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Semantic Segmentation for Skin Melanoma Detection

A convolutional neural network implementation.

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Abstract The approach described in this paper for the detection of the skin cancer melanoma is known as semantic segmentation. The semantic segmentation is a computer vision task where the different regions of an image are classified according to a specific category. The method used for the implementation of a semantic segmentation software was using the convolutional neural network, specifically a feature pyramid network architecture (`FPN`), to train a model which performs the task. With the convolutional neural networks is possible to train models that replicate the necessary transformations to obtain a targeted output, the only requirement is a rich enough database of samples of the input data and the target or the expected output in relation with that input, which in this case was a segmentation mask of the dermoscopic image.

Keywords Neural Network · Convolution · Semantic Segmentation · Classification

1 Introduction

Skin is considered one of the largest organs in the human body, its function is to protect the internal organs and structures from the harsh environmental conditions such as temperature, radiation and bacteria. The skin also functions as a large sensorial interface that let us feel the environment conditions such as the temperature in the ambience and feel the texture of the objects. The skin cancer known as melanoma is one of the deadliest types of cancer if not detected in its early stages, because of the quick spread to other organs caused by the metastasis effect. One way to reduce its mortality rate is by using automatic detection with computer vision technologies, such as the deep learning technology. With deep learning is possible to train models that recognize the presence of the melanoma tissue using a configuration of parameters fine-tuned during a process known as *training* which compares the input of the model and the known output to that input, and then update the parameters to get the computed output closer to the known output.

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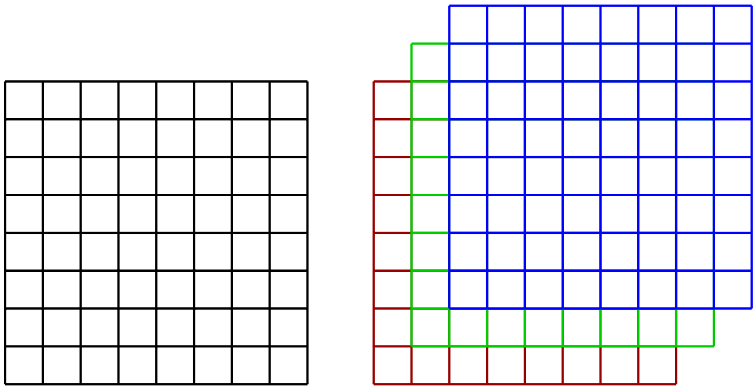
2 Background

In this section are introduced the basic concepts an theories required to understand the following proposals. Starting with some basic background aspects about the melanoma cancer, then continuing with the loss functions and the optimizer functions.

3 Related Work

In this section the related works were summarized to make a comparison between different methods to approach the melanoma detection problem and same approaches for the solution of different problems and get an idea of the opportunity areas and the advantages and disadvantages of the proposed solution.

Work	**Model**	**Classification**	**Segmentation**	**Supervised**	**Pre-train**	**Evaluation**	**Output**
Badrinarayanan *et al.* [1]	`SegNet`	✓	✓	✓	✓	✓	mapa de etiquetas
Ronneberger *et al.* [7]	`U-net`	✓	✓	✓	×	✓	mapa de etiquetas
Chen *et al.* [2]	`DeepLab`	✓	✓	✓	×	✓	mapa de etiquetas
Teichmann *et al.* [8]	`MultiNet`	✓	✓	✓	×	✓	mapa de etiquetas
Kroner *et al.* [5]	`VGG16`	✓	✓	✓	✓	✓	mapa de calor
Kadampur y Al Riyaee [4]	`CNN`	✓	×	✓	×	✓	mapa de etiquetas
Zhou *et al.* [9]	`ML / SVM`	✓	×	✓	×	✓	etiqueta
Luc *et al.* [6]	`CNN/GAN`	✓	✓	✓	✓	✓	mapa de etiquetas
Jain *et al.* [3]	`A.B.C.D`	×	✓	×	×	×	etiqueta
Propuesta de tesis	`FPN`	✓	✓	✓	✓	✓	mapa de etiquetas



$\dim = m \times n$

(a) Grayscale.

$\dim = m \times n \times k$

(b) Color.

Fig. 1: Dimensional comparison between images.

4 Proposed Solution

The approach proposed in this paper for the automated detection of the skin melanoma is the training of a model using a `FPN` convolutional neural network architecture, which output would be the probabilistic map of the regions inside of the dermoscopic input image. The language selected for the implementation of said neural network architecture was `Python`, because is a powerful, dynamic and quick to deploy language which also contains the `Torch` library which is the core tool of the implementation.

5 Experiments

The methods used to evaluate the performance of the training process and also gauge the probabilistic map predictions are described in this section. Also the analysis of the threshold is included here.

$$\mathrm{CD} = \frac{2|A \cap B|}{|A| + |B|} \tag{1}$$

$$\mathrm{CJ} = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}, \tag{2}$$

Epoch	**DL**	**IoU**
1	0.2968	0.5616
2	0.2972	0.5546
3	0.2690	0.5879
4	0.2960	0.6389
5	0.2371	0.8415
6	0.0929	0.8626
7	0.0792	0.8626
8	0.0692	0.8798
9	0.0556	0.9017
10	0.0542	0.9039

6 Conclusion

7 References

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