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Automated Skin Lesion Detection towards Melanoma

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Abstract

Skin cancer melanoma is one of the most dangerous cancers in the world. It is crucial to diagnose it in initial phases before it invades other organs. However, it requires an efficient and reliable diagnostic computer aided system for early detection. In this research study we aim to detect the skin cancer from two different image datasets. We also present the solution for images that contain disk objects. In initial phase we perform pre-processing, which is followed by segmentation phase. Then candidate dataset is evaluated using different measures such as accuracy, specificity, sensitivity and similarity. Obtained results are compared with results of techniques used in academic literature. We claim that our techniques give better accuracy for cancer detection.

Keywords: Skin Cancer, Melanoma, Image Processing, pre-processing, Segmentation, Dermoscopic Images

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1. Introduction

Human skin is known as the most important organ of the body it protects the body from harmful effects like warmness, radiations, mild, injuries, infections, pollution etc. On over exposure of the skin to the sun light the ultraviolet radiation destroys the cells and cancer appears on the outer layer of the skin. It isn't always the only cause for skin cancer to appear, other reasons also result in this disease inclusive of smoking, alcohol, nicotine, modernized diets and so on. Skin additionally incorporates water, fat and nutrition D and those necessities enables skin safety [1, 2].

In keeping with modern-day facts, it is reported that in USA skin cancer is the maximum recognized cancer than other cancers and the annual cost of treating most cancers is said to be around $1.8 billion. it is reported that approximately 9,500 human beings inside the U.S. are identified with skin cancers each day. An envisioned 9,320 human beings will die of melanoma within the U.S. of these 5,990 will be men and 3,330 will be women. The World Health Organization estimates that more than 65,000 people a year worldwide die from melanoma.

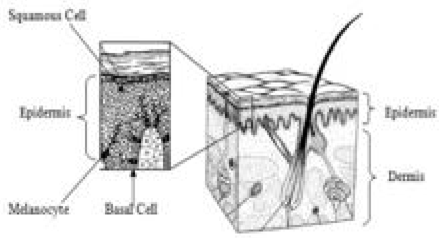

Figure 1. Layers of Skin

Skin is composed of two essential layers called epidermis and dermis. The outer layer is referred to as dermis and this layer consists of three cellular layers known as Squamous, Basal and Melanocytes. these cells offer the protection of skin from the damages. epidermis additionally known as inner layer carries nerves, blood vessels, and sweat glands.

The three types of Skin Cancers are Melanoma, Basal cell carcinoma (BCC) and Squamous cell carcinoma. Melanoma is considered to be one of the deadliest most cancers. It starts in melanocytes. If it isn't detected at early level, the survival chance of sufferers gets decreased. Melanoma can develop anywhere on the skin and at any age. If it isn't detected at early a stage it turns risky and is likely to spread all over the body. Some of the melanoma make melanin and turns in brown or black colour but some of them do not make melanin and may turns into pink, tan, or white colour. Melanoma is likely to appear on chest and back in men and on the legs in women. There are two types of melanoma one is Benign and other is Malignant. Benign melanoma responds to the treatment, and it cannot spread on the whole body, whereas malignant melanoma is a dangerous cancer. If not diagnosed at early stage it spread to the organs and cells and cannot be treated. It invades the nearby tissues. Its growing ratio is more than that of benign.

Figure 2. Benign Melanoma and Malignant Melanoma

Researchers, practitioners and scholars are trying to contribute more and more towards in the field of medical imaging to get accurate results which also helps patients to recover soon. For problems like detection of cancer [30-31], detection of motor-imagery based electroencephalogram (EEG) signals [28][29], multi-modal optimization problems[26][27] and Automatic rat brain segmentation from MRI[25] needs automated system which provides best and accurate results. Hence, we also proposed an automated system that detects skin cancer in its early stage using different image processing techniques.

In this paper our methodology is to detect the skin lesion from the dermoscopic images using image processing techniques. Our main focus is to segment out the skin lesion by applying Pre-processing and Segmentation techniques. The rest of the paper is organized as follows; related work on detection of melanoma is discussed in Section II. Section III explains our proposed methodology a comparison analysis is performed in Section IV. The finding and the results are discussed in Section V. Section VI concludes our results.

2. Related work

Many researchers have addressed the detection of skin lesion in different ways. Different datasets are available and used by the researchers to do comparison of different algorithms. Some of main research work on pre-processing and segmentation stages performed by researchers are discussed below:

2.1. Pre-processing

Santy et al. [3] proposed segmentation techniques to automated skin lesion detection system, their pre-processing techniques includes enhancement techniques to improve the quality of image, removing noise (hairs, artefacts, small particles) from the input images and some illumination correction algorithms. Gopinathan et al. [4] first converts the image from RGB to grayscale and then applied wiener filter to remove noise from the image. Sagar et al. [5] proposed an algorithm for pre-processing step. Firstly, resize the image to 512 x 512 pixels then adjust the gamma values to normalize the irregularity in illuminations and shadows. Applied morphological closing operation to remove thick hairs from the images. For other noises they applied median filter. For removing artefacts like bubbles and hair Kasmi et al. [6] applied 11 x 11 median filter that removes bubbles as well as thin hair from the input images they also used Gabor filter to remove thick hairs from the image. Abuzagleh et al. [7] suggested to segment out the hairs at pre-processing stage for this they used a set of 84 directional filters. Lopez et al. [8] proposed deep learning architecture to detect whether a lesion is melanoma or not. The pre-processing techniques they applied are; input image is normalized in [0-1] range of pixels, cropping the image to square perspective proportion (if essential) and resized the image to 224 x 224 pixels.

2.2. Segmentation

Noting from literature there are numerous segmentation techniques and algorithms are applied for detection of skin lesion. These techniques help to classify the lesion properly.

Abuzaghleh et al. [1] proposed an automated segmentation algorithm that contains number of steps. These steps include conversion of RGB image to greyscale, creating a 2-D filter of Gaussian lowpass filter type, applied Otsu thresholding and applied various algorithms to segment out the object pf interest namely; (binarization, morphological operations, Sparse-Field level-set method, connected components).

Santy et al. [3] applied different segmentation algorithms and performs a comparison between them that includes (i) Statistical region merging(SRM) (ii) Iterative stochastic (iii) Adaptive Thresholding (iv) Colour Enhancement & Iterative Segmentation (v) Multilevel Thresholding from their results it can be noted that Multilevel thresholding has the highest accuracy in comparison with other algorithms.

Table 1. Summary of literature work on skin cancer detection

Cate -gory	Ref	Techniques	Year	Results
Pre-processing	Santy et al. [3]	Image enhancement, noise removal and resizing	2015	96.8% accuracy
	Gopinathan et al. [4]	wiener	2016	-
	Sagar et al. [5]	Filter adjusting the gamma values, morphological operation closing median filter	2016	93.71% Accuracy
	kasmi et al. [6]	11 x 11 median filter, Gabor filter	2015	94.0% Accuracy
	Abuzaghleh et al. [7]	used a set of 84 directional filters	2016	96.3% accuracy
	lopez et al. [8]	normalizing pixels into [0-1] range, resizing, cropping	2017	81.33% Accuracy
Segmentation	Abuzaghleh et al. [1]	binarization, morphological operations, Sparse-Field level-set method connected components	2014	90.6% Accuracy
	Santay et al. [3]	Comparison Statistical region merging (SRM) Iterative stochastic, Adaptive Thresholding Color Enhancement and Iterative Segmentation Multilevel Thresholding	2015	96.8% Accuracy
	Rahman et al. [9]	adaptive thresholding and binarization, Morphological operations (closing, opening) region growing algorithms.	2016	0.822 jaccard score
	Sagar et al. [5]	2D Otsu with morphological operations on color channel derived from RGB and CIELAB color space	2016	93.71% Accuracy
	Gopinathan et al. [4]	Otsu thresholding and boundary tracing algorithm	2016	-
	Munia et al. [10]	combination of Otsu thresholding and K-means clustering	2017	89.7% Accuracy
	Ahn et al. [11]	Robust Saliency-based Skin Lesion Segmentation (RSSLS) Framework	2017	91.05% dice similarity
	Codell et al. [12]	Fully Convolution Network	2017	89.7% accuracy
	yuan et al. [13]	19-layer deep convolutional neural networks (CNNs)	2017	96.3% accuracy

Rahman et al. [9] applied different image processing algorithms for image segmentation. They applied adaptive thresholding and binarization, Morphological operations and region growing algorithms. Sagar et al. [5] discussed different segmentation algorithms and applied on dermoscopic images and compare their results with the proposed segmentation algorithm. They achieved 93.71\% accuracy. Gopinathan et al. [4] used Otsu thresholding and boundary tracing algorithm for image segmentation. Munia et al. [10] combined Otsu thresholding and K-means clustering to segment and extract the borders of input images with accuracy.

Ahn et al. [11] proposed Robust Saliency-based Skin Lesion Segmentation (RSSLS) Framework they achieved accurate results while using this framework. Codella et al. [12] proposed deep learning techniques for melanoma detection. They used a fully CNN for lesion segmentation. Their results achieve better performance in comparison with traditional techniques. Yuan et al. [13] present a fully automatic method for skin lesion segmentation by leveraging a 19-layer deep convolutional neural networks (CNNs) that is trained end-to-end.

It can be noted from preceding discussion that using deep convolution networks achieves more accurate results than using traditional algorithms.

Moreover, not only for the detection of skin lesion researchers also proposed solutions for the detection of breast cancer in which Pandey et al. [21] proposed different segmentation techniques to automatically segment-out the breast region of interest, a comparative analysis is performed by Tripathy et al. [22] in which different techniques of segmentation and classification were applied for the detection of lung cancer, Panday et al. [24] proposed an automatic for the detection of retinal vessel segmentation in which background is separated from the images to minimize noise and other intrinsic problems to accurately segment out the region of interest. Dutta et al. [23] implemented watershed method is used to segment out the cancer cell in liver. The manual detection of these problems is a time- consuming process. Using automated techniques to detect cancer helps in identifying it in initial stages as well as a contribution in medicine field and also leads in achieving accurate and best results in short span of time. The next section briefly discusses our proposed methodology, and the techniques implemented for the detection of skin cancer.

3. Proposed methodology

In our proposed methodology we are trying to cater for different problems that are occur in dataset. Our methodology also involves pre-processing and segmentation steps. The intended methodology is to apply some pre-processing techniques (contrast stretching, image resize, scaling, binarization) for removing the undesired object from the image, these operations apply in sequence and output of one operation is input of the next operation that are shown in Figure 3. Resultant image of the pre-processing steps is not a one single object. To segment out the region of interest, we were using morphological operation and masks [1].

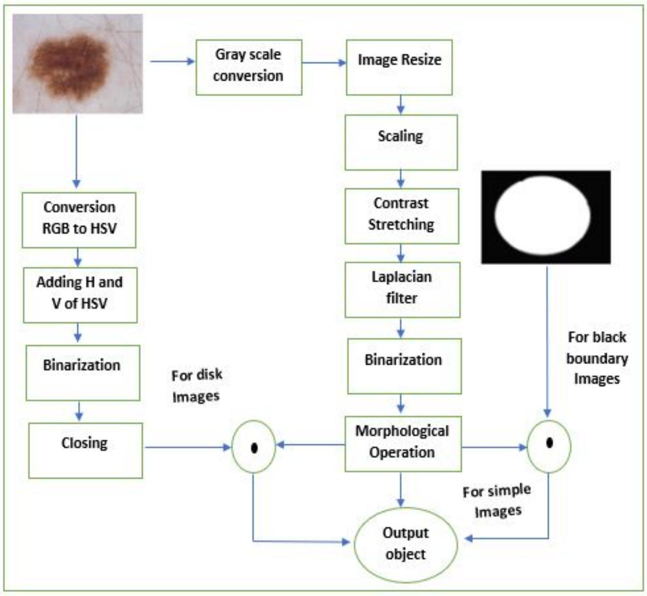

Figure 3. Architecture of Proposed Methodology

3.1. Pre-processing

Pre-processing is the main step in skin cancer detection systems. it's used to enhance the objects of the image and remove noise. Several abnormalities like noise were observed in the history. The main focus of our study was enhancement of image to have a clears view skin lesion. Choosing proper pre-processing steps can have a vital effect on our accuracy. These pre-processing steps many include quality improvement of dermoscopic image. It also eliminates useless elements occurring in the background. The overall framework of techniques followed in pre-processing level of medical image processing is illustrated in Figure 4.

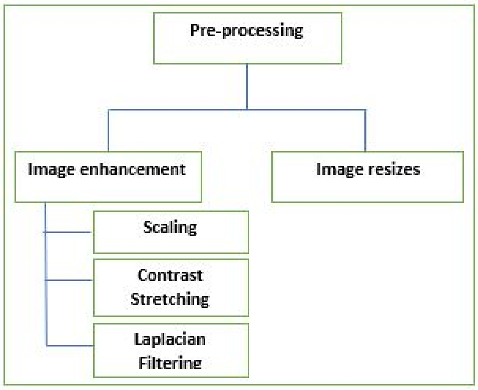

Figure 4. Framework of Proposed Pre-processing Techniques

Image enhancement

To improve the visual appearance of an image we used 4 enhancement techniques.

- Scaling: Scaling improves the brightness of images by using the scaling factor [18]. The scaling factor value is 2.

$$S = T(r) = a.r \qquad (1)$$

- Contrast Stretching: For improving the accuracy of results contrast enhancement is used. It enhanced the image and highlight the difference between foreground and background. Like in our Melanoma images some images have pink background and the colour of skin lesion is also like the background colour so using contrast stretching enhances the contrast of the image [20]. Contrast stretching can be defined as follows:

$$g(x, y) = f(x, y) - r_{min}\left(\frac{L-1}{r_{max} - r_{min}}\right) \qquad (2)$$

g (x, y) is the output image and f (x, y) is the input image after scaling.

- Laplacian Filter: The Laplacian filter removes blurring, edges are sharped and improves the enhancement. The Laplacian filter of two variables is defined as follows:

$$\Delta^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad (3)$$

In order to enhance our image, we used the following equation.

$$g(x, y) = \frac{f(x,y) - \Delta^2, w_5 < 0}{f(x,y) - \Delta^2, w_5 > 0} \qquad (4)$$

In the final sharpened image, edges and fine detail are much more obvious. We applied Laplacian, but some other filters can be applied.

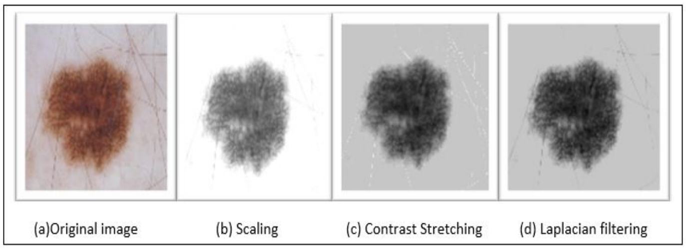

Figure 5. Result of the Image enhancement operations

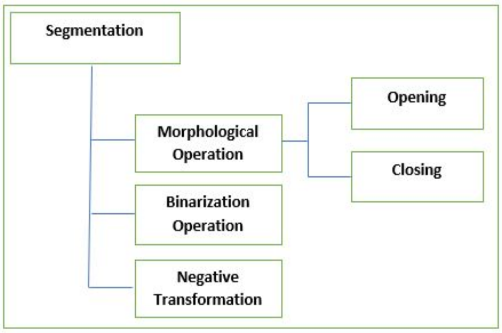

Figure 6. Proposed Segmentation Techniques

3.2. Segmentation

For further post processing steps, segmenting out the object of interest accurately is the main task in Automated Skin Lesion Detection System. To detect object of interest, we used the methodology illustrated in Figure 6.

Image

The image may contain blur and noise. And in Image segmentation step, we deal with these kinds of problems. There are different ways for these problems. The image becomes degraded by some kinds of defects such as imperfection of imaging system, bad focusing, motion etc. and these kinds of defects make an image usually noisy or blur. It is important to select good noise algorithm because Noisy and Blur image may lead to wrong results.

- Noise Removal: Noise removal technique is used to detect unnecessary information that causes defects in image and it is difficult to get appropriate results. The noise can be of different types mainly salt and pepper, Poisson and Speckle. and Gaussian. In our image dataset there are the small dots occurred in background and they are removed by using Global Thresholding. We used grey thresh function on whole image to get the threshold value then applied that value on full image to get foreground object [16].
- Negative Transformation: Negative images are useful for enhancing white or grey detail embedded in dark regions of an image and we need white pixel for foreground that's why applied negative transformation technique.

$$S = (l - 1) - r \tag{5}$$

Figure 7. Results after applying image restoration Techniques

Hair

After applying different techniques, it is possible that some information left which may lead to bad results and they may be thick hairs on an image. For removing thick hairs, we used morphological operations.

Morphological operations: The most widely used of these compound operations are: opening and closing [17]. Firstly, in our case we applied closing and then opening. The equations used for applying these techniques are discussed below:

- The closing of image f by structuring element s, denoted by f * s is simply a dilation followed by an erosion.

$$f \circ s = (f \oplus s) \ominus s \tag{6}$$

- The opening of image f by structuring element s, denoted by f o s is simply an erosion followed by a dilation.

$$f \circ s = (f \ominus s) \oplus s \tag{7}$$

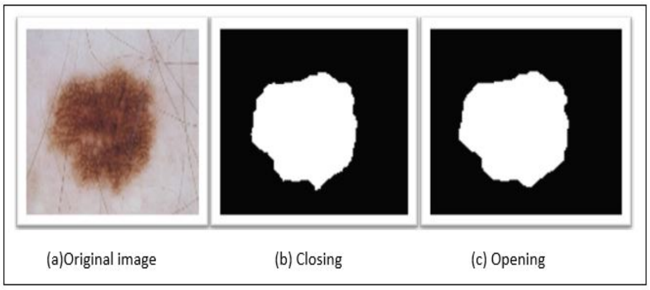

Figure 8. Results after applying Morphological Techniques

Removing disk object

There are some images where a disk object is also present. The system also detects the disk object from images and remove disk from original image to get the final segmented object. For removing disk, we first convert RGB image to HSV then we get the mask of image by performing AND operation with h and v channel of HSV space [19]. Apply morphological operation on resultant image to get the disk mask. Disk mask extraction process illustrated in Figure 9.

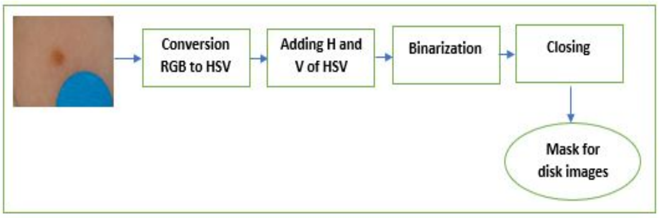

Figure 9. Disk removal mask

This disk mask is used to remove the disk object from images. we applied disk mask to get the resultant image in which the area of segmented object is found that shown in Figure 10.

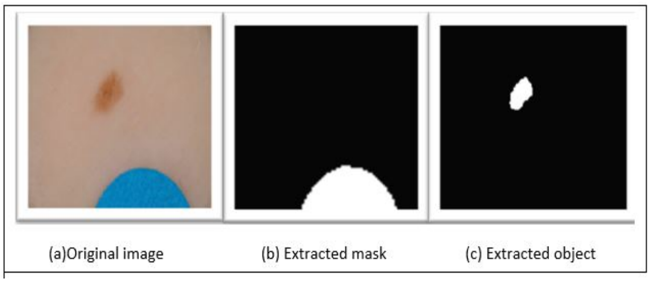

Figure 10. Results of disk removing

4. Result and discussion

4.1. Evaluation metrics

The metrics used for evaluation are:

Pixel Level Accuracy:

$$AC = \frac{TP+TN}{TP+FP+TN+FN} \quad (8)$$

where TP, TN, FP, FN, refer to true positive, true negative, false positive, and false negatives, at the pixel level, respectively. Pixel values above 128 were considered positive, and pixel values below were considered negative.

Pixel-level sensitivity:

$$SE = \frac{TP}{TP+FN} \quad (9)$$

Pixel-level specificity:

$$SP = \frac{TN}{FP+TN} \quad (10)$$

Dice Coefficient:

$$DI = \frac{2.TP}{2.TP+FP+FN} \quad (11)$$

Jaccard Index:

$$SE = \frac{TP}{TP+FP+FN} \quad (12)$$

4.2. Dataset

ISIC Dataset

The worldwide skin Imaging Collaboration (ISIC) is an international effort to enhance melanoma diagnosis which has currently begun efforts to combination a publicly available dataset of dermoscopy images. This venture leveraged a database of dermoscopic skin images from the ISIC data Archive. It contains 13642 images. The associated clinical metadata has been vetted through identified cancer professionals. large and worldwide participation in image contribution ensures that the dataset carries a representative clinically relevant pattern. The overarching intention of this task turned into offer a "image" from the ISIC Archive to guide improvement of computerized melanoma analysis algorithms from dermoscopic images. The assignment became divided into three elements corresponding to every level of lesion analysis: lesion segmentation, lesion dermoscopic characteristic detection, and lesion classification. We performed our analysis on 1500 images out of which 50\% divided into training phase and 50\% divided into testing phase. Our main focus is to perform Segmentation accurately.

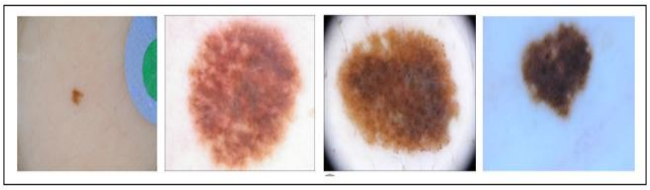

Figure 11. Images from ISIC Melanoma Dataset

Table 2. Comparison results of Proposed Methodology

Accuracy	Dataset1	Adria et al. [8]	Gutman et al. [14]
Sensitivity	78%	78%	39%
Specificity	71%	79%	96%
Accuracy	77%	81%	96%
Dice Coefficient	85%	-	12%
Jaccard Index	81%	-	7%

PH2 Dataset

PH2 dataset is used to evaluate the performance of proposed system for the detection of melanoma. Dataset contains 200 dermoscopic images including 80 common nevi, 80 atypical nevi and 40 melanomas, making up 160 non-melanomas and 40 melanomas. Each image is 8-bit RGB, compressed in JPEG format with the resolution of 768x560. Some of the images from PH2 dataset are shown in Figure 12.

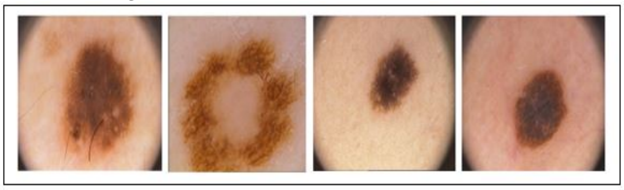

Figure 12. Images from PH2 Melanoma Dataset

Table 3. Comparison result of Proposed Methodology

Accuracy	Dataset2	Otsu-R [15]	Otsu-RGB [15]
Sensitivity	91%	87%	93.6%
Specificity	83%	85.4%	80.3%
Accuracy	90%	84.9%	80.2%
Dice Coefficient	92%	-	-
Jaccard Index	84%	-	-

4.3. Limitation

After applying different techniques our approach detects melanoma accurately, but it has some limitations as well. When the melanoma and the skin colour have same contrast and intensity values are greater, so the detected segment of the image turns into foreground and when intensities are lower it turns it into the background. Another limitation is when the skin lesion is too small it detects as a noise and when applying noise removal techniques, so the lesion is not detected properly.

4.4. Results

Experiments that are performed using proposed methodology are shown in Table 4.

Table 4. Comparison with the Existing Methods

Methods	Accuracy
Otsu-R	84%
Otsu-RGB	80.2%
Adria et al. [8]	81%
Dataset-1	77%
Dataset-2	90%

We applied proposed methodology on dataset and results of dataset images are shown in Figure 14. ISIC dataset is divided into three sets, training, validation and testing set to perform the segmentation. we were using 1500 image of ISIC dataset for performing these experiments. we also evaluated our algorithm on PH2 dataset sets. Performance of our proposed methodology are shown in Table 3.

Experimental results are investigated by measuring performance of system using pixel level features. It is observed that combination of techniques of pre-processing perform better than using separately. While the better performance is achieved using PH2 dataset.

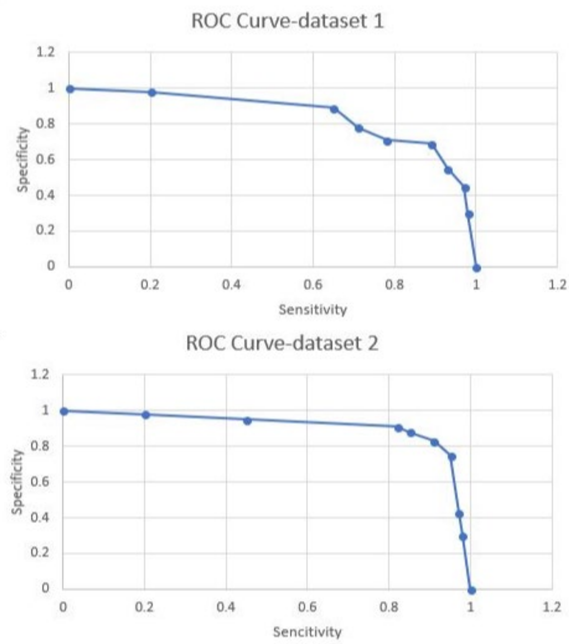

Figure 13. ROC curves

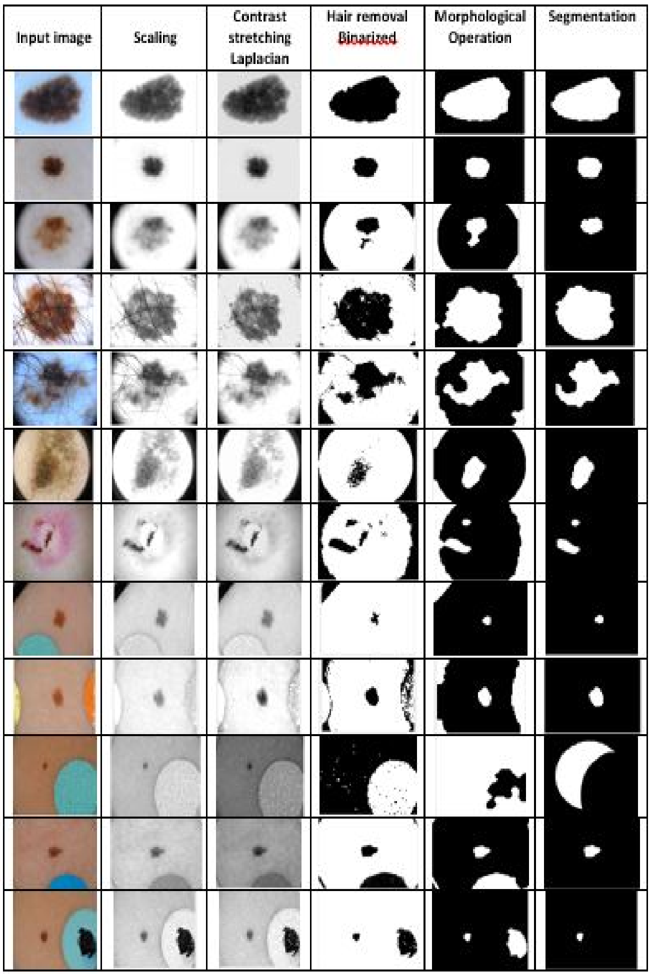

Figure 14. Implementation Results applying on different type of images

5. Conclusion

By applying these different techniques, we can conclude that the object can be identified in the end result. We enhanced the image by applying scaling, contrast stretching and Laplacian filter. It gave us the enhanced version of image. For removing unnecessary objects that disturbed the foreground we removed them by using noise removal techniques and for extracting foreground object from background we applied binarization and morphological operations which detect the object of interest in the end result. After the detection of object some images may be left with some objects which are not melanoma and also have some issues which maybe deal in Segmentation step. In Segmentation steps we first remove white corners from image by applying a mask then to remove disk object we convert image from RGB to HSV. After performing AND operation with enhanced image we find our object of interest for further post-processing. We didn’t get accurate results on some images which divide the image into different regions for that feature extraction and classification methods should be used for better results. Overall for enhancement and segmentation steps we achieve accuracy, sensitivity, specificity, dice coefficient has 77\%, 78\%, 71\%, 85\% respectively. Jaccard index evaluation is performed at runtime. In comparison of dataset 1 results to dataset 2. we achieve accuracy, sensitivity, specificity, dice coefficient and Jaccard index have 90\%, 91\%, 83\%, 92\%, 84\% respectively.

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