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Enhanced Cuckoo Search Optimization Technique for Skin Cancer Diagnosis Application

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Abstract: Skin cancer segmentation is a critical task in a clinical decision support system for skin cancer detection. The suggested enhanced cuckoo search based optimization model will be used to evaluate several metrics in the skin cancer picture segmentation process. Because time and resources are always limited, the proposed enhanced cuckoo search optimization algorithm is one of the most effective strategies for dealing with global optimization difficulties. One of the most significant requirements is to design optimal solutions to optimize their use. There is no particular technique that can answer all optimization issues. The proposed enhanced cuckoo search optimization method indicates a constructive precision for skin cancer over with all image segmentation in computerized diagnosis. The accuracy of the proposed enhanced cuckoo search based optimization for melanoma has increased with a 23% to 29% improvement than other optimization algorithm. The total sensitivity and specificity attained in the proposed system are 99.56% and 99.73% respectively. The proposed method outperforms by offering accuracy of 99.26% in comparisons to other conventional methods. The proposed enhanced optimization technique achieved 98.75%, 98.96% for Dice and Jaccard coefficient. The model trained using the suggested measure outperforms those trained using the conventional method in the segmentation of skin cancer picture data.

Keywords: Cukoo search; optimization technique; fitness function; cancer

1 Introduction

Cancer is a preventable disease that affects the entire bloodstream of the human body. The human body is made up of millions of cells that develop, divide, and die in the normal course of things. When old cells develop or become aberrant, they die and are replaced with new cells based on the human body's cell needs. When the mechanism malfunctions, an uncontrollable number of cells proliferate, resulting in cancer. When all of the cells join to generate additional mass tissue, cancer cells arise [1].

Skin cancer begins as a division of cells and progresses to cancer. It is a disease that begins in the skin cells. Ultra Violet (UV) radiation, which is emitted by sunlight, commercial tanning lamps, and tanning beds, causes the majority of Deoxyribonucleic Acid (DNA) damage in basal cells. Skin cancer that develops on skin that isn't normally exposed to the sun cannot be detected by sun exposure. Melanoma, the most awful method of skin cancer, depictions for more than 70% of the whole thing skin cancer associated deaths, and is estimated to kill 6,850 people in the United States alone in 2020 [2]. Skin cancer segmentation from surrounding skin is a critical step in several skin cancer imaging analyses. This work is important, however, because skin cancer has a wide range of appearances in terms of contour, dimension, and color, as well as different types of human skin and their textures. Meanwhile, the margins of some skin cancers are uneven and hazy, and the contrast between the lesion and the surrounding skin is often poor.

Picture segmentation algorithms are usually based on one of two fundamental aspects of image pixel intensity values: similarity or discontinuity. In the first category, the idea is to divide the image into many regions, each of which has image pixels that are comparable according to a set of predetermined criteria. The concept of partitioning an image on the basis of rapid changes in intensity values is applied in the second category. Image segmentation is a vital technology in digital image processing, and segmentation accuracy has a direct impact on the effectiveness of follow-up operations. Given its complexity and difficulty, the existing segmentation algorithm has had different degrees of success, but research in this area continues to encounter numerous hurdles. Because the clustering analysis algorithm splits data sets into various groups based on a set of criteria, it has a wide range of applications in picture segmentation.

For years, researchers have been working on these two approaches and have devised a number of ways that take those region-based attributes into account. However, there is no one-size-fits-all technique to image segmentation. Many segmentation approaches have been established based on the discontinuity or similarity criterion, and they can be broadly categorized into six such as Edge Detection, Histogram based method, Region based methods Clustering, Physical Model based approach and Neural Network based segmentation methods.

The saliency-based sore division in dermoscopic images using foundation location. It can be used as a saliency optimization calculation for damage division in dermoscopic images; however the division results are not acceptable and need to be improved due to the lack of substantial pre-processing stages. For skin sore division on dermoscopic images, a fully programmed structure based on a deep convolution neural system is adopted. To deal with the difficulties that deep system preparation may face when only limited preparing information is available, a few powerful preparing procedures were created [3]. These are unmistakably exhibited to various image curios and imaging security settings with the least amount of pre-and post-processing.

Clinical diagnostic and decision support systems for skin cancer detection are approaching human expert levels [4,5], and the delineation of the skin lesion boundary to distinguish the afflicted region from the healthy skin, known as lesion segmentation, is an important step in skin cancer diagnosis. Yang et al. invented Cuckoo Search, an evolutionary and metaheuristic optimization technique, in 2009 [6]. The philosophy behind this optimization search algorithm was inspired by the cuckoo bird. Cuckoos are beautiful birds with an aggressive reproduction system. As part of their reproduction strategy, settled cuckoos put their eggs in the shells of another groups, exercise acknowledged as required blood parasitism [7].

A cuckoo search technique that is increased by dimensions [8]. The suggested algorithm takes advantage of all dimensions by observing and updating the dimensions that bring and update the information to provide the best answer. The cuckoo optimization search method and fuzzy logic were used to reduce power losses by positioning the Static Virtual Array Recorder Compensator in the most efficient and ideal location [9]. The Non-Polynomial-Hard Problem in Grid Computing is Transaction Scheduling. Using a combination of cuckoo optimization search and ant colony optimization algorithms [10], an optimal hybrid strategy to solving this problem has been developed. The cuckoo search algorithm was utilized to construct clusters of resources depending on their loads in order to generate an ideal transaction plan.

Cauchy mutation-based cuckoo optimization search method [11], the modified cuckoo search algorithm was utilized for hierarchical resource scheduling in the Internet of Things to achieve optimal service quality. For the detection of deterioration in bridges and beams, an approach based on a flexible combination of cuckoo search and artificial neural network was used. Cuckoo search was employed in the suggested strategy to improve Artificial Neural Network training parameters such as bias and weight [12]. For better prediction, the Cuckoo Search technique can be combined with a machine learning system. Based on artificial neural networks and the cuckoo search algorithm, a model for enhancing the prediction accuracy of the required effort in software is developed [13].

Various clustering approaches are proposed and improved on a regular basis. The suggested algorithm is based on K-means cluster analysis, which is a well-known technique. The approach is commonly utilized in the clustering of large-scale data because of its great efficiency [14]. Based on numerous attributes from the photos, this research provides an efficient skin cancer image segmentation approach employing K-means clustering with cuckoo search optimization technique.

The rest of the article is arranged out as the basic evaluation of image segmentation for skin cancer is presented in Section 2. The proposed Enhanced Cuckoo Search Optimization technique is given and illustrated in Section 3. The outcomes and examination are shown in Division 4. Lastly, Section 5 finishes with a discussion of future possibilities.

2 Overview of Proposed Image Segmentation for Skin Cancer

Segmentation is the division of an image into various different sections, such as color, shape, and information similarity of the image in the same area. All at once, relationship among unusual sections is tremendously low, and the purpose of picture segmentation is to choose the state of importance commencing the image for further image handling algorithms.

The segmentation process is a simple and efficient image segmentation approach with the benefits of low computation, easy implementation, and consistent performance. It entails dividing the image's pixel uses obsessed by some modules constructed on numerous suitable limits discovered across an image with confirming to each collection of pixel contacts separated is reliable in terms of grey equivalent.

As illustrated in Fig. 1, the proposed block of Enhanced Cuckoo search optimization based segmentation. The melanoma image to be segmented is fed into a K-Mean segmentation unit, which uses a proposed enhanced cuckoo search metaheuristic optimization technique to optimize the threshold level for labelling the pixel into K number of clusters. The final segmentation result is the output of the K mean segmentation unit optimized with the proposed enhanced cuckoo search method. The accuracy, sensitivity, precision, specificity, Dice Similarity Coefficient, Jaccard Similarity Index, Multicore Complex and other segmentation scores are compared to a ground truth melanoma lesion provided by a dermatology expert, and the segmentation scores are reviewed. In a certain solution space, start with a specific number of cuckoos. The dimension, number of iterations and inhabitant's number are represented by the initialization procedure and singular embodies an explanation in the clarification area. Calculate the fitness rate of individually element permitting to suitability task using the segmentation algorithm as the fitness value function.

The portions of probability optimization, version layout, and population initialization wholly perform a role in this technique to varying degrees. Determine the singular fitness rate of cuckoo search optimization and domain the relevant fitness function standards via the choice approach to keep an up-to-date ideal fitness function rate, as well as the view of an extreme function rate through each repetition. As soon as the distinct stops to encounter the closure state, subsequent iteration should be passed on view in harmony with the aforementioned conditions, and the optimal effect is obtained by repeating operations until the termination condition is met and the outcome attained is a finest limit for image segmentation.

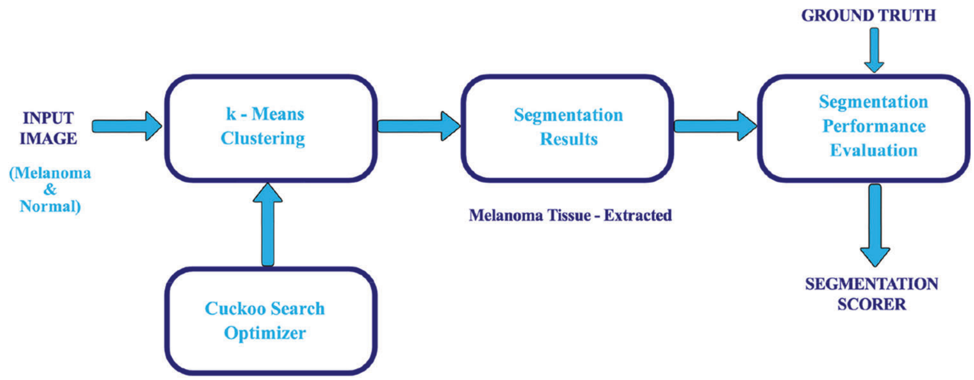

Figure 1: Block diagram of the proposed segmentation using enhanced cuckoo search optimization

This part also goes over the publicly available skin lesion datasets, how to prepare the ground truth, and how to validate the results with performance measurements. Consider the picture segmentation job, in which each pixel is classified as foreground or background. Fig. 2 demonstrates the predicted and ground truth of a skin melanoma image.

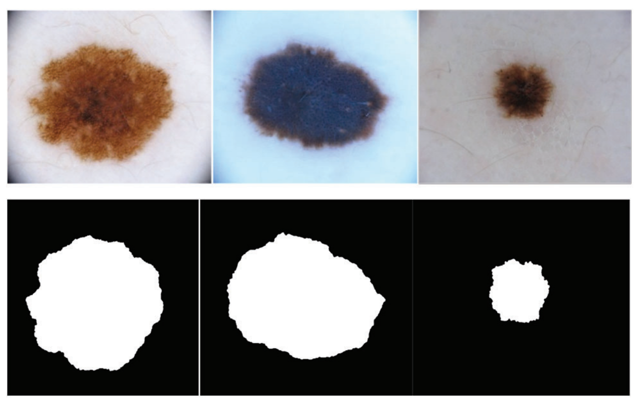

Figure 2: Skin melanoma image of predicted and ground truth

Specificity, Sensitivity, Accuracy, Matthew Correlation Coefficient (MCC), Dice Similarity Coefficient (DSC) and Jaccard Similarity Index (JSI) were used to assess the performance of the segmentation algorithms.

$$accuracy(acc) = \frac{tp + tn}{tp + fp + tn + fn} \tag{1}$$

$$Sensitivity(sen) = \frac{tp}{tp + fn} \tag{2}$$

$$Specificity(spec) = \frac{tn}{fp + tn} \tag{3}$$

Eq. (1) shows the mathematical equation for accuracy. Eq. (2) defines sensitivity, where ‘tp’ set as true positive and ‘fn’ set as false negative. The high Sensitivity denotes excellent image segmentation execution, involving that all lesions were successfully segmented. In Eq. (3) specificity refers to the proportion of non-lesions that are true negative (‘tn’). High specificity refers to a method’s capacity to avoid segmenting non-lesions.

$$JSI = \frac{tp}{tp + fp + fn} \tag{4}$$

$$DSC = \frac{2 * tp}{2 * tp + fp + fn} \tag{5}$$

$$MCC = \frac{tp * tn - fp * fn}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}} \tag{6}$$

As illustrated in Eqs. (4) and (5) JSI and DSC are dealings of how the related calculation and ground truth images are in together with how the lots of ‘tp’ are establish and fining for ‘fp’ so as to the algorithm set up. MCC contain the scale of −1 to 1. As confirmed in Eq. (6) is a valuable metric in favor of appraising the implementation of the recommended image segmentation methods establish at categorization. MCC values vary from −1 to + 1, with −1 representing a fully disjoint prediction and +1 suggesting a flawless prediction.

3 Proposed Enhanced Cuckoo Search Optimization Technique

This technique was motivated as a result of the activities of cuckoos, which put down their eggs within the nests of other class of birds in order to live. A parasitic cuckoo would normally look for a nest where other birds had recently laid their eggs. Cuckoo bird eggs produce ahead of the swarm nest eggs enhancing the chances that swarm bird would feed the cuckoo youngsters. Furthermore, the cuckoo chicks benefit from having approach to supply given that they know how to imitate the tone of swarm bird shell. The cuckoo’s reproduction activities based technique can be utilized to the search optimization challenge. Final respond is represented by every egg placed in swarm nest. Meanwhile the cuckoo egg suggests a fresh approach.

The new solution’s purpose is to replace the prior nest’s worst solution with a larger, more feasible solution. Because this experiment only required a single MCC-based goal function, each nest will only contain one egg. By following the three rules for excellent execution, the cuckoo bird’s performance is capable of romanticized. Every cuckoo bird puts and sinks single egg on particular instance to a different host shell. The most excellent nests will be passed down to the next generation, containing high-quality eggs.

A host bird’s chance of recognizing an alien egg is pa [0,1] and an amount of feasible swarm shells is predetermined. Because of this risk, the host bird has two options such as destroy the egg or leave the shell and create a fresh shell someplace as well.

In favor of a primary location of a shell, each decision variable is given a place of unsystematic standards in the minor and major bound. The fitness is then assessed using an objective function. The initial position of each nest is calculated using Eq. (7).

$$N_{xy} = lb + RANDOM_{xy}(ub - lb) \quad x = 1, \ldots .i; \quad y = 1, \ldots .j \tag{7}$$

Where N_{xy} is a collection of nests that characterize the result between the minor and major bound. A range of 0 to 1 is also allocated to the equation, which is denoted as ‘RANDOM’. The improvement of fresh cuckoos, which imitate a result to an optimized crisis, is the subsequently walk. Since every shell characterizes just individual explanation, an amount of cuckoos is like to the amount of shells.

The investigation of a explore gap is approved away in this work utilizing two techniques: Levy fly and random walk. Because Levy flight contains a likelihood allotment in unsystematic pace extents, it can be used for successful exploration in producing a new solution. It consists of a succession of directly flights tracked with quick degree of 90. Eq. (8) is used to carry out the Levy flights in this algorithm

$$PM_{xy} = \begin{pmatrix} 1 & RANDOM < p_{dp} \\ 0 & RANDOM \geq p_{dp} \end{pmatrix} \tag{8}$$

Where i_x^{a+1} is an individual's current location, n is a unsystematic digit created through a standard allotment, and i_X^b is a present the most excellent shell; and 'R' is a unsystematic move utilizing levy of flights. The step length 'R' is calculated using the Mantegna technique, as stated in Eq. (9).

$$R = \frac{a}{|b|^{1/\alpha}} \tag{9}$$

Where α is a parameter with a range of 1 to 2 and is taken to be 1.5 in this study. As seen in Eq. (10), the values of 'a' and 'b' can be calculated using the normal distribution

$$\sigma_a = \left\{ \frac{\left[\Gamma(1+\alpha)\sin\frac{\pi\alpha}{2}\right]}{\left[\Gamma\left(1+\frac{\alpha}{2}\right)\alpha 2^{(\alpha-1)/2}\right]} \right\}^{1/\alpha}; \sigma_b = 1 \tag{10}$$

The finding of alien eggs is carried out for every element of every result using a likelihood format as an Eq. (11).

$$PM_{xy} = \begin{pmatrix} 1 & RANDOM < p_{dp} \\ 0 & RANDOM \geq p_{dp} \end{pmatrix} \tag{11}$$

The discovery probability is p_{dp} existing eggs are replaced with newly generated ones based on their quality from their existing places via random walks with step size utilizing Eqs. (12) and (13).

$$Step_{size} = RANDOM(NEST(RANDOM\ PERM1(n); :) - NEST(RANDOM\ PERM2(n), :)) \tag{12}$$

$$NEST^{t+1} = NEST^{t} + R. * \ p \tag{13}$$

The random permutation functions RANDOM PERM1 and RANDOM PERM2 are employed for uncommon lines transformation at the nesting atmosphere as well as the probability matrix of 'p'.

Let m = (m_1, $m_{2,}$…,m_X) be the represent image to every segment into N classes and l = (l_1, $l_{2,}$…,l_X) be the segmented image. m_n is rate of pixel in the location 'n' to obtain its rate in dull point window G_M = (0, …,255). l_n is the group of position 'n' and obtain in the separate window G_L= [1,….,N].

The image represent to segment 'm' represent the image of segmented one 'l' represent respectively comprehension of arbitrary fields M = (M_1,$M_{2,}$,….,M_X) and L = (L_1,L_2,….L_X). Configurations set of the image represent to segment 'm' and of the image of segmented one are respectively $\Omega_m = G_m^N$ and $\Omega_l = G_l^N$. To apply the proposed enhanced optimization technique, the new minimizations function as shown in Eq. (14).

$$\psi(\mu) = \sum_{i=1}^{N} f(\mu_i); \mu_i \in RANDOM^N \tag{14}$$

Following that, many cuckoo search optimization parameters were tweaked, including switching probability, number of nests, model order, iteration, and lower and higher border. The cuckoo search parameters were the focus of the initial tweaking, which come after by replica structure and finally iteration. The size of shells was mixed between 20 and 50, while the other parameters were kept constant.

4 Results and Discussion

The experiment was carried out using a dataset that included both ground truth and natural photographs from a database. The values of the parameters are determined, and the number of cuckoo locations is approximately used. The number of iterations and cuckoo search parameters must be adjusted since tuning the parameters of an optimization algorithm is at least as critical as the method creation. In a limited number of repetitions, increasing the number of nests yields a satisfactory outcome, but also increases the running time.

The suggested techniques and several declaring the techniques of segmentation were tested at a collection of 1200 photos in this part. Specificity, Sensitivity and Accuracy are important execution indicators in favor of approaches in medical imaging segmentation. The processed images with more consistent output by using enhanced cuckoo search optimization algorithm as shown in Fig. 3, when compared to segmentation techniques. Tab. 1 summarizes the performance of the proposed techniques.

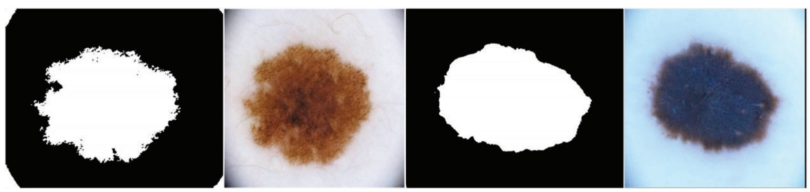

Figure 3: Processed images with more reliable output by enhanced cuckoo search optimization algorithm

Table 1: Performance of the proposed techniques

Method	Sensitivity	Specificity	Accuracy
Capó et al. [15]	67.2	97.2	90.1
Esteva et al. [5]	80.1	95.4	91.8
Ronneberger et al. [16]	85.4	96.7	94
Al-masni et al. [17]	89.9	95	94.1
PROPOSED	94.6	94.4	97.9

Sensitivity, Accuracy, Specificity, Dice and Jaccard Similarity Index (JSI) were used in the direction of evaluate the performance of skin cancer picture segmentation with enhanced cuckoo search optimization. From the Tab. 2 it was observed that the MCC is a loss function that shows how well expected and ground truth images correlate. Even when dealing with skewed distributions, MCC is an informative metric, and it has been proved to be the best metric for developing classifiers for imbalanced classes. The simulation experiment is spitted through two sequences, one of which confirms the performance of proposed optimization and other of which proves the effect of this optimization on the index of image segmentation, in order to better illustrate the benefits of this enhanced cuckoo search optimization in image segmentation. The comparison between the various metrics of the proposed optimization algorithm and conventional algorithm as shown in Figs. 4 and 5.

In order to better illustrate the advantages of the skin cancer image segmentation with enhanced cuckoo search algorithms, in terms of performance and compare it with other algorithm. In terms of sensitivity and other performance metrics, the proposed technique obtained the highest score which would be shown in Fig. 4 for the ISIC trailing set'17, the suggested technique conquered existing techniques with a Jaccard Similarity Index of 97.4%. The JSI, MCC and Dice scores produced by the suggested optimization technique are compared in Fig. 5.

Table 2: Different metrics of the proposed technique

Method	JSI	MCC	DSC
Capó et al. [15]	61.6	72.70	76.3
Esteva et al. [5]	69.6	74.39	82.1
Ronneberger et al. [16]	77.1	73.61	87
Al-masni et al. [17]	79.3	78.08	87.1
PROPOSED	93.4	93.7	94.3

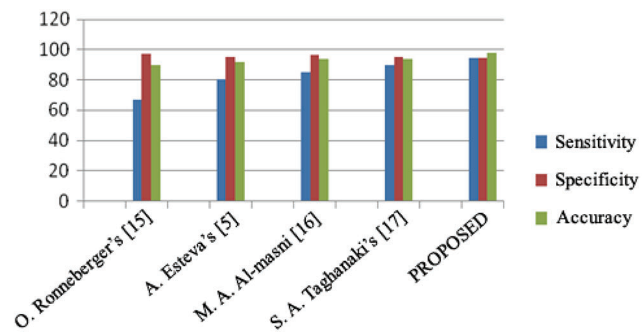

Figure 4: Comparison between proposed with conventional optimization algorithm

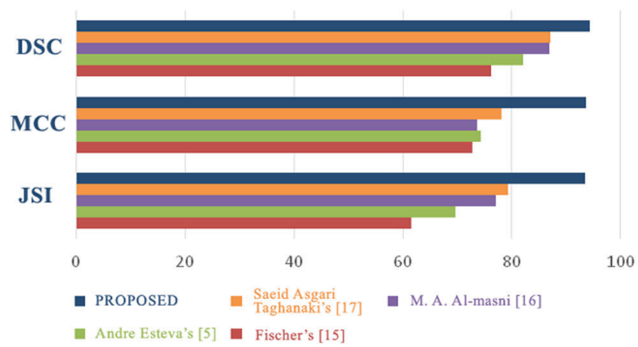

Figure 5: Proposed optimization algorithm with conventional

The minimal error is equivalent with the optimal and best parameter values. With a low error rate, the proposed approach produces good results. On the majority of test image, the proposed enhanced cuckoo search optimization yields the best results.

To validate the effectiveness of the proposed Enhanced Cuckoo Search Optimization Algorithm (ECSOA) is applied to approximate factors of Chen-chaotic approach [18].

$$\hat{I} = \Delta_1(J - I); \hat{J} = (\Delta_3 - \Delta_1)I - \Delta_3 J - IK; \hat{K} = IJ - \Delta_2 K \tag{15}$$

Where (I, J, K) is the state variables and $\Delta_1, \Delta_2, \Delta_3$ are the unspecified chaotic approach factors which require to be projected. The actual factors of the approaches are $\Delta_1 = 40$, $\Delta_2 = 4$, and $\Delta_3 = 34$ which promise a chaotic performance, the 4^{th} order Rungekutta algorithm is utilized to solve the Eq. (15) and then the primary step is S = 0.01. The sequence of 100 state variables are acquired of different times ({(I (n), J (n), K (n)), n = 1, 2….100}) select to be the test data.

The factors of the proposed Enhanced Cuckoo Search Optimization Algorithm (ECSOA) is set as a maximum iteration quantity is $N = 300$, the sample range is $M = 150$ andan annealing form is as shown in the Eq. (16).

$$T(n) = \frac{T_0}{ln(1+n)}; \text{n is the iteration and } T_0 = 100 \tag{16}$$

The fitness function (F) is as shown in Eq. (17).

$$Fittness\ Function(F) = \sqrt{\frac{1}{M}\sum\nolimits_{n=1}^{M}\left[\left(\hat{I}(n) - I(n)\right)^2 + \left(\hat{J}(n) - J(n)\right)^2 + \left(\hat{K}(n) - K(n)\right)^2\right]} \tag{17}$$

Where $I(n)$, J(n), $K(n)$ and $\hat{I}(n)$, $\hat{J}(n)$, $\hat{K}(n)$ are the n^{th} position variable that relates to the true and projected approach factors. The fitness values and three mean factors $(\Delta_1, \Delta_2, \Delta_3)$ during the iterations in a mean of 60 tests is taken as the final projected value and the subsequent outcomes exhibits in Fig. 6 and Tab. 3. From these Tab. 3 and Fig. 6, the greatest fitness value attained by the proposed Enhanced Cuckoo Search Optimization Algorithm (ECSOA) is absolutely superior to the other conventional algorithms. The mean values of recognized factors are in addition with greater accuracy than other optimization algorithm. The projected assessments are nearby the true values. The proposed Enhanced Cuckoo Search Optimization Algorithm (ECSOA) gives to greater implementation with other traditional optimization algorithms like Particle Swarm Optimization (PSO), Cuckoo Search (CS) and Genetic Algorithm(GA).

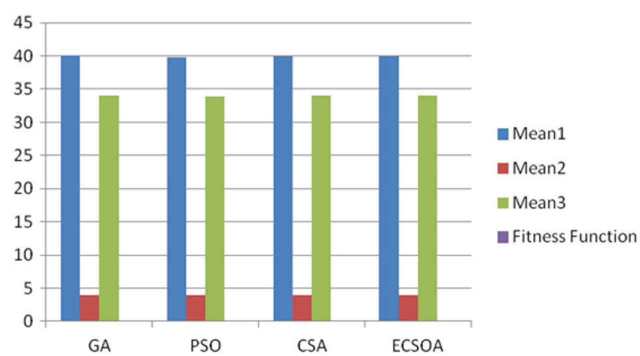

Figure 6: Fitness function of the proposed optimization algorithm

Table 3: Outcomes of the proposed algorithm with noiseless state

Statistical parameter (noiseless condition)	GA	PSO	CSA	ECSOA
Mean1 (Δ_1 = 40)	40.03	39.78	39.97	39.99
Mean2 (Δ_2 = 4)	3.991	3.997	3.998	3.999
Mean3 (Δ_3 = 34)	34.04	33.89	33.97	33.99
Fitness function (F)	0.010	0.003	0.000003	0.000000029

5 Conclusions

In this work, the search of Enhanced Cuckoo Optimization was proposed for the best possible analysis of skin cancer. The final results specified that according to various metrics, the proposed technology has the greatest outcome for the other associated techniques. The exercise of different metric for training of enhanced cuckoo search optimization based melanoma image segmentation technique is higher accuracy with low error in the given image datasets. The proposed method offers good results for skin cancer, as may be seen from the description. On the other hand, this might serve as a version for upcoming effort wherein employ fusion and develop versions of novel computational intelligence problem to enhance structure efficiency. To the accepted evidence, the outcomes of the offered Enhanced Cuckoo Search Optimization technique were applied to the ISIC directory and its outcomes were differentiated with separate techniques like Genetic Algorithm, Artificial Neural Network, Elephant Herding Optimization and Particle Swarm Optimization. The new results exposes that the proposed enhanced algorithm is able to recognize skin cancer. It makes out that the added state of the technique on regular quantity procedures such as accuracy (99.26%), specificity (99.73%) and sensitivity (99.56%). The simulation outcomes established that the proposed technique outperforms the compared techniques with a maximum acceptable accuracy of 98.7% on the utilized skin image dataset. This study can be a motivation to the future work to utilize several hybrid types of different modern computational intelligence optimization algorithms to increase the model efficiency.

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