# DSNet: Automatic Dermoscopic Skin Lesion Segmentation (Reimplementation by Harneet Singh Khanuja)

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## Abstract

*Skin cancer is a very prevalent and deadly problem, killing over 7,200 people in 2019 in US alone. Early diagnosis is the only prevention against this and Computer Aided Diagnosis (CAD) systems help the dermatologists make the task less tedious and more accurate. The paper proposed a new network called DSNet which performs better than baseline models such as U-Net and FCN (Fully Convolution Network). Keras and tensorflow is used to implement the paper and the code can be found at: https://github.com/naman0210/IIIT-Assignment2.*

## 1. Introduction

The paper DSNet [2] is published in the Computers in Biology and Medicine journal published by Elsevier, May 2020 issue. The paper proposes a new architecture which is shown to perform better than baseline U-Net and FCN architectures and also gives state-of-the-art results on ISIC 2017 dataset while being lightweight.

## 2. Architecture

The DSNet encoder architecture mimics DenseNet121[1] architecture and the weights are initialised as pretrained weights of DenseNet121 on ImageNet dataset. The decoder network has skip connections inspired by the U-Net [3] architecture and to reduce the number of parameters depth-wise separable convolution is used. In depth-wise separable convolution we first perform depth wise convolution by running m 2D kernels over the image - m is the number of channels in the image. Then we perform point wise convolution where 1*1*m kernels are applied on the image created after depth wise convolution, we use n such kernels and n is the number of channels in the final output image of the layer. The weights for the decoder network are initialized using He normal Initialization method which has been shown to work well with ReLu activation. The paper also uses Batch Normalisation layers which is pretty much standard practice while working with CNNs. Batch normalization is shown to work best when the batch size is atleast greater than 16. The Adaldelta optimizer is initialized with a learning rate of 1 and a decay factor of 0.95. Along with that when learning loss is stagnated for 8 epochs, the learning rate was reduced by 40%. A new loss function is also introduced which tries to minimize the binary cross entropy loss and at the same time tries to maximize Jaccard coefficient. The paper shows the comparison of results when using just either one of the losses instead of combining them both.

## 3. Dataset

The model is trained on the ISIC 2017 dataset which has 2000 skin lesion images available for training and 150 images for validation. The images were resized to 192*256 to maintain the aspect ratio of 3:4, which is the aspect ratio followed by most images in the dataset. The International Skin Imaging Collaboration (ISIC) is an academia and industry partnership designed to facilitate the application of digital skin imaging to help reduce melanoma mortality.

## 4. Methodology

Having previously worked with autoencoders I first worked in visualising the dataset. The dataset is publicly available and can be easily downloaded from their official website https://challenge.isic-archive.com/data. The images are in jpg format and can be easily read and visualised using the opencv library in Python. I also resized the images using the cv2 library and the input images were standardized to have a zero mean and one unit variance and then both the input and the ground truth images were normalized. I used random augmentation operations such as rotation, flipping and zoom which help the model achieve better generalization.Generator functions are also used in the implementation of the paper so as to eliminate the need to load the entire dataset in the memory at once. In segmentation tasks for the generator to work the directory structure and the filenames should be in a particular format which needed some figuring out. Instead of accuracy, dice coefficient and Jaccard coefficient were used as evaluation metrics. ReduceOnPlateau callback available in

| Metrics | Paper Results | My implementation |
|---|---|---|
| IoU | 0.775 | 0.7705 |
| Sensitivity | 0.875 | 0.807 |
| Specificity | 0.955 | 0.9866 |
| AUC | 0.953 | 0.967 |

Table 1. Result comparison

keras is used to adjust the learning rate when the loss becomes stagnant.

## 5. Issues faced

Apart from understanding all the technical aspects of the paper like He initialization and depth-wise separable convolution,the major issue faced was computation. As mentioned earlier Batch Normalization works best when the mini-batch size is greater than 16. But due to computational constraints I could only use a mini-batch size of 15.

## 6. Results

The best results obtained from my implementation were with a Jaccard coefficient of 0.7705 as shown in table 1. The discrepancy in the result can be attributed to the number of images in each mini-batch. When tried with a batch size of 5 the best Jaccard coefficient achieved was 0.759 while the above mentioned result was achieved with a batch size of 15.

## 7. Discussion

The proposed DSNet possesses the highly desirable trait of having the least number of parameters among all compared networks, all the while outperforming the existing baseline segmentation networks. Due to its lightweight architecture the proposed DSNet appears better suited for eventual CAD systems due to its extremely fast processing time. Further research work in the field of skin lesion segmentation involves but is not limited to the works mentioned below.

[4] uses the concept of GANs, where the generator is slightly modified U-Net architecture and the segmented image from the generator is branched into two discriminators. The first discriminator gets the segmented image and the original image concatenated together and it pays more attention to the spatial information, while the other discriminator gets only the segmented image and focuses on boundary information.

[6] utilises High resolution Feature blocks which have 3 channels, one for local information, one for spatial and the last one for channel information. The paper focuses on preserving spatial details by not downsampling the original image a lot.

[7] introduces a new type of loss called Kappa loss. In essence, Kappa loss can be considered a more generalised version of Dice loss. Dice loss assumes that the lesion area is significantly smaller when compared to the whole image but the size invariance in the dataset proves that Kappa loss performs better than dice loss.

[5] uses a slightly modified version of U-Net for segmentation and data is augmented by ensuring color constancy and removing light variance. It uses Gray World algorithm which assumes the average color in a given scene is gray and any deviations from that are due to the effects of the light source.

## References


[1] Gao Huang; Zhuang Liu; Laurens van der Maaten; Kilian Q. Weinberger. "Densely Connected Convolutional Networks." In: *Proceedings of the IEEE conference on computer vision and pattern recognition* (2017).

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[3] Brox T. Ronneberger O Fischer P. "U-net: Convolutional networks for biomedical image segmentation." In: *International Conference on Medical image computing and computer-assisted intervention* (2015).

[4] Lei B; Xia Z; Jiang F; Jiang X; Ge Z; Xu Y; Qin J; Chen S; Wang T; Wang S. "Skin lesion segmentation via generative adversarial networks with dual discriminators." In: *Medical Image Analysis.* (2020).

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[7] Ainouz S. Zhang J Petitjean C. "Kappa loss for skin lesion segmentation in fully convolutional network." In: *IEEE 17th International Symposium on Biomedical Imaging (ISBI)* (2020).

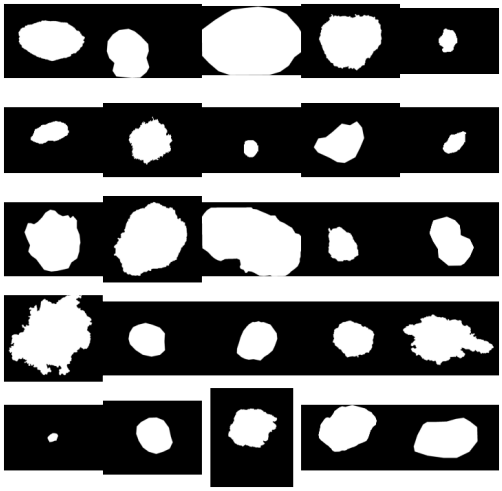

Figure 1. Different segmentation in ISIC 2017 dataset

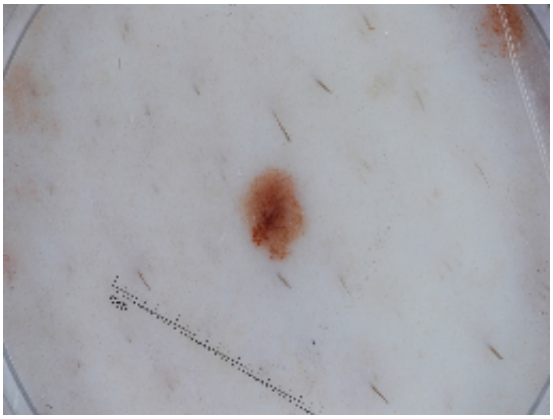

Figure 2. Original Image

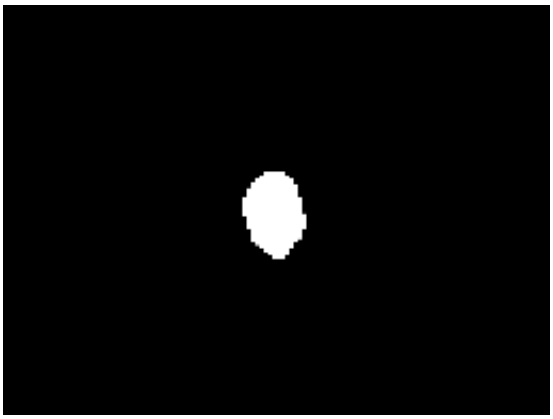

Figure 3. Ground Truth

Figure 4. My implementation

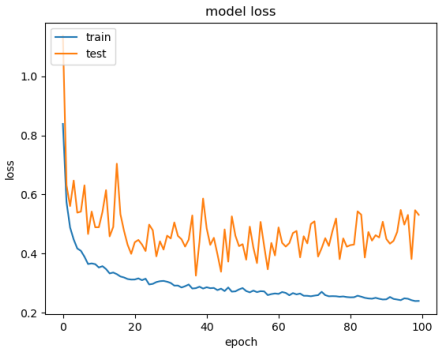


Figure 5. Loss vs epochs

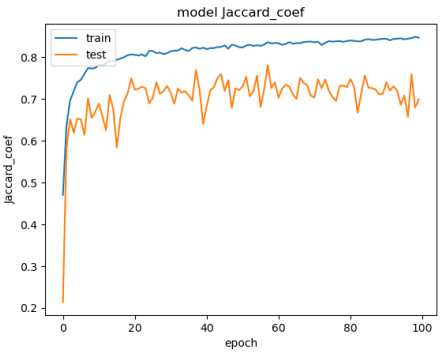


Figure 6. Jaccard coefficient vs epochs