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Deep CNN Based Skin Lesion Image Denoising and Segmentation using Active Contour Method

Abstract- *Automatic skin lesion segmentation on skin images is an essential component in diagnosing skin cancer. Image de-noising in skin cancer lesion is a description of processing image which refers to image restoration techniques to develop an image in predefined touch. Then de-noising is the crucial step of image processing to restore the right quality image after that which can use in many processes like segmentation, detection. This work proposes a new technique for skin lesion tumor denoising and segmentation. Initially, using Deep Convolution Neural Network (CNN) to eliminate noise and undesired structures for the images. Then, a new mechanism is proposed to segment the skin lesion into skin images based on active_contour straight with morphological processes. Different noise removal and segmentation techniques on skin lesion images are applying and comparing. The proposed algorithm shows improvement in the results of both noise reduction and segmentation.*

Keywords- *Convolutional Neural Networks, Skin Cancer, Denoising, Segmentation.*

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1. Introduction

Skin cancer is currently one of the fastest-growing tumors worldwide, and melanoma is the most life-threatening form of skin cancer [1-2]. Computer-aided diagnostics of skin disease is one of the more problematic difficulties in medical image processing [3-5]. That will help the doctor to select if a skin tumor is benign or cancerous. Unfortunately, skin image gets affected with noise at some point in the image acquirement and communication phase.

Image noise reduction helps reduce noise, interpolation, and smoothing. The image is filtered through various techniques that depend on the behaviour and image type; this process help to remove noise from the image though conserving the specifics of the original image.

In this paper, the CNN denoising method to perform image filter was used. The benefit of using CNN denoising is that it always improves the weights of the convolution kernel during the training network. CNN denoising design for comparison with classical linear and nonlinear filtering methods. From the efficiency of filtration processes, noise reduction through CNN proposed model showed better performance in comparison to other types. This method is used to maintain image quality and crutial features in the noise removal process, which has a significant impact on the useful and accurate segmentation of the tumor portion of the image.

The segmentation is a vital processing method utilized to study the image and analyze the image into some attractive regions according to several properties such as; texture, grey level, color, and intensity. Recently, significant challenges have been highlighted for research and development activities in the segmentation of skin cancer images. In the rest of the paper, Part II presents the relevant work, section III details of the proposed method, section IV highlights and discusses the results, and section V concludes the work.

2. Related Works

Skin cancer has been attracting the attention of medical and sciatic communities in the last years because of its high prevalence reign with sever treatment. Although noise in medical images is a trouble for the reason that it can obscure and blur important characteristics in images, many of the proposed noise reduction techniques must own problems. In the past two decades, many studies have proposed nonlinear methods of change, such as the overall reduction [6].

Recently, many ways of filtering the Wiener method have expanded to other linear transforms. A commonly discuss technique is the wavelet threshold scheme, which has been identified by a wavelet transform procedure for a noisy image. A random noise will be represented primarily as small coefficients at high frequencies [7-10]. Recently, the K-SVD algorithm has been widely

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used in the field of medical image denoising [11]. These methods can effectively filter white Gaussian noise in an image and conserve image detail and texture information from the noisy image itself [12].

Convolution Neural networks are used to eliminate image noise because networks rely on nonlinear processes to process digital images; moreover, a nonlinear model can be built to reduce image noise without prior knowledge. At the same time, the possibility of parallel processing of neural networks enables the possibility of reducing image interference and speeding up the process of reducing image confusion [13]. Besides, Soft computing principles like Genetic Algorithms (GA) and Fuzzy Logic (FL) are also be used in designing algorithms for speckle noise reduction in medical images [14-15]. The development of convolution neural network theory, and the increasing image processing problems became possible to treat these problems through a variety of types of networks that have achieved good results. When considering the problems mentioned above, and the application of some of the most potent methods is the convolution neural network to the field of image noise reduction [16]. Segmentation is used as a critical issue in processing digital images to describe and classify the image. There are different methods of the segmented image. An active contour is an active process of segmentation techniques, and to separate the area of interest, the power and force constraints are used in the image. The active environment specifies separate boundaries or curvature of the object to be fragmented. There are many constraints on which the contour depends, based on their classification in different types such as gradient vector flow, balloon models and engineering models. Threshold segmentation represents the most straightforward technique utilized in the image segmentation. The threshold is selected manually by using the histogram of each image or automatically by using the algorithm of the threshold; which select automatically of each image according to the histogram process. Watershed segmentation is an efficient method in image processing. The idea of this method is striaghforward, where the entire image represents a landscape; the depth of every point represents its grey level. When the rain falls on the terrain, the watershed represents the line that distinct catchment basins. There have been many works done in the field of image segmentation using different techniques. Much is done based on different applications. Table 1 presents the results of previous works to diagnose skin cancer based on different algorithms, so higher accuracy of skin cancer diagnoses is the plan of each researcher that trying to stratify.

Table 1: Results of previous works to diagnose skin cancer based on different algorithms

Authors	Features	Classification	Algorithm	Accuracy
Lau and Al-Jumaily [7]	2-D wavelet packet	2 class	BNN	89.9%
			AANN	80.8%
Mahmoud and et al. [10]	wavelet	2 class	BNN	55.94%
	curvelet			70.44%
Sheha and et al. [3]	GLCM features	2 class	Traditional MLP	92%
Mhaske and Phalke [8]	2-D wavelet	2 class	K-means	52.63%
			BNN	60% -75%
			SVM	80% -90%
Alasadi and Alsafy [1]	color, texture and Geometry features	4 class	ANN	93%.
Sharma and Srivastava [5]	2D wavelet transform	2 class	BNN	91%
			AANN	82.6%
Victor, and Ghalib [2]	Area, variance, mean and standard deviation	2 class	SVM	93.70%
			KNN	92.70%
			DT	89.50%
			BT	84.30%

3. The Proposed Method

The proposed algorithm of skin lesion tumor extraction consists of many stages. Figure 1 shows the stages used to denoising and segmentation of skin lesion tumor. Image preprocessing is a necessary step for skin lesion detection by eliminating noise and improve image quality. In this paper, use the convolution neural network (CNN) model for image denoising is presented. The next step after preprocessing is recognizing and segmenting the region of interest (ROI), which shows the area of the tumor. In this research, a new mechanism was proposed to segment the skin lesion image. The mechanism is based on an active contour and then the application of the morphological processes.

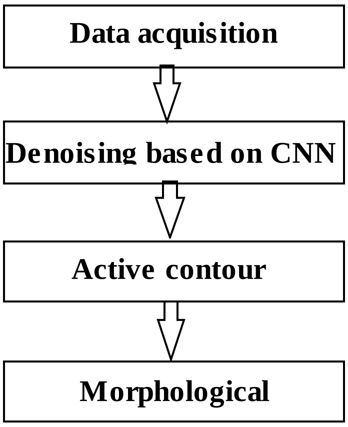

Figure 1: block diagram of the provided approach

I. Deep CNN

CNN is a set of neural networks with many various convolution layers that can be trained to select features from images and the majority used for analyzing images for computer vision responsibilities. During the training phase, Deep CNN will reduce the difference between its current model and rated components. In this process, the features of the different metrics are also extracted in the different wrapping layers. This process will allow reliable detection of structural components and their classification in evaluating a new input image. Thus, Deep CNN can be used to classify the skin lesion in the dermatoscopy data collection. However, the Deep CNN method is not a widely used tool by dermatologists in analyzing skin lesions. Because of the challenges posed by artifacts, deviations, and noise in the Dermoscopy data collection, which prevents robust detection of skin cancer. Also, there is a wide variation in the dermoscopy data set, which may contain skin lesions with structural features and similar color. For example, seborrheic seborrhea (SK) - a benign disease - may be difficult to distinguish from skin cancer. Therefore, an extensive training data set should be used to train the traditional DCNN model, which creates roadblocks for the practical application of Deep CNN technology.

II.Denoising based on Deep CNN

In this paper, use the CNN model for image denoising is presented. Convolution neural networks capable of discovering patterns in images every convolution layer have several filters, and these filters detect the pattern, as shown in Figure 2. Deep CNN Layers proceeds layers of the denoising CNN for gray images. The size of the ConvNet 1×59 layer, is to provide an image input array. In order to facilitate the comparison process, we normalized floating pixel values as a number in [0, 1] of class 1. This layer is the first part of the model CNN. Preference is made improvements and filtration in this layer. The initial size of the ConvNet is 11 × 11 and is adaptable to improve better the image based on practical training. All layers have ReLU is used to send out harmful value. The RGB value of the input ranges from 0 to 255. The size of filter 3×3 and the number of filters is 64 in the convolution layer.

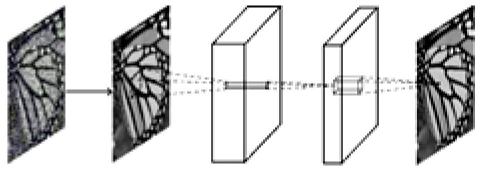

Figure 2: Layers of image denoising.

III. Proposed Segmentation method

In this work, after the active contours, the post-processing processes are performed to find the final split binary result, by keeping large binary objects connected and joining the adjacent binary areas. The processed image at this stage may contain holes because of the difference in the severity of the skin lesion. Therefore, morphological processes are performed to fill the holes and remove any additional elements other than the skin.

Morphology represents powerful tools are used for the representation the section shape in the image processing. Morphological operations comprise two combinations of operations firstly, erosion and dilation — secondly, opening and closing. Often, combinations of these operations are used to perform morphological operations, Opening operation, smoothest the boundary of the object, and removes thin overhangs. In opening operation, extra added pixels can be removed. The closing operation is used to reduce small holes and filling the holes in the boundary region — morphological operators used for both pre and post-processing from reducing the noise and preserving the shape.

4. Result and Performance Analysis

In this section, simulation results are presented, which was performed on PH2 - Dermoscopic Image database [17]. In this database, dermoscopic images are already segmented by specialist physicians for reference. There are 160 in-demelanomadermoscopic images with 40 melanoma from the database. The chief goal of the experimental work of this paper was to prove the achievement of our suggested method in the image de-noising based on the CNN model and the proposed segmentation method. The first step is to denoised the skin lesion images using a deep neural network. The performance of the proposed method is compared with the Wiener filter, average filter, and median filter, as shown in Figure 3.

The comparison of techniques to achieve the most efficient filter on different noises has been estimated by the (PSNR) and (MSE) which are the popular indexes use to compare the original and image after de-noise.

$$PSNR = 10\log_{10}\frac{peakval^2}{MSE} \qquad (1)$$

$$SSIM(x,y) = \left[l(x,y)\right]^{\alpha}\left[c(x,y)\right]^{\beta}\left[s(x,y)\right]^{\gamma} \qquad (2)$$

Generally, when the image has a higher PSNR that means higher quality and less noise from the image. Also, Structural similarity index (SSIM) for measuring image quality. The trials have done on ten digital images. Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) values usually estimate the de-noising performance of these different techniques, as shown in Table 2.

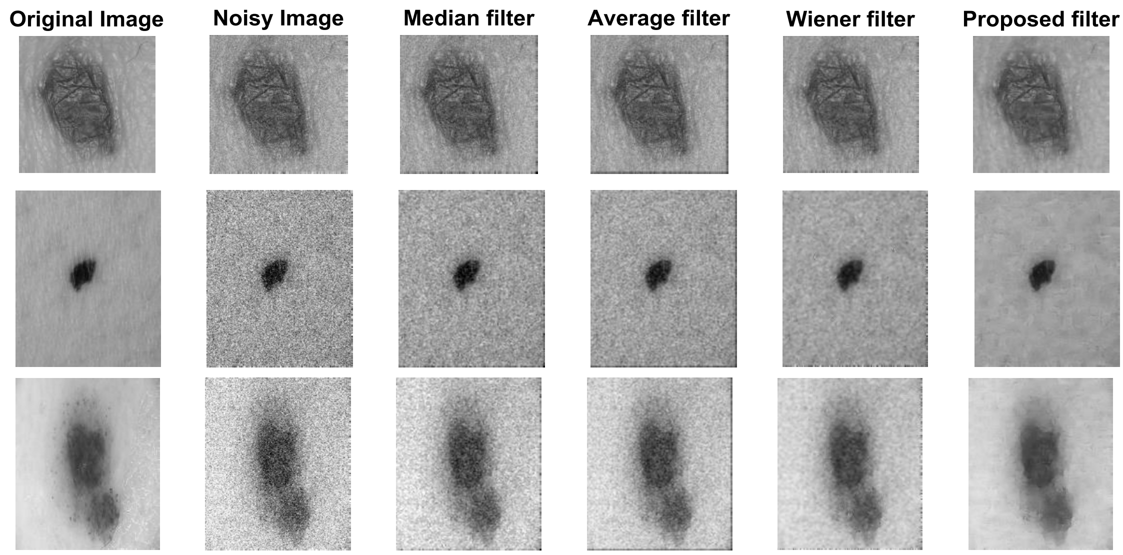

Figure 2: Denoising skin lesion image using different de-noise filters with Gaussian Noise (Variance=0.3)

In order to perform various retail segmentation techniques, including the proposed technique in this paper, statistical methods based on Dice Coefficients *(DC)* and Jaccard index *(JI)* are used. DC is a measure of similarity used mostly in medical image processing to evaluate the performance of segmentation algorithms that have truth-based information on the predefined ground.

JI is also similar to that of the dice index used to calculate the similarity between two sets of images. It also measures the difference or dissimilarity between the two images.

$$DC(A,B) = 2\left|intersection(A,B)\right|\left(\left|A\right|+\left|B\right|\right) \qquad (3)$$

$$JI(A,B) = \left|intersection(A,B)\right| / \left|union(A,B)\right|$$
(4)

The result of different segmentation techniques shown in Figure 4. Table 3 show the performance of different segmentation techniques.

Table 2: Numerical Results using different denoising filters.

Data	Wiener Filter			Average Filter			Median Filter			Proposed		
	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM
1	56.5	30.60	0.69	106.6	27.85	0.58	118.3	27.40	0.50	33.61	32.86	0.77
2	77.72	29.22	0.69	99.01	28.17	0.65	126.3	27.11	0.56	54.97	30.72	0.75
3	98.28	28.20	0.68	119.2	27.36	0.67	135.6	26.80	0.60	70.68	29.63	0.75
4	61.75	30.22	0.69	112.5	27.61	0.60	120.	27.3	0.52	42.43	31.85	0.75
5	53.76	30.82	0.70	97.62	28.2	0.57	115.8	27.49	0.48	27.07	33.80	0.81
6	49.48	31.18	0.73	86.37	28.76	0.58	111.7	27.64	0.49	22.71	34.56	0.85
7	103.5	27.98	0.62	133.9	26.86	0.59	148.6	26.40	0.52	73.77	29.45	0.72
8	62.26	30.18	0.7	99.26	28.16	0.59	120.7	27.31	0.51	36.94	532.4	0.79
9	62.28	30.18	0.73	102.7	28.01	0.63	117.5	27.42	0.55	42.46	31.85	0.79
10	58.1	30.48	0.70	97.26	28.25	0.57	119.7	27.34	0.48	31.25	33.18	0.81

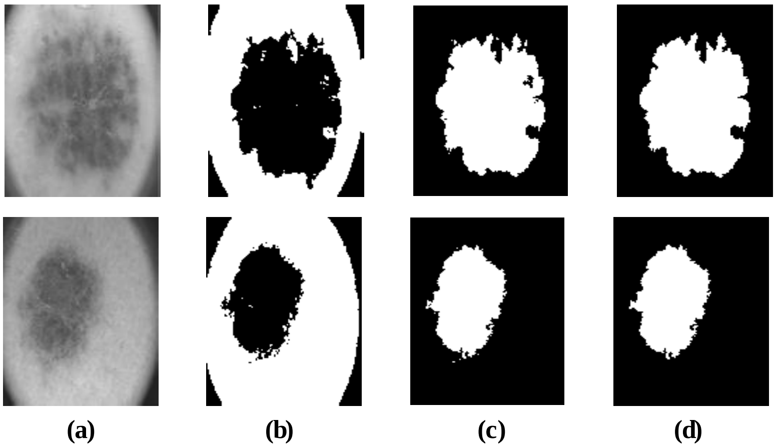

Figure 4: Results of different skin lesion segmentation techniques: (a)original image (b)Otsus method (c) Watershed method (d) Proposed method.

Table 3: Numerical Results of different skin lesion segmentation techniques

Sample	Watershed method		Otsu's method		Proposed Method	
	JI	DC	JI	DC	JI	DC
1	0.87	0.78	0.13	0.07	0.95	0.91
2	0.85	0.74	0.23	0.13	0.94	0.91
3	0.88	0.78	0.07	0.03	0.87	0.77
4	0.94	0.90	0.06	0.03	0.85	0.75
5	0.95	0.91	0.05	0.02	0.84	0.72

5. Conclusion

In this article, presented a new idea of the method that relies on the convolution neural network (CNN). Using a CNN model for denoising images have an advantage for speeding up the training process and also improve the denoising performance of the model. Table 1 show result for image enhancement methods such as median filtering, Wiener filtering, average filtering, and CNN denoising. The best performance for the CNN method superior to the two other filters and close performance to the median filter. The segmentation process used an active contour method and then applied a Morphological Operator to remove the small objects from the region around the tumor.

Tested many types of segmentation such as Watershed, Otsu's and active contour method and improved that active contour with Morphological Operator given the best result as showed in the Table 3.

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