Skin Lesions Segmentation by Intelligent Water Drop Algorithm

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Abstract: Technology help human being at different activity of life directly or indirectly. Our of various area of technology health support plays an vital role to medical professional for diagnosis of diseases. This paper has proposed a model that segment skin lesions from the image. In order to do lesion segmentation proposed Skin Disease Diagnosis by Genetic and Water Drop SDDGWD model extract color feature from the image. SDDGWD use intelligent water drop genetic algorithm to get pixel set as a cluster center for lesion segmentation. Experiment of proposed model SDDGWD was done on skin lesion real dataset images. Evaluation of model was done on various comparing parameters and result shows that SDDGWD improve performance of segmentation with correct class prediction.

Index Terms— Image Processing, Medical Image Diagnosis, Feature Extraction, Segmentation.

I. INTRODUCTION

The technological advances had resulted in the emergence of several interconnected medical applications and tools to revolutionize the medical health care system. This stronglysupports the doctors, health care professionals, and patients to share medical information while providing important medical consultations over the Internet. Although rising interest in skin cancer diagnosis had led to the identification of skin lesion patients who are at higher risk of development of skin cancer that is widely used as a personalized surveillance approach [1]. Automated systems for unbiased diagnosis are required for pigment lesion inquiry. It really has piqued the interest of scientists throughout the last many decades. These systems include or before, feature extraction, separation, classification, and postprocessing. The dermatological lesion must still be properly identified and subdivided. Because recent developments in machine learning algorithms and dermoscopic techniques have reduced the frequency of misinterpretation, the emphasis on desktop systems has increased dramatically in recent years [2, 3].Adegun and Viriri [3] investigated skin lesion segmentation operations under four classes: threshold- and clustering-based [4], edge- and region-based [5], conventional intelligence-based [5], and deep learning methods. They identified the pros and cons of each class. According to their results, the first three methods have disadvantages affecting the segmentation performance, while the last one has no disadvantages impinging on segmentation. Moreover, deep learning methods can analyze complex problems better than conventional methods. There are numerous analytical approaches to medical image analysis. However, recent years have witnessed a dramatic increase in the size and complexity of data and significant advances in computer hardware/software systems. These developments have resulted in the spread and improvement of deep learning methods to analyze medical images with high accuracy and precision.

This paper was organized into few section where second section shows the related work portion brief the skin lesion segmentation models proposed by other researchers. Futher proposed methodology explained the SDDGWD model with input of image to segmentation. Then experimental work was shows the performance of proposed work on different evaluation parameters. Finally whole work get concluded.

II. Related Work

Bin Yu et. al. in [6] create a new multi-scale channel attention module – MS-CA, which can display more accurate and relevant feature channels on multiple scales. And a network segmentation model for multi-scale channel attention (MS-CA) is proposed. The network model embeds the MS-CA module into two different types of benchmark networks, and modifies the two types of benchmark network models to obtain an image segmentation model suitable for skin diseases.

K. Roy et. al. in [7] learn image processing techniques like adaptive thresholding, edge detection, K-means clustering and morphology-based image segmentation have been used to identify the skin diseases from the given image set. The acquired image set was pre-processed by deblurring, noise reduction and then processed. Depending on the definite pattern (pertaining to a distinct disease) present in the processed image the disease is detected at the output for a corresponding input image.

Sudhriti et. al. in [8] better skin lesion detection, an improved colour space-based split and merge process in combination with global thresholding segmentation technique has been proposed. The obtained results have been further enhanced by self-guided edge smoothing-colour space technique. The effectiveness of the proposed self-guided edge smoothing-colour space technique has been verified by quantitatively comparing the obtained results with the existing Otsu thresholding, adaptive thresholding and colour space techniques.

Hongfeng et. al. in [9] present a review on deep learning methods and their applications in skin disease diagnosis. We first present a brief introduction to skin diseases and image acquisition methods in dermatology, and list several publicly available skin datasets. Then, we introduce the conception of deep learning, and review popular deep learning architectures and popular frameworks facilitating the implementation of deep learning algorithms.

Son, H.M. et. al. in [10] shows that CAD may also be a viable option in dermatology by presenting a novel method to sequentially combine accurate segmentation and classification models. Given an image of the skin, we decompose the image to normalize and extract high-level features. Using a neural network-based segmentation model to create a segmented map of the image, we then cluster sections of abnormal skin and pass this information to a classification model.

R. Ramadan et. al. in [11] proposed, The Single Input Color U-Net (SICU-Net), the Dual Input Color U-Net (DICU-Net), and the Triple Input Color U-Net (TICU-Net) are three novel variants of the U-Net model that have been proposed. These variants have single, dual, and triple inputs, respectively. Single, dual, and triple encoder sub-networks are present in the architecture of SICU-Net, DICU-Net, and TICU-Net, respectively, and are only linked together through a single decoder path. Every encoder sub-network is given a different colour space to work with based on the input image. In order to generate a segmented image map, a channel-wise attention module is utilised to fuse the contribution of the learned feature maps from each encoder sub-network. These maps are then fed to the decoder sub-network. In addition, a composite loss function has been developed with the intention of enhancing the overall performance of the suggested CU-Net models.

III. Proposed Work

Proposed Skin Disease Diagnosis by Genetic Water Drop SDDGWD model was explained in this section of paper for image lesion segmentation. The aim of this model is to separate the skin tissues from the non-skin intracranial tissues. Figure 1 is block diagram of various steps of image segmentation by IWD (Intelligent Water Drop) genetic algorithm. Segmented image obtained from genetic algorithm was blocked into mxm two dimension matrix. This work use different abbreviation for detailing of model, so list of those set is shown in table 1.

Input skin image (a)

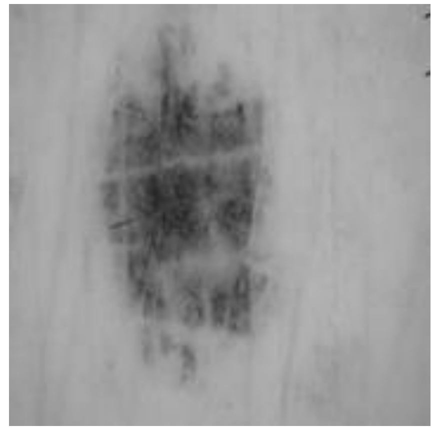


Image after (b)

Fig. 2 Pre-processing of skin image.

Image Pre-Processing

Input image was transformed into fix size dimension pxq as blocked image was passed for the training of neural network. In order to reduce the calculation cost proposed model transform resized image into gray format [12]. So if input image SI is RGB or HSV format then its equivalent gray pixel values were used. This work uses gray color feature for the segmentation of image.

IWD Algorithm

In Intelligent Water Drop (IWD) algorithm a drop moves towards other drop and form a group as per low resistance known as soil for the merging of drops. In this paper drop is pixel and soil is pixel value difference. So a soil values between each drop was summarize in a graph. As graph has node so unique pixel counts are present as graph nodes. While distance between each node from other node act as weight or soil in graph.

$$Soil(x, y) = \text{Euclidian}(p1, p2) \text{ --Eq. 1}$$

Where p1, p2 are node values in graph Soil, and Soil(p1,p2) is distance between pixels.

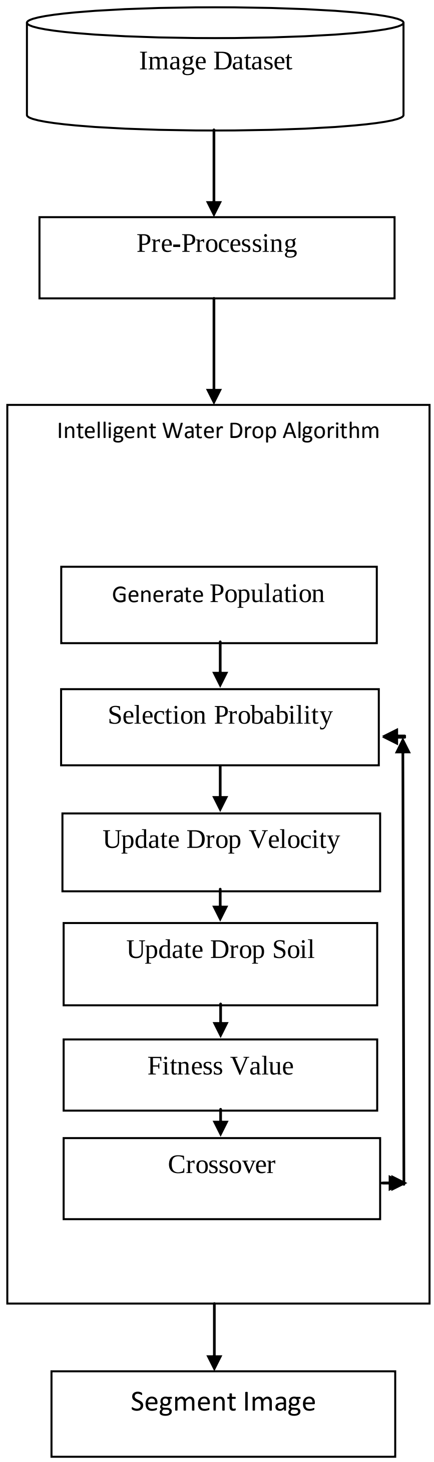


Fig. 1 Image segmentation by intelligent water drop genetic algorithm.

Static and Dynamic Parameter

In this step some of constant were initialize before the start of algorithm such as soil updating parameters $S_1 = 1$, $S_2 = .01$, and $S_3 = 1$, velocity updating parameters $V_1 = 1$, $V_2 = .01$, and $V_3 = 1$. Finally global and local soil constants β_L and β_G are initialize by 0.9 [13]. Values of constants may be vary as per algorithm requirement.

Table 1 SDDGWD model notion list.

Notations	Meaning
SI	**Skin Image**
PSI	**Processed Skin Image**
Soil	**Distance between pixel**
s	**Number of Segment**
SWD	**Skin Water Drops**
DF	**Drop Fitness**
SSDI	

Population Generation

Random set of pixels were collect as a cluster center candidates. Collection of these candidates were termed as population. Each candidate have s pixel value set which is also known as chromosome [12]. So if population PW has n number of candidates then Eq. 2 gives population set for processed image PSI.

SWD←Population_Generation(PSI, s, n)----Eq.2

Drop Movement Probability

Association of a drop towards another drop depends on movement probability. So as per soil weight value obtained from [14]

$$\mathrm{WS(i,j)} = \begin{cases} \mathrm{Soil(i,j)} & \text{if min (Soil(i, all nodes)} > 0 \\ & \text{Otherwise} \\ \mathrm{Soil(i,j)} - \text{min (Soil(i, all nodes)} \end{cases} \quad \text{--Eq. 3}$$

$$\mathrm{FS(i,j)} = \frac{1}{\delta + \mathrm{GS(i,k)}} \text{-----Eq. 4}$$

$$\mathrm{DMP(i,j)} = \frac{\mathrm{FS(i,j)}}{\sum_{k=1}^{N} \mathrm{FS(i,k)}} \text{ -----Eq. 5}$$

Movement Probability MP was evaluated by eq. 3 and 4. FS is feasible value solution as per soil.

Update Drop and Soil Values

Drop movement change velocity of drop as per soil and merging drop velocity. So eq. 5 gives velocity update value for tth iteration.

$$\mathrm{DV(t+1)} = \mathrm{V(t)} + \frac{\mathrm{V_1}}{\mathrm{V_2} + \mathrm{V_3} * \mathrm{Soil(D, D'')^2}} \text{-----Eq. 6}$$

Similarly soil value was update by Eq. 6.

$$\Delta S(\mathrm{D, D''}) = \frac{\mathrm{S_1}}{\mathrm{S_2} + \mathrm{S_3} * \mathrm{T(t+1)^2}} \text{ --------Eq. 7}$$

$$T(t+1) = \frac{h}{V(t+1)} \text{---Eq. 8}$$

$$Soil(i,j) = (1 - \beta_L) * Soil(i,j) - \beta_L * \Delta\mathrm{S(i,j)} \text{---Eq. 9}$$

Where v_1, v_2, h, s_1, s_2, s_3, β_L are constant range between 0 to 1.

Fitness Function

Each chromosome fitness was evaluate by eq. 7. As per cluster center other pixel values were grouped into minimum value cluster center. Summation of each pixel difference was done to get single fitness value.

$$DF \quad = \sum_{x=1}^{Column} \sum_{y=1}^{Row} Min(SWD_s - PSI(x,y))^s \text{--------Eq. 10}$$

Where DF is drop fitness value and $SWD_{c,s}$ is cluster center pixel in chromosome for s number of segment.

Fig. 3 Infected region in skin image.

IWD Crossover

Some groups of chromosomes were prepared and good solution in a group was consider as the local parent which crossover with other chromosome in the group [13]. In crossover one of random position pixel value was copy from the local parent chromosome and replace same position other chromosome pixel value of same group. Obtained new chromosome was further evaluate to get its fitness vale if new chromosome fitness value was better then group chromosome then it replace one of poor parent in population otherwise parent will continue.

Segment Image

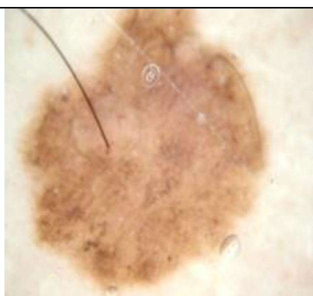
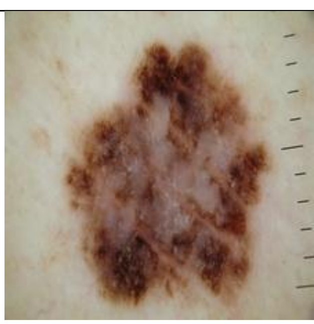
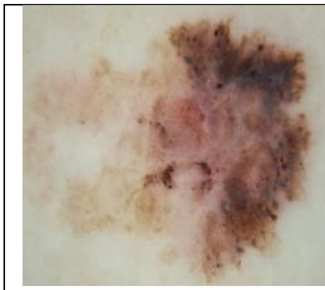
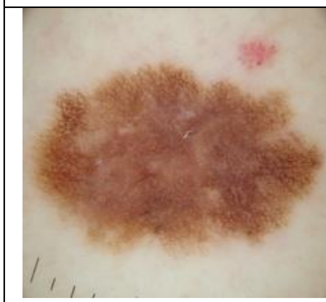
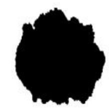
After completing maximum number of T iteration IWD get breaks and fitness value DF of final population SWD gives segment representative pixel set shown in Eq. 11. This pixel set segment whole image into infected and non infected region, shown in fig. 4. Infected region is represent by black color while other potion of image is white.

SSDI$\leftarrow$(PSI, Best(SWD, DF)) ---Eq. 11

IV. Experiment and results

Proposed model was developed on MATLAB software. Experimental system have 4 GB RAM, I3 6^{th} generation processor and windows 10 operating system. Comparing model are SICU-Net in [18]. Experimental dataset was taken from [15] and detail explanation of input images has dimension 224x224, RGB format. Table 2 shows the dataset images.

Table 2 Input Dataset Images.

Input Image	Segmented Image
	
	
	
	
	

Results

Table 3. Skin lesion segmentation models accuracy values.

Skin Image	SDDGWD	SICU-Net
Skin-Set-1	96.6914	93.4497
Skin-Set-2	90.4136	83.0127
Skin-Set-3	93.1605	86.905
Skin-Set-4	94.6944	90.055
Skin-Set-5	92.5123	85.7262

Accuracy of skin region segmentation techniques were shown in table3. It was found that proposed SDDGWD model has improved the performance by 6.05% as compared to previous SICU-Net. Use of genetic algorithm for segmentation with color feature in gray format has perform well.

Table 4. Skin lesion segmentation models precision values.

Skin Image	SDDGWD	SICU-Net
Skin-Set-1	0.9585	0.9686
Skin-Set-2	0.8327	0.8631
Skin-Set-3	0.8766	0.9208
Skin-Set-4	0.9231	0.947
Skin-Set-5	0.8786	0.8893

Skin lesion region segmentation models precision values shown in table 3. Use of IWD algorithm has increased the learning of convolution model.

Table 5. Skin lesion segmentation models recall values.

Skin Image	SDDGWD	SICU-Net
Skin-Set-1	0.9996	0.9636
Skin-Set-2	0.9992	0.956
Skin-Set-3	1	0.9392
Skin-Set-4	0.9991	0.9478
Skin-Set-5	1	0.9597

Use of genetic algorithm intelligent water drop for lesion image segmentation has increases the work performance. As table 5 shows the improved recall value of proposed SDDGWD model by 4.6% as compared to SICU-Net. It was found that paper has enhanced the false class diction as well.

Table 6. Skin lesion segmentation models f-measure values.

Skin Image	SDDGWD	SICU-Net
Skin-Set-1	0.9786	0.9661
Skin-Set-2	0.9084	0.9072
Skin-Set-3	0.9342	0.9299
Skin-Set-4	0.9596	0.9477
Skin-Set-5	0.9354	0.9231

Skin lesion region segmentation models precision values shown in table 3. It was found that SDDGWD model has improved the parameter by 0.89% as compared to SICU-Net model. Use of IWD algorithm has increased the learning of convolution model.

V. CONCLUSION

Medical reports diagnosis depends on experience and that is achieve in years but such specialist availability is tough. So computer vision learn such things and reduce the working load of hospitals. This paper has proposed a medical image segmentation technique that finds the lesion region in image. As each image is different from other hence genetic algorithm based cluster centers were identified to identify infected region and non infected region. Intelligent water drop genetic algorithm gives good set of cluster center without any training or prior knowledge. Experiment was done on read dataset images and implementation results shows that proposed SDDGWD model has improved the infected region segmentation identification. Result shows that SDDGWD model has improved the parameter by 0.89% as compared to SICU-Net model. In future scholars can train the cluster center pixel values to get more effective results.

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