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# بسم الله الرحمن الرحيم

مركز الشبكات وتكنولوجيا المعلومات قسم التوثيق الإلكتروني







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# جامعة عين شمس

التوثيق الإلكتروني والميكروفيلم قسم

نقسم بالله العظيم أن المادة التي تم توثيقها وتسجيلها على هذه الأقراص المدمجة قد أعدت دون أية تغيرات





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# Skin Lesion Image Segmentation Using Machine Learning

Thesis submitted as a partial fulfillment of the requirements for the degree of Master of Science in Computer and Information Sciences

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March 2022

#### Acknowledgement

First of all, I humbly give my deep thank to **God** for giving me the knowledge and strength to finish this thesis.

Second, I would like to thanks my **Dad** and my sister **Nassm** for giving me the opportunity and support and the strength to accomplish this work.

Third, I would like to express my deep appreciation to my supervisors, **Prof. Dr. Mohamed Roushdy** and **Dr. Mohammed Salem**, and **Dr. Maryam Al-Berry** for their support, patience, care, and great help. I thank them, especially for their fast response.

Last but not least, I would like to thank all my professors.

Zahraa

#### **Abstract**

Melanoma is a sort of skin disease that represents more than seventy-five percent of all skin diseases connected to all fatalities. Nonetheless, doctors have demonstrated that the probability rate of patients improves radically with early analysis and diagnosis. This motivated researchers to seek automated techniques that facilitate early diagnosis of skin cancer. Skin lesion segmentation is a significant advance in the analysis and the resulting treatment of melanoma. Automatic lesion segmentation is of major interest for early detection and treatment of skin cancer, because it provides better accuracy and speed, compared to manual analysis. Lately, deep neural networks have provided better results for medical image segmentation, compared to classical approaches based on machine learning.

In this thesis, first an extensive a review of existing deep network architectures that have been suggested to segment skin lesions, pre-processing and post-processing methods with the available datasets that can be used for research in this area, also presented a comparison between the results of different methods used for skin lesion segmentation showing the strengths and weaknesses of each method.

In this thesis, checked the applicability of deep learning approaches: U-NET, Deep RESU-NET, VGG16UNET, U-Net DENSENET121, U-Net EfficientNet-B0, Deeplabv3plus, Inception-ResNet-v2-unet, mobilenetv2\_unet, Resnet50\_unet, and vgg19\_unet to the segmentation of skin lesions to detect lesion boundaries by developing deep learning models that have never been used for skin lesions and producing comparative results that will help detect melanoma and successfully define the lesion boundaries.

The architectures have been trained on four different datasets. The architectures were trained on the original data set, and then the four datasets were pre-processed to be used for training the architectures. Utilized different kinds of original image transformations, such as center crop, random rotation 90, grid distortion, horizontal flip, and vertical flip which resulted in an increasing number of images corresponding to the training set. Utilized different standard evaluation metrics such as Jaccard Index, accuracy, recall, precision, and F-measure to evaluate the acquired results. The results show that out of these architectures, the U-Net DENSENET121 architecture outperforms with segmentation Accuracy as high as 97.23% and F1 as 95.96% and Jaccard as 92.42% and Recall as 96.33% in the PH2 dataset. In general, the architecture of U-Net DENSENET121 showed a significant superiority over the rest of the architectures. Even when comparing the architectures that we used in this study with the rest of the other methods, we found that U-Net DENSENET121 architecture gave higher results than the rest of the architectures.

This thesis is a comprehensive study that tries to evaluate the segmentation step in skin lesions using deep learning approaches.

#### **List of Publications**

- 1) Z. E. Diame, M. N. Al-Berry, M. A. . -M. Salem and M. Roushdy, "Deep Learning Architiectures For Aided Melanoma Skin Disease Recognition: A Review," 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), 2021, pp. 324-329, doi: 10.1109/MIUCC52538.2021.9447615. (Indexed in Scopus)
- 2) Zahraa E. Diame Maryam N. Al-Berry, Mohammed A.-M. Salem, Mohamed Roushdy, "Autoencoder Performance Analysis Of Skin Lesion Detection", Journal Of Southwest Jiaotong University, Volume 56 (6), 2021 (Indexed in Scopus)
- 3) Zahraa E. Diame Maryam N. Al-Berry, Mohammed A.-M. Salem, Mohamed Roushdy, "Experimental Comparative Study on Autoencoder Performance for Aided Melanoma Skin Disease Recognition", International Journal of Intelligent Computing and Information Sciences, Volume 22(1), pp. 88-97, 2022.

### **Table of Contents**

CHAPTER 1. INTRODUCTION
1.1 Overview
1.2 Motivation 2
1.3 Objectives
1.4 Methodology
1.5 Contributions2
1.6 Thesis Organization5
CHAPTER 2. LITERATURE REVIEW
2.1 Introduction
2.2 Deep Learning Models For Skin Image Processing
2.2.1 Convolution Network-based Methods
2.2.2 Autoencoder-based Methods
2.2.3 Generative Adversarial-based Methods
2.3 Pre-Processing & Post-processing Techniques
2.4 Evaluation Metrics and Data Set
2.4.1 Evaluation Metrics
2.4.2 Data Sets
2.4.3 Comparison Performance of Recent Work
CHAPTER 3.THE PROPOSED DEEP NETWORK METHODOLOGIES 31
3.1 Introduction

3.2 Model Architecture	1
3.2.1 U-Net	3
3.2.2 DEEP RESUNET	4
3.2.3 VGG16 UNET	7
3.2.4 U-Net DENSENET121	8
3.2.5 U-NET EFFICIENTNET-B0	0
3.2.6 DEEPLABV3+	1
3.2.7 INCEPTION-RESNET-V2-UNET	2
3.2.8 MOBILENETV2_UNET 4	2
3.2.9 RESNET50_UNET 4	3
3.2.10 VGG19_UNET4	4
3.3 Pre-processing	5
CHAPTER 4. EXPERIMENTAL RESULTS 4	7
4.1 Experimental Setup4	7
Data sets	7
4.2 Implementation4	8
4.3 Results and Comparisons	0
Results of Skin Lesion Segmentation with the Original Dat	a
ets5	0
Results of Skin Lesion Segmentation with the Pre	
rocessing Data Sets5	9
CHAPTER 5. CONCLUSIONS AND FUTURE WORK 6	9

REFERENCES	73
APPENDIX A	89

# **List of Figures**

Figure 1.1 Samples of the skin lesions
Figure 3.1 A sample architecture of the autoencoder
Figure 3.2 A sample architecture of the autoencoder [14] 34
Figure 3.3 The architecture of the deep ResUnet [76]
Figure 3.4 :Segmentation networks based on encoder-decoder
architecture of U-Net family [77]
Figure 3.5 Block diagram of the DeepLabV3+ architecture
Figure 3.6 Block diagram of the Resnet50_unet architecture 44
Figure 3.7 :Data augmentation (a) original image (b) center crop (c)
random rotation 90 (d) grid distortion (e) horizontal flip (f) vertical flip 45
Figure 4.1 Steps of the proposed methods
Figure 4.2 Image segmentation masks for the ISIC 2016 dataset by
using different techniques
Figure 4.3 Image segmentation masks for the ISIC 2017 dataset by
using different techniques
Figure 4.4 Image segmentation masks for the ISIC 2018 dataset by
using different techniques
Figure 4.5 Image segmentation masks for the PH2 dataset by using
different techniques
Figure 4.6 Image segmentation masks for the ISIC 2016 dataset with
pre-processing by using different techniques
Figure 4.7 Image segmentation masks for the ISIC 2017 dataset with
pre-processing by using different techniques

Figure 4.8 Image segmentation masks for the ISIC 2018 dataset with	
pre-processing by using different techniques	
Figure 4.9 Image segmentation masks for the PH2 dataset with pre-	
processing by using different techniques	

### **List of Tables**

Table 2.1 The data set used and the number of images for each
challenge
Table 2.2 Comparison the results, advantages and disadvantages of skin
lesion segmentation
Table 3.1 Contracting path of U-Net DenseNet12139
Table 3.2 Contracting path of U-Net EfficientNet-B0
Table 3.3 Contracting path of Inception-Resnet-v2
Table 4.1 Results of Skin Lesion Segmentation on ISIC 2016 51
Table 4.2 Results of Skin Lesion Segmentation on ISIC 2017 53
Table 4.3 Results of Skin Lesion Segmentation on ISIC 2018 55
Table 4.4 Results of Skin Lesion Segmentation on PH2 57
Table 4.5 Results of Skin Lesion Segmentation on ISIC 2016 After Pre-
processing 60
Table 4.6 Results of Skin Lesion Segmentation on ISIC 2017 After Pre-
processing
Table 4.7 Results of Skin Lesion Segmentation on ISIC 2018 After Pre-
processing
Table 4.8 Results of Skin Lesion Segmentation on PH2 After Pre-
processing

#### **List of Abbreviations**

**Abbreviation Stands for** 

ABCD Asymmetry, Border, Color, Diameter

AC Accuracy

ANFC Adaptive Neural Fuzzy Classifier

ANN Artificial Neural Networks

ASPP Atrous Spatial Pyramid Pooling

BAT Boundary-Aware Transformer

BN Batch Normalization

CNN Convolutional Neural Networks

DI Dice Coefficient

FCN Fully Convolutional Network

FCRN Fully Convolutional Residual Network

FN False Negatives

FP False Positives

GAN Generative Adversarial Networks

PH<sup>2</sup> Hospital Pedro Hispano

ISBI International Symposium on Biomedical

Imaging

ISIC International Skin Imaging Collaboration

LFN Lesion Feature Network

LICU Lesion Index Calculation Unit

LIN Lesion Index Network

PCA Principle Component Analysis

RGBH Red, Green, Blue And Hue Planes

ROI Region Of Interest

SE Sensitivity

SP Specificity

SVM Support Vector Machine

TN True Negatives

TP True Positives

U-Net Autoencoder Networks