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Morphology Based Melanoma Skin Segmentation Method

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Abstract
One of the five sense organs, the skin is the biggest organ in the human body. The human body is protected from heat, sunlight, and harm by the skin. Recently, skin cancer has become one of the most lethal forms of cancer; skin cancer is one of the most severe cancers that may be detected in people. Melanoma, basal cell carcinoma, and squamous cell carcinoma are all forms of skin cancer, but melanoma is the most unexpected. Melanoma cancer can be successfully treated if it is discovered early enough. Having too much sun exposure is the primary cause of this condition. In order to catch an aggressive form of skin cancer in its early stages, image-based computer aided diagnostic methods can be used. Malignant melanoma can be detected using these image processing systems. Noise and other structures, such as hair, are removed during processing of the acquired original image. Principal Component Analysis and Morphological operators are mostly used to extract features in this process. This algorithm can be used on Matlab R2015b or higher end. With this effort, we hope to remove and outline the skin lesion so that it can be detected earlier and treated sooner, potentially saving lives.

Keywords: *Principal Component Analysis, Morphological, Melanoma*

Introduction
The goal of this research is to see how well the major component analysis method performs while segmenting images of melanoma skin cancer taken using a dermatologic scope. Melanomas are cancers that produce melanocytes and are one of the most deadly forms of skin cancer. Sunlight exposure is a common cause of melanoma, which is a form of skin cancer. It comes from the skin and mucous membrane, which contain melanocytes. Melanoma is one of the deadliest forms of skin cancer because of its propensity to metastasize to distant parts of the body. According to reports, the number of cases is rising significantly over the world. There has been a steady rise in the number of patients who have died since it opened. In order to improve melanoma outcomes and reduce the disease's mortality rate, early detection and prevention are indicated as the best measures because treatment at a later stage can be difficult. Melanoma skin lesion segmentation in dermoscopic images is the emphasis of this work, as other diagnostic images follow. Its output is highly dependent. One of the most important aspects of computer-aided melanoma diagnosis with dermoscopic pictures is the segmentation process. Skin hair, specular reflections, varied colours, weak margins, low contrast, and skin lines all contribute to making skin lesion segmentation a difficult task.

Literature Survey

Using image processing, one can manipulate and analyse images. There are numerous biomedical uses for it. There are two processes to the analysis of skin cell images: segmentation and detection. The first step is the process of identifying nuclei in tissue. For segmentation and detection in the past, pathologists relied on manual approaches that were time-consuming. It takes a long time because of human errors. During the 1950s, a threshold-based decision-making system for 1D microscopic line scans of sample pictures was created to automate the classification of exfoliated cell smear.

Automatic techniques for 2D images of differential leukocyte counting were first noticed in 1960, according to this study. Due to the wide variety of cell sizes and shapes, segmenting cells automatically is a tough process. Medical image analysis, as a result, generates incorrect images. Several methods have been presented to interpret sample results. The adoptive attention window is an example of a complex strategy that uses a maximum cell size or gradient flow tracking.

A powerful segmentation technique for detecting objects and defining their shape was proposed in 1988 by Kass M, Witkin A, and Terzopoulous as an effective counter model. As a result of Mumford and Shah's research, we have come up with a strategy for the best possible segmentation. A numerical method known as rate setting is used in image processing to eliminate noise, segment and reconstruct images.With Umesh Aditya Aditya Gang, Lin, and Gang in 2003 a mathematical model and a distance transformation could be used in combination For the automatic segmentation of 3D confocal microscope images.

In 2007, Korzynska and Anna developed a segmentation method that combines a texture-based method with a counter-based method. In 2012, Stephan Wienert was the Cell detection using the 'minimum model' segmentation method. Counters go through a six-step evolution. Searching for and locating all available counters, generating non-overlapping segmentations, honing in on the most effective ones, classifying goals, and separating concavely. It was proposed in 2016 by Neghina, Mihai that the three primary stages of sample segmentation should be: a post-processed image of a Cartesian-to-Polar transformation, and k-means segmentation. Polar transformation is used to reorganise the information contained in the condensed layers of the pictures, such as the cytoplasm, nucleus, and backdrop, in order to enable additional procedures. To make matters even more complicated, only a small portion of the original photos is retained in the resulting images.

Proposed Methodology

Algorithm for melanoma skin segmentation using PCA and morphological is as follows:

Step 1: Image Read
Step 2: Using PCA transform RGB picture to Gray Scale
Step 3: Morphological Closing
Step 4: Complement Image
Step 5:2-D wavelet decomposition using B-spline
Step 6: Otsu Thresholding
Step 7: Calculating New Threshold Value
Step 8: Single level wave transform
Step 9: Black and White Segmentation
Step 10: Post processing
Step 11: Final Image

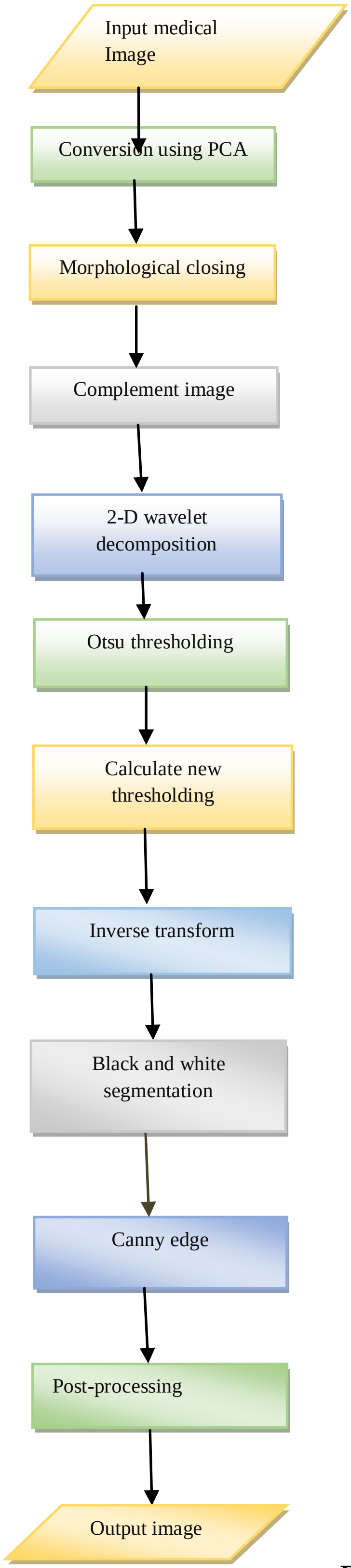

Fig 1: Flowchart of Methodology

Results and Discussion

Fig 2: First Input Image

The proposed method (Principal Components Analysis) is applied to an original image as depicted in Figure 2. With the suggested method, the primary goal is the exact melanoma boundary that can be seen in the original image. First, the image was converted to grayscale using PCA, the primary component analysis method.
An Otsu thresholding procedure is performed on the resulting image. An iterative canny edge detection method has been used in the most recent stages.

Fig 3: Output image after processing the first input image

The process which is explained for figure 2 is applied for all the images represented by figure numbers 4 and 6 and the resulted images are shown in the figures 5 and 7 respectively.

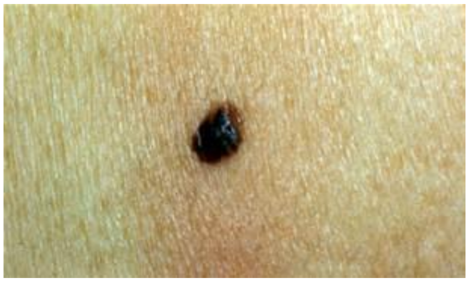

Fig 4: Second Input Image

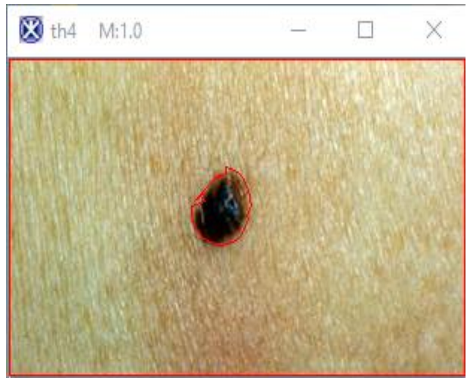

Fig 5: Output image after processing the Second input image

Fig 6: Third Input Image

Fig 7: Output image after processing the third input image

The resulting images are then calculated using MIPAV software which is shown in the table for the statistical values. The parameters for example number of pixels, eccentricity, solidity and circularity have been measured. The below Table 1 illustrates the parameters:

Table 1: Parameters for the Images

ATTRIBUT EIMAGES	Numb er of pixels	Eccent ricity	Solidi ty	Circularit y
Image a	5233	0.6662	0.984	0.8674
Image b	1230	0.6237	0.965 5	0.5865
Image c	8777	0.6059	0.586 5	0.8954

Conclusion:

More accurate melanoma detection tests were achieved by the application of image processing and soft computing approaches in this study. Malignant melanoma is diagnosed in a series of stages that include pre-processing, segmentation, Otsu thresholding, post-processing, and classification. Results from this study show that the PCA algorithm performs exceptionally well when compared to the benchmark algorithms investigated in this study when it comes to segmenting skin lesions in dermoscopic images. Malignant melanoma can be detected using these image processing systems. Noise and other structures, such as hair, are removed during processing of the acquired original image. Principal Component Analysis and Morphological operators are mostly used to extract features in this process. Matlab and a medical image processing, analysis, and visualisation package have been used to develop the algorithm.

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