Budapest University of Technology and Economics
Faculty of Electrical Engineering and Informatics

Team: Molehub

Deep learning a gyakorlatban Python és LUA alapon | VITMAV45

Written by
Dániel Küttel (QPPXW1)
Máté Siket (N1C4Z9)

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Abstract

Several deep neural networks are trained and being trained for the detection of melanoma based on dermoscopic images. On the other hand simple camera utilisation for distant pre selection of moles is not widespread. Distant mole localization could be later used to detect appearances of new moles or to follow up the shape evolution. In our homework we created a dataset which contains more than a 1000 pictures of moles, implemented and investigated different deep neural network architectures in terms of accuracy. Two normalization methods are compared based on the performance of the corresponding convolutional neural networks.

1 Introduction

We study biomedical engineering, thus wanted to work on medical related homework. Both of us are interested in image processing and had projects on this area. The fusion of these scientific fields gave incentive to the investigation of mole localization. This topic is a great example of the utilization of new advances in deep learning in the field of biomedical engineering.

Unfortunately there is an increasing trend regarding the prevalence of melanoma. It has one of the highest increasing rate and ranked as the 15th most common cancer worldwide. In Europe the incidence rate is not equal between countries. A gradient is present from North to South with the highest incidence in the Northern ones. The greatest factor in this gradient is probably the more pigmented skin in the Southern countries as UV radiation considered as one of the most important risk factor[1][2].

The idea that neural networks could be utilized for melanoma detection is not a novel one. One of the first application was in 1994 with manual boundary selection. In 2018 thanks to the presence of high computing capacity, CNN architectures and sufficient datasets deep neural networks can provide dermatologist-level classification[3][4].

In contrast to melanoma detection, general mole localization is not well studied. A decade ago Cho et al. proposed a support vector machine based algorithm[5]. We found that the the state of the art automatic mole mapping system is the *bodystudio ATBM* of the FotoFinder Systems GmbH. It can follow-up the alteration of the individual moles and the appearance of the new ones in an automatic manner by capturing high resolution pictures of the body assisted by laser coordination. Description about the system is insufficient, but based on the brochures of the product we think that deep neural networks only utilized for the assistance of the dermatologist in melanoma detection, mole localization is probably done with other approaches[6].

2 Data preprocessing

Due to the restricted access to pictures about moles and due to the fact that our early thought considered dermoscopic images less relevant we created our own dataset. We collected pictures mostly about upper-bodies and faces on which moles were visible. We labeled more than 300 images, containing more than a 1000 moles. For labeling purposes we used the labelImg software[7]. The outputs are .xml files which contain the corresponding file name, resolution, path, bounding boxes of the selected image regions. Afterwards this information was used to make the cut-outs from the original pictures. Images were saved in 32x32 3-channel 8bit images in .bmp file format.

Since creating a dataset containing multi-thousand images is out of the scope of this work, we utilized data augmentation. Keras environment provides possibility for real time data augmentation, however, we applied it in an off-line manner in order to exactly control our dataset and to check the resulting images. Primarily geometrical transformations were used: rotation, horizontal, vertical offset, shear. A generative adversial network has been put to the proof, it provided mostly good, natural moles, however, it requires more time and investigations to confidently use its outputs. The preliminary test results can be seen in Jupyter Notebook GAN_augmentation.

We investigated two kind of normalization methods. Method 1 is a linear mapping of the 8bit values into the [0..1] range. Method 2 is a normalization with respect to the intensities of the individual pixels, in the resulting three dimensional vectors only two are independent.

Method 1

$$Channel_{i,m1} = \frac{Channel_i}{255}, \tag{1}$$

where $i = [R, G, B]$ channels respectively.

Method 2

$$Channel_{i,m2} = \frac{Channel_i}{Channel_R + Channel_G + Channel_B}. \tag{2}$$

It is important to note when there are zero intensity values, the mapping into the [0..1] range is not satisfied. This unfortunate event can be mitigated by preconditioning, and furthermore, it is very unlikely in real world situation that pixels have zero intensity values.

3 Applied deep neural networks

Multi layer perceptron

Multi layer perceptrons (MLP) are not used in particular for image classification problems, since they can not relate spatial informations. However, it was shown in various cases that in case of sufficiently small pictures can provide reasonably good results[8].

Architecture of the applied MLP:

Table 1: *Applied MLP.*

Layer type	Inputs	Outputs	Activation function	Parameters
Dense	1024	10	ReLu	10250
Dense	10	10	ReLu	110
Dense	10	2	Softmax	22

For the training Adam optimizer, a batch size of 128 with 4 epochs of patience was used. Figure 1 depicts the evolution of validation loss between each epoch. The MLP was trained on grayscale images.

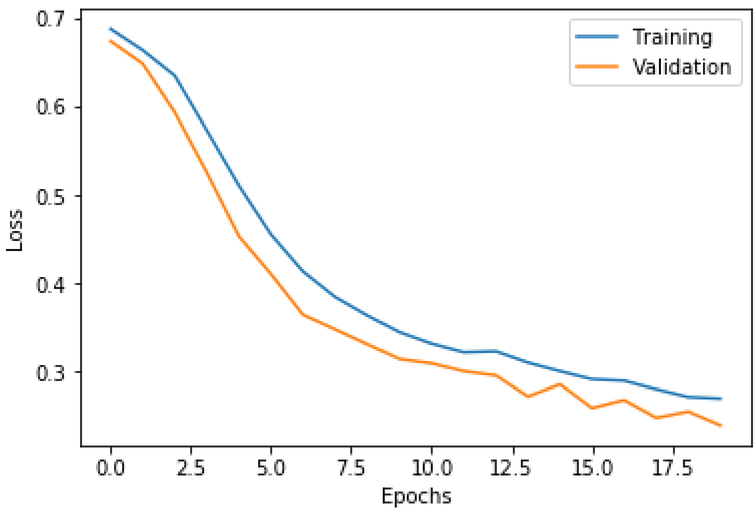

Figure 1: *20 epochs of validation loss during MLP training.*

Convolutional neural network

Convolutional neural networks' (CNN) main benefit regarding image classification problems is the capability to process spatial information by the utilisation of filters. LeNet-5[9] an early CNN designed for handwritten character recognition outperforms the original MLP designed for this task by a significant margin[10].

Architecture of the applied CNN:

The applied CNN considering the limited dataset of ours was implemented based on[11]. For the training Adam optimizer, a batch size of 32 with 4 epochs of patience

Table 2: *Applied CNN.*

Layer type	Inputs	Outputs	Parameters	Comments
Conv 2D	(3)x(32x32)	(3)x(30x30)x(32)	896	size (3x3)
Activation	(3)x(30x30)x(32)	(3)x(30x30)x(32)	0	ReLu
Max-pooling	(3)x(30x30)x(32)	(3)x(15x15)x(32)	0	size (2x2)
Conv 2D	(3)x(15x15)x(32)	(3)x(13x13)x(64)	18496	size (3x3)
Activation	(3)x(13x13)x(64)	(3)x(13x13)x(64)	0	ReLu
Max-pooling	(3)x(13x13)x(64)	(3)x(6x6)x(64)	0	size (2x2)
Conv 2D	(3)x(6x6)x(64)	(3)x(4x4)x(64)	36928	size (3x3)
Activation	(3)x(4x4)x(64)	(3)x(4x4)x(64)	0	ReLu
Max-pooling	(3)x(4x4)x(64)	(3)x(2x2)x(64)	0	size (2x2)
Flatten	(3)x(2x2)x(64)	(3)x(256)	0	-
Dense	(3)x(256)	(3)x(64)	16448	-
Activation	(3)x(64)	(3)x(64)	0	ReLu
Droput	(3)x(64)	(3)x(64)	0	0.5
Dense	(3)x(64)	(2)	130	-
Activation	(2)	(2)	0	Sigmoid

was used. Figure 1 depicts the evolution of validation loss between each epoch.

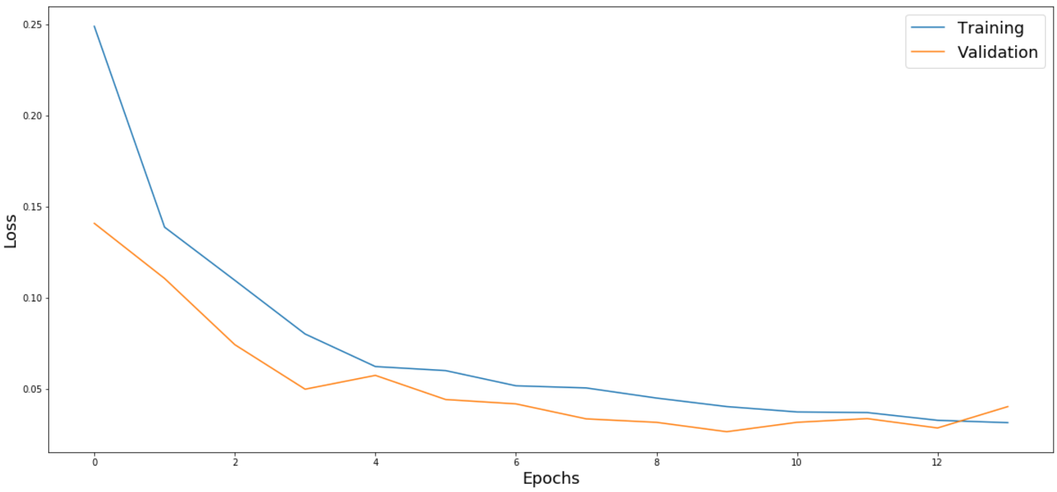

Figure 2: *14 epochs of validation loss during MLP training.*

4 Evaluation

We evaluated 4 different deep neural networks: CNN with method 1 normalized inputs, MLP with method 1 normalized inputs, CNN+MLP with method 1 normalized inputs, CNN with method 2 normalized inputs. In case of CNN+MLP network the CNN classified regions had to be classified as moles by the MLP also. Our conception was that if the two networks learn different features by the combined voting process we could lessen the number of misclassifications. In case of normalization method 2 we wanted to investigate how the CNN performs if we decrease the input's dimension by normalizing with the intensity values. Evaluation was based on the ratio of good and bad classifications. The tests were carried out on a dataset contained picture and on two self captured ones.

In Table 3 we summarized the accuracy of each implemented deep neural network based on three test images. True positive, false positive and sensitivity values are given, where it is possible. In some cases the entities were uncountable. In Figure 3 there are so many moles, it is hard to determine sensitivity. The MLP provided extremist results, thus evaluation was not possible. Results in Table 3 indicate that the CNN with method 1 normalization is the best mole classifier, since it has good sensitivity and low false positive classifications. CNN with method 2 normalization in most of the cases finds more moles than the method 1 version, however, at the cost of significantly more false positive classifications. CNNs outperformed by a large margin the neural networks which involved MLP structure. Only the highest and lowest scoring neural networks' results are showcased here in Figure 4-7.

Figure 3: *CNN with method 2 normalization on back.*

5 Summary

In the course of the semester we created a dataset for distant mole localization. We investigated four different types of deep neural networks. A performance comparison was done based on true positive and false positive classifications. We concluded

Table 3: *Accuracy of the implemented deep neural networks.*

Picture	Network type	True positive	False positive	Sensitivity
Back	MLP method 1	18	approx. 100	-
Face	MLP method 1	0	-	-
Arm	MLP method 1	0	-	-
Back	CNN method 1	38	0	-
Face	CNN method 1	6	1	86%
Arm	CNN method 1	6	2	86%
Back	CNN+MLP method 1	20	0	-
Face	CNN+MLP method 1	0	0	-
Arm	CNN+MLP method 1	0	0	-
Back	CNN method 2	approx. 90	approx. 10	-
Face	CNN method 2	5	4	71%
Arm	CNN method 2	7	6	100%

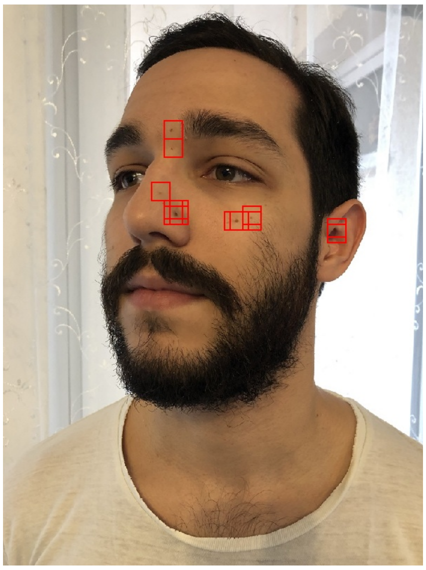

Figure 4: *CNN with method 1 normalization on face.*

Figure 5: *CNN with method 1 normalization on arm.*

that a deep neural network based solution is feasible for mole localization purposes. Further improvements should made by training the network with high numbers of counterexamples. These counterexamples should darkened mid region, because we found that the investigated networks tended to learn this specific characteristics. Moreover region proposal methods for skin regions could be an other development step.

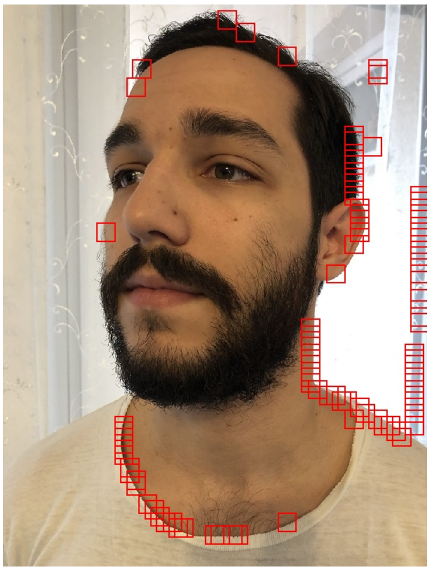

Figure 6: *MLP with method 1 normalization on face.*

Figure 7: *MLP with method 1 normalization on arm.*

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