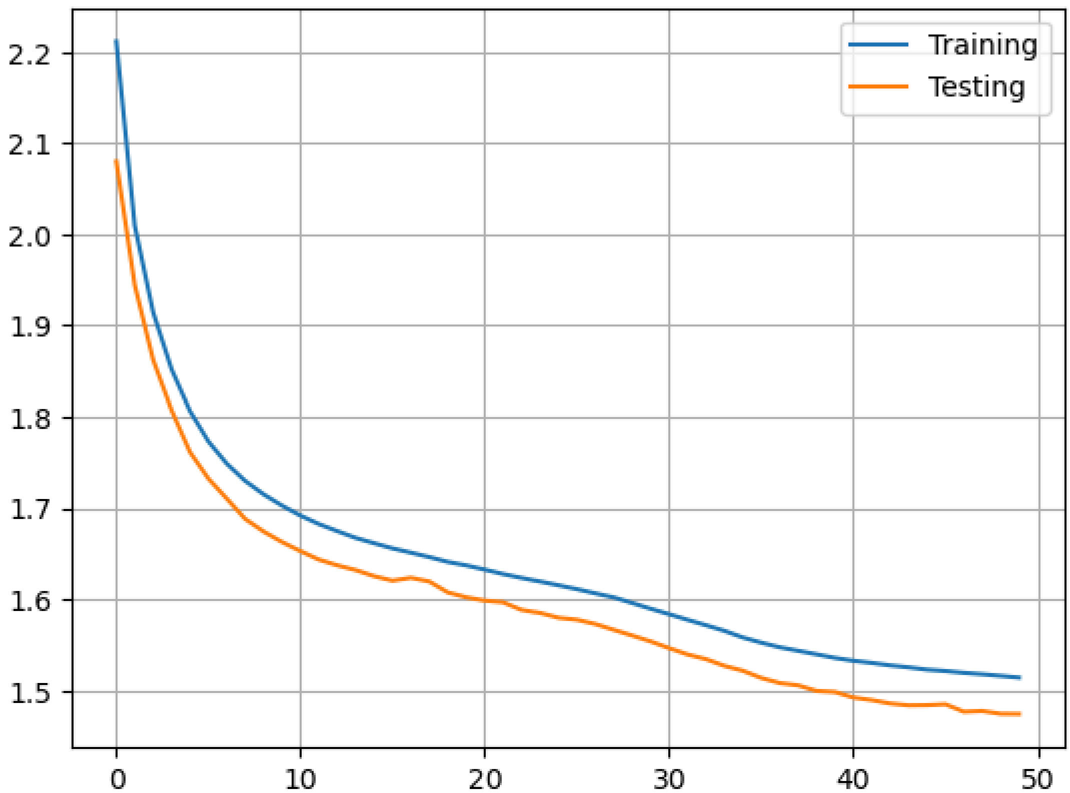
model = functional

Layer	Output Shape	Param #
l0 (InputLayer)	(None, 28, 28, 1)	0
l1 (Conv2D)	(None, 28, 28, 2)	10
l1_mp (MaxPooling2D)	(None, 14, 14, 2)	0
l2 (Conv2D)	(None, 14, 14, 2)	18
l2_mp (MaxPooling2D)	(None, 7, 7, 2)	0
l3 (Conv2D)	(None, 7, 7, 2)	18
l3_mp (MaxPooling2D)	(None, 3, 3, 2)	0
flat (Flatten)	(None, 18)	0
l4 (Dense)	(None, 2)	38
l5 (Dense)	(None, 10)	30

Total params:	114 (456.00 B)
Trainable params:	114 (456.00 B)
Non-trainable params:	0 (0.00 B)

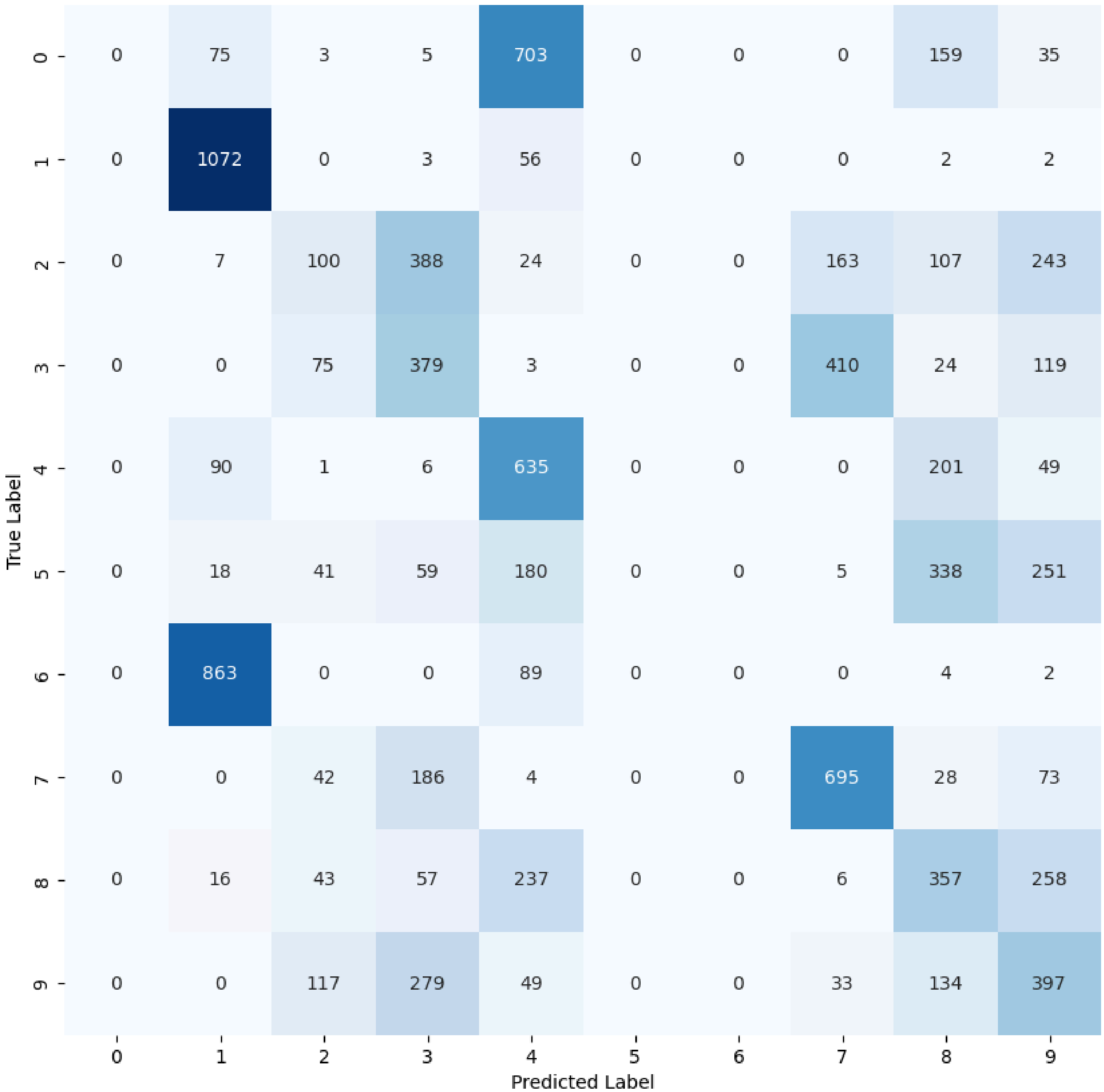
Performance

Test score:	1.4822582006454468
Test accuracy:	0.3634999990463257



Confusion matrix

F1 macro Score:	0.2766729045340783
F1 weighted Score:	0.28665495444409084
F1 micro Score:	0.36349999999999993



Second model

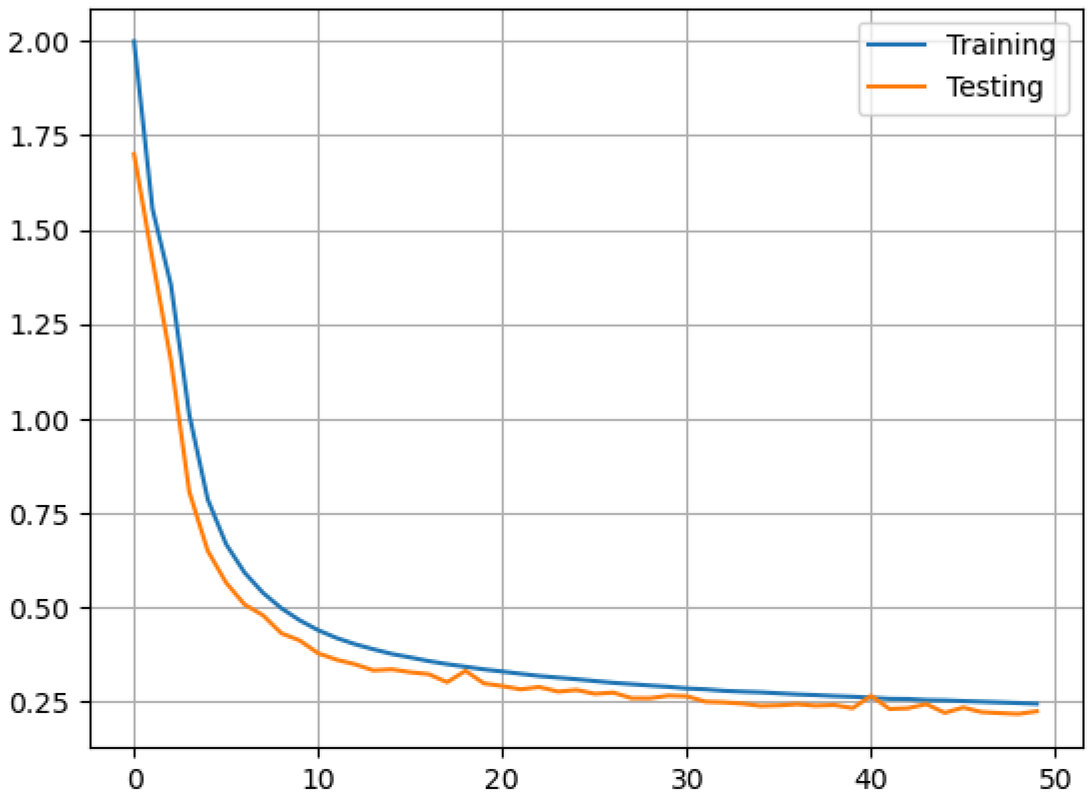
model = functional

Layer	Output Shape	Param #
l0 (InputLayer)	(None, 28, 28, 1)	0
l1 (Conv2D)	(None, 28, 28, 4)	20
l1_mp (MaxPooling2D)	(None, 14, 14, 4)	0
l2 (Conv2D)	(None, 14, 14, 8)	136
l2_mp (MaxPooling2D)	(None, 7, 7, 8)	0
l3 (Conv2D)	(None, 7, 7, 8)	264
l3_mp (MaxPooling2D)	(None, 3, 3, 8)	0
flat (Flatten)	(None, 72)	0
l4 (Dense)	(None, 4)	292
l5 (Dense)	(None, 10)	50

Total params:	762 (2.98 KB)
Trainable params:	762 (2.98 KB)
Non-trainable params:	0 (0.00 B)

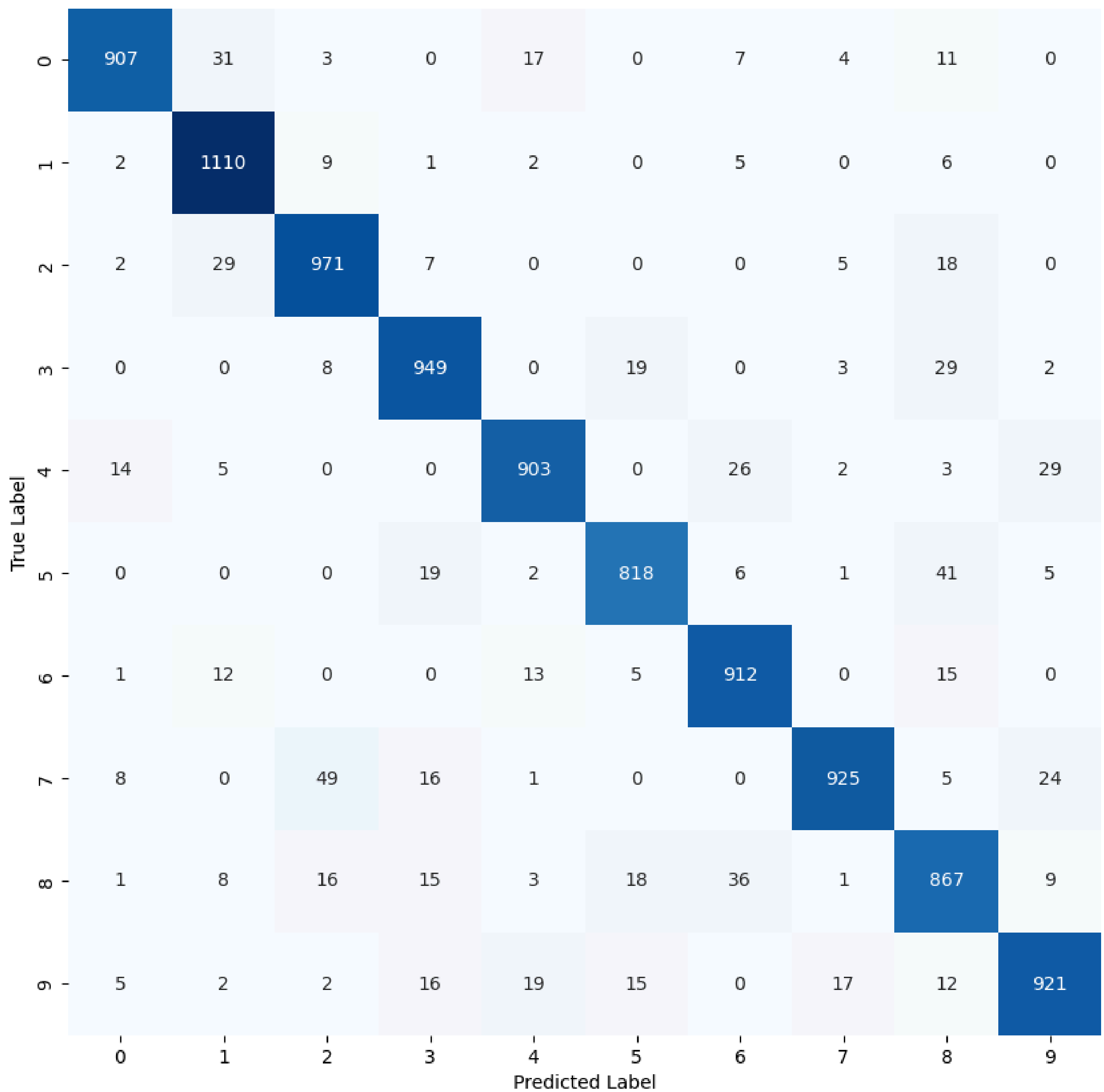
Performance

Test score:	0.24304336309432983
Test accuracy:	0.9283000230789185



Confusion matrix

F1 macro Score:	0.9279060132915193
F1 weighted Score:	0.9283349237758494
F1 micro Score:	0.9283



Third model

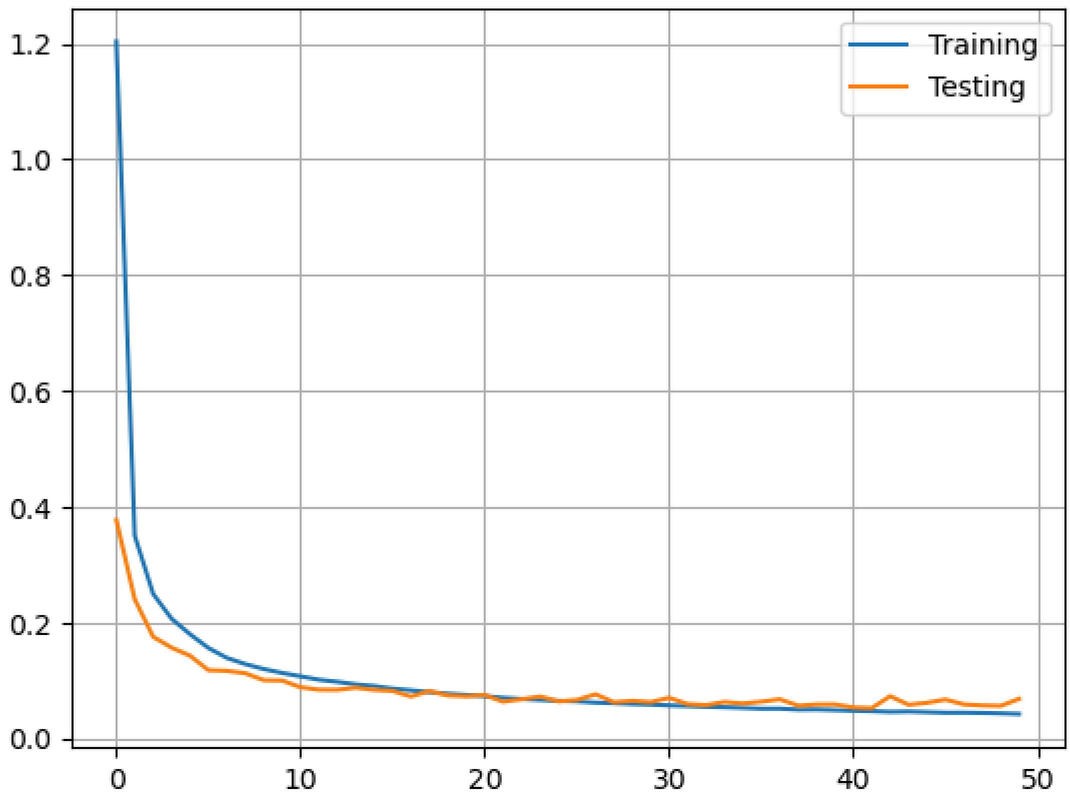
model = functional

Layer	Output Shape	Param #
l0 (InputLayer)	(None, 28, 28, 1)	0
l1 (Conv2D)	(None, 28, 28, 8)	40
l1_mp (MaxPooling2D)	(None, 14, 14, 8)	0
l2 (Conv2D)	(None, 14, 14, 16)	528
l2_mp (MaxPooling2D)	(None, 7, 7, 16)	0
l3 (Conv2D)	(None, 7, 7, 16)	1040
l3_mp (MaxPooling2D)	(None, 3, 3, 16)	0
flat (Flatten)	(None, 144)	0
l4 (Dense)	(None, 8)	1160
l5 (Dense)	(None, 10)	90

Total params:	2,858 (11.16 KB)
Trainable params:	2,858 (11.16 KB)
Non-trainable params:	0 (0.00 B)

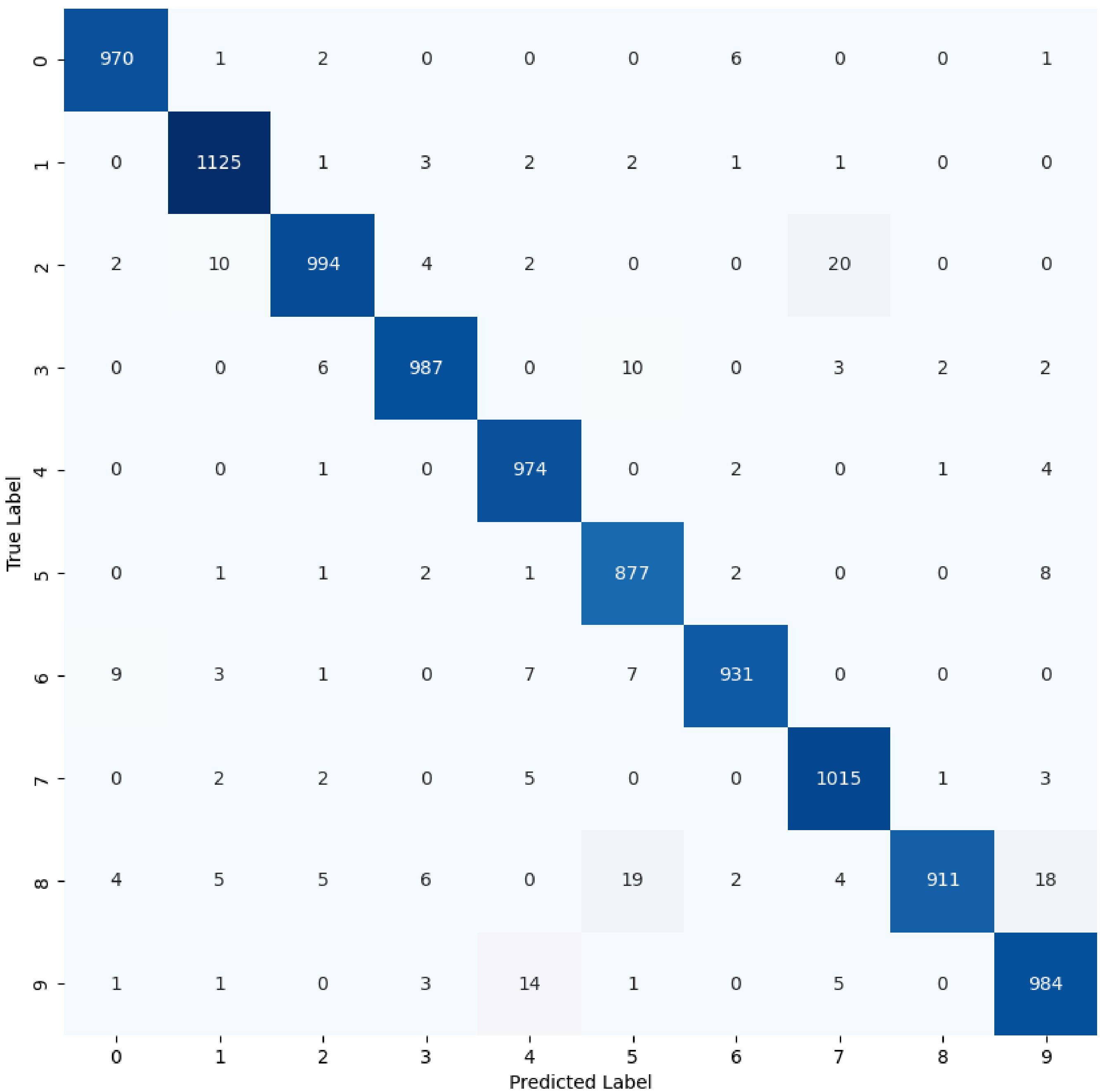
Performance

Test score:	0.07541753351688385
Test accuracy:	0.9768000245094299



Confusion matrix

F1 macro Score:	0.9765884358846029
F1 weighted Score:	0.97675954914543
F1 micro Score:	0.9768



Conclusion of the third exercise

The first model has the lowest performance, as expected, because it has the lowest capacity. It has the worst performance from all first models with a ~36% accuracy.

The second model has a better performance, but the training isn't quite finished with 50 epochs. This shows in the confusion matrix, where it only gets to ~93% accuracy.

The third model has the best performance, but it is also the one which overfits the most. It begins to overfit the training data at ~20 epochs. It still does have the best performance of this experiment with a ~97% accuracy.

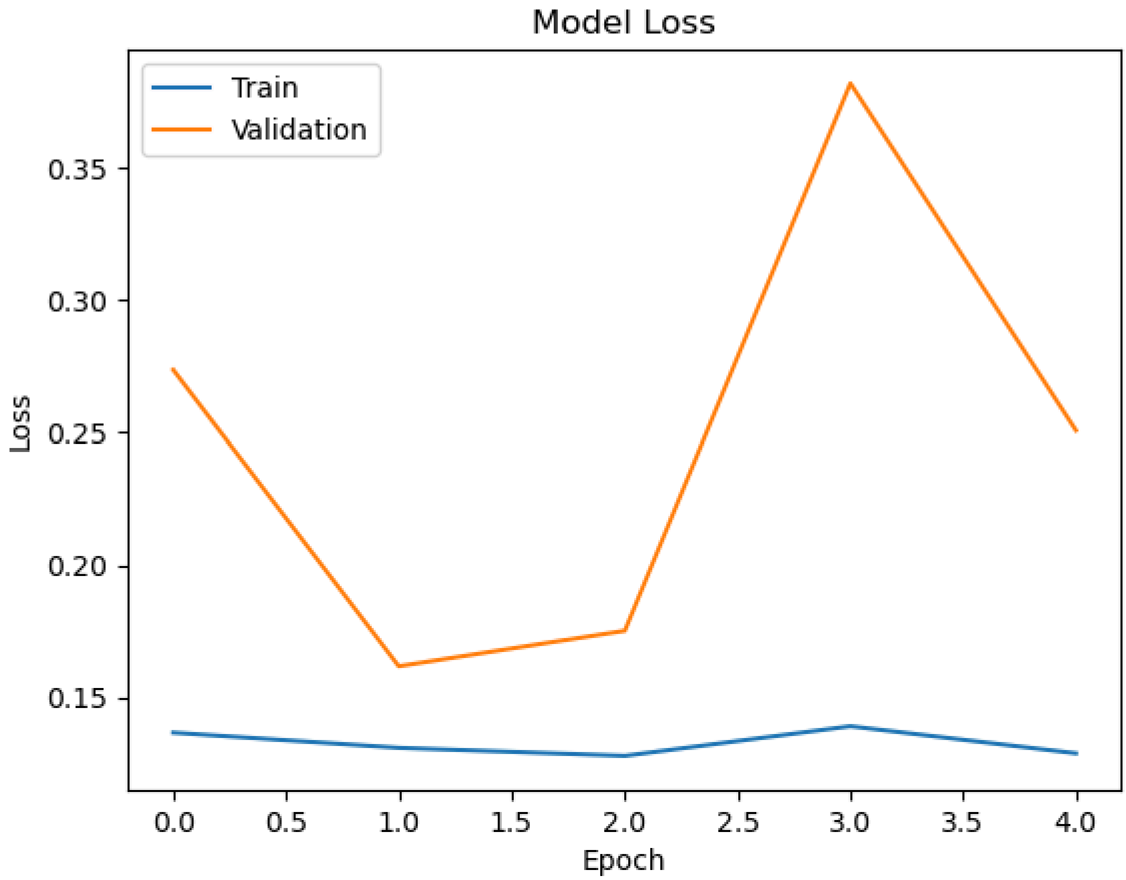
CNN for chest x-ray pneumonia recognition

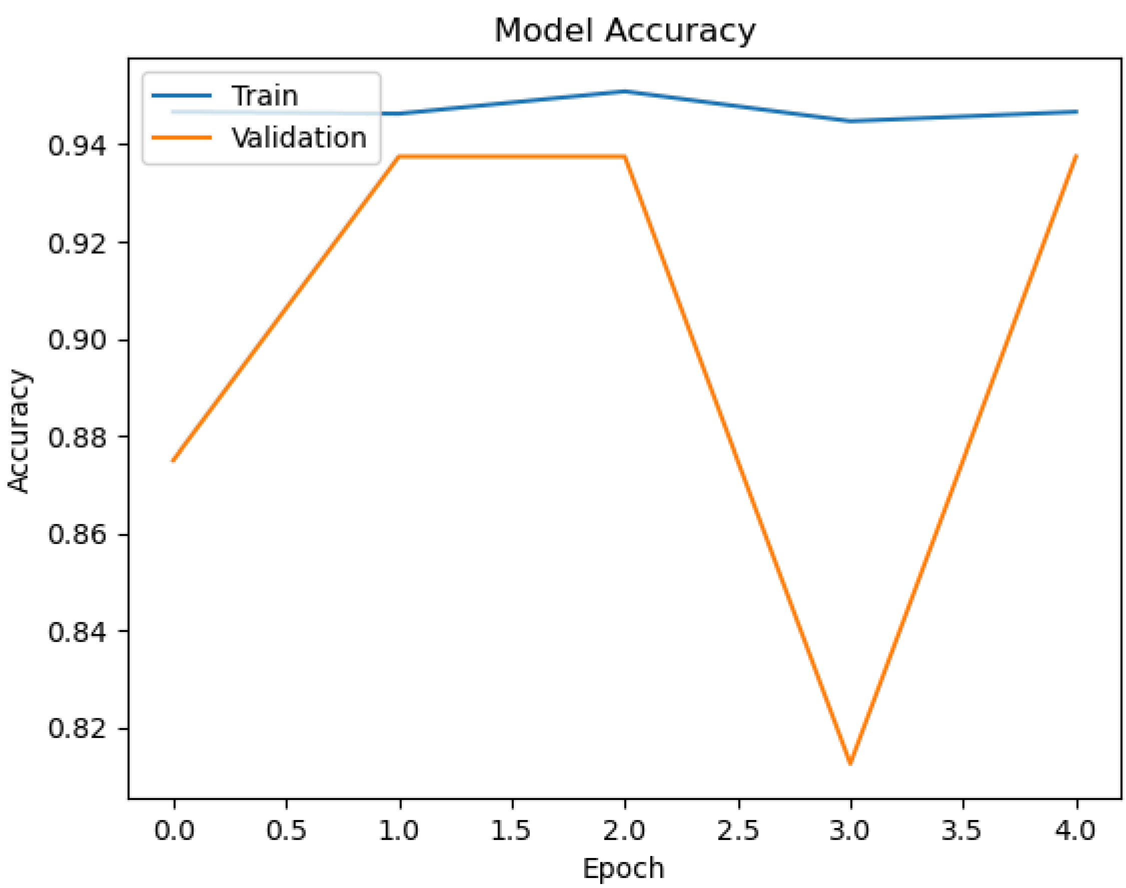
Weights

Layer	Output Shape	Param #
input_layer	(None, 128, 128, 1)	0
conv_1 (Conv2D)	(None, 128, 128, 8)	16
max_pooling_1	(None, 64, 64, 8)	0
conv_2 (Conv2D)	(None, 64, 64, 16)	144
max_pooling_2	(None, 32, 32, 16)	0
conv_3 (Conv2D)	(None, 32, 32, 32)	544
max_pooling_3	(None, 16, 16, 32)	0
conv_4 (Conv2D)	(None, 16, 16, 64)	2,112
max_pooling_4	(None, 8, 8, 64)	0
conv_5 (Conv2D)	(None, 8, 8, 128)	8,320
max_pooling_5	(None, 4, 4, 128)	0
flatten_7	(None, 2048)	0
dense_21 (Dense)	(None, 32)	65,568
dense_22 (Dense)	(None, 16)	528
dense_23 (Dense)	(None, 1)	17

Total params:	77,249 (301.75 KB)

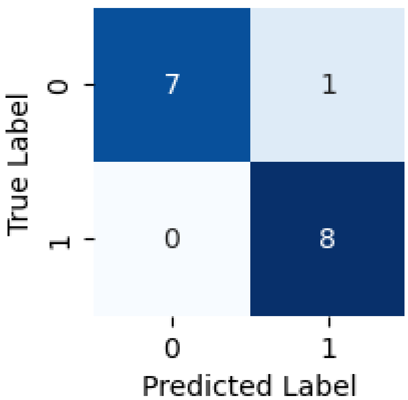
Performance





Validation

F1 score:	0.8889



Conclusion of the fourth exercise

The model has a good performance with a ~89% accuracy. It only classified one of the 16 images wrong. The model could be improved by increasing the number of epochs. At the 3rd epoch, we have a dip in validation accuracy, which could be improved by training the model for more epochs.