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

Mohanad Aljanabi1, Ahmed R. Ajel2, Aws Al-azawi3, Rawaa A. Abdul-Nab1
1Electrical Power Techniques Engineering Department, Technical College /AL-Mausaib, Al-Furat Al-Awsat Technical University Najaf, Iraq.
2Department of Control and Automation Engineering, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq. E-mail: dr_ahmed.R@mtu.edu.iq
3Department of Medical Instrumentation Engineering Techniques, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq.

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.
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].

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.
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.      | **ABC**                    | Inspired by the intelligent behaviour of honeybees                     |
| (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]. |                            |                                                                         |
| Hammouche, D'iaf 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.                             |
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.
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: true positive, TN: true negative, FP: false positive, FN: false negative.

\[
\text{Diagnosis accuracy} = \frac{TP}{TP + FP + FN} \quad (1)
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \quad (2)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100\% \quad (3)
\]

\[
\text{Error Probability} = \frac{FN + FP}{TN + TP + FP + FN} \times 100\% \quad (4)
\]

\[
\text{Index of Suspicious} = \frac{TP + FP}{TP + FN} \times 100\% \quad (5)
\]
Figure 4. The process an early diagnosis skin lesions classification using MASITs.
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 ip 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 oip 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](image_url)

**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$^2$. 


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.

References
[1] Nachbar, F., Stolz, W., Merkle, T., Cognetta, A.B., Vogt, T., Landthaler, M., Bilek, P., Braun-Falco, O., Plewig, G. 1994 The ABCD rule of dermatoscopy. High prospective value in the diagnosis of doubtful melanocytic skin lesions. Journal American Academy of Dermatology, 30(4), 551–559.
[2] J. F. Alcón et al., 2009 Automatic imaging system with decision support for inspection of pigmented skin lesions and melanoma diagnosis, IEEE journal of selected topics in signal processing, 3(1), pp. 14-25.
[3] D. Oliva, E. Cuevas, G. Pajares, D. Zaldivar, and V. Osuna, 2014 A multilevel thresholding algorithm using electromagnetism optimization, Neurocomputing, 139, pp. 357-381.
[4] P. Mesejo, O. Ibáñez, O. Cordón, and S. Cagnoni, 2016 A survey on image segmentation using metaheuristic-based deformable models: state of the art and critical analysis, *Applied Soft Computing*, 44, pp. 1-29.

[5] N. Dey, V. Rajinikanth, A. S. Ashour, and J. M. R. Tavares, 2018 Social group optimization supported segmentation and evaluation of skin melanoma images, "Symmetry, 10(2), p. 51.

[6] R. P. Gallagher *et al.*, 1995 Sunlight exposure, pigmented factors, and risk of nonmelanocytic skin cancer: I. Basal cell carcinoma, *Archives of dermatology*, 131(2), pp. 157-163.

[7] P. G. Cavalcanti and J. Scharcanski, 2011 Automated prescreening of pigmented skin lesions using standard cameras, *Computerized Medical Imaging and Graphics*, 35(6), pp. 481-491.

[8] Pathan, S., Prabhu, K.G., Siddalingaswamy, P.C. 2018 Techniques and algorithms for computer aided diagnosis of pigmented skin lesions – a review. *Biomedical Signal Processing and Control*, 39, 237–262.

[9] P. Tschandl, C. Rosendahl, H. Kittler, 2018 The HAM10000 dataset, a large collection of multi-sources dermatoscopic images of common pigmented skin lesions, *Sci. Data* 5.

[10] Yuan, Y.; Chao, M.; Lo, Y.-C. 2017, Automatic Skin Lesion Segmentation Using Deep Fully Convolutional Networks with Jaccard Distance. *IEEE Trans. Med. Imaging* 36, 1876–86.

[11] Yuan, Y.; Lo, Y.C. 2019 Improving dermoscopic image segmentation with enhanced convolutional-deconvolutional networks. *IEEE J. Biomed. Health Inform*. 23, 519–526.

[12] D. Karaboga and B. Akay, 2009 A comparative study of artificial bee colony algorithm, *Applied mathematics and computation*, 214(1), pp. 108-132.

[13] J. Premaladha and K. Ravichandran, "Novel approaches for diagnosing melanoma skin lesions through supervised and deep learning algorithms," *Journal of medical systems*, vol. 40, no. 4, p. 96, 2016.

[14] D. Karaboga, 2005 An idea based on honey bee swarm for numerical optimization, *Technical report-tr06, Erciyes university, engineering faculty*, computer engineering department.

[15] J.y. Li, Y.-d. Zhao, J.-h. Li, and X.-j. Liu, 2015 Artificial bee colony optimizer with bee-to-bee communication and multipopulation coevolution for multilevel threshold image segmentation," *Mathematical Problems in Engineering*, vol. 2015.

[16] G. Zhu and S. Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," *Applied mathematics and computation*, vol. 217, no. 7, pp. 3166-3173, 2010.

[17] E. Cuevas, F. Sención, D. Zaldívar, M. Pérez-Cisneros, and H. Sossa, 2012 A multi-threshold segmentation approach based on artificial bee colony optimization, *Applied Intelligence*, 37(3), pp. 321-336.

[18] M. A. Al-masni, M. A. Al-antari, M.-T. Choi, S.-M. Han, and T.-S. Kim, 2018 Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks, *Computer methods and programs in biomedicine*, 162, pp. 221-231.

[19] N. Dey, V. Rajinikanth, A. S. Ashour, and J. M. R. Tavares, 2018 Social group optimization supported segmentation and evaluation of skin melanoma images, *Symmetry*, 10(2), p. 51.

[20] A. Esteva *et al.*, 2017 Dermatologist-level classification of skin cancer with deep neural networks, *Nature*, 542(7639), p. 115.

[21] K. Hammouche, M. Diaf, and P. Siarry, 2008 A multilevel automatic thresholding method based on a genetic algorithm for a fast image segmentation, *Computer Vision and Image Understanding*, 109(2), pp. 163-175.

[22] M. M. Oghaz, M. A. Maarof, A. Zainal, M. F. Rohani, and S. H. Yaghoubyan, 2015 A hybrid color space for skin detection using genetic algorithm heuristic search and principal component analysis technique, *PloS one*, 10(8), p. e0134828.

[23] G. Sun, A. Zhang, Y. Yao, and Z. Wang, "A novel hybrid algorithm of gravitational search algorithm with genetic algorithm for multi-level thresholding," *Applied Soft Computing*, vol. 46, pp. 703-730, 2016.

[24] H. Gao, W. Xu, J. Sun, and Y. Tang, 2010 Multilevel thresholding for image segmentation through an improved quantum-behaved particle swarm algorithm, *IEEE Transactions on Instrumentation and Measurement*, 59(4), pp. 934-946.
[25] Y. Liu, C. Mu, W. Kou, and J. Liu, 2015 Modified particle swarm optimization-based multilevel thresholding for image segmentation, Soft computing, 19(5), pp. 1311-27.

[26] M. Taherdangkoo, M. H. Bagheri, M. Yazdi, and K. P. Andriole, 2013 An effective method for segmentation of MR brain images using the ant colony optimization algorithm, Journal of digital imaging, 26(6), pp. 1116-23.

[27] O. Castillo, H. Neyoy, J. Soria, P. Melin, and F. Valdez, 2015 A new approach for dynamic fuzzy logic parameter tuning in ant colony optimization and its application in fuzzy control of a mobile robot,' Applied soft computing, 28, pp. 150-159.

[28] M.-H. Horng, 2011 Multilevel thresholding selection based on the artificial bee colony algorithm for image segmentation, Expert Systems with Applications, 38(11), pp. 13785-91.

[29] Y. Jiang, Z. Hao, Z. Yang, Y. Wang, and H. He, 2014 A cooperative honey bee mating algorithm and its application in multi-threshold image segmentation, in Evolutionary Computation (CEC), 2014 IEEE Congress on, pp. 1579-1585: IEEE.

[30] X.-S. Yang, 2010, A new metaheuristic bat-inspired algorithm, in Nature inspired cooperative strategies for optimization (NICSO 2010): Springer, pp. 65-74.

[31] Z. W. Ye, M.-W. Wang, W. Liu, and S.-B. Chen, 2015 Fuzzy entropy based optimal thresholding using bat algorithm," Applied Soft Computing, 31, pp. 381-395.

[32] M. Maitra and A. Chatterjee, 2008 A novel technique for multilevel optimal magnetic resonance brain image thresholding using bacterial foraging, Measurement, 41(10), pp. 1124-34.

[33] C. Yang, J. Ji, J. Liu, J. Liu, and B. Yin, 2016 Structural learning of Bayesian networks by bacterial foraging optimization, International Journal of Approximate Reasoning, 69, pp. 147-167.

[34] I. Fister, I. Fister Jr, X.-S. Yang, and J. Brest, 2013 A comprehensive review of firefly algorithms, Swarm and Evolutionary Computation, 13, pp. 34-46.

[35] S. Chen, L. Yao, and B. Chen, 2016 A parameterized logarithmic image processing method with Laplacian of Gaussian filtering for lung nodule enhancement in chest radiographs, Medical & biological engineering & computing, 54(11), pp. 1793-1806.

[36] J. Tillett, T. Rao, F. Sahin, and R. Rao, Darwinian particle swarm optimization, 2005.

[37] L. Cheng, X.-h. Wu, and Y. Wang, 2018 Artificial Flora (AF) Optimization Algorithm, Applied Sciences, 8(3), p. 329.

[38] J. Zhang, H. Li, Z. Tang, Q. Lu, X. Zheng, and J. Zhou, 2014 An improved quantum-inspired genetic algorithm for image multilevel thresholding segmentation, Mathematical Problems in Engineering, vol. 2014.

[39] O. Olugbara and B. N. Ndhlou, Constructing frugal sales system for small enterprises, 2014.

[40] R. Sumithra, M. Suhil, and D. Guru, 2015 Segmentation and classification of skin lesions for disease diagnosis, Procedia Computer Science, 45, pp. 76-85.

[41] A. Fahradyan, A. C. Howell, E. M. Wolfswinkel, M. Tsuha, P. Sheth, and A. K. Wong, 2017 Updates on the management of non-melanoma skin cancer (NMSC), Healthcare, 5(4), p. 82: Multidisciplinary Digital Publishing Institute.

[42] Y. Guo, A. S. Ashour, and F. Smarandache, 2018 A Novel Skin Lesion Detection Approach Using Neutrosophic Clustering and Adaptive Region Growing in Dermoscopy Images, Symmetry, 10(4), p. 119.

[43] G. Li, P. Niu, and X. Xiao, 2012 Development and investigation of efficient artificial bee colony algorithm for numerical function optimization, Applied soft computing,12(1), pp. 320-332.

[44] Engelbrecht, A.P. 2005 Fundamentals of Computational Swarm Intelligence. John Wiley and Sons, Chichester, England.

[45] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, A. Jemal, 2018 Global cancer statistics 2018: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries, CA: a cancer journal for clinicians 68(6) 394–424.