Algorithms and Application in Computer Vision - 046746

Homework #2

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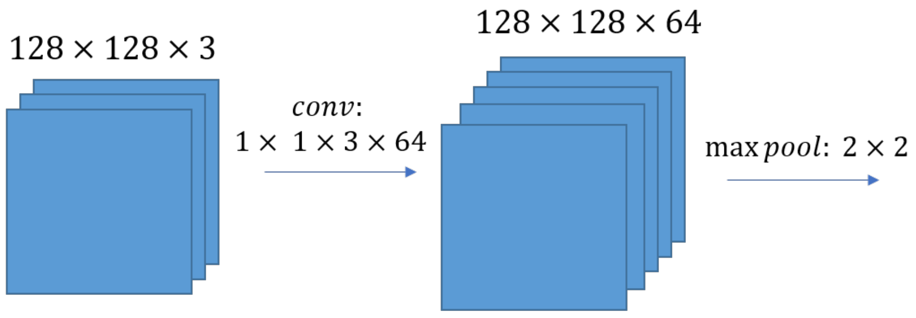
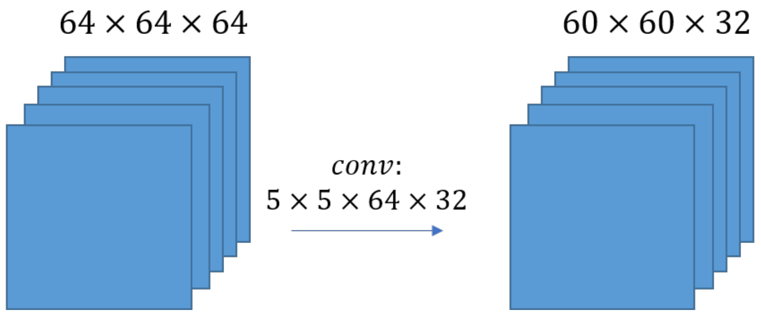
I. Dry section

A. Question 1.

1. a.

The dimensions of the layers change in the following way:


$128 \times 128 \times 3$
$conv$: $1 \times 1 \times 3 \times 64$
$128 \times 128 \times 64$
$\max pool$: 2×2



2. b.

The convolution of the size 1X1X(?) performs convolution on the same pixes in different channels. The input image contains 3 channels in our case, thus the convolution of the size 1X1X3 fits perfectly to result in a block of new layers without changing size (no need for padding). One kernel results in an output layer of size 128×128, but since we have 64 kernels, the depth of the next layers block is 64, accordingly.

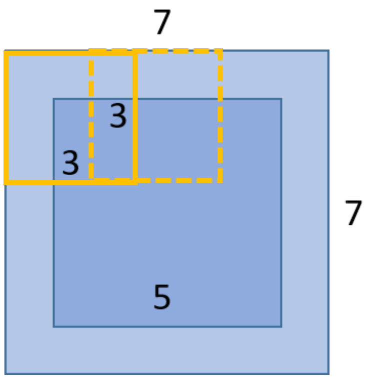
3. c.

Let's say, our normalized filter is the following:

$$\begin{bmatrix} 0.1 & 0.2 & 0.05 \\ 0.05 & 0.2 & 0.1 \\ 0.15 & 0.1 & 0.05 \end{bmatrix}$$

We choose 2 options for stride and padding:

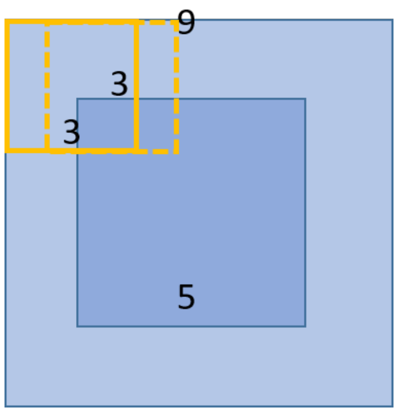
1. $stride = 2, padding = 1$ The image now has a dimensions of 9×9, and with a stride of 1 it gives an output dimensions: 3×3



Output result is the following:

$$\begin{bmatrix} 1.3 & 2.7 & 1.9 \\ 1.9 & 5.25 & 3.1 \\ 0.5 & 3.5 & 1.7 \end{bmatrix}$$

2. $stride = 1, padding = 2$ The image now has a dimensions of 7×7, but with stride of 2 it fits with the filter. Output dimensions: 7×7



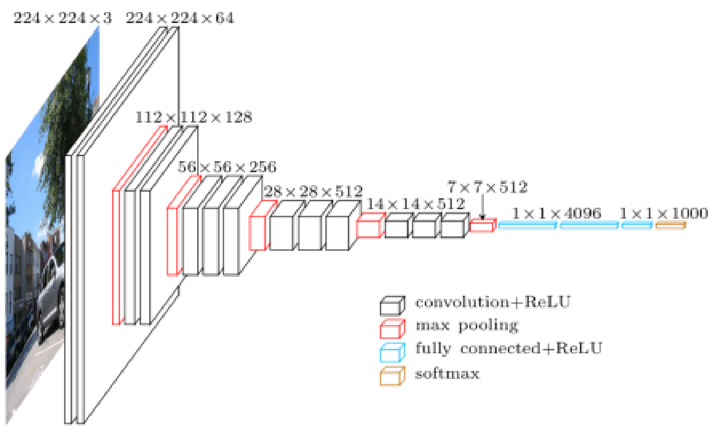
Output result is the following:

$$\begin{bmatrix} 0.2 & 0.45 & 1 & 0.8 & 1.15 & 0.45 & 0.45 \\ 0.55 & 1.3 & 2.0 & 2.7 & 2.65 & 1.9 & 0.45 \\ 0.6 & 2.1 & 3.3 & 5.15 & 4.6 & 2.6 & 1.45 \\ 0.4 & 1.9 & 3.75 & 5.25 & 5.145 & 3.1 & 1 \\ 0.2 & 1.3 & 3.5 & 4.7 & 4.0 & 3.35 & 1.45 \\ 0.05 & 0.5 & 2.05 & 3.5 & 2.55 & 1.7 & 0.5 \\ 0 & 0.05 & 0.5 & 1.5 & 1.6 & 1.2 & 0.4 \end{bmatrix}$$

. The code is provided in the appendix.

B. Question 2.

The architecture selected is the VGG16 architecture. The image found in the internet which describes the structure is the following:

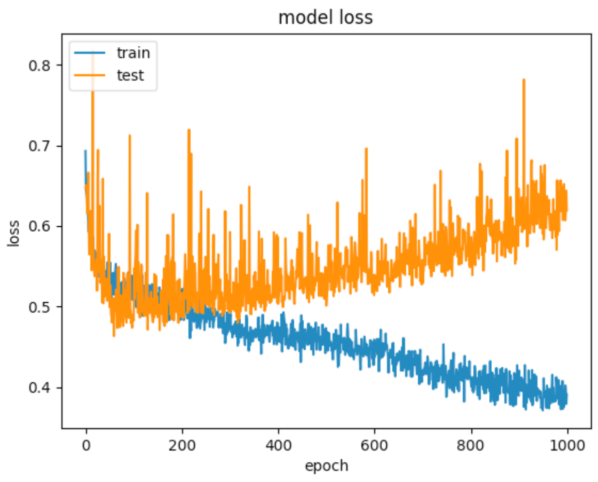


Writing the exact outputs for every layer:

Operation	Size	Padding	Stride	Output size
Conv block	[3X3X3]X64	[1 1]	1	[224X224X64]
Conv block	[3X3X64]X64	[1 1]	1	[224X224X64]
Pool 2D	[2 2]	N/A	N/A	[112X112X64]
Conv block	[3X3X64]X128	[1 1]	1	[112X112X128]
Conv block	[3X3X128]X128	[1 1]	1	[112X112X128]
Pool 2D	[2 2]	N/A	N/A	56X56X128
Conv block	[3X3X128]X256	[1 1]	1	[56X56X256]
Conv block	[3X3X256]X256	[1 1]	1	[56X56X256]
Conv block	[3X3X256]X256	[1 1]	1	[56X56X256]
Pool 2D	[2 2]	N/A	N/A	[28X28X256]
Conv block	[3X3X256]X512	[2 2]	1	[28X28X512]
Conv block	[3X3X512]X512	[2 2]	1	[28X28X512]
Conv block	[3X3X512]X512	[2 2]	1	[28X28X512]
Pool 2D	[2 2]	N/A	N/A	[14X14X512]
Conv block	[3X3X512]X512	[1 1]	1	[14X14X512]
Conv block	[3X3X512]X512	[1 1]	1	[14X14X512]
Conv block	[3X3X512]X512	[1 1]	1	[14X14X512]
Conv block	[3X3X512]X512	[1 1]	1	[14X14X512]
Pool 2D	[2 2]	N/A	N/A	[7X7X512]
Fully connected	[7·7·512]X4096	N/A	N/A	[1X1X4096]
Fully connected	[4096X4096]	N/A	N/A	[1X1X4096]
Fully connected	[4096X1000]	N/A	N/A	[1X1X1000]

C. Question 3.

Definition: Overfitting - is a situation, where network is fitted too much to the training data, and finds it difficult to generalize to create predictions for the new data.
How to spot: First of all, a researcher will notice that the accuracy of the model on the Test Dataset decreases, while the accuracy on the Training Set will still be increasing. The typical graph vizuasing error on the Test & Training set may be seen, demonstrating this exact situation:



How to avoid: There are numerous way to avoid overfitting:

1. Stop the training before the accuracy for the validation set starts increasing. If the accuracy does not satisfy, find a better dataset / improve the network / apply other changes. Training for more time will worsen the situation.

2. Use one of the following methods: regularisation, lambda factor, dropout, etc.

3. Increase the dataset size. Feed the network new examples for learning.

D. Question 4.

The learned parameters are being updated using the backpropagation algorithm. The name derives from the way that the Error value propagates backward through the network, affecting the parameters according to the contribution that those gave to the error value. In the general view, this may be seen in update function for the parameters (in this case - weights):

$$W := W - \alpha \cdot \frac{\delta E}{\delta W}$$

where:

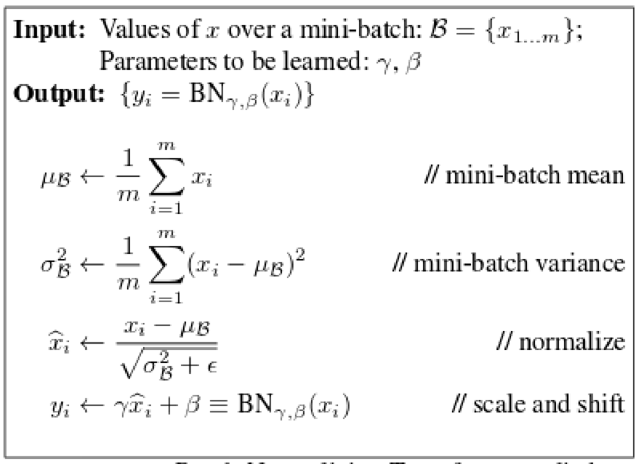
$$\begin{aligned} W &- \text{lweight parameter} \\ \alpha &- \text{learning rate} \\ \frac{\delta E}{\delta W} &- \text{"contribution" of the parameter to the loss} \end{aligned}$$

E. Question 5.

Definition: Batch normalization - is a method which is used to normalize the layer inputs, in order to solve the problem called *internal covariate shift.*

internal covariate shift: the problem which arises in the intermediate layers during training because the distribution of the activations is constantly changing during training. This slows down the training by requiring lower learning rates and careful parameter initialization, and makes it notoriously hard to train models with saturating nonlinearities. [1] [2]

So, actually we force the input of a specific layer to have approximately the same distribution in every training step. The batch normalization is performed in 4 steps (image taken from the original article):



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \text{BN}_{\gamma,\beta}(x_i)\}$

```
$\mu_\mathcal{B} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i$    // mini-batch mean
$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_\mathcal{B})^2$    // mini-batch variance
$\widehat{x}_i \leftarrow \frac{x_i - \mu_\mathcal{B}}{\sqrt{\sigma_\mathcal{B}^2 + \epsilon}}$    // normalize
$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \text{BN}_{\gamma,\beta}(x_i)$    // scale and shift
```

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

Steps are the following:

1. Calculate the batch mean of the values x of a particular layer (that we do the normalization on) μ_β
2. Similarly, calculate the variance of those values x for this layer σ_β^2
3. Normalize the values, substracting the mean μ_β and dividing by STD (+constant) $\sqrt{\sigma_\beta^2 + \epsilon}$. This will result in a new Gaussian distribution with mean of 0 and Variance of 1.
4. Scale and Shift by learnable parameters γ and β. Those parameters are being learned, and are inserted to make it possible to the distribution to be scaled and

[1]Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift , Sergey Ioffe, Christian Szegedy

[2]Towards Data Science: Batch normalization: theory and how to use it with Tensorflow

shifted if such is needed. For example, if it is of our interest to make the batch normalization an identity transform.

II. Wet section

A. Question 1.

The question is being answered in parts, in the order which was requested in the homework booklet, but with the different answers numbers.

1. ***a.***

This subsection answers the steps 1-6.
Network is the following:

- Network as defined in step 2
- Loss function = CE (Cross Entropy)
- Optimizer: SDGM (momentum = 0.5)
- Learning rate = 0.01
- Epochs = 8
- Training minibatch size = 128
- Training/validation split = 50000/10000. (MNIST dataset includes 60000 examples)

Answering the step 5 question:

1. Loss value graphs:

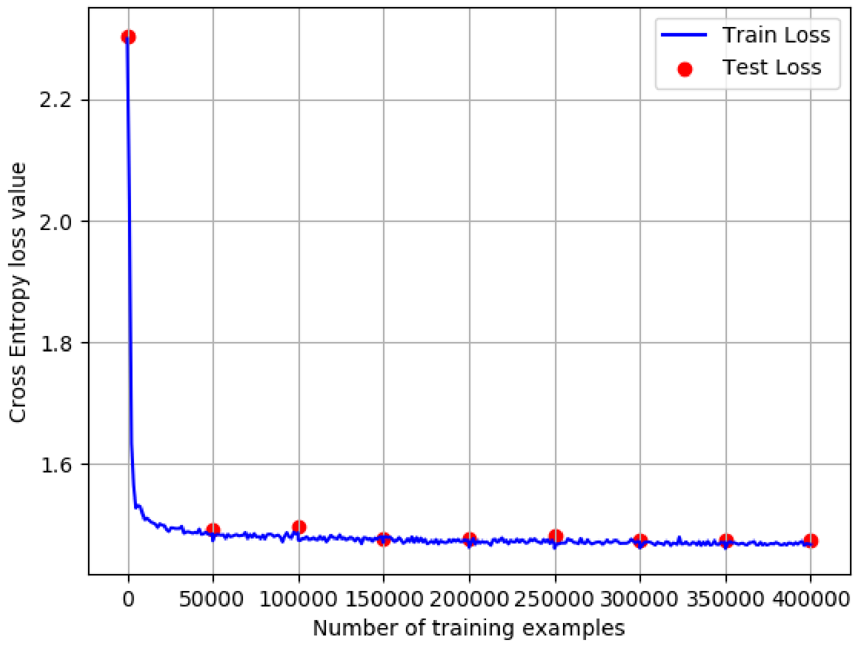


Figure 1: Loss value as a function of the training examples seen

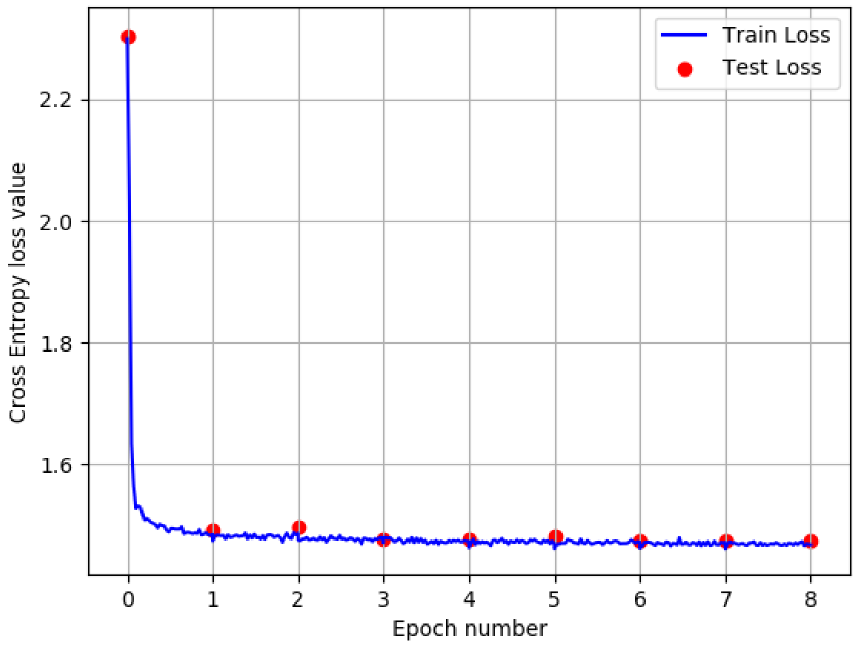


Figure 2: Loss value as a function of the Epoch number

2. Classification accuracy graphs

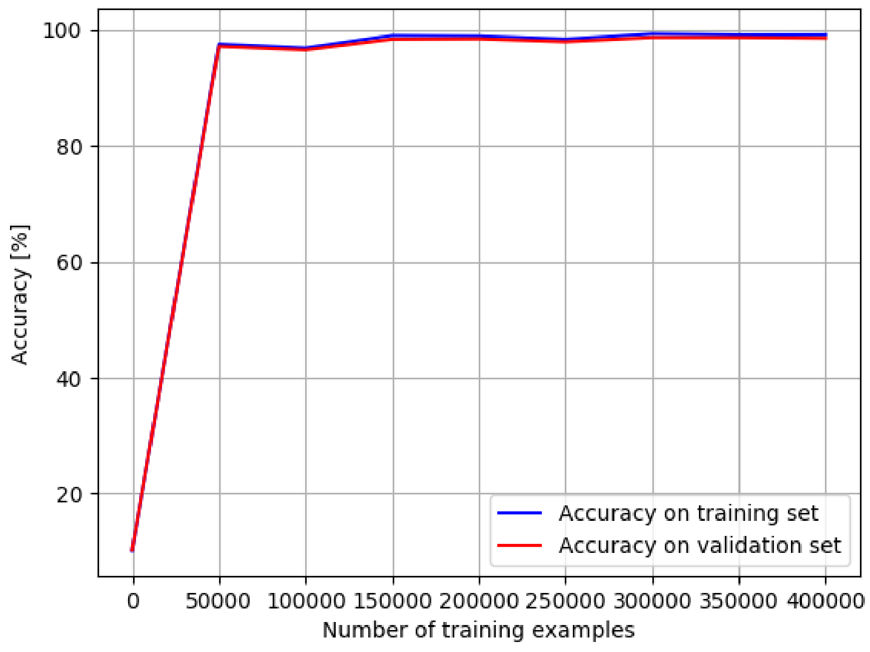


Figure 3: Classification accuracy as a function of the training examples seen

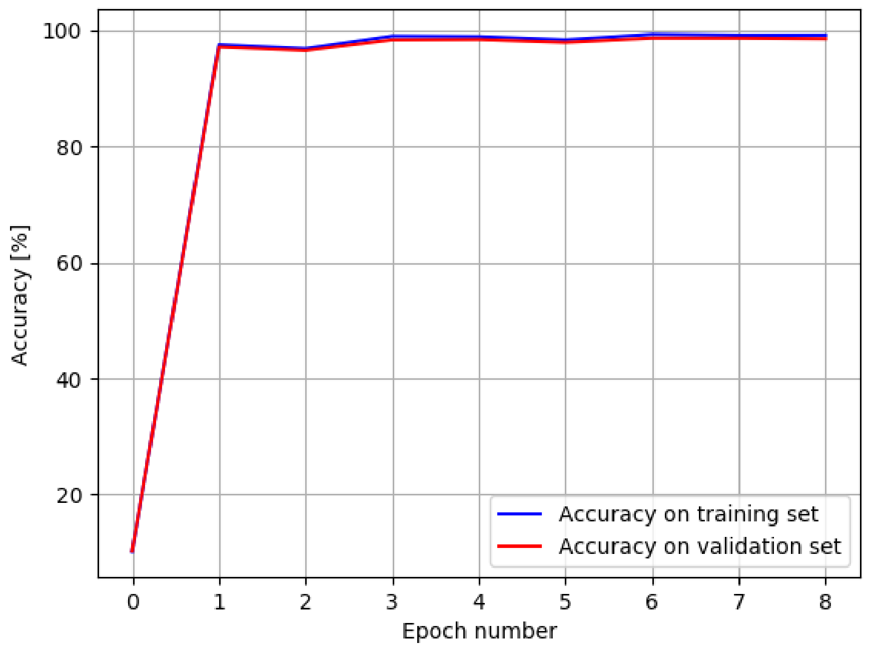


Figure 4: Classification accuracy as a function of the Epoch number

Answering the step 6 question: The classification accuracy reported is the following:

1. Training set: 99.186%
2. Test set: 98.58 %

2. ***b.***

This subsection answers the step 7 - part 1.
First, we repeat the process with the different learning rate values, whereas all the other parameters defined in the previous subsection remain the same. And the results we get are the following:

1. For the same network with the learning rate of **0.1**:

   (a) Loss value graphs:

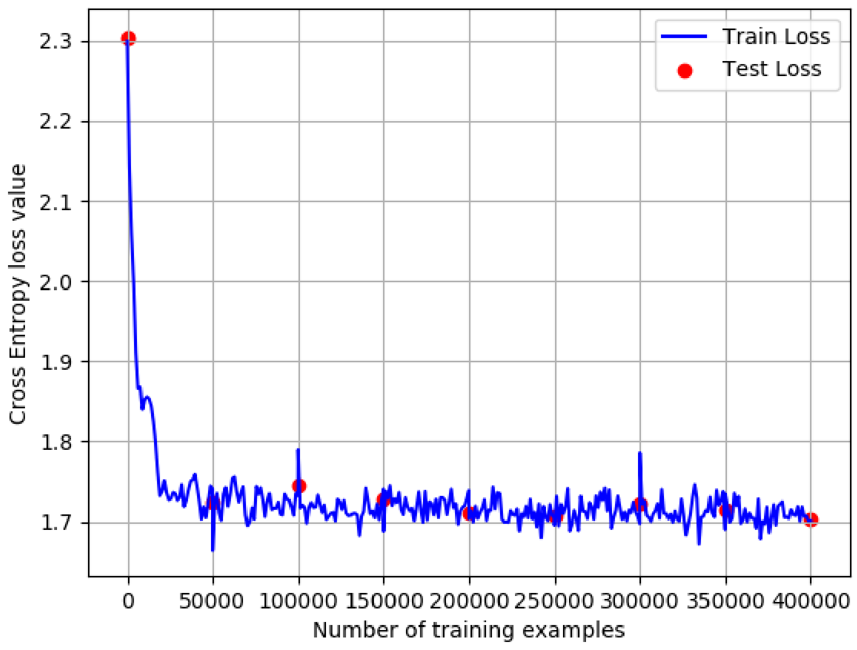


Figure 5: Loss vs. Training examples

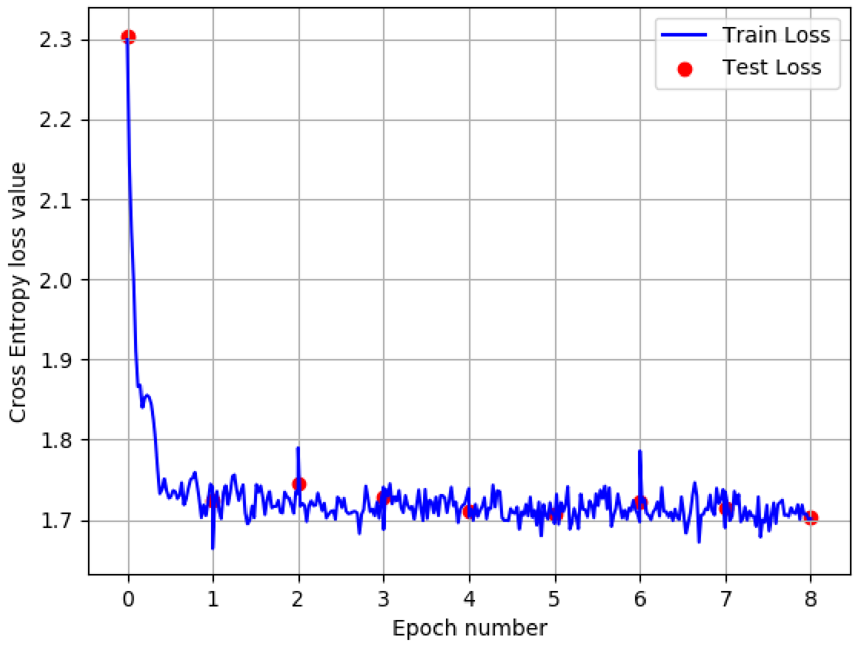


Figure 6: Loss vs. Epoch number

(b) Classification accuracy graphs

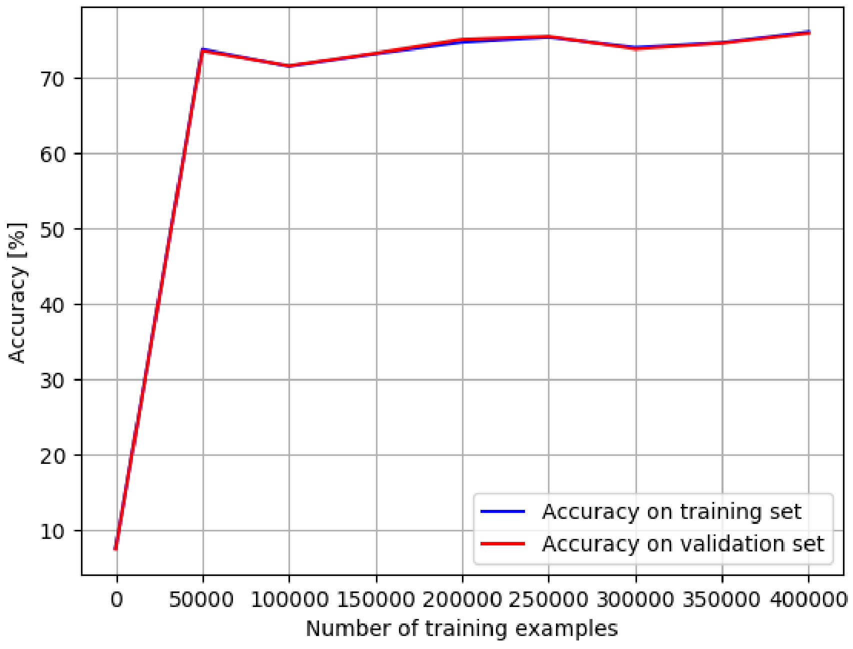


Figure 7: Accuracy vs. Training examples

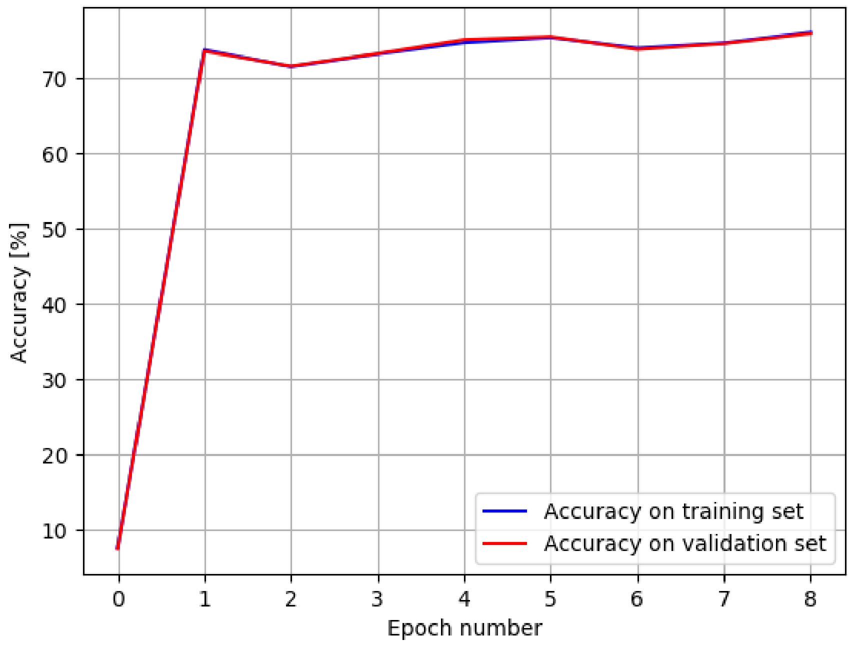


Figure 8: Accuracy vs. Epoch number

2. For the same network with the learning rate of **0.0001**:

   (a) Loss value graphs:

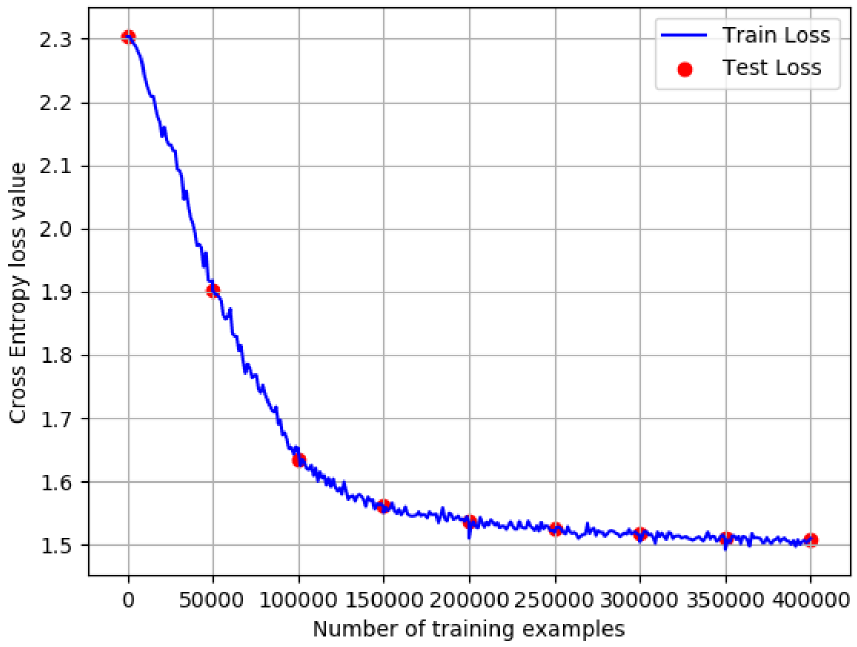


Figure 9: Loss vs. Training examples

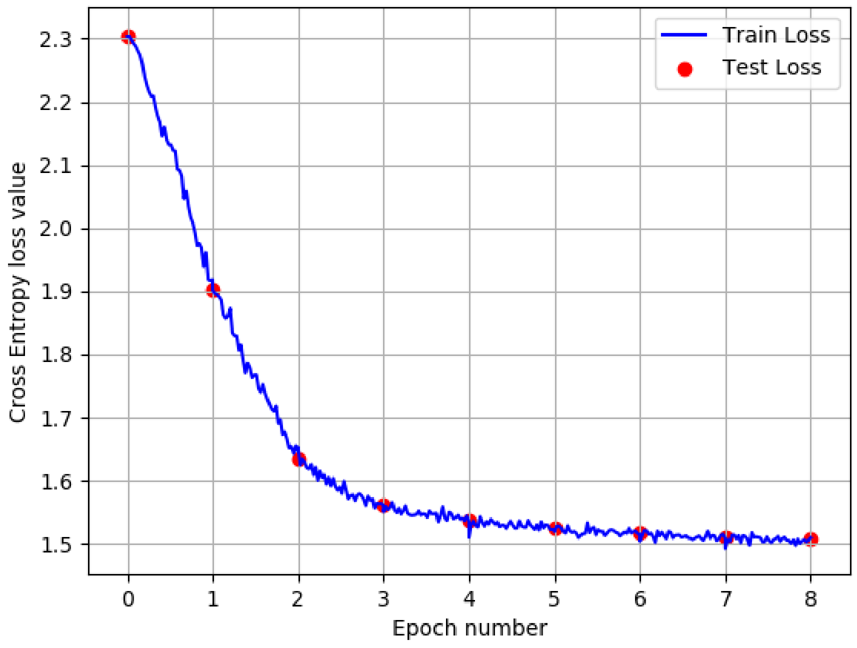


Figure 10: Loss vs. Epoch number

(b) Classification accuracy graphs

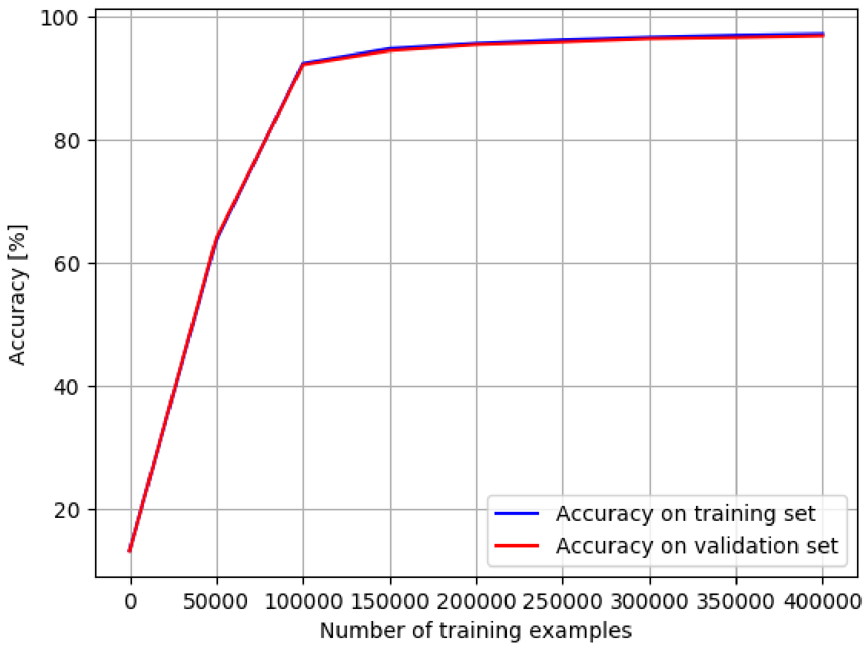


Figure 11: Accuracy vs. Training examples

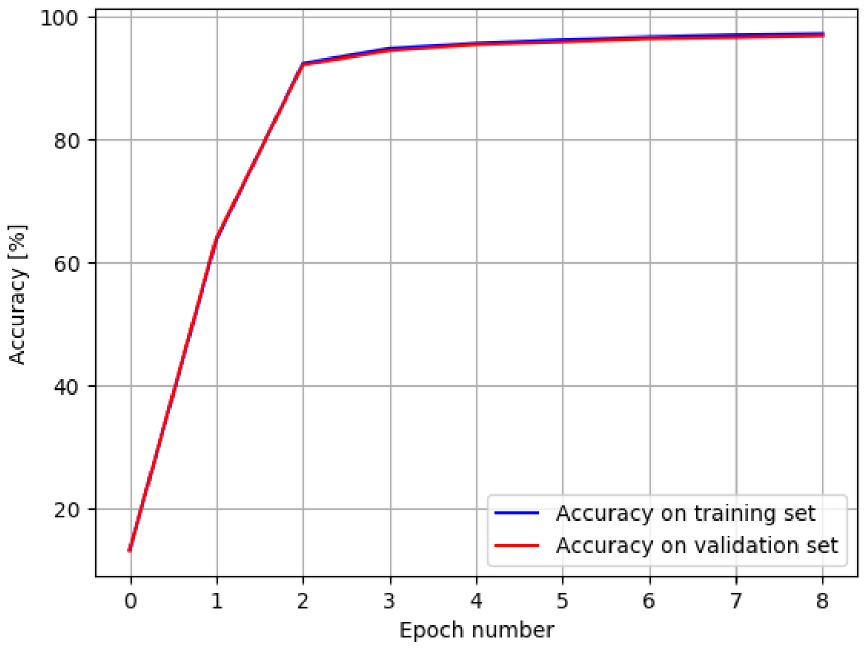


Figure 12: Accuracy vs. Epoch number

Answering the question asked, we compare the results and then draw conclusions. First, We compare the final accuracy on the validation set for 3 of the networks:

Network LR	Final test accuracy [%]	Final training accuracy [%]
0.01	98.58	99.186
0.1	75.88	76.036
0.0001	96.94	97.23

Then, we compare the accuracy of those 3 networks vs. the learning rate:

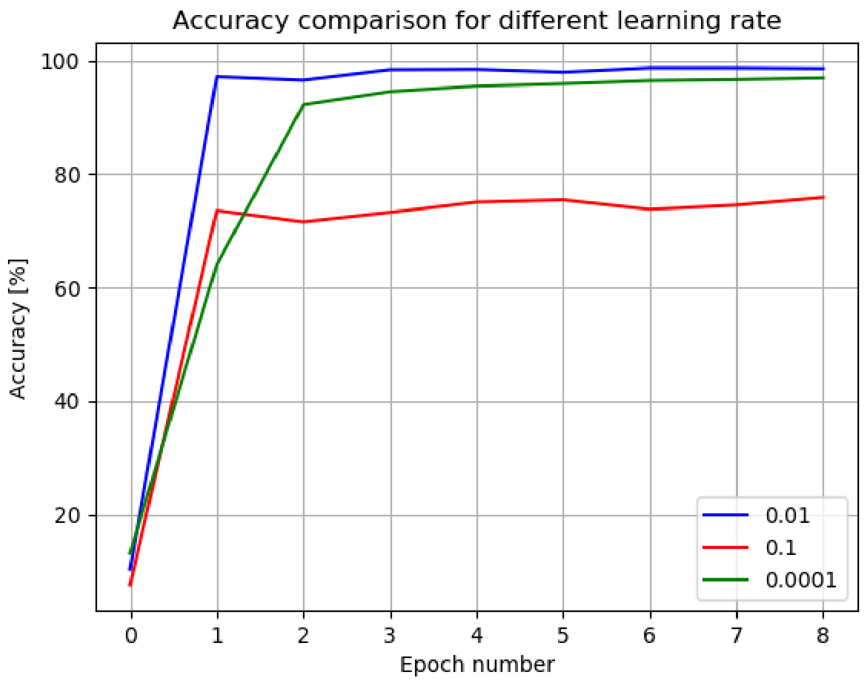


Figure 13: Accuracy vs. Epoch number

Several conclusions can be drawn from the overall results:

1. As we can see, the learning can is a parameter which has to be tuned in order to obtain optimal results:

   (a) Small learning rate leads to a network which will take a lot of time to converge, and this convergence will slow down even more when the Loss will decrease. We can see it in the case with $\alpha = 0.0001$

   (b) Large learning rate may give a quick jump towards the optimal solution in the beginning, but the network may never converge, since the parameters will be changed very drastically, and the Loss will not decrease. We can see it in the case with $\alpha = 0.1$ (which is high learning rate)

   There have been made a lot of research on this matter, and often the adaptive learning rate is being used. (which changes its value over time). From our example, over the given training time, the case with $\alpha = 0.01$ showed the best results

2. As mentioned above, the small learning rate makes small changes to the network parameter, so that the Loss value changes in a smooth way (Figure 10). Opposite is true for the high learning rate (Figure 6)

3. As mentioned above, high learning rate will reach a point where is can no longer decrease the Loss value, since the changes made for the parameters are very big. This is visible good in the Figure 6.

4. In all the cases, we can observe that the accuracy on the validation set is slightly smaller than the one on the training set. Which is logical, the network copes better with the data it has already seen and was trained on.

3. ***c.***

This subsection answers the step 7 - part 2.
First, we repeat the process with the the same learning rate ($\alpha = 0.01$), but with a different Loss Function, using the L2 Norm function as the loss value. Reporting the same results, we obtain the following Loss valueand the following Accuracy graphs:

1. Loss value graphs:

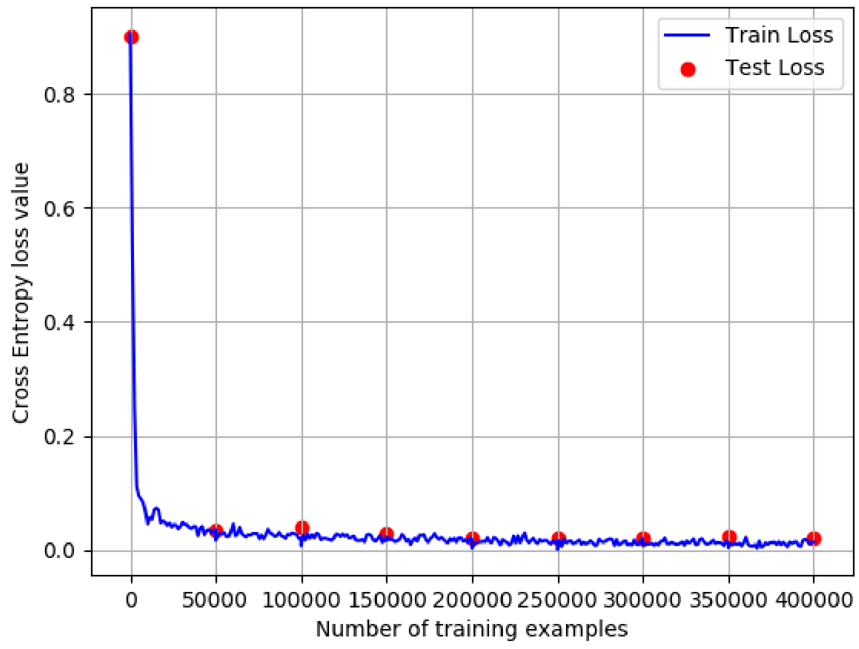


Figure 14: Loss vs. Training examples

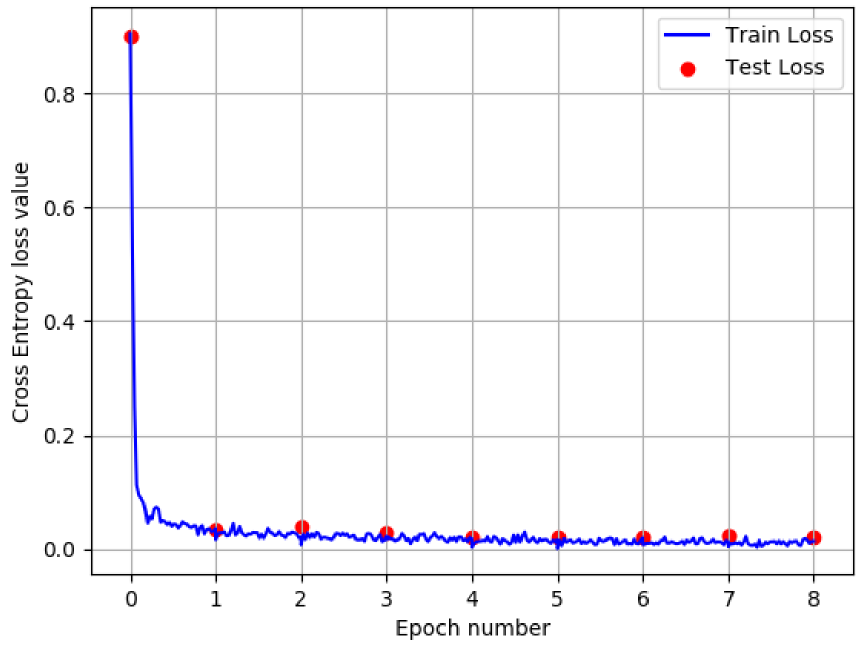


Figure 15: Loss vs. Epoch number

2. Classification accuracy graphs

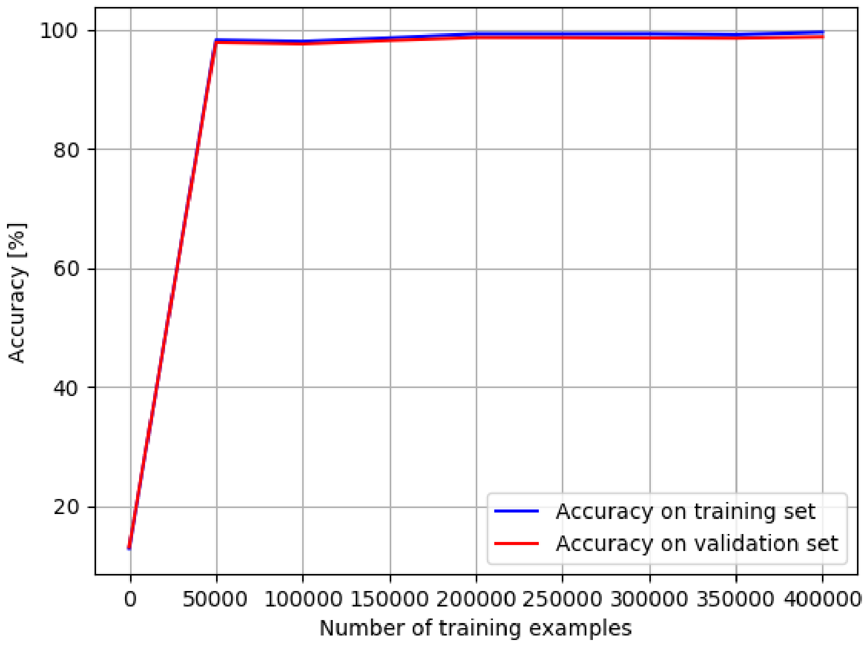


Figure 16: Accuracy vs. Training examples

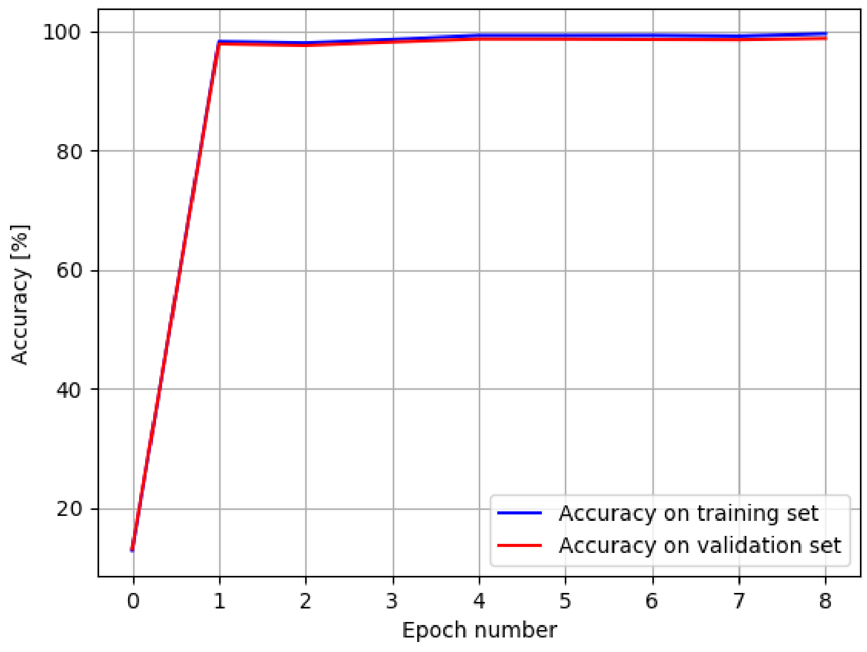


Figure 17: Accuracy vs. Epoch number

Comparing the accuracy rate on the trained network for both cases gives:

Network Loss function	Final test accuracy [%]	Final training accuracy [%]
Cross Entropy	98.58	99.186
N2 norm	98.77	99.514

Then, we compare the accuracy of those 2 networks:

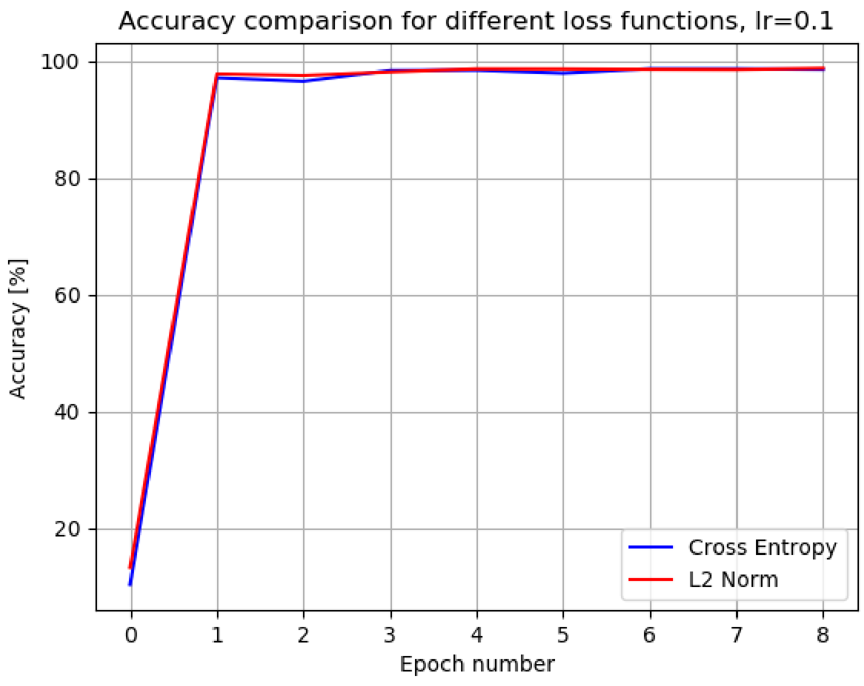


Figure 18: Accuracy vs. Epoch number

Several conclusions can be drawn from the overall results:

1. As we can observe, there is no much difference in the performance of both networks, and both classify the validation examples approximately on the same level. Although this is the case in our example, choosing the correct Loss Function is vital for a successful Network training in other, more complex environments.

4. ***d.***

This subsection answers the step 8.
First, we repeat the process with all the same parameters, but the network structure is different. The following results are being obtained (for the new network):

1. Loss value graphs:

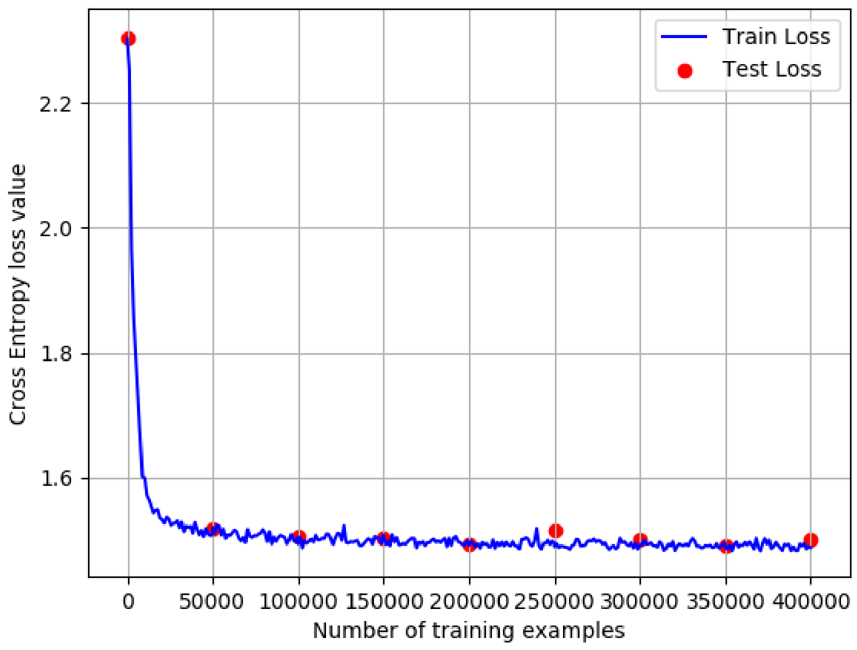


Figure 19: Loss vs. Training examples

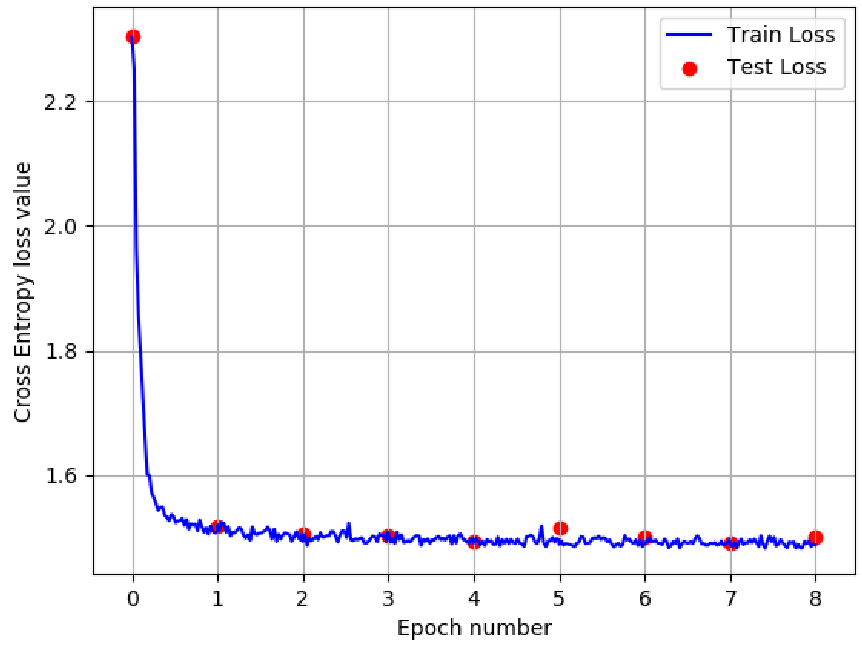


Figure 20: Loss vs. Epoch number

2. Classification accuracy graphs

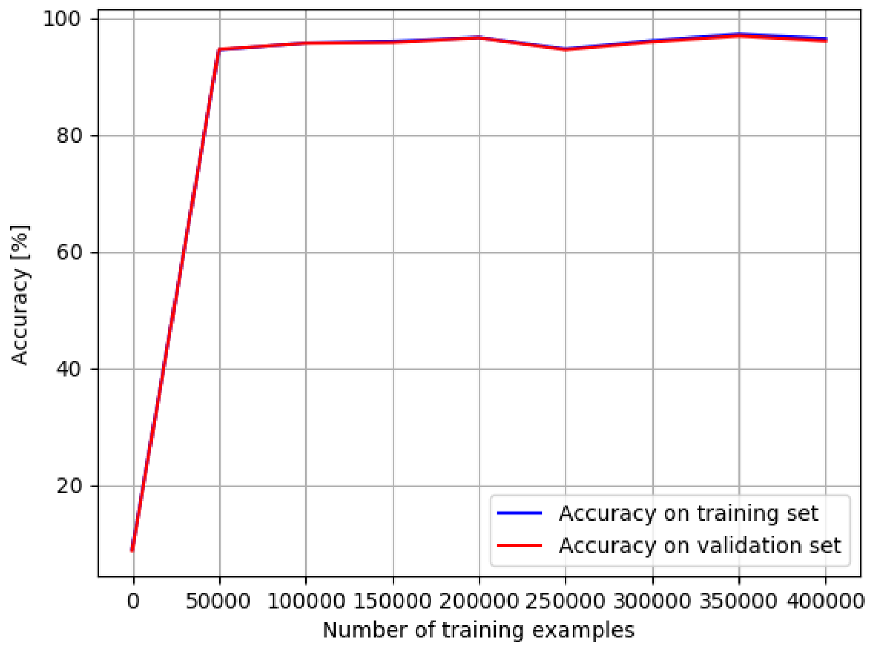


Figure 21: Accuracy vs. Training examples

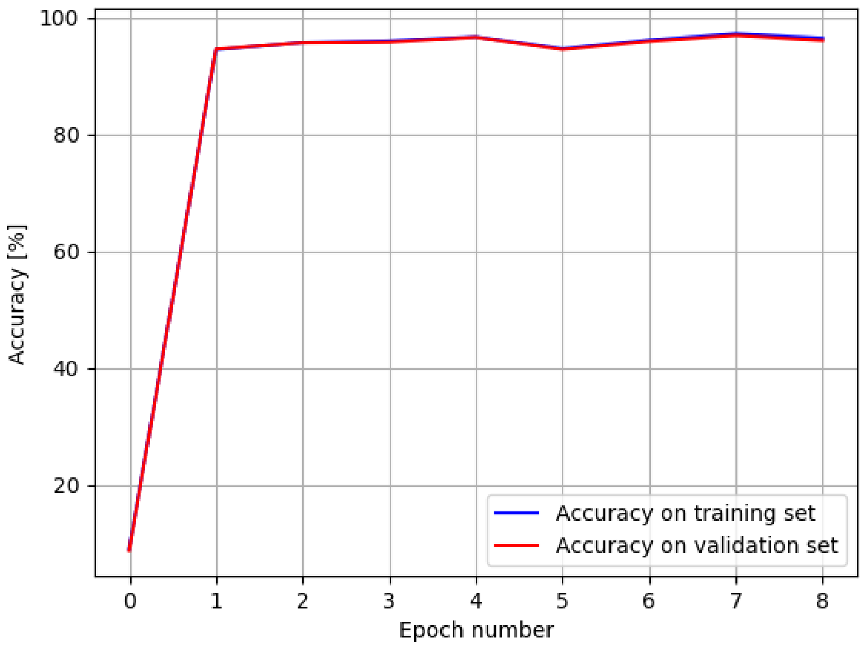


Figure 22: Accuracy vs. Epoch number

Comparing the accuracy rate on the trained network for both cases gives:

Network No.	Final test accuracy [%]	Final training accuracy [%]
1	98.76	99.25
2	96.13	96.52

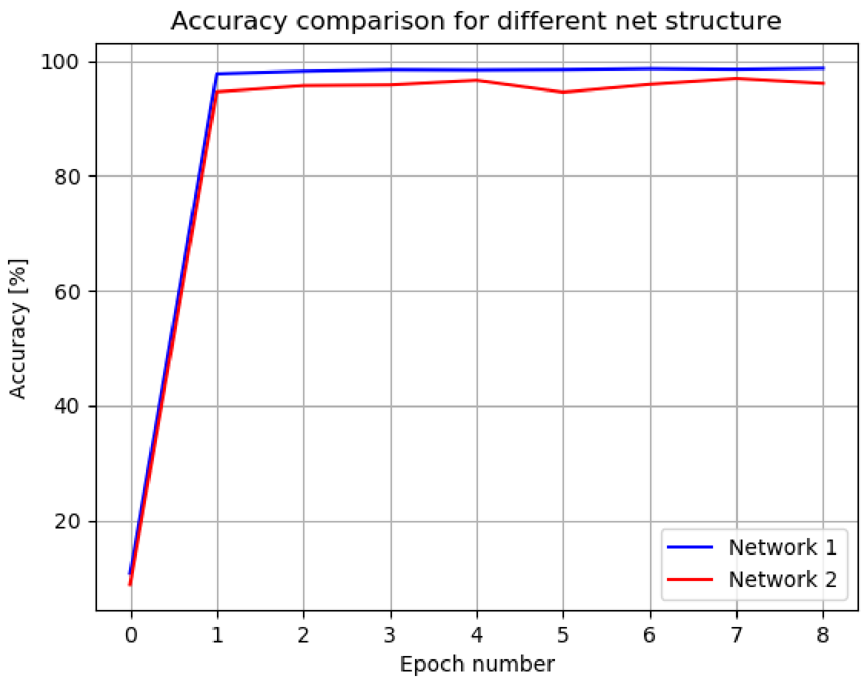


Figure 23: Accuracy vs. Epoch number

Several conclusions can be drawn from the overall results:

1. As we can observe, the new network structure contains **less** parameters, which means, its performance abilities are smaller than from the network with more parameters. This is also one of the big considerations when creating the network architecture - finding the optimal amount of layers & parameters / convolution size / etc. in each layer. From one side, the network should have enough parameters to supply the desired accuracy, from another side, an abundance of the parameters will lead to longer training time, and some other known problems (vanishing/exploding gradient, etc.)

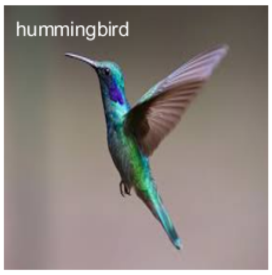
B. Question 2.

1.

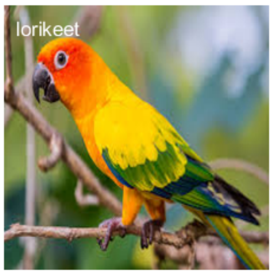
We have used the MATLAB version of the network, out of its simplicity to comply with the required tasks in this question.

2.

The bird images were loaded. Since their size differed from the input size to the VGG16 network ([224X224X3]), we had to resize them in order to fit into the network. This was done thoughtout the exercise without saving the Aspect Ratio of the images. The predictions for the birds are the following:



(a) Bird #0 prediction



(b) Bird #1 prediction

Figure 24: Prediction on the input birds

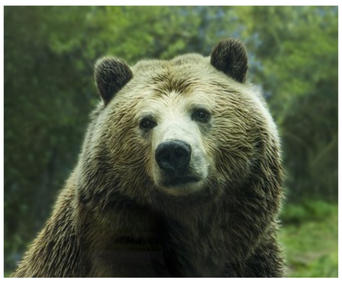
3.

The random image on the web that we have found is the image of the bear. The image was resized as well and has produced the following classification output, which is correct. (it says "Brown bear") (See Figure 25)

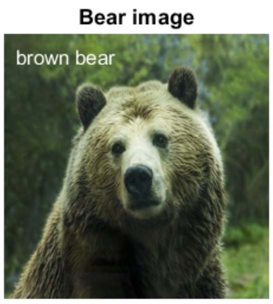
4.

The following transformations have been applied:

1. **Geometric transformation:** we have used the 'shear', which is represented by the following affine transformation matrix:



(a) Bear input image



(b) Bear resized and classified

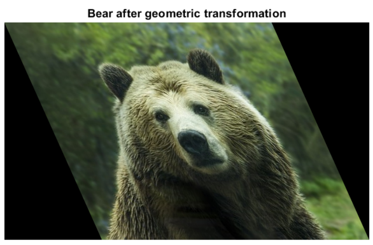
Figure 25: Bear prediction

$$\begin{bmatrix} 1 & 0 & 0 \\ 0.45 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

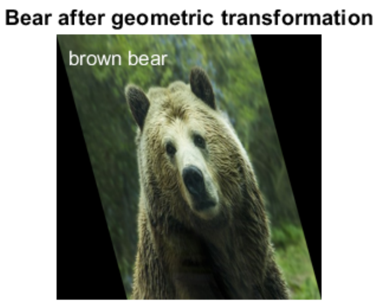
2. **Color transformation:** we have affected the Hue channel, multiplying its values by 2.5

3. **Filter:** we used the Motion Blur filter defined in MATLAB, of size 20, with angle of 45 degrees

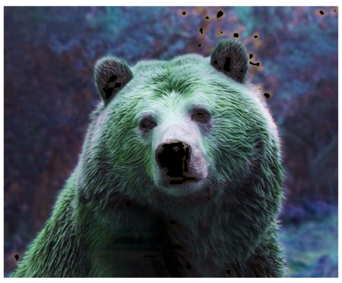
The results are presented in the next image. As we can see, all the classifications are still correct, which signals that the network is robust enough to all those modifications. (See Figure 26)



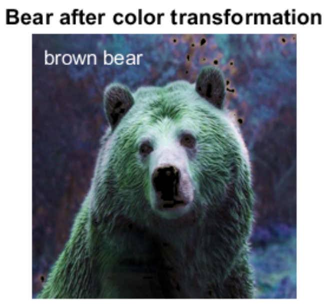
(a) Bear sheared input image



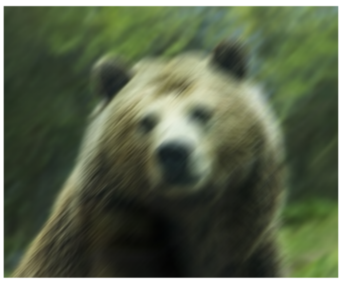
(b) Bear sheared classified



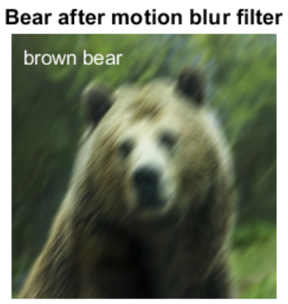
(c) Modified color bear



(d) Modified color bear classified



(e) Blurred bear



(f) Blurred bear classified

Figure 26: Bear modifications and its prediction