EOCNet:Improving Edge Omni-Scale Convolutional Networks for skin lesion segmentation

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1. INTRODUCTION

Skin lesion segmentation is the process of identifying the boundaries of skin lesions in medical images, which is an essential task for diagnosing skin diseases. Accurate segmentation of skin lesions can help dermatologists to identify the type and stage of a skin disease, which is critical for determining the appropriate treatment.Skin cancer is one of the most common types of cancer, and early detection is critical for successful treatment. Skin lesion segmentation can aid in the early detection of skin cancer by identifying potentially cancerous lesions. Moreover, accurate segmentation of skin lesions can also help in the diagnosis of other skin diseases such as psoriasis, eczema, and dermatitis.

2.Problem Statement

The problem statement as explained in the paper is to improve the convolutional network so that it can be useful to detect the disease easier and faster.

3.Understanding the EOC-Net Architecture

The EOCNet architecture consists of three modules: 1.the main encoder module, 2.boundary extraction module, 3. Omni-scale module. Here what happens is that the features extracted by the encoded module are improved by passing them through the Omni-Scale module which helps in increasing the spatial resolution of the images through which features can be extracted.

- The EOCNet architecture proposed in the paper "EOCNet-Improving Edge Omni-Scale Convolutional Networks for Skin Lesion Segmentation" is a deep learning model designed for skin lesion segmentation. The architecture comprises several modules, including the Edge Detection Module, the Feature Pyramid Pooling Module, and the Segmentation Module.

- The Edge Detection Module is responsible for detecting the edges of skin lesions. It consists of a series of dilated convolutional layers that learn to detect edge features at different scales. The outputs of these layers are then fused to produce an edge map that is used to guide the segmentation process.

- The Feature Pyramid Pooling Module is designed to extract features from multiple scales of the input image. It uses dilated convolutional layers with different dilation rates to capture features at various scales. The module also includes a pyramid pooling layer that aggregates features from different scales and fuses them to produce a multi-scale feature map.

- The Segmentation Module takes the multi-scale feature map produced by the Feature Pyramid Pooling Module and generates a pixel-level segmentation map. The module consists of a series of convolutional and upsampling layers that gradually increase the resolution of the feature map until it reaches the same size as the input image. The final output is a binary mask that indicates the boundary of the skin lesion.

Overall, the EOCNet architecture combines the strengths of edge detection and multi-scale feature extraction to improve the accuracy of skin lesion segmentation. The edge information provided by the Edge Detection Module helps to guide the segmentation process, while the multi-scale feature extraction provided by the Feature Pyramid Pooling Module enables the network to capture features at different scales, allowing it to accurately segment lesions of varying sizes and shapes.

4.EOC-Net Implementation

3.1 Preprocessing the data

The data is first loaded and the following preprocessing using the following techniques:

- Resizing
- Flipping
- Rotating
- Cropping

3.2 Model

The model contains the following modules in detail:

1. Feature Extraction Module: This module is responsible for extracting high-level feature representations from the input image. The authors have used the ResNet50 architecture as the backbone of the feature extractor module.

2. Extraction Boundary Module: This module is used to extract the boundary information of the input image, which helps in distinguishing the object boundaries from the background.

3. Fusion Module: The fusion module is used to combine the boundary information and feature maps extracted from the input image. This helps in improving the segmentation performance by incorporating both global and local information.

4. Omni-Scale Module: This module is used to integrate feature maps from multiple scales, which helps in capturing objects of different sizes and shapes.

5. Final Classification Module: This module is used to produce the final segmentation output. It takes the integrated feature maps from the Omni-Scale Module as input and produces the segmentation output with the same size as the input image.

The other model implemented is just a basic UNet model which is also a segmentation model.

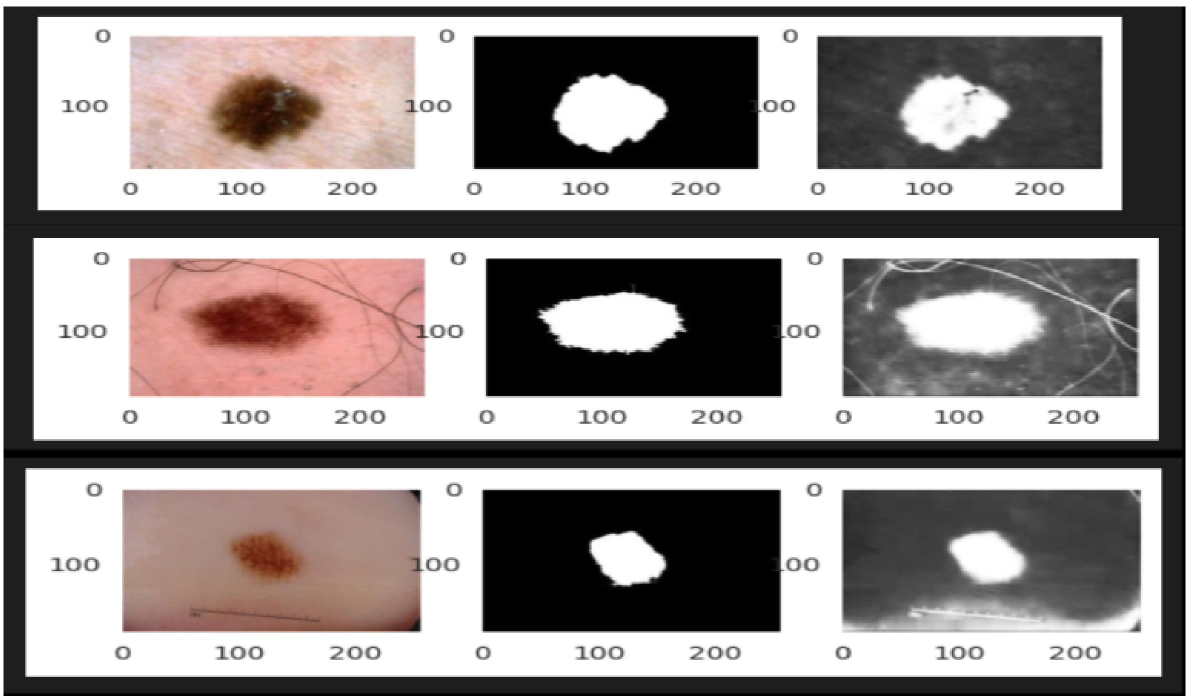
3.2.1 Training the Model

The dataset is trained using two models one is our paper implemented model and the other is a general segmentation model UNet. The learning rate for the training is set 0.001 and the num_epochs taken are 25.

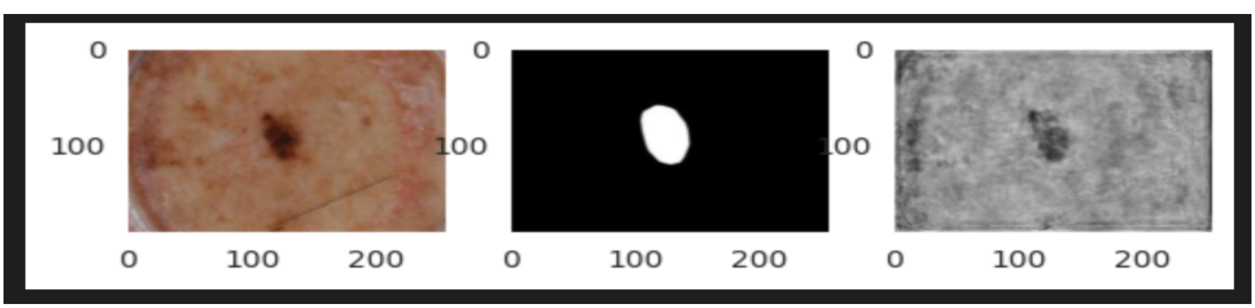
After each epoch the loss is calculated and while training the data the loss decreased continuously and finally gave some better result.

3.3 Showing the results and the Plots

Finally the results I got using the EOCNet model are



Comparing this to the UNet model



The EOCNet model showed better results than the UNet model because of the usage of Omni-Scale Module in it.

To quantitatively analyze the experimental results, we consider the following evaluation indicators: Pixel-level accuracy: (AC), Pixel-level sensitivity: (SE), Pixel-level specificity (SP), Dice coefficient (DC), and Jaccard similarity (JS)

The results of these values obtained are:

For the EOCNet model:

```
Accuracy:  0.7889013886451721
Sensitivity:  0.6196677684783936
Specificity:  0.8332734107971191
Dice Coefficient:  0.5494586825370789
Jaccard Similarity:  0.3787955939769745
```

For the UNet model:

```
Accuracy :  0.7663573622703552
Sensitivity :  0.7217565178871155
Specificity :  0.777529299259185 8
Dice Coefficient :  0.5530897974967957
Jaccard Similarity :  0.38225579261779785
```

THE END