Deep Learning for Image Analysis

DL4IA – Report for Assignment 3

Student Linus Falk

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Introduction

Third assignment in the course Deep learning for image analysis

1 Classification of hand-written digits using a Convolutional Neural Network

Exercise 1.1 In this exercise we implemented the same neural network as in assignment 2. But this time we used the PyTorch library and GPU support for training. The task was to compare the performance in accuracy and training time. The weight were initialized in the same way as in assignment 2 and training was done with the same hyperparameters, see table:1. As we can see in table 2 the accuracy performance is very similar since the architecture and the training methods is the same. The difference between the training times are on the other hand noticeably shorter for the PyTorch version. This is much thanks to the GPU support, but also more effective data handling then the "homeCooked" version has. In 1 we can see signs that the model is starting to overfit. The test loss has stopped to improve while the training loss on the subset (6000 samples) of the training set is still improving. The model is overfitting to the training data and if we would continue to train we would we decrease in performance on the test set.

Hyperparameters	
BatchSize	30
Epochs	60
lr	0.01
Optimizer	SGD

Table 1: Hyperparameters Exercise 1.1

	"HomeCooked NN"	**PyTorch**
Accuracy (%)	97.26	97.22
Time (sec)	289	22.28

Table 2: Result Exercise 1.1

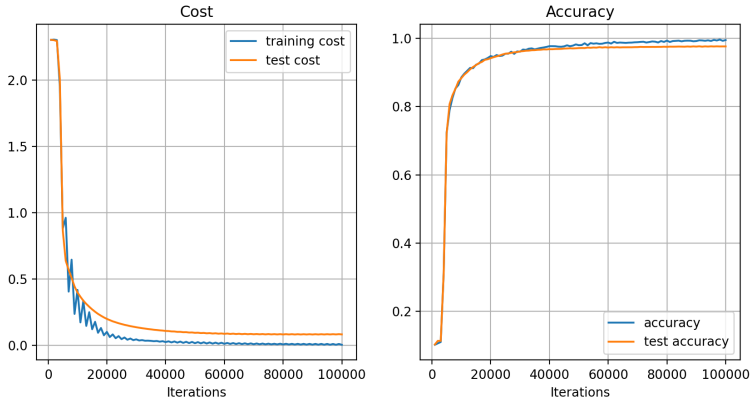


Figure 1: Training history: Assignment 2 Torch version, Accuracy: 97.22%

Exercise 1.2 In this exercise we construct a convolutional neural network with the PyTorch library according to the instructions. We compare the accuracy and number of weights between the Fully connected and the convolutional NN in table: 4. Looking at the training history we can conclude that this network doesn't show the same signs of overfitting. The convolutional neural network has improved accuracy with fewer trainable weights. By using the CNN we improve the accuracy be preserving the spatial information and reduce the risk of overfitting by having fewer trainable parameters.

Hyperparameters	
BatchSize	100
Epochs	60
lr	0.005
Optimizer	SGD

Table 3: Hyperparameters Exercise 1.2

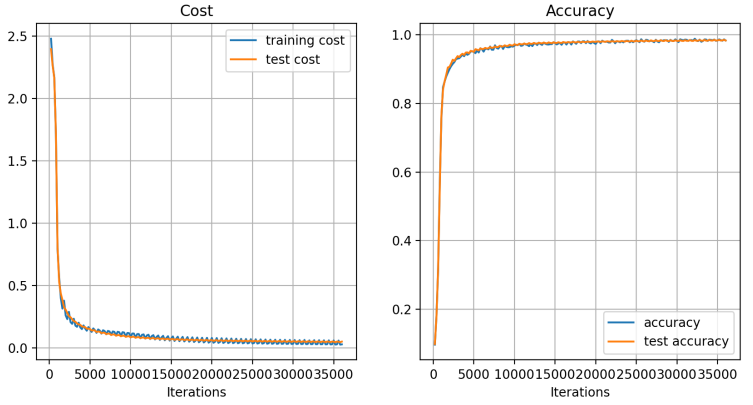


Figure 2: Training history Exercise 1.2, Accuracy: 98.35%

Architecture	Accuracy (%)	Number of weights
FF	97.22	109386
CNN	98.55	21688

Table 4: Result Exercise 1.2

Exercise 1.3 Here we are asked to swap place of the maxpooling layer and take the maxpooling before the activation function instead. This will result in fewer connections to the activation function making the time for calculating the activations fewer and therefore reducing the training time which we can see in: Table 5. If we would use a more complicated activation function like the *hyperbolic tangent* the time difference would increase. The worse accuracy in the swapped layer case can be caused by the fact that we are passing on less information to the activation function.

	CNN without swapped layers	**CNN with swapped layers**
Accuracy (%)	98.55	96.87
Time (sec)	202	135

Table 5: Result Exercise 1.3

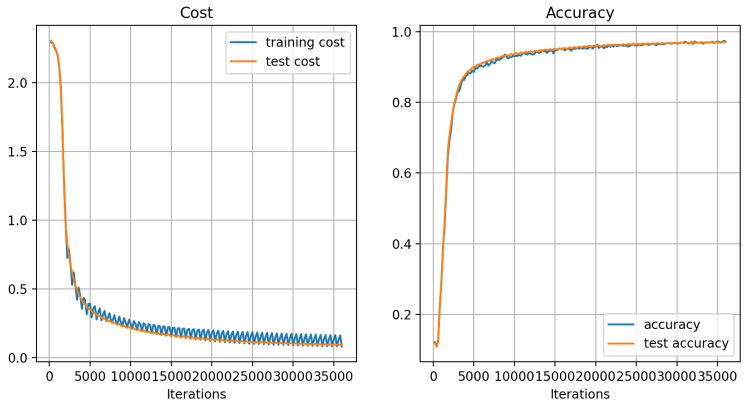


Figure 3: Training history Exercise 1.3

Exercise 1.4 To investigate how the choice of optimizer effects the training time, we are here asked to use the optimizer: *ADAM* (with default parameters) instead of *SGD* and compare how much faster the training becomes.*ADAM* is in many cases the best choice of optimizer and we can conclude from the result of our test in Table: 7 that we need fewer epochs to achieve the same (or better) accuracy as *SGD* when using *ADAM*. We can see that the training accuracy, in figure: 4 improving slightly more in the last iterations compared to the test set, indicating that were starting to get some overfitting.

Hyperparameters	
BatchSize	100
Epochs	15
Optimizer	Adam
lr	0.001
betas	(0.9, 0.999)
eps	1e-8
weight_decay	0

Table 6: Hyperparameters Exercise 1.4

	CNN trained with SGD	**CNN trained with ADAM**
Accuracy (%)	98.55	98.69
Time (sec)	202	73

Table 7: Result Exercise 1.4

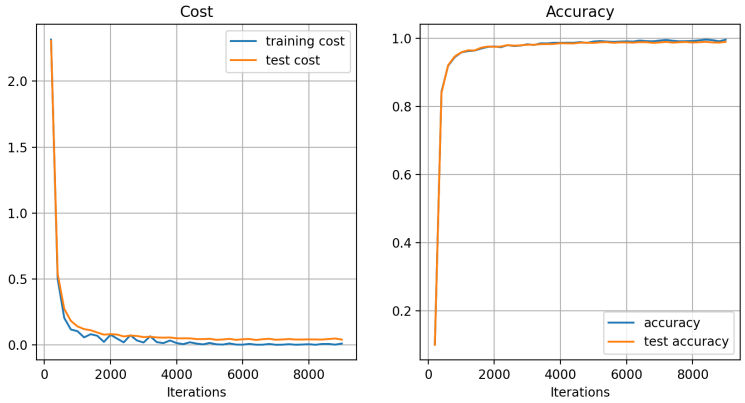


Figure 4: Training history Exercise 1.4

Exercise 1.5 In this exercise we try out at least 3 different ways to improve our model by changing for example architecture, learning rate or using different types of regularization methods. The result is presented below with tables of changes for each model and performance measure. The result from the best model is also presented with a confusion matrix of the test set.

Model 1: We increase the last, fully connected layers to 50 nodes to improve see if we can improve the model with more learnable parameters. To reduce the risk of overfitting we also include a dropout layer after this layer with a probability, p=0,25.

Hyperparameters	
BatchSize	100
Epochs	10
Optimizer	Adam
lr	0.003
Result:	98.8%

Table 8: Hyperparameters Exercise 1.5, Model 1

Model 2: Including batch normalization layers between layers can improve the training by normalizing the activation [2]. In this case it didn't give major improvement since we didn't have a problem with vanishing or exploding gradients which it is commonly used to improve.

Hyperparameters	
BatchSize	100
Epochs	10
Optimizer	Adam
lr	0.003
Result:	98.89%

Table 9: Hyperparameters Exercise 1.5, Model 2

Model 3: Here we change the learning rate strategy by changing the learning rate such that i depends on the iteration number (i) with the function below [3].

$$\gamma^{(i)} = \gamma_{\min} + (\gamma_{\max} - \gamma_{\min}) e^{\frac{i}{\text{totalNumberOfIterations}}} \tag{1}$$

We set $\gamma_{\max} = 0.003$ and $\gamma_{\min} = 0.0001$ and update it throughout the training.

Hyperparameters	
BatchSize	100
Epochs	10
Optimizer	Adam
lr	0.003 - 0.0001
Result:	99.04%

Table 10: Hyperparameters Exercise 1.5, Model 3

Model 4: Here we simply combine model 1 and model 3. Increasing the number of nodes to 200 in the final fully connected layer, add a dropout layer after that and then use the changing training rate through the training. Even though we use the drop out layer we can see some indication of overfitting in the training history, looking at the accuracy. The training accuracy continue to improve but the test accuracy stays pretty much the same. Since this was the best performing model we also take a look at the confusion matrix. Here we can see that the most miss-classification is done on the actual digit 9, often being miss-classified as a 4, which is understandable considering the shape of the two digits.

Hyperparameters	
BatchSize	100
Epochs	10
Optimizer	Adam
lr	0.003 - 0.0001
Result:	99.11%

Table 11: Hyperparameters Exercise 1.5, Model 4

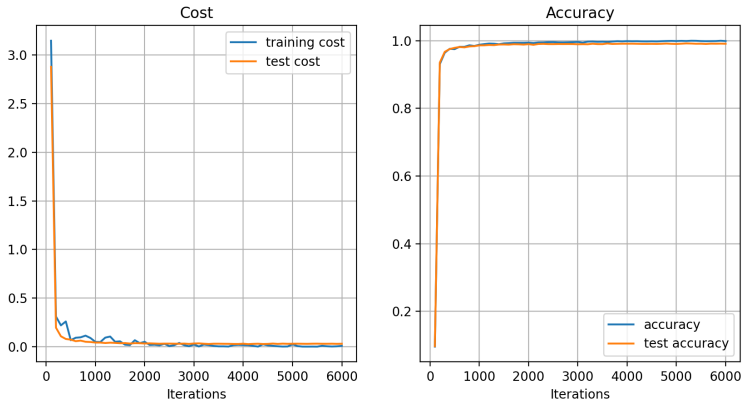


Figure 5: Training history Exercise 1.5

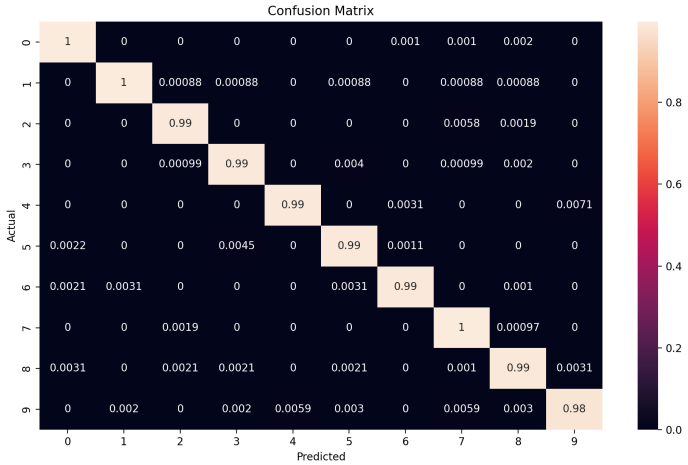


Figure 6: Exercise 1.5 confusion matrix

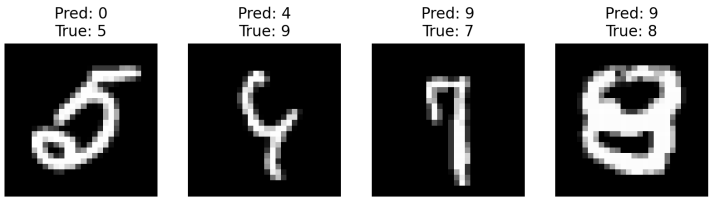


Figure 7: Exercise 1.5 examples of miss-classification

2 Semantic segmentation of Biomedical images

Exercise 2.1 Modifying our previous neural network by removing the fully connected layers replacing it with a 1×1 convolutional layer, we will now tackle a segmentation problem and evaluate it with Sørensen–Dice coefficient as performance measurement. In Figure: 11 we can see the result from the segmentation of a randomly picked test image. The segmentation models worst performance on the test set is presented in Figure: 12. Here we can see that it seems like the specimen is ending abrupt in the image, showing a lot of dark areas, presumably the "background". Since this case is not well represented in the training set it is not so surprising that it performed badly on this image.

Layer	**Input Channels**	**Output Channels**	**Kernel Size / Stride / Padding**	**Activation**
Conv1	2	8	3x3 / 1 / 1	ReLU
MaxPool1	-	-	2x2 / 2 / 0	-
ConvTranspose1	8	8	4x4 / 2 / 1	-
Conv2	8	16	3x3 / 1 / 1	ReLU
MaxPool2	-	-	2x2 / 2 / 0	-
ConvTranspose2	16	16	4x4 / 2 / 1	-
Conv3	16	32	3x3 / 1 / 1	ReLU
MaxPool3	-	-	2x2 / 2 / 0	-
ConvTranspose3	32	32	4x4 / 2 / 1	-
Conv4	32	2	1x1 / 1 / 0	SoftMax

Table 12: Neural network architecture Exercise 2.1

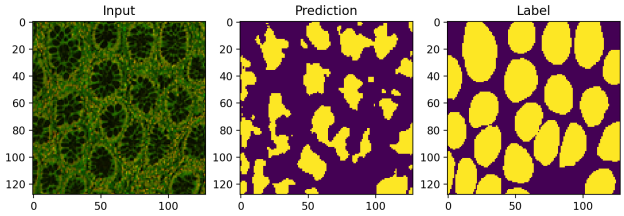


Figure 8: Exercise 2.1: Segmentation of test-image: image_05.png,

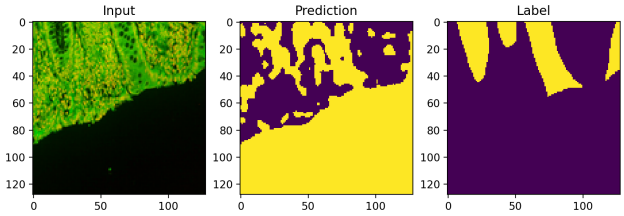


Figure 9: Exercise 2.1: Segmentation of test-image: image_11.png

Exercise 2.2 We are asked to improve the model with various regularization techniques and other methods that are presented throughout the course. When testing different hyperparameters we split up the training set into a validation set and training set (20% and 80%). We train and test the different hyperparameters with the validation set and when we decided on a good model we train it with the whole training set and test it with the test set.

Hyperparameters	
Epochs	150
Optimizer	Adam
learning	0.003
Result:	0.76

Table 13: Hyperparameters Exercise 2.1

Model 1: We here try to increase the sparse training set by using the methods data augmentation. We rotate each image -90 degrees and 180 degrees and add them to the training set before splitting it to a validation and training set. Same architecture as in Exercise 2.1

Model 2: Here we change the learning rate strategy the same way as described in Exercise 1.5.

Model 3: Batch-regularization is used to normalize the data before the activation, improving the training by avoiding vanishing or exploding gradients. We also add a learning schedule similar to **model 2** in exercise 1.5. This method showed best improvement on the validation set and was therefore best

Model 4-5: architecture:

Layer	**Input Channels**	**Output Channels**	**Kernel Size / Stride / Padding**	**Activation**
Conv1	2	32	3x3 / 1 / 1	ReLu
MaxPool1	-	-	2x2 / 2 / 0	-
Conv2	32	64	3x3 / 1 / 1	ReLu
MaxPool2	-	-	2x2 / 2 / 0	-
Conv3	64	128	3x3 / 1 / 1	ReLu
MaxPool3	-	-	2x2 / 2 / 0	-
ConvTranspose1	128	64	4x4 / 2 / 1	-
Conv4	64	64	3x3 / 1 / 1	ReLU
ConvTranspose2	64	32	4x4 / 2 / 1	-
Conv5	32	32	3x3 / 1 / 1	ReLU
ConvTranspose3	32	4	4x4 / 2 / 1	-
Conv6	4	2	1x1 / 1 / 0	-

Table 14: Neural network architecture Exercise 2.2 model 4 & 5

Model 4: New architecture with the more classic "wasp-waist" structure.

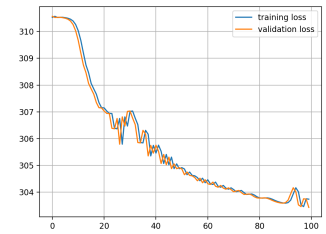
Model 5: The new architecture but with Batch-regularization layers.

Hyperparameters	**Model 1**	**Model 2**	**Model 3**
Method	Data Augmentation	Learning Rate Scheduling	Batch-normalization
Epochs	100	100	100
Optimizer	Adam	Adam	Adam
learningRate	0.003	$\gamma^{(i)}$	0.003
Result:	0.73	0.77	0.84

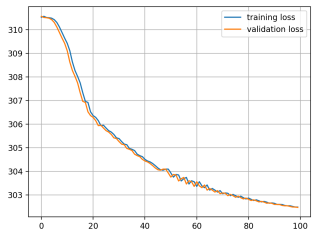
Table 15: Hyperparameters Exercise 2.1, Model 1

Hyperparameters	**Model 4**	**Model 5**
Method	-	Batch-normalization
Epochs	100	100
Optimizer	Adam	Adam
learningRate	0.003	0.003
Result:	0.66	0.94

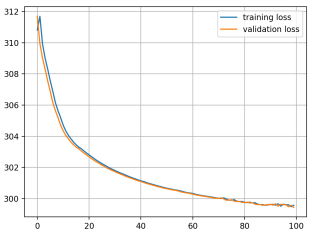
Table 16: Hyperparameters Exercise 2.1, Model 1



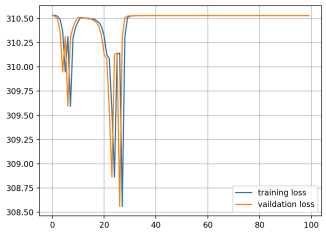
(a) Model 1



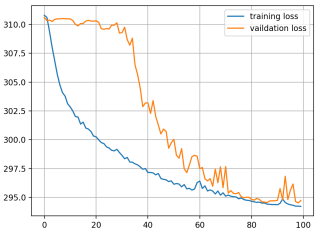
(b) Model 2



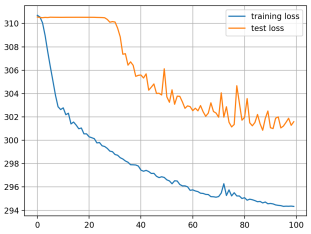
(c) Model 3



(d) Model 4



(e) Model 5



(f) Model 5 on training & test set

Looking at the training history for model 1-3 see no sign of overfitting the validation set. In the case of model 4 it seems to having problem with vanishing gradients being a much "deeper" than the previous design. The batch normalization in model 5 seems to solve some of the problems. Taking the model 5 setup and training it with the whole training set and test it on the test set resulted in a dice coefficient of: **0.82**. Looking at the training history we can see that the training loss is still reducing but the test loss is not, indicating that it has stopped improving in terms of generalization and started to overfit. Interesting to notice is that the result from exercise 2.1 seem to be better at identifying the individual glands even though it scored lower in the the test.

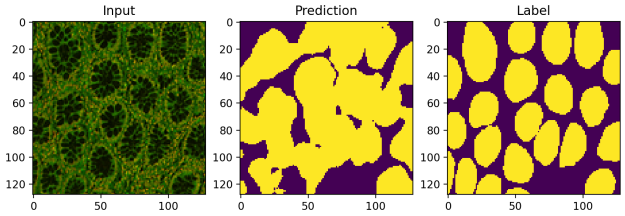


Figure 11: Exercise 2.2: Segmentation of test-image: image_05.png,

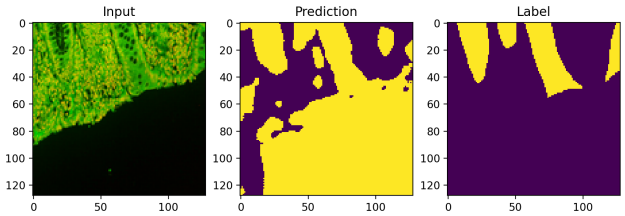


Figure 12: Exercise 2.2: Segmentation of test-image: image_11.png

References

[1] Asimov, Isaac (1942). Runaround

[2] Ian J. Goodfellow, Yoshua Bengio and Aaron Courville (2016). Deep Learning

[3] Lindholm, Andreas and Wahlström, Niklas and Lindsten, Fredrik (2022). Machine Learning - A First Course for Engineers and Scientists