Unet for Skin Lesion Analysis towards Melanoma Detection

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I. INTRODUCTION

The International Skin Imaging Collaboration (ISIC) is hosting a challenge to support development of automated melanoma diagnosis algorithms with three tasks [1]. Our team participate task 1 lesion segmentation and task 2 the lesion attribute detection. The goal of task 1 is to generate automated predictions of lesion segmentation boundaries within dermoscopic images. The goal of task 2 is to generate automated predictions of the locations of dermoscopic attributes (established clinically-meaningful visual skin lesion patterns) within dermoscopic images. The following dermoscopic attributes should be identified: pigment network, negative network, streaks, milia-like cysts and globules.

II. METHOD

A. Lesion Segmentation

Unet [3] is a widely used deep learning architecture for biomedical images segmentation, which can achieve good performance by training on very few samples. Thus, we employ Unet as the main method of our framework. Our Unet is based on the revised version of Menegola [2]. We did the following adaptations on this task:

- Data preprocessing. We adopt contrast-limited adaptive histogram equalization, standard normalization and data augmentation on images before training.
- Test data augmentation. We transform a test image into several images and predict using our model. Then we transform these masks inversely to obtain a final one.
- External data. We download external public ISIC archive dataset and PH2 dataset for model training.
- Loss functions. We adopt different loss functions for Unet, including Jaccard Index, Dice Index and Binary Cross-Entropy.
- Model architectures. We also explore different architectures of Unet.

B. Lesion Attribute Detection

For lesion attribute detection, we first crop out region of interest from an input image according to task 1 result. Then we analyze the cropped image using the three-step pipeline.

1) We first classifiy whether a image contains any lesion attributes or not. This step is necessary since many images has none of the attributes at all.
2) We then classify whether a image contain one of the five attributes. Here we train five classifiers seperately.
3) We finally use a Unet model to locate lesion attribute if it is believed to have this attribute. Again, we need to train five Unets for five lesion attributes.

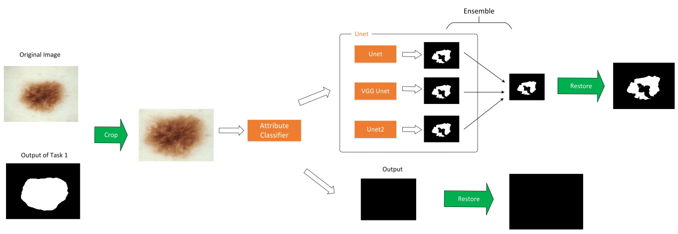

Fig. 1. Pipeline for lesion attribute detection

III. RESULTS & CONCLUSIONS

We trained 192 models for task 1 and 60 models for task 2. We observed that, for task 1, models with input size 128 are generally better than 256, meanwhile models with input size 256 are better for task 2. Hence we finally choose models with input size 128 to obtain an ensemble model by majority voting for task 1, and those with inpu size 256 for task 2. We achieved quite good performance on the Validation dataset containing 100 images as shown in the following tables.

best single model	unet2_128_jacc_preproc_archive	0.797
ensemble model	ensemble_128_10best	0.820

TABLE I
TASK 1 LESION SEGMENTATION VALIDATION SCORE

best single model	vgg_unet_256_dice_preproc_crop_seg_testaug	0.393
ensemble model	ensemble_256	0.432

TABLE II
TASK 2 LESION ATTRIBUTE DETECTION VALIDATION SCORE

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