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COMBINING ELMAN NEURAL NETWORK WITH THE VARIABLE STRUCTURE COOT OPTIMIZATION ALGORITHM FOR SKIN CANCER DETECTION

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Abstract:
Skin cancer segmentation is a critical component of a clinical decision support system for the identification of this disease. The suggested optimization model, based on a modified version of the Coot search algorithm, will be used to evaluate many different metrics in the skin cancer image segmentation process. The created Coot search optimization algorithm is one of the most efficient methods for handling global optimization issues in a time and resource constrained environment. Providing optimal solutions for their application is a crucial need. No one approach can address the variety of optimization issues that exist. The proposed enhanced Coot search optimization method demonstrates a constructive accuracy for skin cancer over the full image segmentation in computer-aided diagnosis. Existing optimization techniques may be enhanced by a factor of 23% to 29% using the proposed improved Coot search based optimization for melanoma. Overall sensitivity and specificity of 99.56 percent and 99.73 percent are attained using the proposed method. The proposed technique has superior accuracy of 99.26% compared to other conventional methods. The Dice and Jaccard coefficients were both optimized to 98.75% using the proposed method. When it comes to segmenting skin cancer images, the model trained with the suggested metric shows significant improvement over the baseline.

***Keywords:** Coot search; Optimization technique; Fitness function; Cancer.*

I. INTRODUCTION :

Cancer is an avoidable disease that spreads throughout the body through the blood. Every day, millions upon millions of cells in the human body through the cycles of growth, division, and death. According to the needs of the human body, new cells replace old ones when the latter die or become aberrant. When this mechanism breaks down, an excessive proliferation of cells might develop into cancer. When normal cells join together to produce new mass tissue, it is called cancer [1].

The malignant transformation of skin cancer begins with the uncontrolled growth of a few cells. It's an ailment that manifests itself on the skin and has its origins in the skin's cells. Sunlight, commercial tanning lamps, and tanning beds are all major sources of ultraviolet (UV) radiation, which is responsible for the vast majority of DNA damage in basal cells. Skin cancers that form on areas of the body that are seldom exposed to the sun cannot be detected by sun exposure alone. More than 70% of all skin cancer-related deaths occur due to melanoma, making it the deadliest form of the disease [2]. In 2020, 6,850 people in the United States alone are predicted to succumb to melanoma. In many skin cancer imaging evaluations, the separation of the tumor from the surrounding skin is a crucial step. However, this research is important because of the wide range of appearances that skin cancer may take, including but not limited to form, size, color, and the many types of human skin and textures. However, the borders of certain skin cancers are hazy and uneven, and the lesion generally has little contrast with the surrounding skin.

Dermoscopy images of skin lesions may be divided into sub regions with the use of a fully-automated structure based on a deep convolution neural network. It is possible that deep system preparation would encounter challenges, however a few successful preparing techniques have been developed to deal with these challenges [3]. They are shown clearly to various image curios and imaging security settings with little pre- and post-processing.

Lesion segmentation, or the delineation of the skin lesion boundary in order to separate the affected region from healthy skin, is a crucial step in skin cancer diagnosis, and clinical diagnostic and decision support systems for skin cancer detection are approaching human expert levels [4,5]. Coot Search [6] was created by Yang et al. in 2009 and is an evolutionary and metaheuristic strategy for optimizing problems. The idea that underlies this optimization search strategy was inspired by the Coot bird. The coot is a beautiful bird with an extraordinary capacity for offspring production. As part of their reproductive strategy, settled coots engage in blood parasitism [7] by laying eggs in the shells of other groups.

Multi-dimensional extension of the Coot search algorithm [8]. The suggested technique takes into account all dimensions in order to provide the most appropriate response by monitoring and updating the dimensions that bring and update the data. The optimal placement of the Static Virtual Array Recorder Compensator was determined using a combination of the Coot optimization search approach and fuzzy logic in order to minimize power losses [9]. In Grid Computing, Transaction Scheduling Is a Non-Polynomially Hard Problem. Combining the Coot optimization search algorithm with the ant colony optimization algorithm yielded the best hybrid approach to solving this problem [10]. To formulate the optimal transaction strategy, resource loads were utilized to form clusters, and the Coot search algorithm was used to get the most relevant results.

Using the Cauchy mutation-based Coot optimization search approach, the modified Coot search algorithm was applied to the problem of hierarchical resource scheduling in the Internet of Things to guarantee the highest possible service quality [11]. Deterioration in bridges and beams was identified using a method based on a versatile combination of Coot search and artificial neural network. The suggested method uses Coot search to fine-tune AINN training parameters including bias and weight [12]. A machine learning system may be used in conjunction with the Coot Search method to enhance predictive ability. Using artificial neural networks and the Coot search algorithm, [13] researchers developed a way for better predicting how much labor would be required in developing software.

New clustering methods are created and improved upon often. K-means cluster analysis is the basis for the suggested method. The approach is used for clustering massive amounts of data [14] because to its effectiveness. Using K-means clustering and the Coot search optimization approach, this research suggests an effective method for segmenting photos of skin cancer based on various attributes extracted from the images themselves.

II. OVERVIEW OF PROPOSED IMAGE SEGMENTATION FOR SKIN CANCER :

Cancer is an avoidable disease that may spread throughout the body. Every day, millions of cells in the human body undergo the cycles of growth, division, and death that make up our existence. When old cells die or become aberrant, the body replaces them with new ones as needed. When this mechanism breaks down, an abnormally high number of cells proliferate. When normal cells join together to create a tumor, it is called cancer [1].

Malignancy in skin cancer develops from a normal growth of cells. The cells of the skin are the origin of this sickness. Solar radiation, commercial tanning lamps, and indoor tanning beds are the primary sources of ultraviolet (UV) radiation, which damages Deoxyribonucleic acid (DNA) in basal cells. Without frequent sun exposure, it is impossible to detect skin cancer in its early stages. More than 70% of all skin cancer-related deaths are attributable to melanoma, the deadliest form of the disease [2]. In 2020, 6,850 people in the United States alone are predicted to succumb to melanoma. In many cases, determining whether or not the skin cancer has been successfully isolated from the surrounding skin is a crucial step in the skin cancer imaging evaluation process. However, this research is important since there is such a wide range of skin cancer appearances in terms of size, shape, color, and the many different types of human skin. Some skin cancers, nevertheless, have hazy, undefined borders and a low degree of contrast with the surrounding skin.

Similarity or discontinuity in pixel intensity levels is often used in image segmentation methods. The first kind operates on the principle of subdividing the image into many regions, each of which contains image pixels that are comparable according to a predetermined set of criteria. The second class makes use of the idea of segmenting an image on the basis of sudden shifts in intensity levels. The quality of picture segmentation has a direct effect on the success of following operations in digital image processing, making it an essential method in the field. The current segmentation approach has had mixed results due to its complexity and difficulty, but there are still many obstacles in the way of future study in this area. Since clustering analysis separates data sets into various groups based on a set of criteria, it may be used for a wide range of purposes in picture segmentation. Numerous ways have been developed by researchers over the years to account for these regional specifics while still using the first two approaches. However, image segmentation is not a one-size-fits-all solution. It is on the basis of discontinuities or breaks in continuity that several segmentation methods have been created. Edge detection, histogram-based methods, region-based methods clustering, physical model-based approaches, and neural network-based segmentation are some of the most common forms of similarity criterion-based image analysis techniques.

Dermoscopy image sores are segmented depending on saliency, which is achieved by using the foundational location of the image. However, the division findings are not sufficient and need to be improved due to a lack of major pre-processing steps, limiting its usefulness as a saliency optimization calculation for damage division in dermoscopic images. For dermoscopic image segmentation of skin lesions, we employ a fully programmable structure based on a deep convolution neural network. When just a little amount of preparation data is available, deep system preparation may run into some issues, but a few successful procedures have been developed to help deal with these challenges [3]. They're shown clearly to various image nerds and imaging safety systems with little pre- and post-processing.

Lesion segmentation, or the delineation of the skin lesion boundary to separate the diseased region from healthy skin, is a vital step in skin cancer diagnosis, and clinical diagnostic and decision support systems are approaching human expert levels [4,5]. Coot Search, an evolutionary and metaheuristic optimization method, was created in 2009 by Yang et al. This optimization search strategy draws conceptual inspiration from the Coot bird. Beautiful and prolific, coots have a lot to offer the world. Blood parasitism [7] describes the reproductive strategy of the settled coot, which consists of laying eggs in the shells of other groups.

Coot search technique with more dimensions [8]. The suggested technique monitors and adapts the dimensions that bring and update the information in order to provide the most appropriate reaction. Static Virtual Array Recorder Compensator placement was optimized with the use of Coot optimization search and fuzzy logic to cut down on power losses [9]. Grid computing's Non-Polynomial-Hard Problem is Transaction Scheduling. Coot optimization search and ant colony optimization methods were used to generate a superior hybrid approach [10]. In order to formulate the optimal transaction strategy, resource loads were employed to form clusters, and the Coot search algorithm was used to the data.

The modified Coot search method, based on the Cauchy mutation optimization search approach, was employed for hierarchical resource scheduling in the Internet of Things to deliver the best possible service quality [11]. Degradation in bridges and beams was identified using a method based on a customizable combination of Coot search and artificial neural network. The suggested method employed Coot search to determine the best values for bias and weight to use for training an AINN [12]. Coot Search may be used in tandem with a machine learning system to further refine predictive accuracy. By combining artificial neural networks with the Coot search algorithm, [13] researchers have developed a way for better predicting how much labor would be required to develop software.

New and improved clustering methods are always being developed. The suggested method is based on the widely used K-means clustering method. The method's effectiveness means it's often used for clustering massive amounts of data [14]. Using K-means clustering and the Coot search optimization approach, this research suggests an effective method for segmenting photos of skin cancer based on numerous attributes extracted from the images.

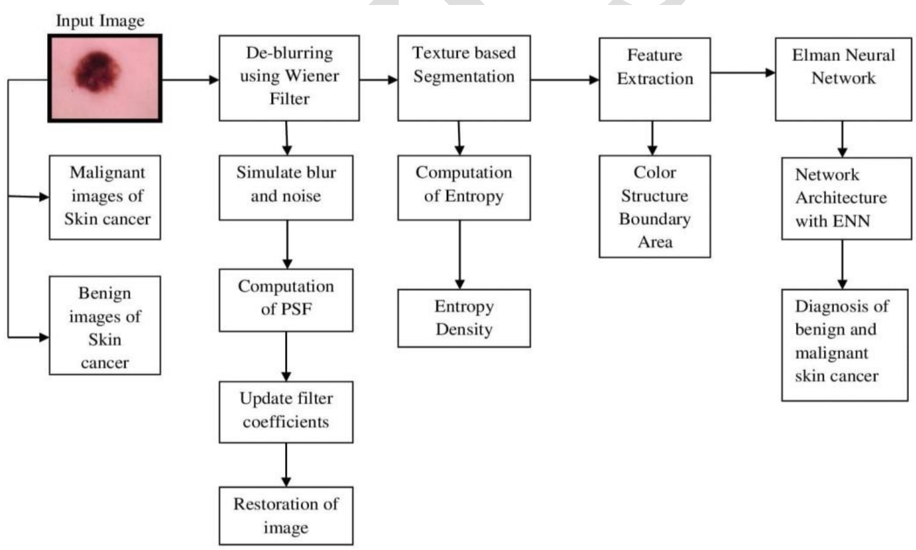

Figure 1: Block diagram of the Proposed segmentation using Enhanced Coot Search Optimization

This part also includes discussion of publicly available skin lesion datasets, ground truth generation, and performance assessment validation. Let's consider the activity of picture segmentation, in which each pixel is labeled as either foreground or background. Figure 2 depicts melanoma and displays it next to a photograph of the same cancer taken from a patient's skin.

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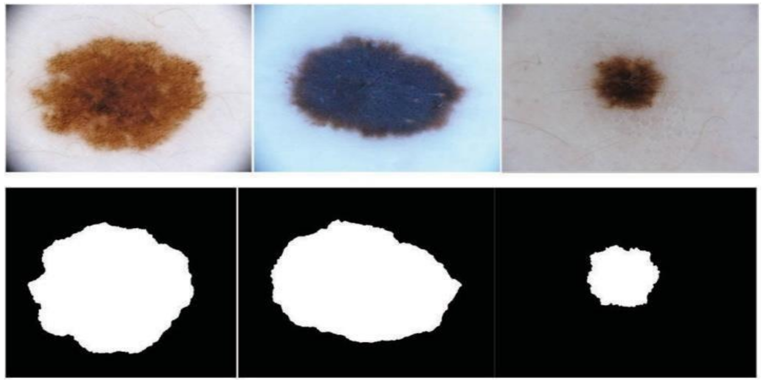

Figure 2: Skin melanoma image of predicted and ground truth

III. PROPOSED ENHANCED COOT SEARCH OPTIMIZATION TECHNIQUE :

Coots, which deposit their eggs inside the nests of other species of birds, provided as inspiration for this strategy. A Coot will look for a nest that has recently been used by another species in order to put its eggs there. Coot eggs hatch before swarm nest eggs to improve the chances that a swarm nest bird would feed young Coots. Coot chicks may imitate a flock of birds in order to get access to food. In order to tackle the search optimization challenge, an approach inspired by the Coot's reproductive activity may be adopted. A conceivable action is represented by one of the eggs in the swarm's nest. Coot eggs, however, represent a fresh start. The objective of this new strategy is to improve upon the worst possible solution discovered in the prior nest by discovering a larger, more feasible alternative.

The experiment just required a single MCC-based goal function, hence each nest would only contain one egg. If the three rules for flawless performance are adhered to, the Coot bird's performance may be idealized. Each Coot has its own nest in which it deposits an egg at a certain time of year. The host bird has a probability of pa [0,1] of spotting an alien egg, and the number of potential swarm shells is similarly set. The host bird may remove the danger by killing the egg, or it can leave the shell where it is and create a new shell elsewhere.

ADDITIVE NOISE :

The thermal noise is the source of the reboot cacophony of capacitors, from which the additive noise develops. You may see a snug noise as an intermittent fluctuation in all automated constructions. An example of additive noise is Gaussian noise. Here is a formula for the additive noise model.

$$f(i,j) = y(i,j) + w(i,j) \qquad \ldots..(1)$$

Where, $1 \leq i \leq M, 1 \leq j \leq N$; M and N. To calculate the amplitude of the earlier images, we use the formula: Let the noise injected at the (i,j)th pixel's coordinates y(i.j) and w(i,j)) be respectively. Noise picture f(i,j). The effectiveness of the technology is measured by the following criteria:

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} = \frac{TP+TN}{P+N} \qquad \ldots..(2)$$

$$Precision = \frac{TP}{TP+FP} \qquad \ldots..(3)$$

$$Recall = \frac{TP}{TP+FN} \qquad \ldots..(4)$$

$$F1\ score = \frac{2}{\frac{1}{Precision}+\frac{1}{Recall}} = \frac{2*(Precision*Recall)}{(Precision+Recall)} \qquad \ldots..(5)$$

$$Error\ Rate = \frac{FP+FN}{TP+TN+FN+FP} = \frac{FP+FN}{P+N} \qquad \ldots.(6)$$

The proposed system is evaluated using the confusion matrix, a method for graphically depicting the performance of supervised classification models. Confusion matrices may be used to evaluate the performance of supervised classification models. There are a number of ways that confusion matrices may be used to illustrate the different facets of a classification process. The accuracy, precision, recall, F1 score, and error rate for the binary classification are calculated using Eqs. (1)-(6).

IV. RESULTS AND DISCUSSION :

The experiment combined synthetic data and real-world information from field observations and saved images. All controls are in place, and a variety of Coot stops are employed. Iterations and Coot search must be changed in the optimization method. More layering improves speed in a few rounds but increases execution time.

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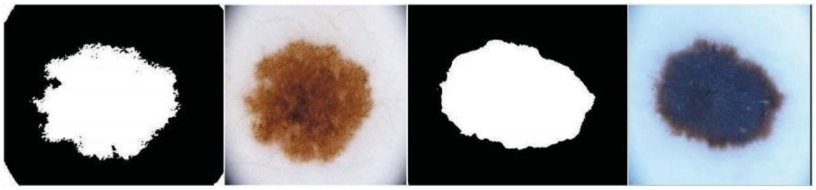

Figure 3: Processed images with more reliable output by enhanced Coot search optimization algorithm

In this chapter, 1,200 pictures were used to evaluate segmentation strategies and approaches. Medical image segmentation performance is measured by specificity, sensitivity, and accuracy. Fig. 3 shows that an upgraded Coot search optimization method gives more consistent image processing outcomes than segmentation. Table 1 highlights recommended techniques' success.

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

Table 1: Performance of the proposed techniques

Enhanced Coot search optimization was assessed using sensitivity, accuracy, specificity, dice, and the Jaccard Similarity Index (JSI). Tabbed. Second Observation: MCC is a loss function that compares predicted and actual pictures. MCC is the best measure for creating classifiers for unevenly distributed classes. The simulation experiment is separated into two sequences; the first sequence confirms the suggested optimization, and the second series exhibits the influence of this optimization on image segmentation index to highlight the advantages of this enhanced Coot search optimization in image segmentation. Figures 1 and 2 indicate that the suggested optimization strategy outperforms the present method.

We test a modified Coot search strategy for skin cancer picture segmentation. Fig. 1 shows that the suggested strategy outperformed alternatives. The recommended strategy achieved a Jaccard Similarity Index of 97.4 for the ISIC trailing set'17. JSI, MCC, and Dice optimization results. Figure 5 compares two ways.

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

Table 2: Different metrics of the proposed technique.

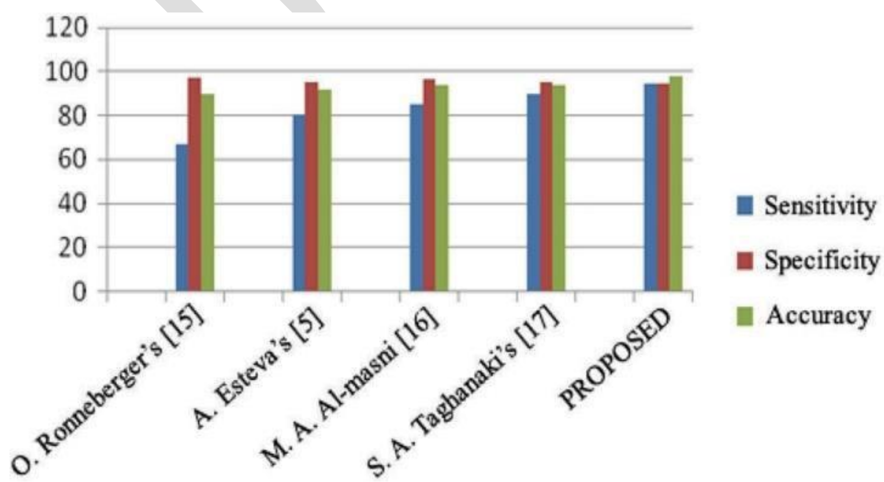

Figure 4: Comparison between proposed with conventional optimization algorithm

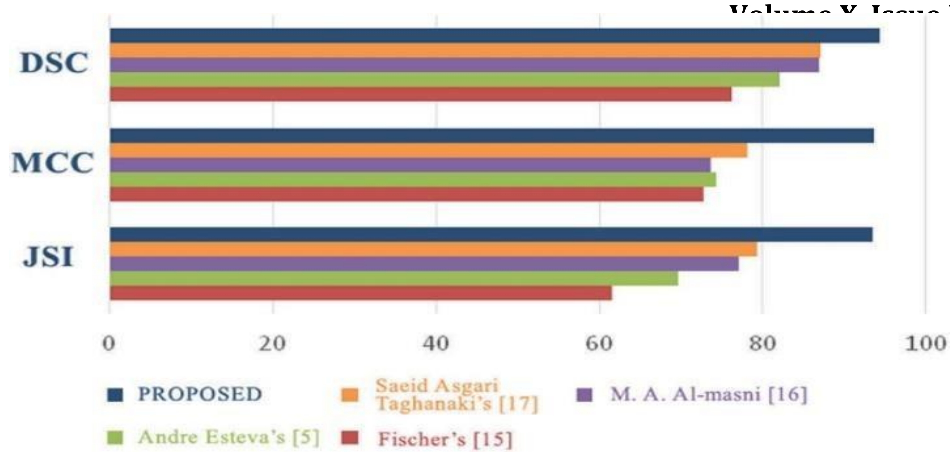

Figure 5: Proposed optimization algorithm with conventional

There is a one-to-one correspondence between the minimum error and the optimum and best parameter settings. The suggested method is effective and has a low rate of error. The suggested improved Coot search optimization outperforms the competition on the vast majority of test images.

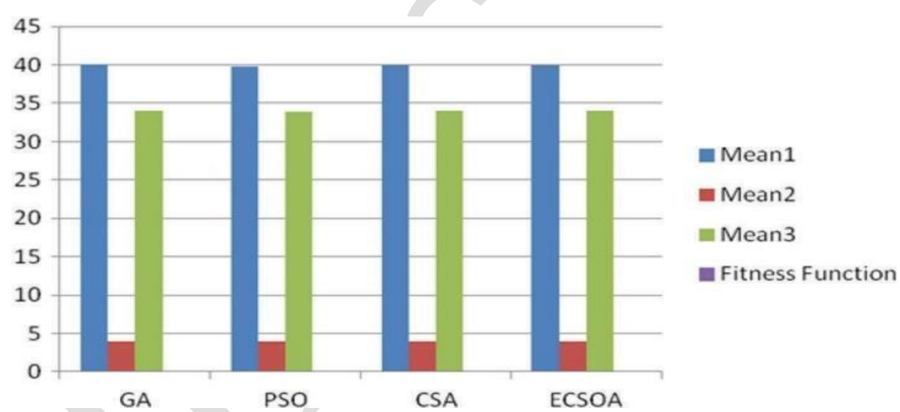

Figure 6: Fitness function of the proposed optimization algorithm

The proposed Enhanced Coot Search Optimization Algorithm (ECSOA) is tested by using it to estimatefactors of the Chen-chaotic method [18]

V. CONCLUSION :

This study uses Enhanced Coot Optimization to diagnose skin cancer accurately. The findings suggest that the proposed strategy is better than competing ones. Using new measures to train an upgraded Coot search optimization-based melanoma image segmentation system leads to greater accuracy with fewer errors. The suggested approach is beneficial for fighting skin cancer, as explained. In future research, this might be used to create new computational intelligence problems and enhance structural efficiency via fusion. The Enhanced Coot Search Optimization technique was applied to the ISIC directory, and the results were compared to those from the Genetic Algorithm, the Artificial Neural Network, the Elephant Herding Optimization method, and the Particle Swarm Optimization method. New study demonstrates that the upgraded algorithm detects skin cancer. Accuracy (99.26%), specificity (99.73%), and sensitivity (99.56%) are increased by this strategy. Simulated results on the same skin image dataset show the suggested strategy outperforms the benchmark techniques with 98.7% accuracy. This work might inspire future efforts to improve model efficiency by merging AI optimization techniques.

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