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Modeling and Anlysis for Diagnosis Skin Lesions using Modern Artificial Swarm Intelligence Techniques (MASITs)

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Abstract: MASITs provides an optimum outcomes if it is not probable to become the solutions of huge inflexible optimization difficulties. Computerized investigation of skin lesions is a significant problem in data retrieval for medical imaging,it supports human experts to enhance their choice construction for rapid and accurate analysis of unhealthy nevi and other skin diseases. In this article, computerized investigation of skin lesions has been addressed, by an adjustment of controlling swarm intelligence system (Artifical Bee Colony{ABC}).The modified system is hybridized with a search technique for improved performance. Experimental outcomes on a level of medical images of early diagnosis skin lesions confirmation that this technique outclasses conventional mathematical approaches for the cases in the standard. It is identical good and regularly higher to advanced systems in the area in relationships of mathematical accuracy. The chief benefit of the proposed technique is that this diagnosis can segment skin lesions by resolve images. So, additional comprehensive features can be found from the segmented portion of the lesion, which in turn contributes on organization medical service accuracy.

Keywords: Boundary Detection, Dermatologist, Skin Lesions, MASITs System, Medical Imaging.

1.Introduction

The image segmentation is a main zone for present study and several works has been completed for survey of this field. The nature optimization systems are very hopeful with image segmentation procedures to offer a stage for dealing out of image processing [1].

The rise in the occurrence of skin tumors lesions results from extreme exposure to the sun; persons with skin that shows visible signs of aging are particularly susceptible to pre-malignant melanoma (MM) and melanoma lesions. However, the rise in human occurrence is diminishing. According to [2], as there has been no important development in the handling of metastatic MM, it was decided that the reduction in death is associated to early diagnosis. Meanwhile, accuracy and speed in image processing systems is required for professional diagnosis through the segmentation of moles and taking out of its structures. Figure 1.shows the image of an early-level unhealthy moles.

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Figure 2. Image of an premature-stage tumor**[**2**].**

MASITs algorithms for finding optimal thresholds have increasingly gained the attention of scientists in this field to address multilevel thresholding difficulties since the computational period for result various thresholds increases exponentially with the quantity of favorite edges [3]. Compared to other approaches considered for all kinds of optimization tasks, meta-heuristic algorithms are general-solve algorithms and require no knowledge about the problem's structure [4].

There are several studies that have been prepared on skin cancer in the past few years that have grouped all the demographic data for melanoma skin cancer: occurrence rate , types of people affected survival rates, spread, and potential years of life lost [5].

A report appeared, in Canada in 2017, 6,500 and 76,100 people were diagnosed with melanoma and non-melanoma, respectively; and 1050 and 440 will die due to melanoma and non- melanoma (healthy and unhealthy nevi), respectively. The studies show that the mortality rate for all cancers is 1.6% in men in 2009 and the occurrence of all cancers in men has raised to 3.6% in 2016.We can also see the same trend in humans generally; the incidence in woman increased 2% in a year. The survival rate for melanoma skin cancer was 85 % in women and 92% in men from 2012 to 2018 [6].

In the researches of Cavalcanti and Scharcanski (2011) [7] and proposed an approach to identify pigments in dermatoscopic images of melanoma lesions. The pre-processing step corrects lesions with morphological closure operations in the ABC method. In the segmentation and suggested the use of a new method that uses text and colors to identify only the lesion area[8]. The operations performed in this step make the identification of brightness by means of a color channel normalization with an adaptive threshold. In the characteristic extraction stage, the area, perimeter, diameter, magnitude, similarity, gradients, statistics and quantization of color descriptors are prioritized[9]. In this work, the classification is performed using the KNN and decision tree methods. The tests of this approach used 220 images and their results reached a 91.7% accuracy in the identification of melanoma [10,11]. Figure 2. illustration of various categories of dermoscopic skin lesion

This article is prearranged as surveys: Section 2 designates the problem to be resolved, which is expressed an optimization method. At that point, Section 3 defines the metaheuristic system applied in this study. The organization of the article is designated in aspect in Section 4. The information our investigational outcomes. A proportional investigation of our technique with other substitutions in the arena is deliberated in that section.

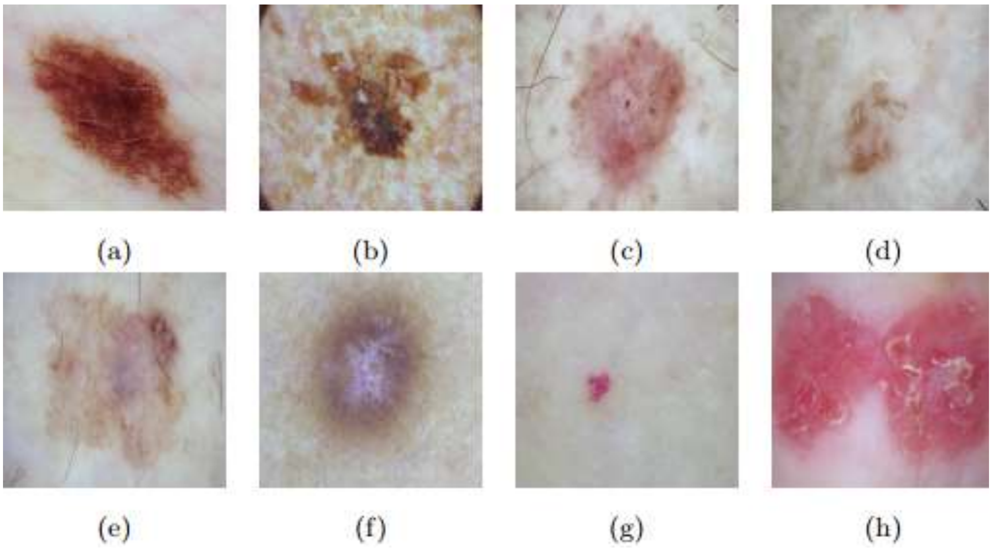

Figure 2. Diagram of various categories of dermoscopic skin lesion :- (a)Moles (b) MM (c) BCC (d) Unhealthy Keratosis (e) Healthy Keratosis (f) Dermatofibroma (g) Vascular Zone (h) SCC [9].

2.Methodology

Swarm intelligence (SI) has developed in recent years as study notices for several researchers in different regions[12].Numerous existing metaheuristics methods for image segmentation evaluation have been used to lessen comprehensive search difficulties. These metaheuristics methods have been able to provide good resolutions for difficult optimization issues and have given promising performances in enhancing the efficiency of image segmentation methods; however, as the statistics of thresholds continue to rise, there is no guarantee that optimal resolutions can be stretched[13]. Table 1. presents several of the examples of metaheuristic methods for image segmentation evaluation. Furthermore, the computational difficulty of these meta-heuristic algorithms makes it problematic to use in real-life situations [14,15,19,35, 38-42]. Diagram of the ABC algorithm is assumed in Figure 3.

Table 1. Nature inspired metaheuristic methods for image segmentation evaluation[13].

Authors	Algorithm	Method
D. Karaboga [14]; Li et al. (2015)[15]; Zhu and Kwong (2010)[16] ; Cuevas et al.(2012)[17] ;M. A. Al-masni et al.; [18]; Dey et al. [19]; A. Esteva et al. [20].	ABC	Inspired by the intelligent behaviour of honeybees
Hammouche, Diaf and Siarry (2008)[21] ; Oghuz et al. (2015) [22]; Sun et al. (2016)[23].	Genetic Algorithm (GA)	Imitates the process of natural selection
Gao et al. (2010) [24] ; Liu et al. (2015) [25].	Particle Swarm Optimization (PSO)	Based on social behaviour of bird flocking and fish schooling
Taherdangkoo et al. (2013)[26] ; Castillo et al. (2015)[27]	Ant Colony Optimization (ACO)	Based on the foraging behaviour of ants selecting a path important from its nest to source
Horng (2011)[28]; Jiang et al. (2014)[29]	Honey bee mating optimization algorithm (HBMO)	Inspired by the process of mating in real honey bees.
Yang (2010)[30] ; (Ye et al. (2015)[31]	Bat Algorithm	Inspired by the echolocation behaviour of micro bats
Maitra and Chatterjee (2008) [32]; Yang et al. (2016)[33]	Bacterial colony optimization (BCO)	Simulates some typical behaviour of E. coli bacteria using their whole life cycle.
Fister, Yang and Brest (2013) [34]; Chen et al. (2016)[35]:	Firefly Algorithm (FA)	Inspired by the flashing light patterns of tropic fireflies
Tillett et al. 2005[36]	Darwinian Particle Swarm Optimization (DPSO)	Swarm intelligence algorithms together with Particle Swarm Optimization.
L. Cheng et al. [37]	Artificial Flora (AF)	Inspired by the Artificial Flora processes.

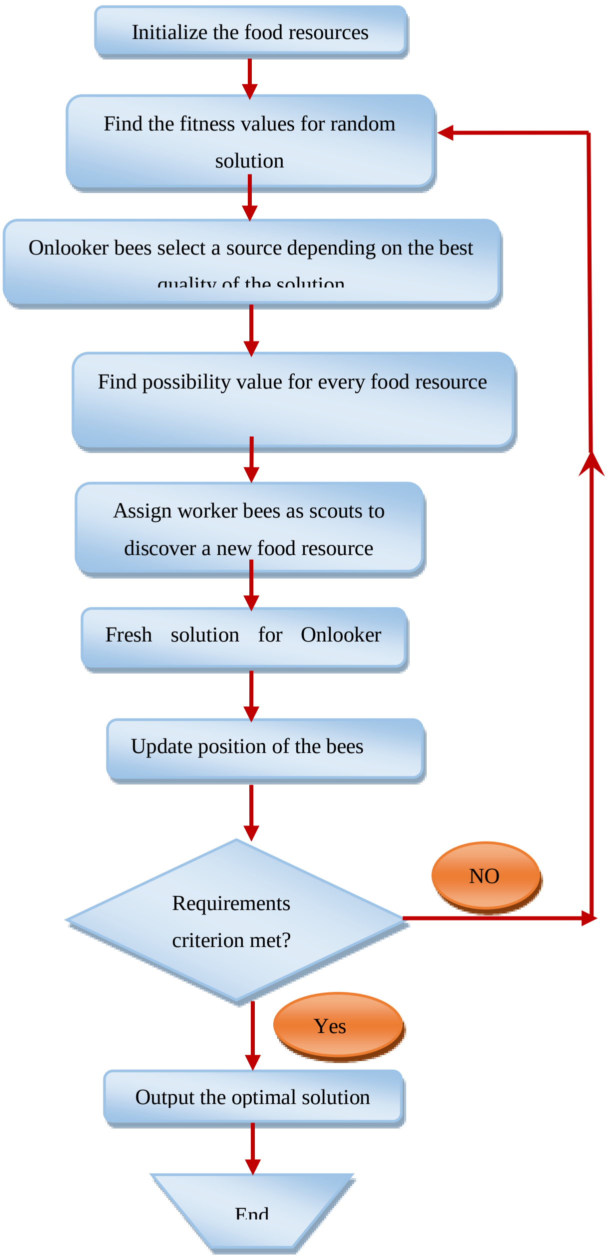

Figure Error! No text of specified style in document.. Flowchart for ABC algorithm

Essentially, a good technique should be able to perform optimally over diverse databases to draw both qualitative and quantitative conclusions. Therefore, in this study, the researcher chooses to explore four publicly available segmentation databases: the PH2, the ISBI2016 challenge, the ISBI 2017 challenge, and the Dermis melanoma skin lesion image databases. Moreover, the selection of diverse image databases will inject diversity to avoid the tendency for the segmentation results to be biased. These image databases are chosen to depend on the subsequent accompanying features:

1. They make diverse image types and quality steps but challenging images for different computer vision uses.
2. They are public and easily accessible.
3. They are prospective image databases.
4. They consist of a substantial number of images.

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Figure 4. Show the steps of an early diagnosis skin lesions classification using MASITs.

The performance of measure for evaluating of many classifications of the MASITs of TP:-ture positive,TN: ture negative,FP: fulse positive,FN: fulse negative.

$$\text{Diagnosis accuracy} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}} \qquad (1)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100\% \qquad (2)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} * 100\% \qquad (3)$$

$$\text{Error Probility} = \frac{\text{FN} + \text{FP}}{\text{TN} + \text{TP} + \text{FP} + \text{FN}} * 100\% \qquad (4)$$

$$\text{Index of Suspicious} = \frac{\text{TP} + \text{FP}}{\text{TP} + \text{FN}} * 100\% \qquad (5)$$

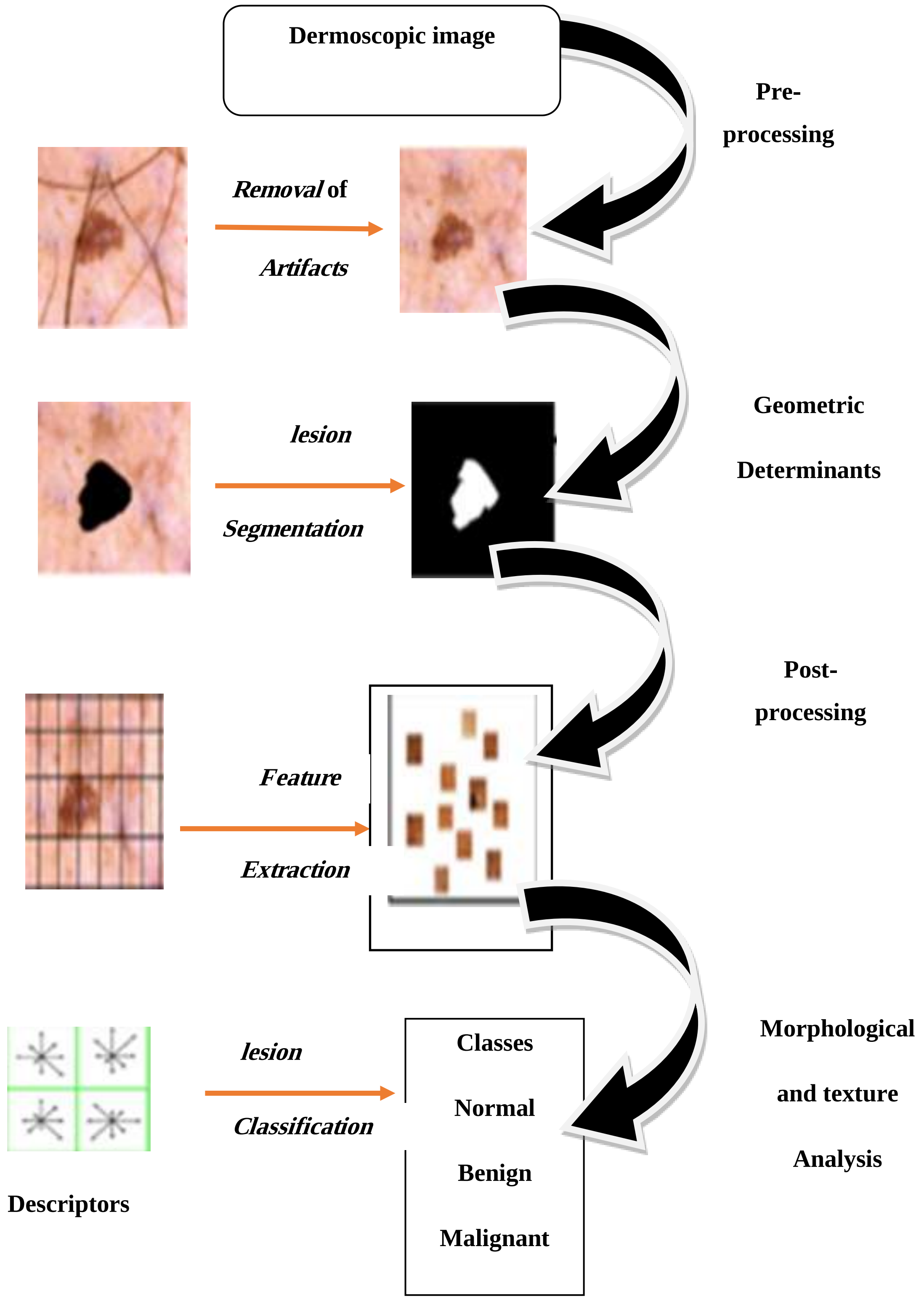

Figure 4. The process an early diagnosis skin lesions classification using MASITs.

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3. Results and Discussion

It is recognized that the MASITs systems need suitable constraint modification for good performance [44]. Inappropriately, the optimal of appropriate coefficient principles is correspondingly strongly problematic. The normal method in health image processing of early diagnosis skin lesions involves of 3 steps: 1) segmentation; 2) feature extraction and assortment. 3) lesion cataloguing. The segmentation step is significant, not only because it is the initial point for the total development then correspondingly because it marks the accuracy of the successive steps.

A significant job in image segmentation is boundary detection, for example, the purpose of the border between the lesion and the neighboring benign skin ranges. This is a respected i\p for analysis, for example the lesion boundary gives data about approximately medical structures (asymmetrical boundaries are a good indicator of probable MM cancers). Regularly, the boundary detection is done manually by the dermatologists, principal to an edge polyline got by construction sturcture opinions concluded segments. This o\p does not characterize healthy the physical procedure, the boundary of early diagnosis lesions not often occurs to be piecewise linear.

Premature analysis of lesion is a keystone to enlightening results and is associated with 99% total survival (TS). But, when disease developments outside the skin, survival is unfortunate [45]. The recognition of healthy nevi and pre-cancerous lesions has effectively been finished with the investigation of histopathological images.

The detection parameters were designed seeing four parameters. The recognition coefficients of the scheme for the PH2 data group provided a 94.21% accuracy. The prototypical was incompetent to variety at 98.77% on the ISBI 2017 databases. Figure 5. illustrations samples from both databases distinguished healthy and unhealthy nevi. Figure 6. illustrations the modified MASITs system does not distinguish the lesion since of the comparison between the lesion and neighboring lesions in the images.

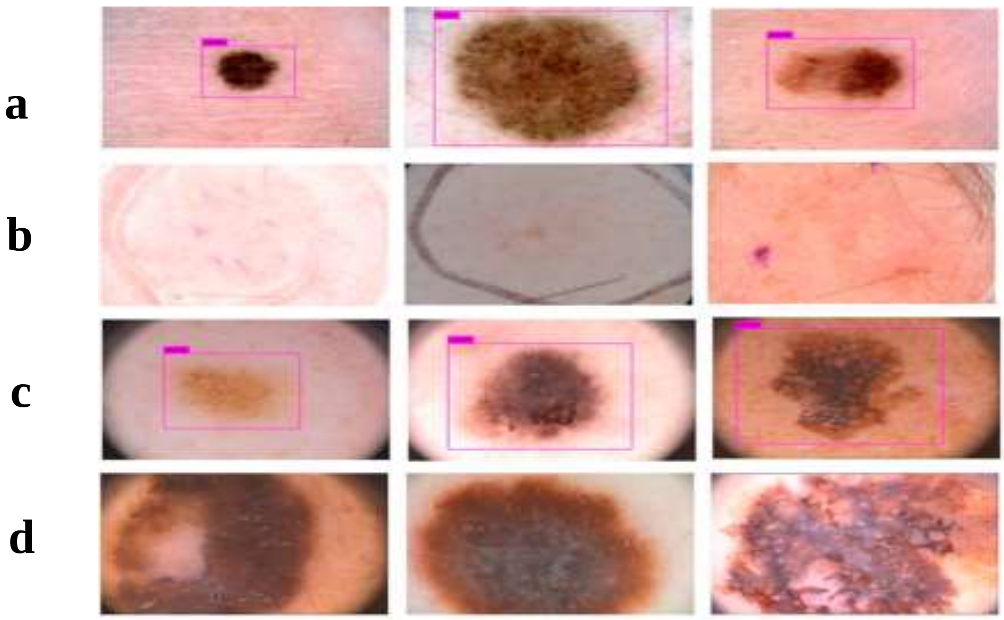

Figure 5. Outcomes of early skin lesion position detection by ABC technique. (a, c) are succeed recognition on the ISBI 2017 and PH^2. (b, d) show ineffective recognitions on the ISBI 2017 and PH^2.

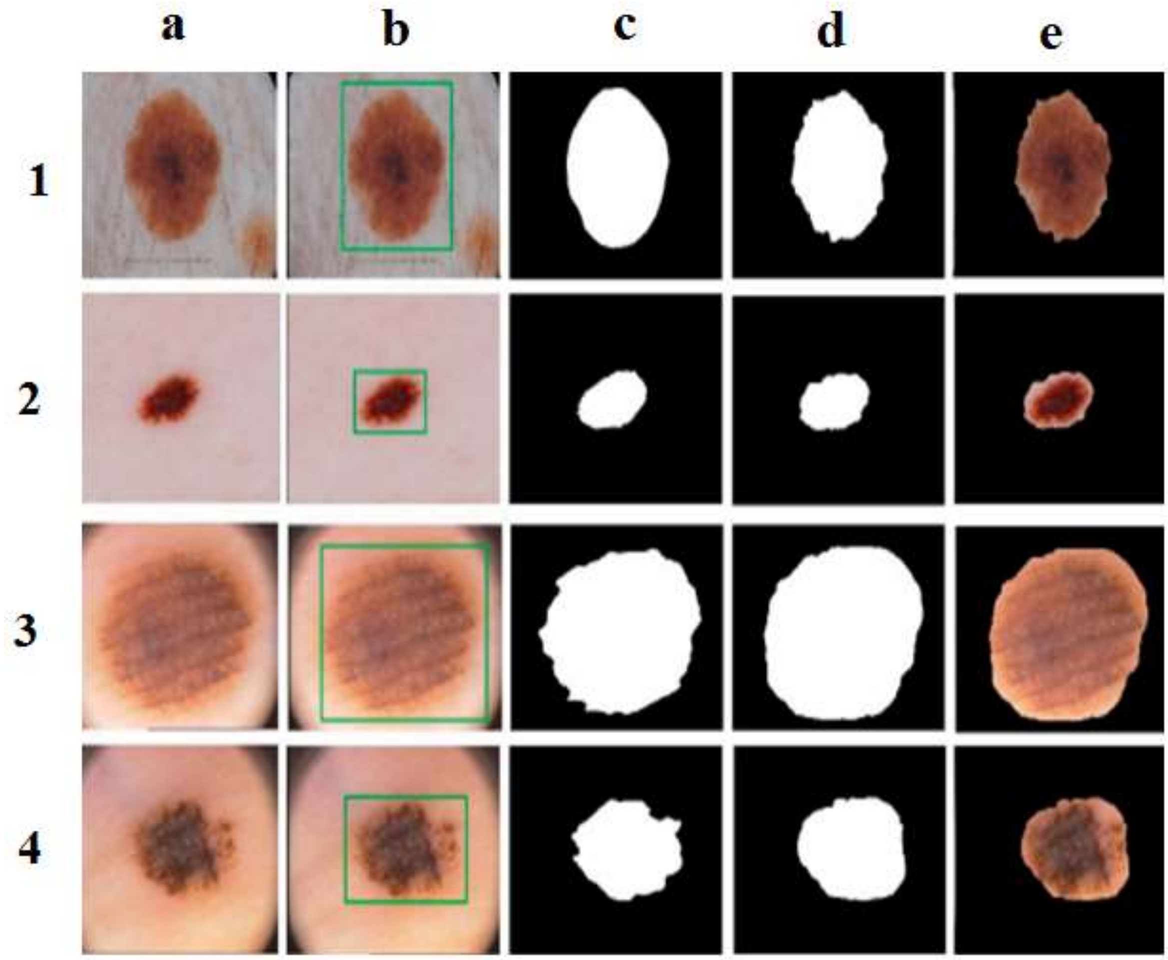

Figure 6. premature skin lesion outcomes methodology. (a) Original image, (b) lesion position detection by ABC technique, (c) GT, (d) Segmented Lesions, (e) Final outcome.

4. Conclusions and Future Work

Experimental outcomes on a level of health images illustrate that the projected technique outclasses standard mathematical technique**.** MASITs have the possible to carry a pattern shift in the analysis of skin lesion, and so, a cost-active, remotely reachable, and precise healthcare resolution for numerical dermatology. So, dropping the operative error and the related health costs with skin lesions diagnosis.

MASITs system offer a probable resolution to healthcare that needs intelligent approaches to make it likely to make available required services to international society, government, company, hospital, university, home, and person. Related to neural network and comprehensive search procedures, metaheuristics characteristically can find an estimated resolution more speedily.

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