Multi-class Semantic Segmentation of Skin Lesions via Fully Convolutional Networks

Manu Goyal[1][a], Moi Hoon Yap[2][b] and Saeed Hassanpour[3][c]

[1]*Department of Biomedical Data Science, Dartmouth College, Hanover, NH, U.S.A.*

[2]*Visual Computing Lab, Manchester Metropolitan University, Manchester, U.K.*

[3]*Departments of Biomedical Data Science, Computer Science and Epidemiology, Dartmouth College, Hanover, NH, U.S.A.*

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Abstract: Melanoma is clinically difficult to distinguish from common benign skin lesions, particularly melanocytic naevus and seborrhoeic keratosis. The dermoscopic appearance of these lesions has huge intra-class variations and high inter-class visual similarities. Most current research is focusing on single-class segmentation irrespective of classes of skin lesions. In this work, we evaluate the performance of deep learning on multi-class segmentation of ISIC-2017 challenge dataset, which consists of 2,750 dermoscopic images. We propose an end-to-end solution using fully convolutional networks (FCNs) for multi-class semantic segmentation to automatically segment the melanoma, seborrhoeic keratosis and naevus. To improve the performance of FCNs, transfer learning and a hybrid loss function are used. We evaluate the performance of the deep learning segmentation methods for multi-class segmentation and lesion diagnosis (with post-processing method) on the testing set of the ISIC-2017 challenge dataset. The results showed that the two-tier level transfer learning FCN-8s achieved the overall best result with *Dice* score of 78.5% in a naevus category, 65.3% in melanoma, and 55.7% in seborrhoeic keratosis in multi-class segmentation and *Accuracy* of 84.62% for recognition of melanoma in lesion diagnosis.

1 INTRODUCTION

Skin cancers are more common than all other cancers (Pathan et al., 2018). Malignant skin lesions are classified as melanocytic, i.e. melanoma, and non-melanocytic. The most common non-melanocytic cancers are keratinocytic: basal cell carcinoma and squamous cell carcinoma. Melanoma is less common but is more likely to prove fatal than keratinocytic skin cancers due to aggressive invasion and metastasis (National Cancer Institute, 2017)(Dvořánková et al., 2017). Hence, early detection is important to save lives. According to the prediction of the Melanoma Foundation (Melanoma Foundation (AIM), 2017), the estimated diagnosed cases of melanoma in the United States in 2018 is 178,560 with 91,270 cases will be invasive.

Melanocytic naevi and seborrhoeic keratosis are very common benign skin lesions that may be clinically difficult to differentiate from skin cancer. Both melanoma and melanocytic naevi are melanocytic lesion as uncontrolled growth of melanocytes (pigmented cells) results in melanoma whereas non-cancerous growth in moles results in benign melanocytic naevus. Seborrheic keratosis is a type of non-melanocytic skin lesion. But, it is very hard to distinguish the SK lesions from melanocytic lesions (moles and melanoma) even with the help of dermoscopy as these skin lesions share similar features such as irregular shapes and multiple colors.

With the rapid growth of deep learning approaches, many researchers (Yuan et al., 2017), (Yu et al., 2017), (Bi et al., 2017), (Goyal et al., 2019) have proposed Deep Convolutional Neural Networks for skin lesion segmentation (single-class). We have found no previous research on multi-class semantic segmentation for different types of skin lesions.

Our contributions are three fold. Firstly, we propose multi-class semantic lesions segmentation for melanoma, seborrhoeic keratosis and naevus. To overcome data deficiency, a two-tier transfer learning is used in skin lesions segmentation to train the fully convolutional networks (FCNs). Secondly, we design a hybrid loss function to handle class imbalance in the multi-class segmentation. Thirdly, we assess the performance of state-of-the-art deep learning

[a] https://orcid.org/0000-0002-9201-1385

[b] https://orcid.org/0000-0001-7681-4287

[c] https://orcid.org/0000-0001-9460-6414

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Table 1: Distribution of images for multi-class segmentation task.

	Naevi	Melanoma	Seborrheic Keratosis	Total
Training set	1372	521	387	2000
Validation set	92	34	23	150
Testing set	393	117	90	600
Total	1843	521	386	2750

algorithms using our proposed multi-class segmentation and a post-processing method to determine lesion diagnosis on ISIC-2017 Challenge dataset. Our proposed method can be generalised into other multi-class segmentation tasks in medical imaging.

2 METHODOLOGY

This section discusses the publicly available ISIC-2017 skin lesion dataset and its ground truth labeling, the two-tier transfer learning approach, and the hybrid loss function.

2.1 Datasets and Ground Truth

We used the publicly available ISIC-2017 *Skin Lesion Analysis Towards Melanoma Detection Challenge* dataset (Codella et al., 2017) to train the fully convolutional deep learning models. RGB colorspace is used to represent all the images in this dataset. It includes 3 skin lesion types using dermoscopy images: naevi, melanomas and seborrhoeic keratosis. The segmentation task on these dermoscopy images is very challenging due to high inter-class similarity between the 3 types of skin lesions. This dataset is imbalanced as there are only a total of 521 melanoma and 386 seborrheic keratosis compared to 1843 melanocytic naevi dermoscopic images. There are a total of 2750 dermoscopy images in the ISIC-2017 challenge dataset, as summarised in Table 1.

In this dataset, the size of images varies between 540×722 and 4499×6748. To improve the performance and reduce the computational cost, all the images are resized to 500×375. In ISIC-2017 segmentation challenge, the task is to segment the lesion boundaries, which was a one-class segmentation task. Here we are targeting on automatic multi-class segmentation. The ground truths are all defined in RGB colorspace and 8-bit paletted images. Figure 1 illustrates the dermoscopic images with the corresponding ground truth labeling in PASCAL-VOC format (Garcia-Garcia et al., 2017)(Everingham et al., 2015). Index 1 indicates naevus, index 2 indicates melanoma and index 3 represents seborrhoeic keratosis.

2.2 Fully Convolutional Networks for Multi-class Semantic Segmentation

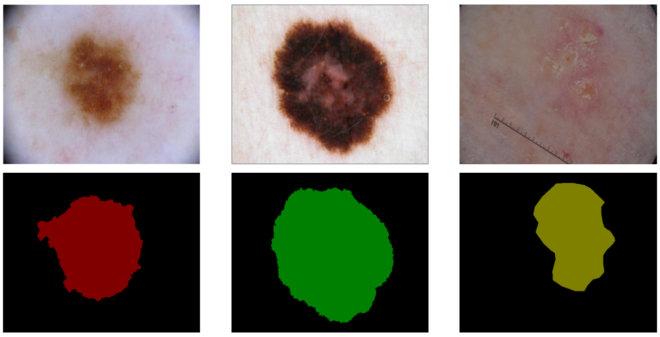
FCNs and encoder-decoder CNNs can detect the multiple objects as well as localize the objects by using pixel-wise prediction. This enables to learn which pixel of an image belongs to which class of object. Recently, FCNs have become the state-of-the-art methods for segmentation tasks on both non-medical and medical imaging, which are superior to conventional machine learning and other deep learning methods. We used the four different variants of FCNs (FCN-AlexNet, FCN-32s, FCN-16s, and FCN-8s) and assessed their performance on multi-class skin lesions segmentation.

The first variant FCN-AlexNet is a modified version of original state-of-the-art classification model called AlexNet, which won ImageNet ILSVRC-2012 competition in the classification category (Long et al., 2015)(Krizhevsky et al., 2012). The FCN-AlexNet enables the pixel-wise prediction by using the deconvolutional layers which up-sample the features learned by the earlier convolutional layers. We have trained the FCN-AlexNet on the Caffe deep learning framework (Jia et al., 2014). The input and ground truth images are both 500×375. We have fine-tuned the network parameters to allow the method more time to learn the features from dermoscopy images by using 100 epochs, stochastic gradient descent with a learning rate of 0.0001.

The other FCNs variants, FCN-32s, FCN-16s and FCN-8s, are based on another state-of-the-art classification network called VGG-16, which won the localization challenge and was in second position for the classification challenge in the ImageNet ILSVRC-2014 competition (Simonyan and Zisserman, 2014)(Long et al., 2015). The differences between these models are the up-sampling layers with different pixel stride. As the name suggested by these FCNs variants, in FCN-32s, up-sampling is performed with the help of 32-pixel stride whereas 16-pixel stride is used for FCN-16s and 8-pixel stride for FCN-8s. With the small pixel stride, the models were able to predict finer-grained analysis of the objects. The same network parameters as FCN-AlexNet were used to train these models.

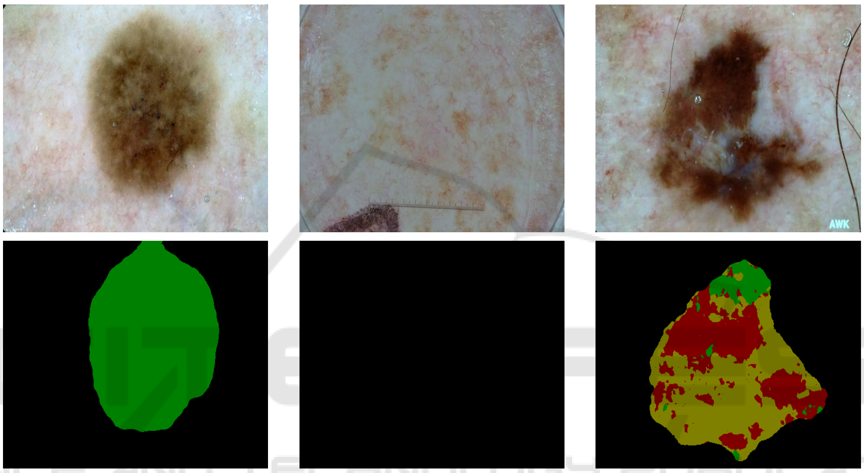
2.3 The Two-tier Transfer Learning Approach

Convolutional neural networks generally require a huge dataset to learn the features and detect objects



(a) (b) (c)

Figure 1: Original images (first row) and PASCAL-VOC format (second row). The skin lesion diagnosis from left to right: (a) naevus, (b) melanoma and (c) seborrhoeic keratosis.



(a) Single-detection (b) No-detection (c) Multi-detection

Figure 2: Examples of different types of semantic segmentation in ISIC-2017 testing set: (a) result with one class lesion type; (b) result with no lesion detected; and (c) result with multiple lesion types. Where green color represents melanocytic naevus, red color represents melanoma, and yellow color represents seborrhoeic keratosis.

Table 2: Number of cases for each type of inference in ISIC-2017 Testing Set.

Inference	Single-detection	Multi-detection	No-detection
Testing Set	395	192	13

in images (LeCun et al., 2015). Since, we have RGB images in dermoscopic images, it is good to use two-tier transfer learning from huge datasets in non-medical backgrounds such as ImageNet and Pascal-VOC dataset to converge the weights associated with each convolutional layer of networks (Russakovsky et al., 2014)(Everingham et al., 2015)(Goyal et al., 2017). The transfer learning transfers the feature learned by previous models on huge non-medical datasets to medical image datasets. There are two types of transfer learning, i.e. partial transfer learning in which only the features from few convolutional layers are transferred, and full transfer learning in which features are transferred from all the layers of previous pre- trained models. For the first tier of two-tier transfer learning, we used partial transfer learning by transferring the features from the convolutional layers trained on ImageNet. For the second tier, we used full transfer learning from a model trained on Pascal-VOC.

2.4 Custom Hybrid Loss Function

For imbalanced dataset as summarized in Table 1, we used a hybrid loss function, which is a combination of softmax cross-entropy loss and *Dice* score loss function, to optimize the objective function. *Dice* Score is a commonly used performance metric in medical imaging segmentation. Softmax cross-entropy loss function is a sum of per-pixel softmax cross-entropy

Table 3: Comparison of different FCN architectures using the ISIC-2017 Challenge Dataset (SK denotes Seborrheic Keratosis).

Method	*Dice*			*Specificity*			*Sensitivity*			*MCC*		
	Naevi	Melanoma	SK	Naevi	Melanoma	SK	Naevi	Melanoma	SK	Naevi	Melanomas	SK
FCN-AlexNet	**0.819**	0.609	0.488	0.989	0.982	0.987	**0.798**	0.4864	0.456	**0.814**	0.541	0.484
FCN-32s	0.779	0.549	0.484	**0.991**	0.977	0.968	0.751	0.430	0.478	0.775	0.484	0.463
FCN-16s	0.761	0.590	0.506	0.988	0.979	0.978	0.706	0.471	0.466	0.764	0.528	0.501
FCN-8s	0.785	**0.653**	**0.557**	0.990	**0.984**	**0.988**	0.747	**0.527**	**0.509**	0.779	**0.582**	**0.5683**

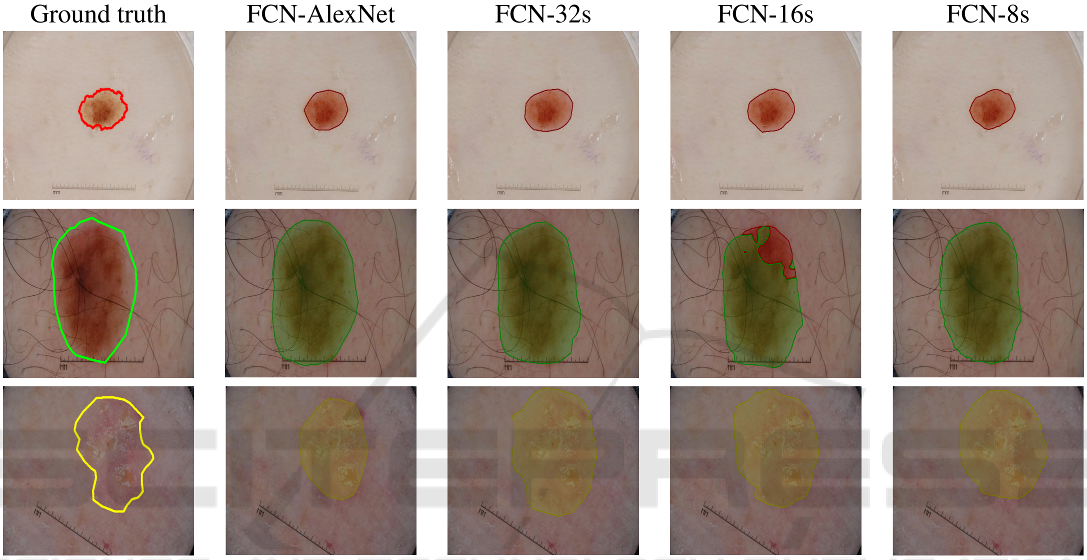


Figure 3: Illustration of segmentation results to visually compare the performance of ground truth delineation and four FCNs on multi-class segmentation for a naevus (top row), a melanoma (middle row), and a seborrhoeic keratosis (bottom row).

loss whereas *Dice* score loss function take care of overall segmentation score on whole image.

$$L_s = Softmax(cross - entropy) \tag{1}$$

where $\mathrm{L_s}$ is overall softmax cross entropy loss function and cross-entropy is per-pixel cross-entropy loss.

$$L_d = \frac{2|S \cap G|}{|S| + |G|} \tag{2}$$

where $\mathrm{L_d}$ is *Dice* score loss function, S is segmented image and G is ground truth.

$$L_h = L_s + L_d \tag{3}$$

where $\mathrm{L_h}$ is a hybrid loss function which is combination of both softmax cross entropy loss function and dice loss function.

3 RESULT AND DISCUSSION

We experimented with four state-of-the-art fully convolutional networks for our proposed segmentation task as described above. We trained the models on the ISIC-2017 training set of 2000 dermoscopic images with an input-size of 500×375 using stochastic gradient descent with a learning rate of 0.0001, 60 epochs with a dropout rate of 33%. In Table 3, we report *Dice Similarity Coefficient (Dice)*, *Sensitivity*, *Specificity*, *Matthews Correlation Coefficient (MCC)* as metrics for performance evaluation of multi-class segmentation of skin lesions. We used the trained model based on the best *Dice* score on the ISIC-2017 validation set to perform inference on the ISIC-2017 test set.

Configuration of GPU Machine for Experiments. (1) Hardware: CPU - Intel i7-6700 @ 4.00Ghz, GPU - NVIDIA TITAN X 12Gb, RAM - 32GB DDR5 (2) Software: Caffe.

In performance measure for multi-class segmentation, we received three types of results from the inference as shown in the Fig. 2 and number of cases for each type of detection is shown in Table 2. In Table 3, we report the performance evaluation of fully convolutional networks for multi-class segmentation on ISIC-2017 test set. In the naevi category, all FCNs achieved good segmentation results, but FCN-AlexNet achieved the best results with *Dice* score of 0.819, *MCC* score of 0.814, and *Sensitivity* is 0.798. In this category, FCN-8s performed 2nd best with *Dice* score of 0.779 and *MCC* score of 0.779. In the melanoma and seborrhoeic keratosis catergories, FCN-8s has achieved *Dice* score of 0.653 and 0.557 respectively, which was also the best performer for all the metrics. Fig. 3 visually compares the segmentation results on different lesion types. FCNs performed best in the class of naevi because we have more images of naevi than melanoma and seborrhoeic keratosis. Due to high intra-class and inter-class visual similarities, performance for both melanoma and seborrhoeic keratosis suffer due to fewer images in the dataset. Melanoma images are approx. 37% and keratosis images are approx. 22% of the total of images of naevi in the dataset.

The results demonstrated that deep learning techniques are reliant on the size of dataset. The segmentation results for melanoma and seborrhoeic keratosis were notably poorer than for naevi as a consequence of data deficiency. Despite the limitation on dataset, we have provided a fully automated end-to-end solution for multi-class segmentation.

3.1 Post-processing Method to Determine Lesion Diagnosis

We used a post-processing method to determine a single label for lesion diagnosis especially for multi-detection. We only used FCN-8s for this stage as it provided best scores for the segmentation of melanoma and seborrhoeic keratosis. For single-detection, we directly assumed the detected lesion class as same. There were very few cases of no detection (13 cases out of 600) in testing set, we assumed these cases as naevi for performance evaluation. For multi-class detection, we adopted an priority based strategy for class prediction with preference of the malignant lesions over the benign and number of images in the training set according to the Table 4. For example, the (c) multi-detection case in Fig. 2 is classified as melanoma according to priority based strategy.

In Table 5, we report the performance of selected FCN-8s with post-processing method to determine lesion diagnosis. We achieved an *Accuracy* of 84.62% for recognition of melanoma and 74.44% for seborrhoeic keratosis with our proposed post-processing method despite the poor performance of FCNs for segmentation of melanoma and seborrhoeic keratosis.

Table 4: Priority strategy based on benign/malignant and number of images in ISIC-2017 training set. Where SK is seborrhoeic keratosis.

Priority	Class	Benign/Malignant	No. of Images
1	Melanoma	Malignant	541
2	SK	Benign	387
3	Naevi	Benign	1372

Table 5: The performance of FCN-8s with post-processing method for lesion diagnosis on ISIC-2017 testing set. Where SK is seborrhoeic keratosis.

Class	No. of Cases	Correct	Incorrect	Accuracy
Naevi	393	319	74	81.17
Melanoma	117	99	18	84.62
SK	90	67	23	74.44
Overall	600	485	115	80.83

4 CONCLUSION

We propose a fully automated multi-class semantic segmentation for melanomas, naevi and seborrhoeic keratosis in the ISIC 2017 Challenge dataset. Segmentation of skin lesions is very challenging as there are high intra-class variations and inter-class similarities in terms of visual appearance, size and colour. The literature on skin lesion segmentation only describes one-class solutions. Computer vision algorithms can easily segment one class of skin lesion from the surrounding healthy skin. But it remains a major challenge to achieve good multi-class segmentation results for multiple categories. We designed a hybrid loss function and implemented two-tier transfer learning and successfully established a new baseline for multi-class segmentation for skin lesions. We further investigated the post-processing method to improve the lesion diagnosis of FCNs. With balanced skin lesion dataset and expert annotation, the method has potential to further improve the lesion diagnosis with multi-class segmentation.

REFERENCES

Bi, L., Kim, J., Ahn, E., Kumar, A., Fulham, M., and Feng, D. (2017). Dermoscopic image segmentation via multi-stage fully convolutional networks. *IEEE Transactions on Biomedical Engineering*.

Codella, N. C., Gutman, D., Celebi, M. E., Helba, B., Marchetti, M. A., Dusza, S. W., Kalloo, A., Liopyris, K., Mishra, N., Kittler, H., et al. (2017). Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic). *arXiv preprint arXiv:1710.05006*.

Dvořánková, B., Szabo, P., Kodet, O., Strnad, H., Kolář, M., Lacina, L., Krejčí, E., Naňka, O., Šedo, A., and Smetana, K. (2017). Intercellular crosstalk in human malignant melanoma. *Protoplasma*, pages 1–8.

Everingham, M., Eslami, S. M. A., Van Gool, L., Williams, C. K. I., Winn, J., and Zisserman, A. (2015). The pascal visual object classes challenge: A retrospective. *International Journal of Computer Vision*, 111(1):98–136.

Garcia-Garcia, A., Orts-Escolano, S., Oprea, S., Villena-Martinez, V., and Garcia-Rodriguez, J. (2017). A review on deep learning techniques applied to semantic segmentation. *arXiv preprint arXiv:1704.06857*.

Goyal, M., Oakley, A., Bansal, P., Dancey, D., and Yap, M. H. (2019). Skin lesion segmentation in dermoscopic images with ensemble deep learning methods. *IEEE Access*, pages 1–1.

Goyal, M., Reeves, N. D., Rajbhandari, S., Spragg, J., and Yap, M. H. (2017). Fully convolutional networks for diabetic foot ulcer segmentation. *arXiv preprint arXiv:1708.01928*.

Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S., and Darrell, T. (2014). Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM international conference on Multimedia*, pages 675–678. ACM.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521(7553):436–444.

Long, J., Shelhamer, E., and Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3431–3440.

Melanoma Foundation (AIM) (2017). Melanoma stats, facts and figures. last access: 27/10/2017.

National Cancer Institute (2017). Cancer stat facts: Melanoma of the skin. last access: 26/10/17.

Pathan, S., Prabhu, K. G., and Siddalingaswamy, P. (2018). Techniques and algorithms for computer aided diagnosis of pigmented skin lesions—a review. *Biomedical Signal Processing and Control*, 39:237–262.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., et al. (2014). Imagenet large scale visual recognition challenge. *arXiv preprint arXiv:1409.0575*.

Simonyan, K. and Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Yu, L., Chen, H., Dou, Q., Qin, J., and Heng, P.-A. (2017). Automated melanoma recognition in dermoscopy images via very deep residual networks. *IEEE transactions on medical imaging*, 36(4):994–1004.

Yuan, Y., Chao, M., and Lo, Y.-C. (2017). Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance. *IEEE Transactions on Medical Imaging*.