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RESEARCH ARTICLE

GOA-CRA: CLASSIFICATION AND SEGMENTATION OF SKIN CANCER USING OPTIMIZED CONTEXUAL RESIDUAL AGGREGATION NETWORK

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Abstract – Skin cancer is one of the most prevalent types of cancer, has been rising quickly in recent decades. Smoking, Ultraviolet rays, DNA changes and poor lifestyle choices are the main contributors of skin cancer. This paper presented a novel deep learning-based GOA-CRA method is used for sequentially identifying images in the skin cancer. Initially, the images are gathered from the ISIC dataset and undergo multi-scale retinex pre-processing (MSR) to improve the quality of the images. Then, the pre-processed images are used as input for the Grasshopper Optimization Algorithm (GOA) for removing the hairs overlapping in the area of skin. The segmented hair region with the mask and the pre-processed images are taken as an input to the Contextual Residual Aggregation (CRA) network for recreating the image by inpainting the missing pixels. Finally, the proposed GOA-CRA method is used to classify the skin cancer as melanoma skin cancer or not. The proposed GOA-CRA improves the overall accuracy of 5.42%, 4.21%, 5.06% and 2.93% better than U-Net, Link Net, Dense Net, Res Net respectively.

Keywords *– Multi-Scale Retinex (MSR), Grasshopper Optimization Algorithm (GOA), Contextual Residual Aggregation (CRA) network.*

1. INTRODUCTION

Cells proliferate abnormally in cancer, which cells reproduce in an abandoned way with the capacity to disseminate to additional tissues. The cancer that strikes Skin cancer more often than any other variety affects both men and women. They can be classified as either non-melanoma or melanoma [1]. If cancer is found and treated in a timely manner appropriately. It is essential to identify the lesion as soon as possible in contrast to previously treated instances, the survival rate is comparatively high. An ocular examination for lesion type identification may need a dermoscopic image analysis [2]. utilizing a deep learning network that picks up on the relationship between a benign lesion and a colorful patch could lead to an artificially high prediction accuracy [3]. One common non-invasive medical imaging method is dermoscopy procedure used for early identification and screening for skin cancer. The equipment creates a dermoscopic image of the skin by using a microscope and incident light to the subsurface features of the skin [4]. When compared to an untrained visual inspection, dermoscopy demonstrates a considerable improvement in accuracy. When performed by a dermatologist with extensive experience, the accuracy rises from roughly 50% to 80% [5].

Digital images are used by certain systems to diagnose melanoma, whereas dermoscopic images are used by others. Many features and machine learning methods were employed to diagnose melanoma, however most systems relied on the ABCD criterion [6] for feature extraction and detection (Asymmetry, Border, Color, and Diameter). The framed skin lesion is classified utilizing the ABCD principles and neural network based on the computed features. All of this information could be helpful to the dermatologist as they examine skin lesions in an effort to find melanoma [7]. Cervical cancer diagnosis and various CIN grades are directly correlated with the presence of AW lesions [8]. Only labels are present throughout the network is trained in a manner that uses the skin lesion images poorly monitored manner under the direction of an attention block made up of spatial attention and channel-wise attention [9]. Image inpainting based on partial differential equations (PDE) is used to fix hair-occluded information. Since, nonlinear inpainting with PDEs algorithms do not take texture into account, they are unable to accurately restore lost information [10]. This study's primary goal is to illustrate a revolutionary deep learning technique known as GOA-CRA method is used for Skin Cancer.

- At first, multi-scale retinex (MSR) is used for pre-processing of the collected images. to improve the quality of the images.
- The previously processed images are used as input for the Grasshopper Optimization Algorithm (GOA) for removing the hairs (segments) overlapped on the skin region.

- The segmented hair region with the mask and the pre-processed images are taken as an input to the Contextual Residual Aggregation network for recreating the image by inpainting the missing pixels.
- The proposed method's quantitative analysis is determined by utilizing characteristics such as accuracy, specificity, recall, precision, and F1-score.

The remaining sections of this research were separated into the five categories listed below. Section 2 displays the literature review, and the GOA-CRA approach is the suggested approach in Section 3, results and discussion are presented in Section 4, and the conclusion and recommendations for future work are presented in Section 5.

2. LITERATURE SURVEY

These days, Skin cancer is among the deadliest types of cancer. It appears when any of the three types of skin cells divides erratically. This section offers a concise synopsis of a few of those study papers.

In 2021 Wei Li, et al., [11] proposed a deep learning-based hair removal technique. The hair mask dataset, which was produced using the U-Net model in order to produce reliable results for hair segmentation, is also freely accessible to other researchers so that they can utilize it to advance the field. It is applied to accurately delete particular things. Mesh and watermarks, for instance, are examples of visual content.

In 2022 Ashwini, et al., [12] proposed an algorithm that eliminates hairs without changing the lesion area. In order to identify and eliminate hair from dermoscopy images, an image processing technique is used. The interruption method utilized to replace the hair pixels in the method can be enhanced.

In 2020 Giuliana, et al., [13] presented an HR-SSC based on the combined use of saliency, shape, and colour. Moreover, a technique for quantitative and qualitative analysis of a hair removal process. Furthermore, it quickly locates hair regions using simple techniques.

In 2020 Salian, et al., [14] proposed a model for automatic picture pre-processing that successfully removes problems. A few examples include the vignette effect, hair, and ink markings from dermoscopic images. Otsu thresholding and Canny edge approach are used to detect lesion edges and segment the necessary lesion region. Dermoscopic image noise artifacts can be successfully removed with this technique.

In 2022 Chan, et al., [15] suggested the LinkNet-B7 model, which integrates the essential elements of the current Efficient Net and Link Net models. It demonstrated that in terms of Image segmentation of lesions and noise reduction for skin cancer, the LinkNet-B7 model performed better than previous Link Net models. Training accuracy estimates for lesion segmentation and noise reduction were 95.72% and 97.80%, respectively.

In 2022 Garg, et al., [16] A suggested technique for automatically dividing a region affected by skin lesions is explained. It is used to pinpoint the sites of skin lesions in dermoscopy images. These datasets have a corresponding accuracy value of 91.9%, indicating high accuracy. The proposed method delivers lower mistake rate and higher accuracy when compared to earlier solutions.

In 2021 Javier, et al., [17] proposed digital images are processed using a variety of methods, such as hair removal, lesion shape detection, areal measurement-based lesion categorization, and nipple recognition and marker-based image limitation characterisation utilizing red and white concentration. In order to keep track of the various current typologies, it gives experts a shared software device.

In 2021 Zhao, et al., [18] A GAN-based data augmentation technique was used to create a skin lesion image classification model, which was reported to enhance Performance classification of skin lesions. A neural network for transfer learning was used to build the classification DenseNet201.

In 2021 Fresca, et al., [19] proposed a categorization of melanoma using several deep learning methods. Three alternative neural network approaches—2D CNN, Res Net, and SOM—have also been contrasted in relation to the classification of melanoma. For the Res Net, pre-processing raises accuracy by up to 2.5%.

In 2019 Naronglerdrit, et al., [20] presented an explanation of pigmented skin lesions based on dermatoscopic images Convolutional neural networks are employed in pre-processing images, extracting regions of interest, normalizing images, and classifying images. The classification accuracy of CNN layers is 76.83%.

Because noise removal and segmentation cannot be done well, one of the most serious issues with employing such automated approaches is the imprecision in cancer detection. Then, the developed models do not make any claims to be able to replace human experts because there is still no substitute for the direct interaction between a patient and a doctor.

3. PROPOSED METHOD

In this module, the images of the skin lesions are initially gathered from ISIC datasets and these images are multi-scale retinex (MSR) pre-processed to enhance the images' quality. These previously processed images are used as the input for the Grasshopper Optimization Algorithm (GOA) for removing the hairs (segments) overlapping in the area of skin. The segmented hair region with the mask and pre-processed images are used as an input source for the Contextual Residual Aggregation network for recreating the image by inpainting the missing pixels. Figure 1 shows the proposed methodology.

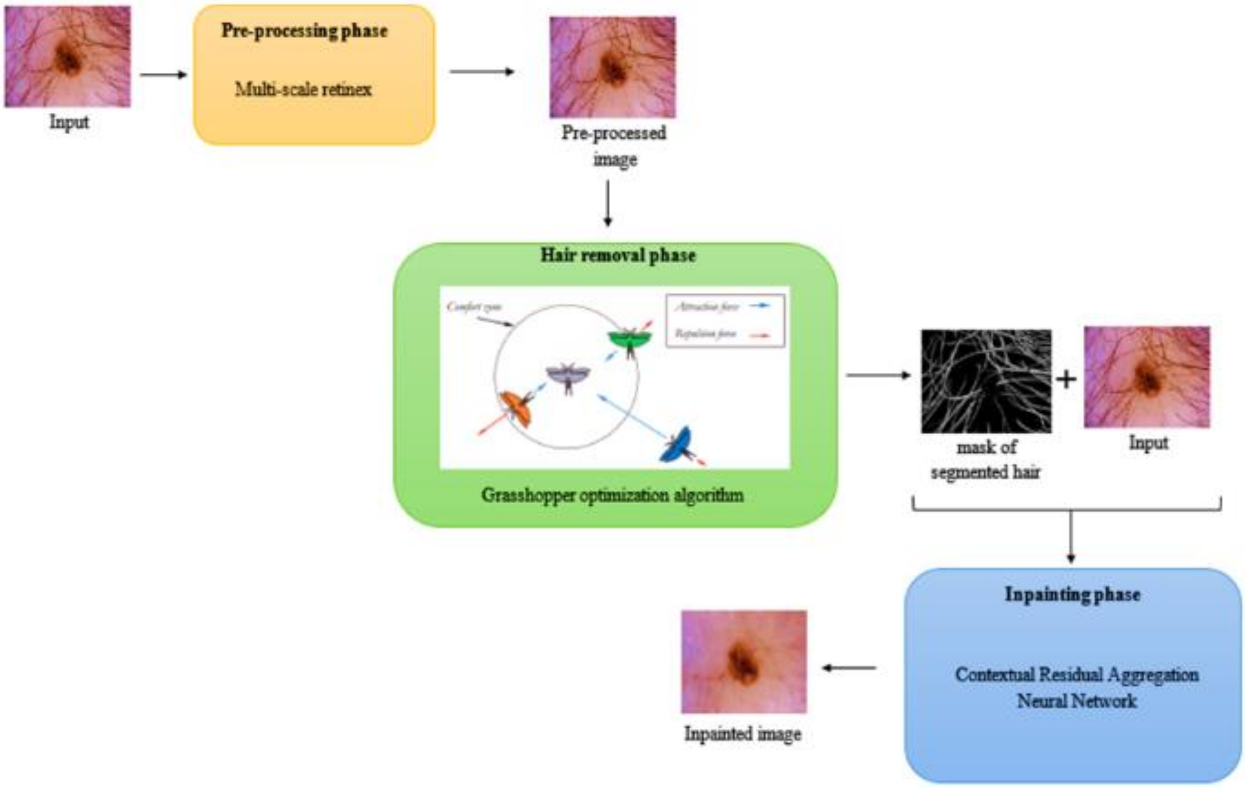

Figure 1. The overall workflow of Proposed model

3.1. Dataset description

The Collaboration for International Skin Imaging produced the images in the dataset (ISIC). The collection consists of 33,126 dermoscopic training photos of over 2,000 individuals with a range of benign and malignant skin diseases. Each image is linked to one of these people using a distinct patient ID. Each image has a resolution of 600 × 450 pixels. The ISIC archive has the largest publicly accessible collection of high-quality dermoscopic images of skin lesions.

3.2. Pre-processing

Multi-Scale Retinex (MSR) is used as a pre-processing tool to enhance the quality of the images in the dataset. The Multi-Scale Retinex (MSR) algorithm filters low-light images by using Gaussian filtering at several scales. That, the average and sum of the filtering results on various scales, which can remember the high fidelity of the image, reduce the dynamic range of the image, and also accomplish colour enhancement and colour consistency. This algorithm is more adept at recovering details and maintaining colour's ability. The regulation phrase is written as, Equation (1).

$$R_{MSR_i}(y,z) = \sum_l^L W_l \, R_{SSR_i} \quad (1)$$

Where, l is the number of scale parameters, W_k is the weight of each scale. The multi-scale Retinex method provides improved robustness and a decent recovery impact on grayscale photos. However, during processing, the noise in the image could be magnified, resulting in colour distortion and an inability to reveal the object is true. To correct the colour distortion brought on by the contrast enhancing of the local area of the picture defect, colour restoration and colour balance are done. Equation (2).

$$M_i' = M_i(y,z) \div \sum_{i=1}^{k} M_i\,(y,z) \quad (2)$$

Where, $M_i(y,z)$ represents the I channel, the colour restoration factor $C_i(y,z)$ is used to change the colour contrast between the three channels. Equation (3).

$$C_i(y,z) = f[M_i'(y,z)] = \beta\big[\log(\alpha\, M_i(y,z))\big] - \log(\textstyle\sum_i^k M_i\,(y,z)) \quad (3)$$

Where, β is the gain constant and α is the controlled non-linear strength. The expression of the multi-scale retinex enhanced algorithm is follow as, Equation (4).

$$R_{MSRCR_i}(y,z) = M_i(y,z) R_{MCR_i}(y,z) = \log Q_i\,(y,z) - \log[\,F(Y,Z) * Q_i(y,z)] \quad (4)$$

The three-color channels of the original image are proportionally altered by the MSRCR algorithm using the colour restoration factor C.

3.3. Grasshopper optimization algorithm (GOA)

The GOA algorithm, a recently created and fascinating swarm intelligence system, mimics the swarming and natural foraging of grasshopper's behaviours. These insects are well-known for being harmful pests that have an adverse effect on agricultural productivity and agriculture. There are two phases in their life cycle: nymphaeum and maturity. The nymph phase is typified by slow, steady motions and small steps, whereas the adult phase is distinguished by long, swift movements. Adult and nymphal movements are used to depict the phases of GOA, which are increase and modification. The behaviour of grasshoppers is mathematically showed as, Equation (5).

$$P_j = S_j + G_j + A_j \quad (5)$$

Where P_j shows the j^{th} grasshopper position, S_j is the social communication between grasshopper, G_j represents the gravity force on the j^{th} grasshoppers and A_j is the breeze convection. Equation (6) can be rewritten as,

$$P_j = n_1 S_j + n_2 G_j + n_3 A_j \tag{6}$$

Where n_1, n_2 and n_3 are the numbers in the range. The social communication S_j is the following well defined, Equation (7).

$$S_j = \sum_{\substack{i=1 \\ i \neq 1}}^{N} S\left(M_{ij}\right) \widehat{M_{ij}} \tag{7}$$

The gravity force G_j is given by, Equation (8).

$$G_j = g_{\widehat{e_g}} \tag{8}$$

Where g indicates the gravitational constant as well as $\widehat{e_g}$ indicates a unit vector near the center of the earth. The breeze convection B_j is given by the Equation (9).

$$B_j = V_{\widehat{e_w}} \tag{9}$$

Where V stands for the drift constant, and $\widehat{e_w}$ in the wind path, is a unit vector. After that, changing the values of S, G and A can arrive at the following Equation. (10).

$$P_j = \sum_{\substack{i=1 \\ i \neq 1}}^{N} K\left(\left|P_i - P_j\right|\right) \frac{P_{j-P_i}}{M_{ij}} - g_{\widehat{e_g}} + V_{\widehat{e_w}} \tag{10}$$

D_1 and D_2 are treated as a single parameter for explanation, and expressed as follows: Equation (11).

$$D = D_{max} - t\,\frac{D_{max}}{t_{max}} - \frac{D_{min}}{t_{max}} \tag{11}$$

Where D_{max} and D_{min} indicate the highest and lowest values of C, correspondingly. t is the momentary iteration and t_{max} is the most iterations possible.

The positions of other grasshoppers in the swarm as well as the grasshopper's current position and global best position are taken into consideration while updating a grasshopper's position. This makes it easier for GOA to stay out of local optima. Algorithm .1 contains the Grasshopper Optimization Algorithm pseudo-code.

Algorithm 1 The Pseudo-code of the Grasshopper Optimization Algorithm

1. Generate the initial residents of Grasshoppers P_j(j = 1, 2....n) randomly.
2. Initialize D_{min},D_{max} and maximum number of iterations t_{max}
3. Evaluate the fitness $f_{(P_j)}$ of each grasshopper P_j
4. T = the best solution
5. While ($t < t_{max}$) do
6. Update $D_1$and D_2 using equation (11)
7. for j=1 to N (all N grasshoppers in the population) do
8. Normalize the range of grasshopper distances [1,4]
9. Equation can be used to modify the grasshopper present location (10)
10. If the grasshopper leaves the designated area, bring it back
11. end for
12. Update T if there is a well solution
13. $t = t + 1$
14. end while
15. Return the top solution T

3.4. Contextual Residual Aggregation neural network

The Contextual Residual Aggregation (CRA) method extracts features and residuals from contexts. Consider contextual attention in particular by determining the area affinity between patches inside and outside missing sections when computing attention scores. As a result, residuals and external components that are pertinent to the context may be added to the hole. Our system two primary parts are the modules for attention transfer and attention computing.

3.4.1. Attention Computing Module (ACM)

Regional attraction from a high-level feature map is used to determine the attention scores. P is divided interested in patches by ACM, which then determines the cosine similarity of patches both inside and outside of sections that are missing: Equation (12).

$$C_{j,k} = \langle \frac{M_j}{\left\|M_j\right\|}, \frac{M_k}{\left\|M_k\right\|} \rangle \tag{12}$$

where M_j is the j^{th} patch taken from the outside of the M mask, $M_k$is the k^{th}patch taken from M inside of the mask. SoftMax is then useful to the comparison scores once the attention scores for each patch have been established. Equation (13).

$$S_{j,k} = \frac{e^{c_{j,k}}}{\sum_{j=1}^{N} e^{c_{j,k}}} \tag{13}$$

N represents the quantity of patches that are present external the gap.

3.4.2. Attention Transfer Module (ATM)

After getting M consideration ratings, lower-level feature maps with gaps (M^l) that relate to such gaps could be filled with attention-weighted contextual patches. Equation (14).

$$M_k^l = \sum_{j=1}^{N} S_{j,k}\, M_j^l \tag{14}$$

where $l \in 1,2,3$ is the layer number and $M_j^l$is the j^{th}patch taken from p^loutside masked regions, and $M_k^l$is the k^{th}patch to be occupied from the private masked regions. N shows the number of contextual patches.

Computing residuals for the entire region is the aim of residual aggregation in order to reconstruct the precise features of the missing parts. It is possible to calculate the weighted contextual residuals to obtain the residuals for the missing contents produced by earlier phases. Equation (15).

$$R_k = \sum_{j=1}^{N} S_{j,k}\, R_j \tag{15}$$

where N is the remaining image and R_j is the j^{th} patch taken external to the mask contextual residual image, and R_k is k^{th} patch to be occupied from the inside the mask. The filled residuals are made to match the surrounding areas by carefully choosing patch sizes that completely cover all pixels without any overlap.

4. RESULTS AND DISCUSSION

In this section, the proposed GOA-CRA method is used for Skin Cancer. It is assessed utilizing a range of measurements, such as recall, specificity, accuracy, and precision. The model's efficacy is evaluated using multiple angles. The Figure.2 shows the hair removal images.

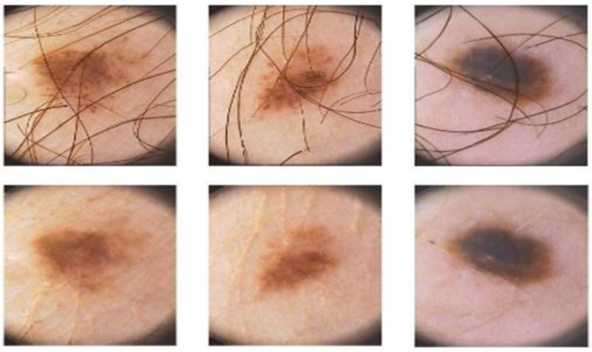

Figure 2. Hair removal images

The Figure 2 shows images of hair removal utilizing the inpainting technique of the segmentation region of the skin cancer.

4.1. Performance Analysis

The following statistical metrics are used to assess the effectiveness of the classification method such as specificity, recall, accuracy, precision, and F1 score. Equation (16), (17), (18), (19) and (20).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (16)$$

$$Precision = \frac{TP}{TP+FP} \quad (17)$$

$$Recall = \frac{TP}{TP+TN} \quad (18)$$

$$Specificity = \frac{TN}{TN+FP} \quad (19)$$

$$F1\ score = 2\left(\frac{Precision*Recall}{Precision+Recall}\right) \quad (20)$$

Where TP, FP stands for the sample true and false, and TN, FN for the true and false negatives.

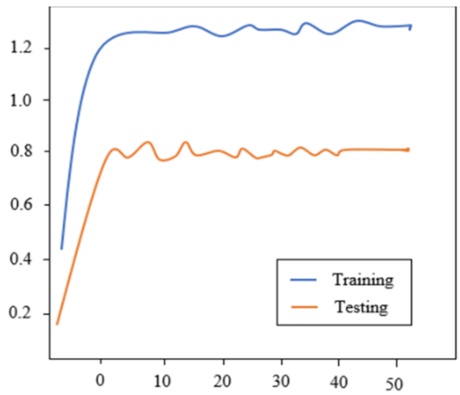

Figure 3. Training and Testing accuracy curve of GOA-CRA

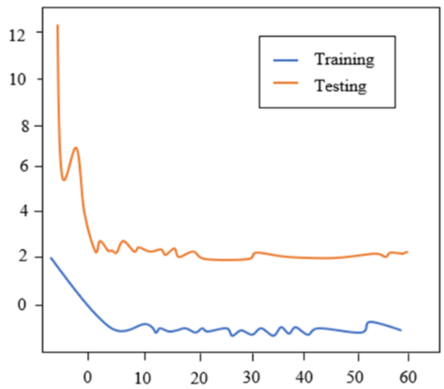

Figure 4. Training and Testing loss curve of GOA-CRA

If the quantity of epochs is expanded, accuracy of the approach increases as shown in Figure 3 shows accuracy curve, where the axes representing accuracy and epochs are opposed. The loss curve in relation to epoch Figure 4 shows the quantity of epochs rises, the model's loss diminishes. Thus, the anticipated accuracy of 96.68% for the proposed GOA-CRA method are highly reliable for public available dataset.

4.2. Comparative analysis

This section provides a comparison study comparing the proposed model with the existing deep learning models. Accuracy, recall, precision, specificity, and F1 score were utilized to compare the performance of the existing methodologies to show that the proposed strategy yields better results. The deep learning models' total performance is compared with the recommended method in Table.1. U-Net, LinkNet, Dense Net and Res Net.

Table 1. Comparative analysis of existing deep learning networks with the proposed model

Networks	Accuracy	Specificity	Precision	Recall	F1 Score
U-Net	93.21	90.47	86.34	85.86	88.89
Link Net	94.41	92.56	89.27	86.75	88.75
Dense Net	93.57	91.24	88.45	85.28	90.24
Res Net	95.67	93.64	87.47	83.78	92.87
GOA-CRA	98.56	96.34	95.37	93.64	91.68

The proposed GOA-CRA improves the overall specificity of 6.09%, 3.92%, 5.29% and 2.8% better than U-Net, Link Net, Dense Net, Res Net respectively. The proposed GOA-CRA raises the overall accuracy of 9.46%, 6.39%, 7.25% and 8.28% better than U-Net, Link Net, Dense Net, Res Net respectively. The overall recall of is improved by the suggested GOA-CRA 8.3%, 7.35%, 8.92% and 10.5% better than U-Net, Link Net, Dense Net, Res Net respectively. The proposed GOA-CRA improves the overall F1 score of 3.04%, 3.19%, 1.57% and 1.11% better than U-Net, Link Net, Dense Net, Res Net respectively. The proposed GOA-CRA improves the overall accuracy of 5.42%, 4.21%, 5.06% and 2.93% better than U-Net, Link Net, Dense Net, Res Net respectively. Based on the unique network parameters displayed in Figure 5, the suggested network efficiency is assessed.

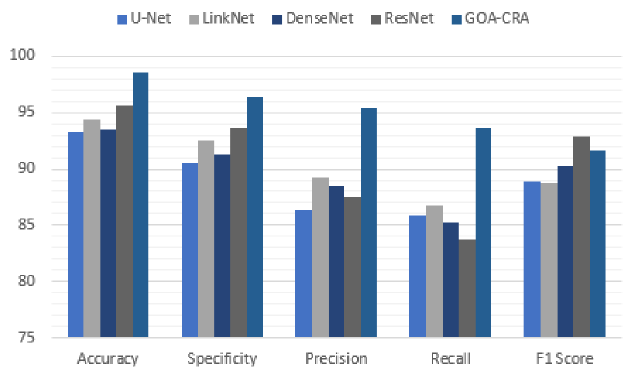

Figure 5. Training and Testing loss curve of GOA-CRA

Table 2. Comparison of existing versus proposed GOA-CRA model

Authors	Methods	Accuracy
Chan [15]	Deep learning	95.72%
Naronglerdrit [20]	CNN	76.83%
Garg [16]	Deep learning	91.9%
Proposed	GOA-CRA	98.56%

From table.2 the proposed GOA-CRA enhances overall accuracy more than 2.88%, 2.04%, 6.75% Chan, Naronglerdrit and Garg. Table.2 evaluates and contrasts the various techniques' algorithms. It is evident from the table that the GOA-CRA classifier has an average accuracy value of 98.56%, it gives higher accuracy values.

5. CONCLUSION

This study proposed the GOA-CRA approach, which uses deep learning to progressively detect images of skin cancer. Initially, the images are taken from the ISIC dataset and undergo pre-processing using multi-scale retinex (MSR) to enhancing the images quality. Then, the input is the pre-processed images to the Grasshopper Optimization Algorithm (GOA) for removing the hairs overlapping in the area of skin. The segmented hair region with the mask and pre-processed images are used as an input source for the Contextual Residual Aggregation (CRA) network for recreating the image by inpainting the missing pixels. Finally, the proposed GOA-CRA method is used to classify the melanoma as skin cancer skin cancer or not. The proposed GOA-CRA improves the overall accuracy of 5.42%, 4.21%, 5.06% and 2.93% better than U-Net, Link Net, Dense Net, Res Net respectively. In future work, this technique can also be used to classify various skin conditions and malignancies.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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