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AN AUTOMATIC SKIN LESION SEGMENTATION FOR DETECTION OF MELANOMA FROM META DATA OF DERMOSCOPIC IMAGES.

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Abstract: Skin melanoma, which accounts for more than 75% of deaths from skin lesions worldwide, is one of the most severe medical problems. Melanoma is typically identified by dermatologists visually examining lesions. The method can increase the effectiveness for identifying clinically unknown lesions against ordinarily indistinguishable lesions, which will ultimately increase the diagnostic accuracy. Traditional machine learning techniques are still unable to fully address the issue of information loss or determine the precise boundary area division. To efficiently learn feature information and successfully separate melanoma images, we employ an enhanced semantic segmentation frame work that is reported in this paper. The experiments in this article demonstrate that our enhanced neural network design produces higher segmentation accuracy of 96.6% for melanoma images than conventional methods.
Keywords: Melanoma, Deep Learning, Machine learning, Segmentation.

1. Introduction

Thousands of people worldwide pass away each year as a result of the deadly skin cancer disease melanoma [1]. Its primary target areas are the human body parts that are still in the sun, such as the face, arms, legs, or neck. The highest fatality rate is, unfortunately, also associated with melanoma [2]. Melanoma is primarily caused by the unexpected growth of the bodily cells that produce the skin colors. Based on the degree of the disease's severity, distinct melanoma moles are created, including those that are pink, red, black, brown, and others [3]. A dermatologist should check moles with an abnormal colour and a diameter of more than 6 mm to rule out the possibility of melanoma [4].Dermatologists first physically assess such behaviour by examining the shape, size, abnormal skin colour, and diameter of the generated moles [5].However, because dermatologists are scarce, the time it takes to diagnose a condition may reduce the likelihood that the patient will survive [6].However, if the illness is discovered in its earlier stages, it can not only spare people from the painful procedure of biopsies but also improve a victim's likelihood of life [7].Therefore, in order to overcome the difficulties in diagnosing melanoma, researchers are now focusing on the automated identification of this deadly condition [8].Melanoma detection via dermoscopic images has been the subject of extensive research in recent years. The ABCDE method [16] and the seven-point checklist [17,18] were previously used to identify skin cancer.

Low-level visual characteristics such as colour, edge, and texture descriptors are extracted using these approaches [16, 17, 18,19]. The automatic detection of a skin area afflicted by melanoma has been proposed using a number of techniques [9]. First, handmade features-based melanoma detection algorithms are presented [10]. The shape, size, and colour of melanoma moles can vary, therefore these methods aren't producing positive outcomes [11].Then, to increase the detection precision of these automated systems, segmentation-based approaches such adaptive thresholding and iterative selection thresholding (ISO) are introduced. These methods operate on the region of interest (ROI), a segmented area of the melanoma [12]. These methods work better because it is simpler to identify the impacted area if the extracted feature step focused more on the harmful area. The non-affected area is primarily left out of the impacted area since including it could result in a poor feature vector, which could impair the system's ability to detect changes. Therefore, segmentation is the first stage in creating an automated melanoma detection system [13]. However, when there is no fluctuation in image contrast, or when there are only minor changes in lighting within the image content, and the image is displaying a uniform distribution of chrominance, the region of interest or thresholding-based algorithms perform effectively. However, it can be challenging or nearly impossible to prevent lighting and chrominance changes in real-world situations [14]. Therefore, in these situations, the melanoma-affected portion's detection performance using threshold-based approaches is less effective. Deep-learning-based techniques are being more widely used in medical imaging today. CNN uses the small portions of images with melanoma-affected areas to train its automated detection algorithm. On the basis of the training model, these strategies segment the test pictures. When it comes to the detection and segmentation of melanoma, deep learning-based systems outperform hand-crafted feature-based techniques. These techniques demonstrated improved localization and identification capabilities for melanoma-affected skin areas and can automatically compute the complicated and representative set of characteristics directly from the input images. Additionally, deep-learning methods may quickly find skin lesions of various sizes even when there is noise, blurring, and a change in the amount of light or colour.

2. Materials and Methods:

The International Skin Imaging Collaboration (ISIC) is collaboration between academics and business that aims to make it easier to use digital skin imaging to lower the mortality rate from melanoma [11].These Datasets are made up of carefully chosen, high-resolution images that have been examined, grouped, and possibly subdivided by specialists in the field of medicine. In this study we used ISIC2018 dataset which contain 2594 skin lesion images and 1000 images are use to test the model. Based on the literature currently accessible, this study intends to highlight the growing trend of automated systems capable of diagnosing, segmenting, or recognizing Skin Lesion.

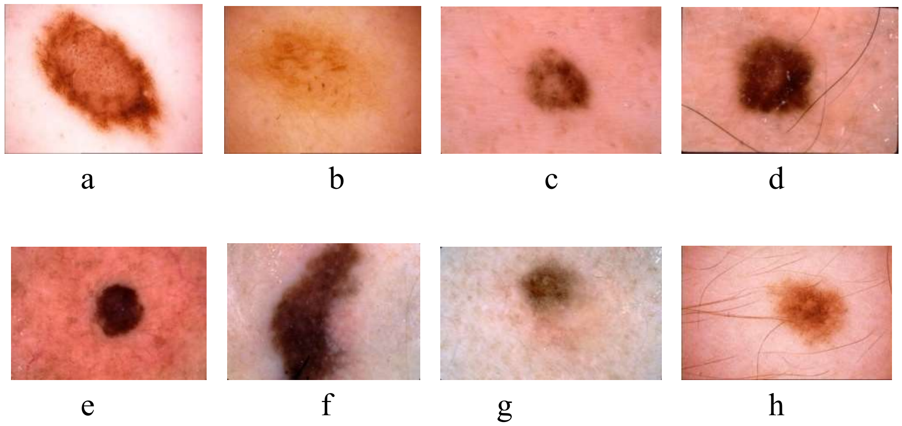

Figure 1: Sample Dermoscopic Images.

3. System Architecture:

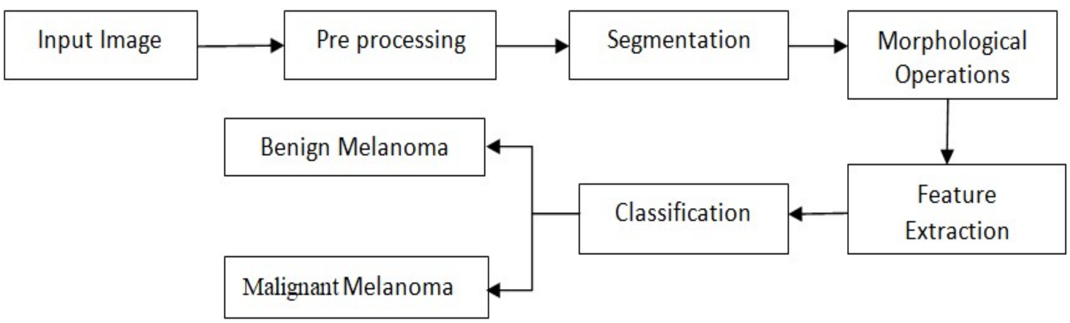

Figure. 2.Block diagram of melanoma detection system

3.1. Preprocessing

To help in segmentation, a pre-processing step is needed to get rid of tiny image artifacts and to improve the image by removing noise, hair , sharpening, changing image contrast, and reducing undesired distortions while enhancing some image qualities.. In order to achieve this, a morphological transformation attempts to remove any outlier pixels from the image while keeping the lesion region's visual characteristics. All of the images have been downsized and scaled to 224 by 224, and these undesired structures have been removed using an inpainting algorithm and morphological filters. Even though inpainting in computer vision is used to recover the lost portions of images, we have increased the utility of the method by utilizing it to eliminate hair structures from dermoscopic images. The method creates a clear dermoscopic image by replacing the portions of the image with hair structures with the nearby pixels. The original RGB dermoscopic image is first turned into a grayscale version, and the morphological filter known as the "black top-hat" is then applied to the grayscale version. Thresholding is a technique for converting an image into binary form, which allows certain operations to be performed on the pixels to achieve the desired outcome.

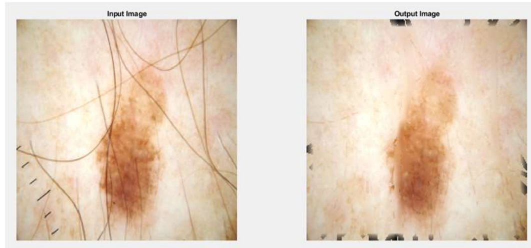

Figure 3: Hair removal

3.2. Image Segmentation

This approach is used to split an image in order to extract a specific region to which other methods can be applied. It is the most significant phase because it aids in identifying the kind and nature of the skin. It is necessary to determine the skin type prior to feature extraction. To assess the segmentation, we employed the specificity (Spe), sensitivity (Sen.), accuracy, and Jaccard index (Jac) and Dice coefficient (Dic). The rate of pixels successfully labeled as background is measured by specificity, whereas the rate of pixels correctly classified as foreground is determined by sensitivity.

$$Sen = \frac{TP}{TP + FN}$$

$$Spe = \frac{TN}{TN + FP}$$

$$Dic = \frac{2 * TP}{(2 * TP) + FP + FN}$$

$$Jac = \frac{TP}{TP + FN + FP}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

The TP is true positive, FP is false positive, FN is false negative, and TN is true negative. If the lesion pixels in the image are successfully segmented, they are treated as TPs; if not, they are viewed as FNs. The non-lesion pixels in the image, on the other hand, are treated as TNs if their prediction is non-lesion pixel and FPs otherwise.

3.3. Morphological Operations

Erosion and dilation are the two most common types of morphological operations. Erosion subtracts a pixel from the image's boundary, whereas dilation adds a pixel to the image's boundary. Morphological operations use an organizing intrinsic to create an output image with the same size and parameters as the input image. The following is the morphological operation formula:

3.4 Feature Extraction

The feature extraction method is thought to be the most crucial phase in the classification process. The process of extracting relevant features from the input dataset for use in later calculations like detection and classification is known as feature extraction. Features including the asymmetry index, diameter, standard vector, mean colour channel values, energy, entropy, autocorrelation, correlation, homogeneity, and contrast are generated for the purpose of further categorization.

4. Results:

We introduced our developed neural network based methodology using DeepLabv3 in this section, and then present and discuss the findings after it was trained and tested on the datasets. It is important to note right away that we presented an approach, also known as the intersection over union overlap that outperformed other comparable methods, both in terms of model accuracy and in pixel-by-pixel similarity measure (sometimes also referred to as the Jaccard Index).

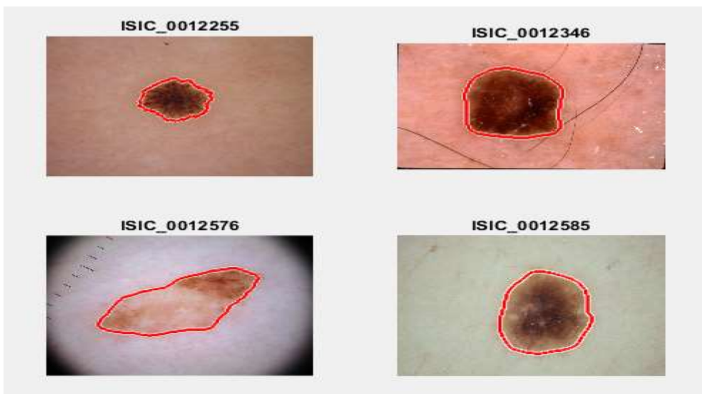

Figure 4: Segmentation of Images

The table 1 contains the result of semantic segmentation. In this we found the Global accuracy, Mean accuracy, Mean IOU, Weighted IOU, and Mean BFScore.

Metric	Values
Global Accuracy	0.93926
Mean Accuracy	0.91457
Mean IOU	0.82725
Weighted IOU	0.89049
Mean BFScore	0.50651

Table 1: Semantic Segmentation Results Evaluation Metrics

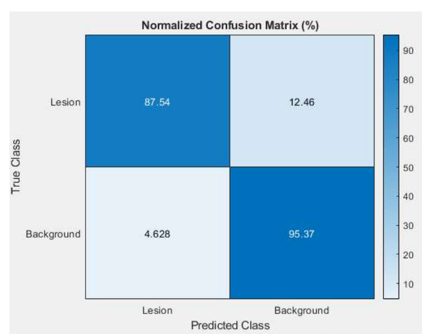

Figure 5: Performance

5. Conclusion:

In this article, we proposed a new fully automated enhanced semantic segmentation frame work. The experiments in this article demonstrate that our enhanced neural network design produces higher segmentation accuracy of 96.6% for melanoma images than conventional methods. The proposed system's accuracy is higher than that of current cutting-edge segmentation and recognition algorithms, demonstrating the validity of our approach. Additionally, based on the results, we deduce that choosing the lesion regions' most pertinent pixels leads to effective segmentation outcomes, which in turn influence the recognition process.

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