Skin Lesion Analysis Towards Melanoma Detection for ISIC 2018

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Abstract

In this paper we summarize our methods for the ISIC 2018 Competition: Skin Lesion Analysis Towards Melanoma Detection.

1 Introduction

In this paper we briefly discuss our methods for addressing Task 1 (lesion segmentation), Task 2 (lesion attribute detection) and Task 3 (classification) of the ISIC 2018 Competition on skin cancer.

For Task 1 and Task 2, we used a convolutional neuron network (CNN) model called *GrassNet*, which we developed earlier this year for another problem (satellite image segmentation), and which is a combination of U-Net [4] and ResNet [5]. For Task 3, we use a new CNN model that we developed called *Z-Net* (Z for zig-zag), and pre-process the images using Task 1.

For Task 1 and Task 2, we used only the official data of the ISIC 2018 Competition [2] and [3]. For Task 3, due to the fact that the official dataset is very imbalanced (e.g., the number of images in the category "NV" is almost 60 times higher than "DF"), we added some data that we could find on the internet using searches by keywords, from free sources such as DermanetNZ, to reduce this imbalance.

2 Task 1: Lesion Segmentation

2.1 Model

We designed an architecture using Keras/Tensorflow, called *GrassNet*, which combines the U-Net of Ronneberger et al. [4] and the ResNet structures of He et al. [5]. More precisely, the network contains down-sampling and up-sampling layers as in the U-Net, and residual blocks are added to down-sampling layers as in ResNet. In addition, we concatenate down-sampling layers to up-sampling layers in order to preserve the information. Our GrassNet has 37 million trainable parameters.

The droupout with $p = 0.5$ is also added at the two last down-sampling convolution blocks to reduce overfitting. The Batch normalization and the Selu activation are added after each Convolution2D layer. The last activation function is Sigmoid.

The architecture operates on an input image of 256×256 pixels and produces a probability map of the same dimensions.

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2.2 Preprocessing and Training

We resized each training image to 256×256, then trained the network using the Adam optimization algorithm [1]. In order to improve the robustness of the model, we applied a set of transformations (augmentations): rotation with a random angle, flipping, and random noise.

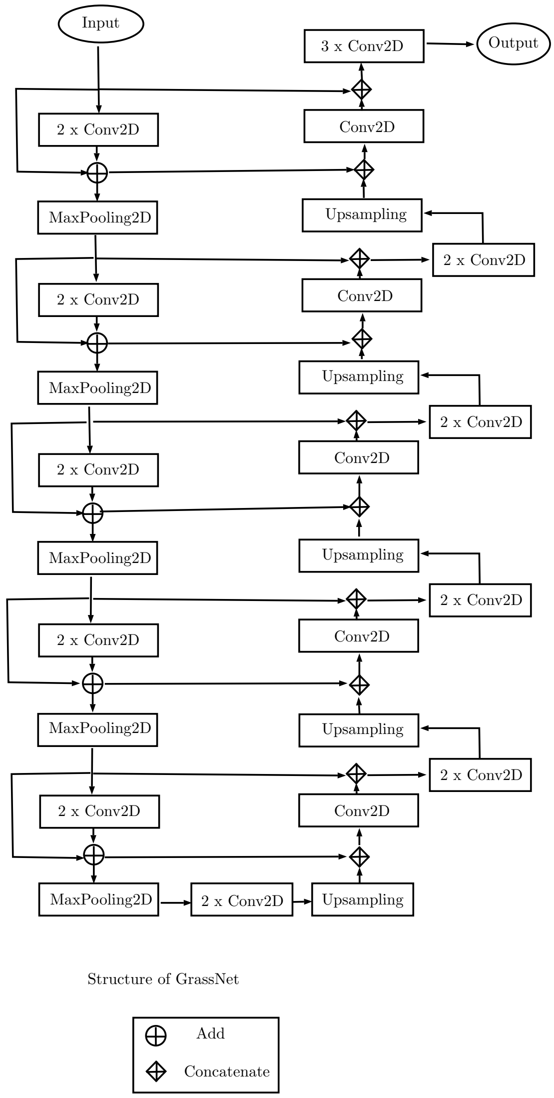

Figure 1: GrassNet

2.3 Validation results

We obtained a Jaccard score of 0.781 on our first validation submission, after 280 epochs of training (11 minutes per epoch), on a PC with a GTX 1070 graphic card.

3 Task 2: Lesion Attribute Detection

3.1 Model

For Task 2, we use the same architecture GrassNet as for Task 1.

3.2 Preprocessing

In order to improve accuracy, we first apply Task 1 to find the lesion on the image, cut down the image to a smallest possible square which contains the lesion, and then resize that square to 256×256, before feeding it to GrassNet.

3.3 Augmentation and Training

We trained each attribute separately, using the Adam optimization algorithm [1]. Data augmentations similar to Task 1 (random rotations, flipping, and random noises) are used in order to improve the robustness of the model.

We did not submit our results for validation yet, due to lack of time. (We entered this competition late, on July 4th).

4 Task 3: Lesion Classification

4.1 Model

We designed a new network, called *Z-Net* (Z for zig-zag) by combining the GrassNet in Task 1 and an additional down-sampling structure. The idea is that the hidden segmentation inside Z-Net will improve the accuracy of the classification. Our test runs on this architecture show promising results compared to previously well-known architectures.

See Figure 2 for the schema of a version of Z-Net. A more sophisticated version also has bagging.

4.2 Preprocessing

We pre-process in a way similar to Task 2, using the results of Task 1.

4.3 Augmentation and Training

Since the data is extremely imbalanced, we use the up-sampling technique by multiplying the data with different ratios on different classes. Then we apply a random mix-up [6] with random weights: for a random couple of image (img_1, img_2) extracted from data set, we replace it by a new image $img = \alpha * img_1 + (1 - \alpha) * img_2$ with the same label as img_1, where α is a random number in $[0.5, 1]$. Standard augmentation operations are also used (random rotations, random zooming, random noise, etc.) in the training process.

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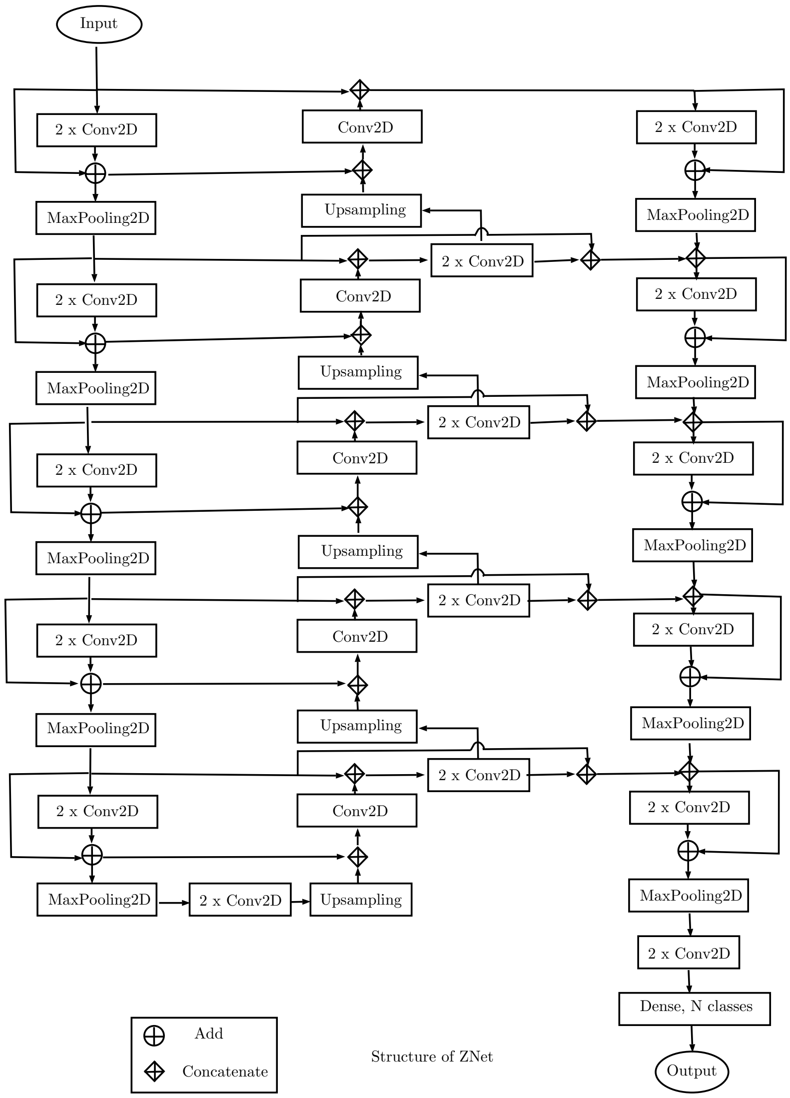

Figure 2: Z-Net

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