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A Computational Method for the Image Segmentation of Pigmented Skin Lesions

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Abstract

Skin cancer affects millions of people worldwide. Computational methods for the segmentation of pigmented skin lesions in dermoscopy images have been developed in order to assist dermatologists in their diagnosis. This project aims to propose a method for the segmentation of skin lesions with a comparative analysis to other published methods in regards to several fundamental steps of image processing, such as preprocessing and segmentation.

Contents

Dedication

I would like to dedicate this project to my mom for everything she has given me.

Acknowledgments

I would like to acknowledge the help I received from my advisor Kerri-Ann Norton as well as the support from my professors, including the Conservatory on this project. I would also like to thank my family, friends, and ducky for all their support.

1
Introduction

The largest organ of the human body is the skin [1]. It performs many essential tasks, protecting our internals parts from external factors. The skin regulates our body temperature, keeping it at a constant level, and protecting our bodies from viruses and bacteria, as well as undesirable sun radiation such as UV light exposure [2]. There is a greater attention to protecting the skin due to its over exposure to the outer environment.

Pigmented skin lesions, which can be classified as benign or malignant, are caused when healthy skin cells change and grow out of control, forming a mass called a tumor. Benign tumors are more organized than malignant lesions, with common types being seborrheic keratosis [Figure 1.0.1 a] and Nevi. For malignant lesions, i.e. skin cancer, the cells are highly metastatic making its ability to spread much easier [3]. Skin cancer can further be broken up into two categories: melanocytic [Figure 1.0.1

b] and non-melanocytic skin cancer[Figure 1.0.1 c]. Non-melanocytic skin cancer has less capability to spread, but account for a larger variety of lesion types such as basal cell carcinoma (BCC) and squamous cell carcinoma with variety in morphology, colors, borders, etc. However, these types of cancer have a higher chance of cure than melanoma, since they have a reduced capacity to spread to other parts of the body. Melanoma is much more aggressive, as it is most deadly form of skin cancer, accounting for about 75 % of deaths associated with skin cancer [2]. Early and accurate diagnosis of these types of cancer are essential as many patients lives depend on the proper treatments such as medications, dermatology procedures or surgery for a higher probably of being cured.

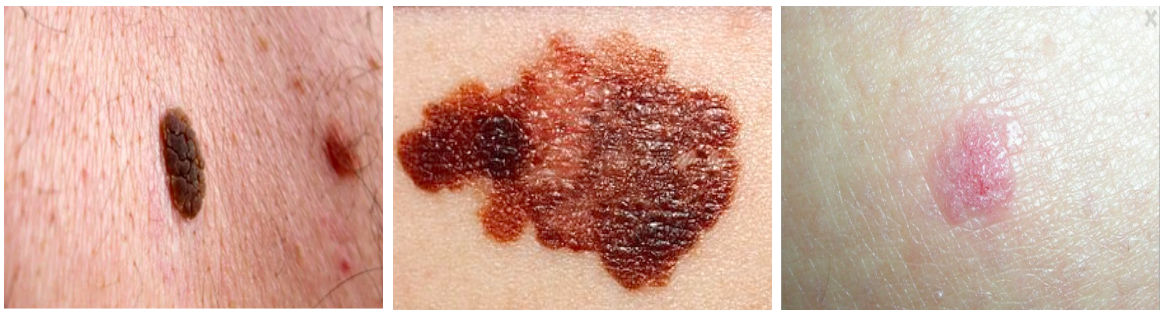

Figure 1.0.1. Examples of skin lesions a) Seborrheic keratosis, b) Melanoma, and c) Non Melanoma. [2]

1.0.1 Motivation

In the past, there has been a great interest in the development of computer-aided diagnosis (CAD) systems for the detection and analysis of pigmented skin lesions from images, in order to assist dermatologists in preventing the development of malignant

lesions. CAD systems use dermoscopy images, a non-invasive dermatology imaging technique, to observe pigmented skin lesions. By using polarized light to magnify certain structures and clarify subtle features, these images are used for classifying and detecting skin cancer [5]. Before computer aided diagnosis, skin lesions were detected manually by dermatologist, but manual detection proposed several challenges such as inaccuracy, subjectivity and irreproducibility [6]. Computer aided diagnosis systems helped lower the need for well-trained specialists, becoming a useful and consistent way to detect and classify skin lesions.

Professor Kerri-Ann Norton, Hitoshi Iyatomi, M. Emre Celebi, et al.[7] worked on developing a computer aided diagnosis system for a general skin lesion segmentation as a first step in developing a classification method for non-cancerous skin lesions from cancerous ones. My motivation for this project was based on recreating the work done by Professor Norton, et al. and further improving the efficiency. The replication of the code was focused on translating from Matlab to Python. The reason being to make the code more accessible to others, since Python is a free and open-source language. Matlab require licenses, while Python is freely available with a reasonable set of libraries such as NumPy, SciPy, matplotlib and several other useful libraries. Replicating the Matlab code in Python had the motivation to make it usable and distributively available for everyone to use. Furthermore, researching other studies

with relevant solutions gave the motivation to improve and further develop Professor Nortons code.

Segmentation is an important first step for the overall goal of distinguishing between different types of skin lesions and classifying them as an automatic diagnosis. My focus for this project was on the segmentation step, as this step is essential in accurately diagnosing skin cancer.

2
Background

The recognition of skin lesions from dermoscopy images proposes several challenges. Distinguishing between the different types of skin lesions, variation in skin conditions such as different skin color, presence of hairs, veins, etc., other outside factors like the presence of a microscope border, a shadow, air bubbles, as well as a possible low contrast between skin lesions and the normal skin regions [8]. Previous studies [9]-[14] have shown that computational methods for image segmentation may provide suitable results for the identification of skin lesions in dermoscopy images. Commonly, the images are pre-processed for enhancement and artefact removal, for achievement of more accurate segmentation results. An overview of lesion border detection methods, which include pre-processing steps, segmentation steps and post-processing steps is presented in Celebi, et al. [15]. A background on the computational techniques that have been suggested for image segmentation of pigmented skin lesions are studied

in order to gain knowledge so as to try and achieve my own reliable pigmented skin lesion detection system.

2.1 Pre-Processing

Pre-processing steps aim to improve the images as an important aspect for effective identification and analysis of pigmented skin lesions. The goal of the pre-processing step is to suppress unwanted distortions and enhance features which may be essential for further processing [14]. This is essential in order to effectively identify and analyze lesions, as the accuracy of future steps may be negatively affected when proper pre-steps are not done successfully. Previous research shows different ways to reduce unwanted artefacts and enhance necessary features. Essential methods, such as color space transformation[16]-[18], illumination correction [19][20], artifact removal[16][17], and contrast enhancement[16][17][21][22], are commonly used in order to improve the accuracy for segmentation.

2.1.1 Color Space Transformation

Color space transformation is a pre-processing method that is used in order to translate the representation of a color from one basis to another. This method can use applications of either single channel(scalar) processing or multichannel(vector) processing. In single channel processing, the image is converted to a scalar image in order to retain one color channel, for example retaining only the blue channel or con-

verting to a grey scale image [15]. This is a useful technique because lesions can be more evident in certain color channels. In multichannel processing, the color space can be converted from one color model to another, such as the CIE L*a*b [17], CIE L*u*v*[10], and HSV (hue, saturation, value) spaces[19]. These different color spaces are commonly used to enhance color images in order to show high level intensity variations in colours for proper detection of lesion edges.

2.1.2 Illumination Correction

Artifacts, such as shadows or reflections, that are caused from illumination variation from the microscope can negatively affect segmentation results. A method proposed by Glaister, et al. [20]. uses a multistep illumination modelling method to correct for illumination variation. A nonparametric model of the illumination is determined by using a Monte Carlo sampling method. Then, a parametric quadratic surface model is used to determine the final illumination estimation by using a reflectance component computed from the final estimated illumination. Another method that has been developed for illumination variation uses modelling with a quadratic function [19]. An RGB image is converted to HSV color space and the V channel is retained in order to get a higher visibility of the shading effect. An estimate of the quadratic function computed from the local illumination intensity in the V channel is applied to the normalized image. The normalized image is converted back to the RGB colour space with the shading effects significantly reduced.

2.1.3 Artifact Removal

Artifact removal is a pre-processing step that removes the presence of other unwanted outside factors that can negatively affect the segmentation process. The most common way to remove artifacts is by applications of image smoothing methods [16]. Filters, such as a mean, median, Gaussian and anisotropic diffusion filter are commonly used since they do not cause any loss of relevant information on the lesions. The median filter [25], which is a non-linear image filtering method, has been commonly applied on noisy images to remove artifacts such as hair, dirt, etc., showing successful results. It often smooths the original image without blurring and thinning edges and important details. To find the best median filtering mask for the smoothing of skin lesion images, a theory presented by Celebi, et al. [27]. finds that the size of the filtering mask should be proportional to the size of the input image. Anisotropic diffusion [28] has also been used for smoothing skin lesion images. The number of iterations for how many times the filter is applied is determined according to the amount of noise present in the input image, which is important because relevant edges may be removed when the number of iterations is too large.

Some algorithms specialize in removing specific artifacts, for example in removing unwanted hairs. One algorithm presented by Lee, et al. [29] is based on identifying the hair location by applying morphological operation to the RGB channels, creating a binary image to distinguish between hair and non-hair regions, replacing values of

detected hair pixels by values of corresponding nearby non-hair pixels and applying morphological operation and median filter to smooth the thin lines. Abbas, et al. [30]. suggested an effective method which consists of specular reflection reduction by applying homomorphic filtering [31], Fast Fourier Transform, and filtering to modify the illumination. Air bubble artefacts are reduced based on adaptive and recursive weighted median filter.

2.1.4 Contrast Enhancement

Another factor that complicates the segmentation of skin lesions can be the low contrast between the lesions and the background of the image. Many algorithms have been developed for accomplishing contrast enhancement and have been applied in pre-processing steps. Image borders can be sharpened and accuracy can be improved by emphasizing on the brightness difference between background and foreground. Furthermore, enhancing contrast can also improve the quality of an image. Celebi, et al. [22]. presented a method which finds the optimal weight in the image to convert a RGB image to the corresponding grey-level image. Another algorithm by Barata, et al [24]. uses a shades of grey method for color compensation by estimating the color of the light source. Histogram equilization, adaptive histogram equilization, and unsharp masking are also popular contrast enhancement techniques which help sharpen the image and transform it to one of higher contrast [20]. Morphological filtering are also

commonly applied to include areas with low contrast borders in the detected lesion regions, and to removed image noise [19][25].

2.2 Segmentation

The segmentation step involves the extraction of the region of interest(ROI) in an image. The pigmented skin lesion in this case is the ROI in the image under analysis. Once pre-processing techniques are applied to facilitate the segmenting process, the extraction of skin lesions can be properly done. Segmentation steps are based on the discontinuity and similarity of the properties of the region of interests to be segmented [32]. Common segmentation strategies include edge based methods[33][34], region based methods[35][36], thresholding[37][38][39], artificial intelligence based[40][41], and methods based on active contours [42].

2.2.1 Edge Based Methods

Edge detection methods involve the detection of borders with the assumption that different objects are separated by edges. Using edge operators, abrupt changes or discontinuities in the intensity of the pixels relative to their neighboring pixels are searched for. Examples of edge based detectors include the Prewitt, Sobel, Roberts, Laplacian and Canny operators [32]. Some challenges faced by edge detectors include the detection of an edge where no real border exists, the non-detection of an edge where a real border exists, generating double edges and sensitivity to noise [43]. Commonly,

edge detectors are used with other segmentation method to achieve full segmentation with improved results.

2.2.2 Region Based Methods

Region-based methods group similar pixels into homogeneous areas using merging, splitting and region growing operations.[36] The growing algorithm consists of grouping similar neighbouring pixels into larger homogeneous regions based on a growing criterion such as grouping pixels with similar properties like color together. Splitting and merging operations are region based techniques which split the image based on homogeneity criterion and merge similar regions to create the segmented result [35].

2.2.3 Thresholding

Thresholding techniques are commonly used in skin lesion segmentation methods. This technique selects one or multiple threshold values based on the histogram of the input image to separate the region of interest in the image. Among various methods to define the threshold value, Otsu thresholding is an example which is based on a normalized histogram to separate pixels into foreground and background while minimizing variance [37]. Another technique to define the threshold value is shown by Xu, et al. [38], which considers the average intensity of the strongest gradient pixels in the input image. A method based on Renyi's entropy [39] led to segmentation's that preserved the shape of the lesion.

2.2.4 Artificial Intelligence

Techniques based on artificial intelligence have also been proposed for segmentation. These techniques work to perform tasks similar to humans which include learning, natural evolution and human reasoning. Algorithms based on active contours work by determining a boundary for the regions of target for segmentation [41]. Active contours can be defined as the process to obtain deformable models or structures with constraints and forces in an image for segmentation. These models can be parametric or geometric according to the technique used to track the curve movement [42]. Parametric models include the traditional active contour models and snake models and represent contours explicitly as parameterized curves. Geometric active contours are less dependent on the initial curve conditions. Chan-Vese's model [44] is an example of a geometric active contour model which is characteriezd by the topological change that the curve may experience during the process, and less so on the initial curve.

2.3 Classification

The classification stage is in charge of making the inference about the extracted information in order to diagnose the input image. Common classification algorithms previously researched include Support Vector Machine (SVM), artificial neural networks, k-nearest neighbours, logistic regression, and decision trees [45][46][47]. SVM solves problems of nonlinear classification and also prevents overfitting by selecting a

hyper-plane to separate the data [45]. K-Nearest-Neighbourhood algorithm uses the Euclidean distance to evaluate the distribution of data and classify the objects according to their closeness to the training set [48]. Decision trees are also a commonly used where the data is continuously split according to a certain parameter [46]. Dreiseitl et.al, [49] compared the different classification techniques of artificial neural network, k-nearest neighbourhood, support vector machines, logistic regression and decision tree in skin cancer detection systems showing highly effective performances in these techniques.

2.4 Previous Research

The methods presented in this senior project were based on Norton, Iyatomi, Celebi [7], which present a computer-aided diagnosis of dermoscopy images for pigmented skin lesions. The challenges faced include the large variety of lesion types and the ambiguous borders that lesions can have. The research focused on the segmentation step, since proper segmentation is essential for accurate classification performance.

A major pre-processing step that was done included removing pixels that were present as a microscope border, as these pixels could inaccurately be picked up as skin lesions. To be sure that a lesion touching the border is not falsely identified as a microscope borer, the object is checked if it is overlapping the center of the image. Any objects not touching a border is kept, and if an object is touching the border but not the center of the image, it is kept if the centroid of the object is closest to the image

centroid. To reduce unwanted artefacts and noise, a filter was used to smooth the original RGB image. The red, blue, and green channel were obtained separately and used to determine the binarization of the image. For segmenting the skin lesion from the background area, Otsu thresholding was done without including the micrscope border regions. Some dermoscopy images had an issue with shadow areas being darker than the rest of the image background. It was necessary for this to be corrected for so that the shadow areas were not falsely identified as lesion pixels. This was done by calculating the largest object in the segmentation and determining if the area needed to be corrected for non uniform lighting. Contrast-limited adaptive histogram equalization was used on the green channel if the effect needed to be reduced.

In order to reduce the noise even further, morphological operations were applied to the image, removing any remaining unwanted artefacts and closing up holes. Opening and closing, two important operators for morphology were used with a structuring element that was determined experimentally. Opening allowed for removing small objects while closing was used for filling in small holes.

The brighter regions of the image were also a challenge, as sometimes skin lesions with these areas were not accounted for during the general lesion segmentation step. This was accounted for in the algorithm by calculating the average intensity of the pixels without including the segmented region and the microscope border. The thresholding is then done using 1.7 standard deviations above this found intensity and the

regions of the bright segmentation that overlap with the base segmentation are added together. However, these areas tend to be small, so if the area is found to be too large, the bright segmentation is excluded.

The accuracy of the results were statistically measured, using precion and recall as the main metrics. The results were found by comparing the accuracy to a "ground truth" of manual segmentations done by dermatologists. The results were then compared to other methods previously published including a standard Otsu thresholding on the blue channel [35] and Iyatomi's dermatologist-like method for segmenting [50].

3
Approach and Methods

3.1 Overview

Based on the methods presented by Norton, Iyatomi, Celebi [7] for a method to segment non-melanocytic skin lesions, I produced code implementing a similar method using Python 3.7. OpenCV, NumPy, SciPy and matplotlib were helpful image processing libraries in Python for the problem being solved. Three programs were written: The main segmentation for the dataset of dermoscopy images, the conversion to binary for the gold standard dataset, and the comparison of my method to the gold standard to verify accuracy. The dataset used consisted of 107 dermoscopy images which included 34 basal-cell carcinoma, 59 seborrhoeic keratosis, 26 from the face, 3 hemangioma, and 11 hematoma from Keio University [7]. The dataset of gold standards consisted of the same dermoscopy images segmented in red. The steps taken

included pre-processing steps, general lesion segmentation and certain conditionals to improve accuracy.

3.1.1 Microscope Removal

As stated before, some images had a dark microscope border present, which needed to be accounted for in order to accurately segment out the skin lesions. The microscope border was identified as the darkest pixel in the image, and I experimentally determined the structuring element used to dilate the microscope border. This was done because the microscope border sometimes tended to grow lighter towards the center, causing some pixels to not be picked up. In matlab, the function imclearborder was used to get rid of the microscope border. Python did not have an equivalent function, so in order to determine whether or not to remove the border object, findcontours in OpenCV was used. The contours found were curves joining all the continuous points, having the same color or intensity. An issue with findcontours occurred due to the function not taking into account 1-pixel border of the image, therefore not picking up contours touching the image border. In order for this to be fixed, copyMakeBorder was used and a white border of pixel value 1 was added around the image. The contours touching the border were then picked up and the contour list was iterated through and added to a another list for the border. These contours were checked whether they overlapped the image center, and were determined as the microscope border if they matched these parameters.

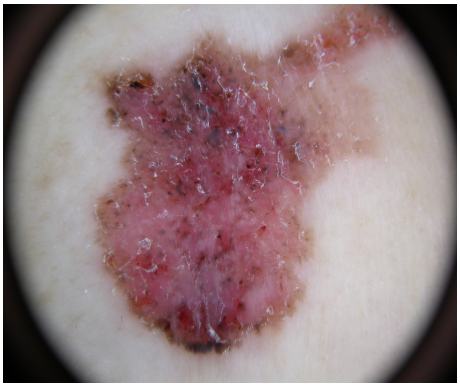

Figure 3.1.1. Dermoscopy image with a microscope border [11].

3.1.2 Lesion Segmentation

Further pre-processing steps were done before segmentation of the lesion area, such as an application of a Gaussian Blur filter and an averaging filter to further smooth out unwanted artefacts such as hairs.

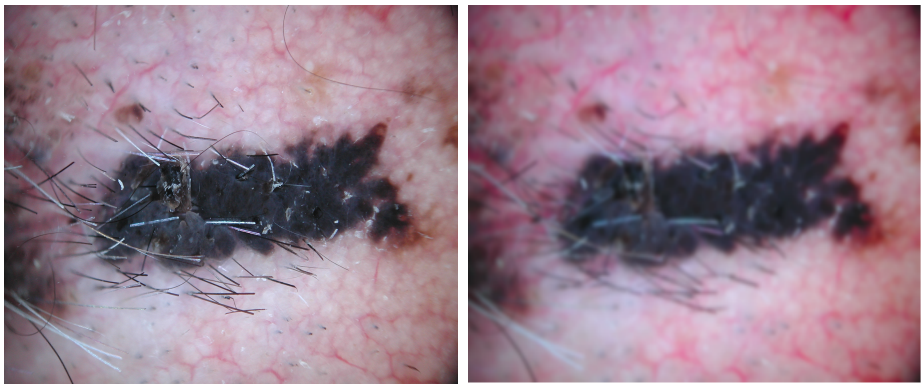

Figure 3.1.2. Application of Gaussian Blur to reduce visibility of hairs.

Information from the red, blue and green channels were obtained and put in a histogram, in order to determine which channel lesions are more evident in. Otsu thresholding was done on the green channel, and did not include pixels from the microscope border.

3.1.3 Noise Reduction

Further morphology operations were applied to the segmented images to remove any remaining unwanted artefacts. Opening and closing operations were used on the images with an structuring element that again was determined experimentally in order to remove any remaining hair or artefacts and close up any small holes. Bigger holes in the region of interest that were present and needed to be filled in was done so by using findcontour to identify connected components, which returned a list of contours. This was iterated through to find the area of the largest object and the contours that were smaller than an certain parameter founded experimentally according to the area of the largest object were filled in using drawcontour. Previously published work has shown that similar segmentation methods result in the area of segmentation being less than segmentation done by expert dermatologists. To account for this, the segmented area was dilated in order to expand the lesion area.

3.2 Gold Standard Conversion

The data set given as the "ground truth" consisted of the same dermoscopy images that were manually segmented by dermatologists. The segmented lesion area provided was in red, and therefore was converted to binary in order to be compared to my segmentation results. The images were split into the RGB channels, and the pixels were iterated through to convert to black and white. If the red channel was greater

than 0, the pixels were set to white (255), and if they equaled zero, the pixels were set to black(0). Sometimes the dark microscope border would be picked up as lesions, so a condition of when red channel equals to 0 and the green and blue have low intensities, set the pixels to white(255).

3.3 Gold Standard Comparison

In order to verify the accuracy of my border detection result, I needed to statically measure how precise the segmentation is. In this study, I used precision and recall to compare the segmentation's. They are defined as:

$$Precision = \frac{TP}{TP + FP} x100\%$$

$$Recall = \frac{TP}{TP + FN} x100\%$$

where TP is the true positive pixels(lesions), TN is the true negative pixels(background), FP is the false positive pixels and FN is the false negative pixels. Precision refers to the percentage of the results which are relevant, and recall refers to the percentage of total relevant results correctly classified by my algorithm. The "ground truth" were the segmented dermatologist data set that was given and converted into binary. The pixels in both the ground truth and my segmentation were then looped through, and compared in order to determine TP, FP, TN, FN values: if my segmentation pixels and the ground truth pixels are both 255, TP is incremented, if my segmentation pixels and ground truth pixels are both 0, increment TN, if the

ground truth pixels are 255 and my segmentation pixels are not 255, increment FP, and if the ground truth pixels are 0 and my segmentation pixels are not 0, increment FN. Using the formulas stated with the calculated TP, TN, FP, and FN values, the precision and recall formulas are calculated.

4
Results and Discussion

4.1 Segmentation of Skin Lesions Results

To show the accuracy of my method, I compared the precision and recall scores of my method to the ground truth segmentations as well as Professor Norton's segmentation, a standard segmentation based on Otsu thresholding on the blue channel [35] and a dermatologist like segmentation from Iyatomi [50]. The Otsu threshold uses a maximization of the between class variance and does not perform pre-processing techniques such as microscope border and removing unwanted artefacts. Iyatomi's method was published for melanocytic skin lesions and is a competitive method to the one I developed. The segmentation performance is summarized in table 4.1.1. for the different methods.

I achieved an average precision score of 85.5 % and a recall score 83.4 %.This is competitive to Kerri-Ann, Iyatomi and Celebi's method, and shows better extractions

	My Method	Kerri-Ann, Iyatomi, Celebi	Otsu	Iyatomi
Precision	85.5	84.5	73.3	93.7
Recall	83.4	88.5	64.2	66.7

Table 4.1.1. Precision/Recall scores (%) for segmentation methods

than the other two methods compared to. Examples of the segmentation's are displayed in Figure 4.1.1., comparing the original dermoscopy image, the Gold Standard segmentations, my segmentation's, and the segmentations done by Kerri-Ann,Iyatomi, Celebi et al. The images shown face challenges such as a different background tone, a microscope border being present, and artefacts such as bubbles, hair, etc. I was able to segment out lesions under different lighting conditions and background color tones, and also those including foreign objects. Most images with microscope borders were able to accurately segment out the lesions, however, the results sometimes were not as accurate when more than two objects are present and touch the border. This part of the algorithm could have been further improved by putting in further conditionals for the border clearing. Regions with bright spots could have also been further developed, as sometimes they are not picked up during segmentation.

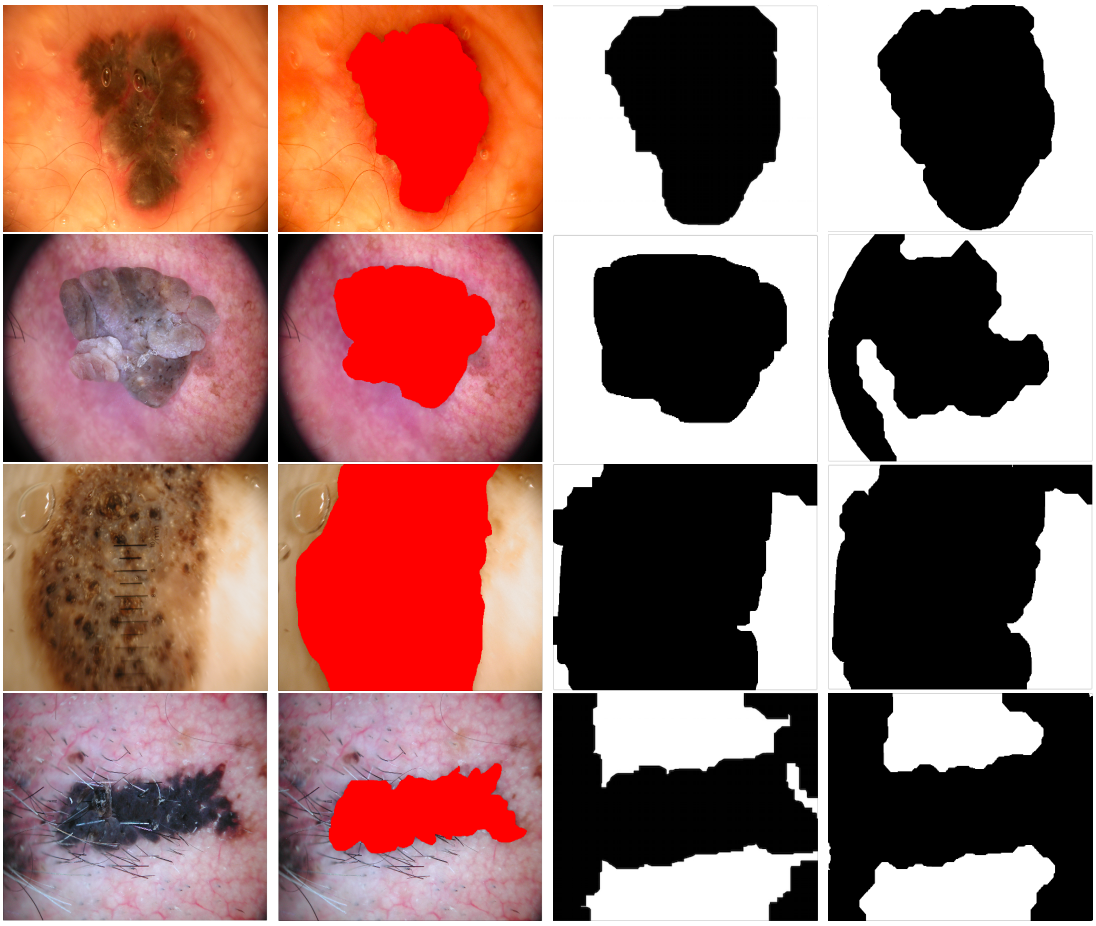

Figure 4.1.1. The left column shows the original dermoscopy image, the second column shows the Gold Standards, the third column shows my segmented region, and the fourth column shows Professor Norton, Iyatomi, Celebi et al. segmentations.

5
Conclusion and Future Work

After recreating the work that Professor Norton and her team did translating from Matlab to Python, my results came out competitive to theirs. I was able to compare the different methods between the two languages and find alternative ways in Python to solve segmentation challenges. However, due to the COVID-19 pandemic and relocation/lifestyle changes, I was cut short on making further improvements for my code. I was also hoping to test my results on other datasets to see how well it performs. The border removal sometimes does not work as well as hoped with certain conditions and could be improved on, as well as better results for bright region areas. The results presented were what I was able to get done with the extenuating circumstances, and I hope to continue to improve on them.

The avenue that I was originally considering for my senior project was segmentation using convolution neural networks. After reviewing published methods to date, a cur-

rent development which overcomes challenges and limitations from existing methods was a deep learning method based on convolutional neural networks.

Deep learning methods imitates the work of the human brain by processing data and creating patterns for use in decision making. Convolutional neural networks(CNN) uses deep learning in image analysis and processing through convolution operators [51]. The outline of a convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. CNN has had success for image segmentation, object detection, and image classification [52]. It uses relatively little pre-processing compared to other image classification algorithms, with few challenges and limitations due to its capability to learn image feature representations that carry a high level of semantic meaning.

My original hopes for this project was to minimize as many segmentation challenges that current methods face. My starting point was to reproduce Kerri-Anns method in Python to compare challenges in both languages. In the future I hope to not only further develop my method, but also be able to explore deep learning methods as a tool for segmentation.

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