Skin Lesion Analysis Towards Melanoma Detection

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Abstract

In the project, we implement classification and segmentation models in skin lesion analysis towards Melanoma detection. We use the dermoscopic image data released by the International Skin Imaging Collaboration (ISIC) (N. Codella et al. (2019)). In the classification task, we implement pre-trained deep neural network models, combined with color constancy method, data augmentation and weighted cross-entropy loss. In the segmentation task, we implement pre-trained models and design new custom models.All codes and related material are available in `https://github.com/ChaojieZhang-cz/CV-Project-Skin-Lesion-Analysis`.
Keywords: Lesion Classification, Lesion Segmentation, Deep Learning

1 Introduction

Melanoma is the most dangerous type of skin cancer (New Engl (n.d.)). In the US, the incidence of malignant melanoma is rising faster than that of any other cancer (Rigel and Carucci (2000)). Early detection and treatment of melanoma are important, and will improve the patient survival rates (Rigel and Carucci (2000)). When detected early, melanoma survival exceeds 95% (N. Codella et al. (2019)). Accurate and early detection of melanoma requires highly trained expert clinicians with dermoscopic devices, but the number of qualified experts has not kept up with demand. Automated dermoscopy images analysis can help mitigate the problems of limited supply of experts. There are different analysis techniques, including classical computer vision approaches using low-level visual feature representations (Mishra and Celebi (2016), Stoecker, Mishra, LeAnder, Rader, and Stanley (2013)), and deep learning methods using a large number of labeled data (N. C. Codella et al. (2017), Li and Shen (2018)). In our project, we implement convolutional neural network models to achieve dermoscopic images classification and lesion segmentation.

ISIC holds the "ISIC: Skin Lesion Analysis Towards Melanoma Detection" challenges every year since 2016 (N. Codella et al. (2019)), to help with the research in automated dermoscopy images analysis. In the previous challenge, researchers apply color constancy, and different data augmentation methods in the image preprocess (N. Codella et al. (2019)). Some models give good performance (DenseNet, EfficientNet, SE-ResNeXt for classification, MaskRcnn, CA-Net for segmentation) (N. Codella et al. (2019)).

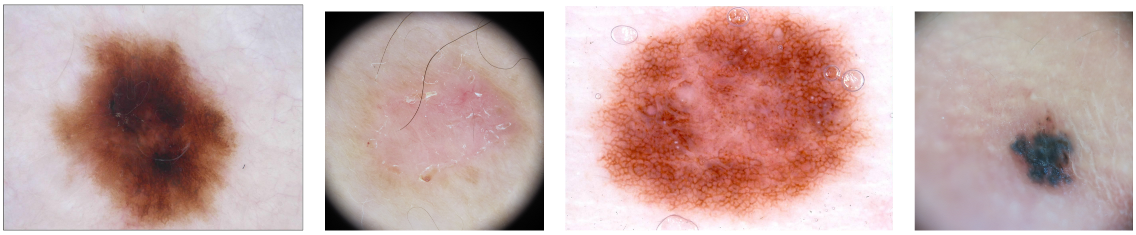
2 Methodology

2.1 Task

There are two tasks in our project. Task 1 is to classify dermoscopic images among nine different diagnostic categories. The nine categories are: (1) Melanoma (2) Melanocytic nevus (3) Basal cell carcinoma (4) Actinic keratosis (5) Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis) (6) Dermatofibroma (7) Vascular lesion (8) Squamous cell carcinoma (9) None of the others. Task 2 is to predict the lesion segmentation boundaries of dermoscopic images.

2.2 Data

We use the data released by the International Skin Imaging Collaboration (ISIC). For the classification task, we use the data from ISIC 2019, there are 25,331 images across 8 different categories. These dermoscopic images are from different platforms and preprocessed with different methods. Some images are uncropped, and contain black edges. For the segmentation task, we use the data from ISIC 2018, there are 2,594 images and 2,594 corresponding ground truth response masks. Some example data is shown in Figure 1.



(a) (b) (c) (d)

Figure 1: Dermoscopic images of lesion

2.3 Preprocess

In the image preprocess, we first crop the black edges in the dermoscopic images, then resize the short side of the image to 512 pixels (1024 pixels for the segmentation images) and preserve the aspect ratio. Since the dermoscopic images are from different platforms and preprocessed with different methods, we apply the Shades of Gray color constancy method for data standardization (N. Codella et al. (2019)). We also apply extensive data augmentation approaches, including random brightness, contrast changes, random flipping, random rotation, random scaling, random cropping and random shear. Figure 2 shows the example of data preprocess.

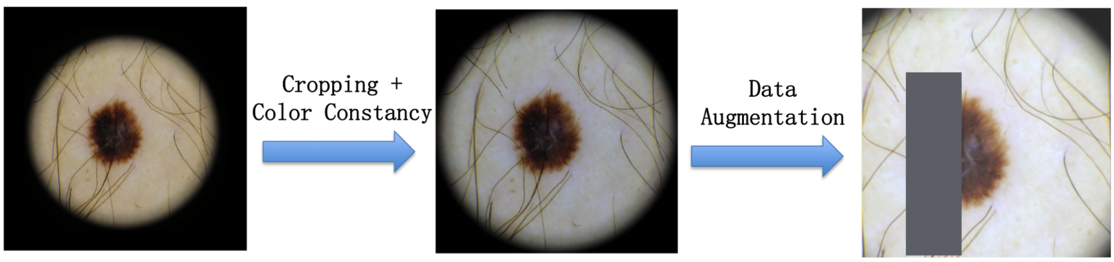


Figure 2: Data preprocess

2.4 Classification Models

We implement pretrained models, ResNet-18 (He, Zhang, Ren, and Sun (2016)), SE-ResNeXt-152 (Hu, Shen, and Sun (2018)) and efficientnet-b4 (Tan and Le (2019)) in classification. We set the learning rate=0.00005, and train all models for 100 epochs using Adam optimizer. With the problem of severe class imbalance, we use weighted cross-entropy loss as our loss function. The weight of each category corresponds to its ratio in the training set (Table 1).

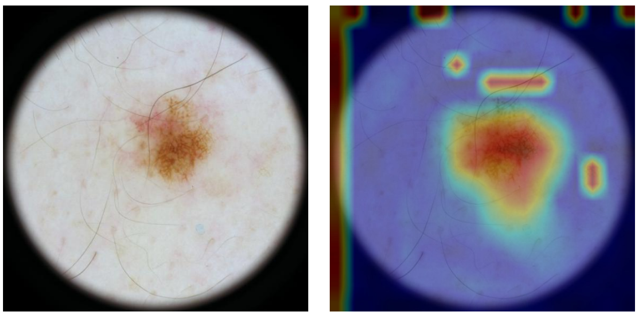
	MEL	NV	BCC	AK	BKL	DF	VASC	SCC	UNK
Number	2683	7707	2025	509	1595	136	150	394	0
Ratio	0.1765	0.5071	0.1332	0.0335	0.1049	0.0089	0.0099	0.0259	0

Table 1: Number and ratio of the night categories in the training set

2.5 Segmentation Models

We implement pretrained models, U-Net (Ronneberger, Fischer, and Brox (2015)) and CA-Net (Gu et al. (2020)) in the segmentation task. We set the learning rate=0.001, and train all models for 300 epochs using RMSprop optimizer. We generate a new loss function combining binary cross-entropy loss (BCE loss) and intersection over union loss (IoU loss), the weights of the two losses are the same. In the loss function, BCE loss could consider the prediction information of each pixel, and IoU loss could consider global information about the lesion.

We also design a new segmentation model based on the structure of ResNet-18 and U-Net. We implement the class activation mapping (Zhou, Khosla, Lapedriza, Oliva, and Torralba (2016)) to our ResNet-18 classifier, we find that the classification model is able to localize lesion regions in some dermoscopic images. Figure 3 shows an example of class activation mapping implementation using pre-trained ResNet-18, the lesion is in the highlight area. Since there is only a small number of available data in the segmentation task, we implement the pre-trained classifier trained in a large dermoscopic images dataset, to improve the localization ability of the segmentation model. We apply the pre-trained ResNet-18 as our down-sampling blocks, remove the fully connected layer and global average pooling layer, connect with the up-sampling blocks from U-Net (Figure 4).



(a) Dermoscopic image (b) Class activation map

Figure 3: Class activation mapping result using ResNet-18

3 Evaluation

3.1 Classification Evaluation

In the classification task, we use normalized multi-class accuracy, weighted sensitivity, weighted F1-score and AUC to evaluate the model performance. Table 2 shows the evaluation results of different models. Among all models, efficient-b4 gives best performance.

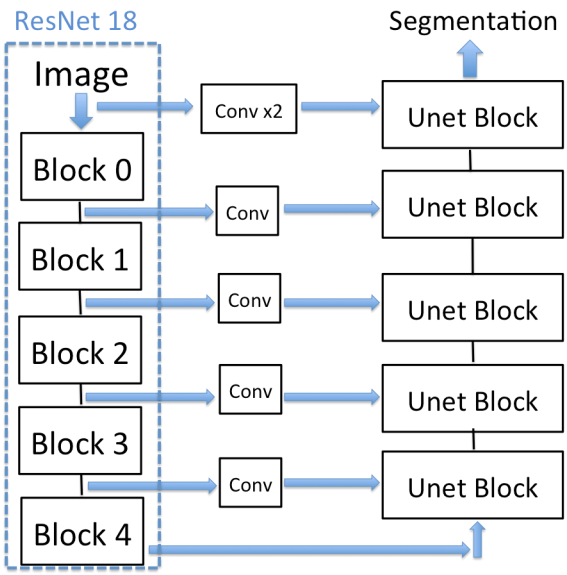


Figure 4: Data preprocess

	Normalized Multi-class Accuracy	Weighted Sensitivity	Weighted F1-score	AUC
ResNet-18	0.53	0.79	0.77	0.915~0.993
SeReNet-152	0.65	0.85	0.84	0.938~0.997
efficientnet-b4	0.76	0.87	0.87	0.949~0.996

Table 2: Classification evaluation

3.2 Segmentation Evaluation

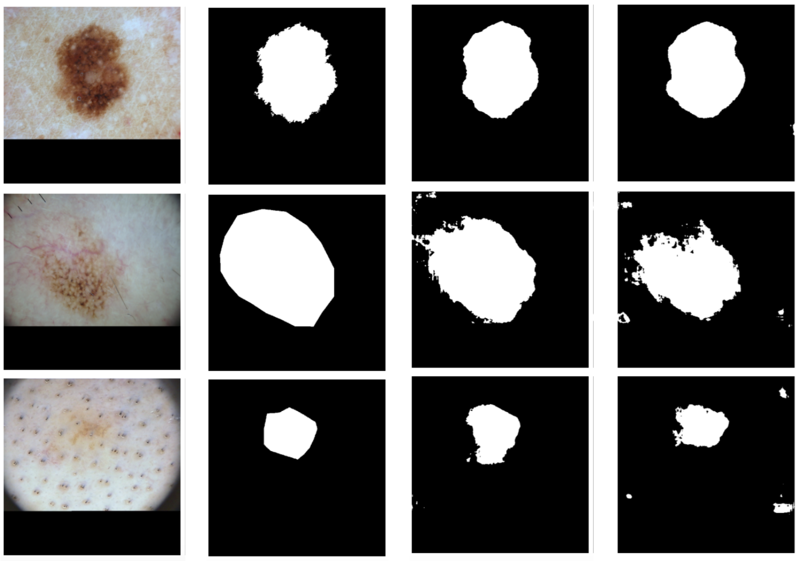
In the segmentation task, we use intersection over union (IoU) score and dice coefficient score to evaluate the model performance. Table 3 shows the evaluation results of different models. We compare the segmentation result from the U-Net and our custom model, there are more wrong outliers in the predicted mask from the custom model (Figure 5).

	IoU	Dice Coefficient
ResNet18+Unet	0.677	0.762
U-Net	0.745	0.837
CA-Net	0.869	0.919

Table 3: Segmentation evaluation

4 Discussion and Conclusions

We apply ResNet, SE-ResNeXt, EfficientNet for dermoscopic images classification, combined with color constancy method, data augmentation and weighted cross-entropy loss. Among all three models, the EfficientNet-4 gives best performance. In the segmentation task, we apply pre-trained U-Net and CA-Net, and design the new custom model. We have found that the classification model contains region localization ability, we use the pre-trained ResNet-18 as part of our segmentation model. But our new implementation didn't



(a) (b) (c) (d)

Figure 5: Segmentation result (a) dermoscopic image (b) true mask (resized using nearest pixels) (c) predicted mask from U-Net (d) predicted mask from custom model

give better performance in the segmentation task, and there are more wrong outliers in the predicted mask compared with U-Net. We also trained the U-Net downsampling part as a classifier in the classification dataset, but we didn't see any obvious improvement in the segmentation performance. So far, we don't have any evidence that training the downsampling part of the segmentation model as a classifier can contribute better performance to the segmentation model.

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